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Computing Paradigms for Mental Health
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Foreword

This volume contains the proceedings of the 2nd International Workshop on Computing Paradigms for Mental Health - MindCare 2012.

There is an increasing number of research initiatives that utilize modern technology in order to support patients in maintaining or regaining a healthy mental state. Advanced technological solutions have been exploited for treating depression, anxiety disorders, and for coping with stress. This is of utmost importance to provide people with higher quality of life and also to shift a part of monitoring tasks from therapists and caregivers to unobtrusive technological systems. Efforts have started with Internet-based self-help therapies, but recently systems make an increasing use of ambient intelligence, pervasive computing, smart phones and sensor systems. Their common goal is to provide effective solutions for maintaining and improving mental health.

This workshop is held for the second year (following the first MindCare workshop organized as part of Pervasive Health Conference, Dublin, 2011) aiming to bring together researchers and practitioners from technological fields (such as computer science, artificial intelligence, and information systems) but also from medical and psychological disciplines that share the same interest of strengthening or maintaining mental health by exploiting pervasive computing solutions. The goal of MindCare workshop is to exchange ideas aiming to support synergy of the two domains for further progress in this field.

The program of the workshop encompasses a total of 13 papers: 9 full papers, 2 short papers, and 2 posters, covering a range of topics and disciplines in the theme described above. We wish to thank all the authors for their admirable scientific works which reflect both the cutting edge technologies and the most prominent psychological approaches thus contributing to innovative ways of employing technology in favor of mental health. In order to establish such a high quality program, the papers underwent a rigorous reviewing process by a program committee that consisted of world renowned experts in the related fields. We are grateful for their efforts and their flexibility to work in a short time frame. We appreciate their great scientific level, professionalism, and above all their unrequested but most appreciated friendliness.
Last but not least, we would like to send special thanks to all members of the INSTICC, especially Vera Coelho from the conference secretariat, whose cooperation made possible the success of this workshop. We hope that our workshop will afford a brainstorming platform to discuss very exiting themes of computing paradigms for mental health and moreover that it will leave nice memories of this event in the context of the wonderful Vilamoura (Algarve, Portugal).

February 2012,

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# Table of Contents

Foreword ................................................................. iii

Workshop Chairs ....................................................... v

Program Committee ................................................... v

## Full Papers

The Current State of EMA and ESM Study Design in Mood Disorders Research: A Comprehensive Summary and Analysis ................................................................. 3  
*Meredith L. Wallace, Molly H. Carter and Satish Iyengar*

Managing Data in Help4Mood .......................................... 17  
*Maria K. Wolters, Juan Martínez-Miranda, Helen F. Hastie and Colin Matheson*

An Event-driven Psychophysiological Assessment for Health Care ................................................................. 25  
*Silvia Serino, Pietro Cipresso, Gennaro Tartarisco, Giovanni Baldus, Daniele Corda, Giovanni Pioggia, Andrea Gaggioli and Giuseppe Riva*

Study and Evaluation of Palmar Blood Volume Pulse for Heart Rate Monitoring in a Multimodal Framework .............. 35  
*Hugo Silva, Joana Sousa and Hugo Gamboa*

Localized Electroencephalography Sensor and Detection of Evoked Potentials ................................................................. 41  
*Tiago Araújo, Neuza Nunes, Carla Quintão and Hugo Gamboa*

A Mobile System for Treatment of Depression ...................... 47  
*Pepijn van de Ven, Mário Ricardo Henriques, Mark Hoogendoorn, Michel Klein, Elaine McGovern, John Nelson, Hugo Silva and Eric Tousset*

Applicability of Multi-modal Electrophysiological Data Acquisition and Processing to Emotion Recognition ............ 59  
*Filipe Canento, Hugo Silva and Ana Fred*
Towards Emotion Related Feature Extraction based on Generalized Source-Independent Event Detection ............ 71
Rui Santos, Joana Sousa, Carlos J. Marques, Hugo Gamboa and Hugo Silva

Brain Computer Interface and Eye-tracking for Neuropsychological Assessment of Executive Functions: A Pilot Study ............................................. 79
Pietro Cipresso, Paolo Meriggi, Laura Carelli, Federica Solca, Barbara Poletti, Dorothee Lule, Albert C. Ludolph, Vincenzo Silani and Giuseppe Riva

Short Papers

Real Time Dose-Response Assessment Tool Applicable in Exercise Therapy ................................................. 91
Joao Santinha, Joana Sousa, Hugo Gamboa and Hugo Silva

Sedentary Work Style and Heart Rate Variability: A Short Term Analysis ...................................................... 96
Aleksandar Matic, Pietro Cipresso, Venet Osmani, Silvia Serino, Andrei Popleteev, Andrea Gaggioli, Oscar Mayora and Giuseppe Riva

Posters

The Role of Smartphones as an Assistive Aid in Mental Health 105
John J. Guiry, Lisanne Warmerdam, Patrick van der Hilst, Heleen Riper, Pepijn van de Ven and John Nelson

Wireless User-computer Interface Platform for Mental Health Improvement through Social Inclusion ............... 114
Ana Londral, Neuza Nunes, Hugo Silva and Luis Azevedo

Author Index ................................................................. 119
The Current State of EMA and ESM Study Design in Mood Disorders Research: A Comprehensive Summary and Analysis

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Abstract. Ecological momentary assessment (EMA) and experience sampling methods (ESM) are becoming increasingly prevalent in mood disorders research due to their potential for capturing underlying dynamic mood processes that cannot be observed through traditional clinical visits. There have also been recent statistical developments that allow for innovative EMA/ESM-related research questions to be answered. However, even the most sophisticated statistical methods cannot glean accurate representations of underlying mood processes when the data are sampled inappropriately. Unfortunately, there are few resources investigators can use to make informed decisions about EMA/ESM study design. Thus, we perform a comprehensive summary of current EMA/ESM study design methods used in mood disorders research, explore the rationale behind study design decisions, and investigate the relationship between compliance and various study design features. Results from these analyses are used to suggest improvements for designing and reporting future EMA/ESM studies.

1 Introduction

Clinical researchers and psychologists base their patient evaluations and diagnoses largely on retrospective self-report of experiences. However, this type of information can be biased by current mood state and day-to-day and even hour-to-hour variability in experiences and symptoms [1–3]. Because mood disorders such as unipolar depression (DEP), bipolar spectrum disorders (BD) and disorders of mood dysregulation such as borderline personality disorder (BPD) are defined by changes in mood state and mood variability [4], recall bias may be a particularly salient problem in this area. As a result, information conventionally collected in clinical settings can fail to capture the continuous, dynamic processes underlying mood disorders, thereby hindering researchers’ abilities to characterize disease processes that may lead to specific and effective treatments. Furthermore, information collected in a clinical setting may not provide a sufficiently detailed understanding of a patient’s course of illness, potentially contributing to the high rate of misdiagnosis across mood disorders [5–9].

Ecological momentary assessment (EMA) [1, 2] and experience sampling methodology (ESM) [10, 11] are data collection methods that allow clinical researchers and
psychologists to capture a patient’s course of illness with greater frequency and sensitivity through the use of hand-held technological devices. When studying disorders of mood and mood dysregulation (henceforth, we will refer to them collectively as “mood disorders”), EMA and ESM are particularly useful for capturing both the mean and instability of mood [12]. EMA accomplishes this through the use of portable technological devices, such as hand-held computers and cellular phones, to capture self-reported measurements as they occur naturally in real time. In this way, EMA allows investigators to control timing precisely and track compliance [13]. EMA can also be used to capture behavioral and physiological data; however, the focus herein is on self-reported EMA. Like EMA, ESM also uses technological devices to capture data in real time; however, ESM typically uses a digital watch or pager to prompt participants to record their experiences in a paper-and-pencil diary [10, 11]. In this manuscript we focus on self-reported EMA and ESM, referring to them collectively as EMA.

As with any type of data collection method, EMA study design is of utmost importance. In general, there is consensus that random sampling should be employed and that the sampling frequency should match the temporal dynamics of the process of interest [11, 14, 15]. However, there is a paucity of formal empirical evidence regarding EMA study design methodology and rationale, particularly as it relates to the capture of underlying mood processes. One important breakthrough study in this area was performed by Ebner-Priemer and Sawitzki [14], who showed that a sampling interval of less than 30 minutes could optimally capture underlying dynamic processes in BPD, while intervals greater than 30 minutes could not. However, few research studies (especially those in clinical populations) are expected to support sampling intervals of less than 30 minutes due to concerns of participant burden [14].

The field of mental health, and mood disorders in particular, could benefit from the development of a more standardized set of EMA study design methods so that future researchers can make more informed decisions (e.g., consider the stringency with which clinical trials are designed and reported). As an initial step towards this end goal we present a comprehensive summary and analysis of study design features in mood disorders research, focusing on three specific aims:

1. Summarize the current state of EMA study design
2. Explore factors that researchers have considered when making EMA study design decisions
3. Investigate the relationships among study design features and compliance

Results from these three aims are used to suggest ways that EMA investigators could improve on the design and reporting of their studies.

2 Methods

To empirically describe and evaluate EMA study design in mood disorders research it is necessary to use the actual studies, rather than manuscripts generated from these studies, as the units of analysis. This presents a challenge because manuscripts and studies are not related on a one-to-one basis. That is, multiple manuscripts may stem
from one study or, alternatively, one manuscript may analyze data from multiple studies. We employed the following strategy to develop a data base with the study as the unit of analysis. First, we set inclusion and exclusion criteria for the types of studies that would be considered. Second, we used literature search engines to locate manuscripts that described studies meeting the inclusion and exclusion criteria. Third, we compared manuscripts to determine which stemmed from the same studies and which merged data from multiple studies. We contacted corresponding authors when questions or ambiguities arose. Fourth, we used the manuscripts and additional resources from authors (e.g., EMA study questionnaires and protocols) to enter the study-level data. We describe these steps in further detail below.

2.1 Study Inclusion and Exclusion Criteria

Study inclusion criteria were: 1) at least one subset of participants was clinically diagnosed with a mood disorder (BPD, DEP, or BD) and 2) an electronic ambulatory device, including but not limited to beepers, hand-held computers, cellular phones, and wrist-watches, was used to capture self-report data at multiple time points. Self-report EMA may be either event-based (participant enters data before and/or after a prespecified event occurs), prompt-based (participant enters data when prompted by a technological device), or a combination of the two; however, the focus herein lies specifically in prompt-based EMA because it relies heavily on *a priori* decisions regarding sampling frequency. Thus, we excluded studies that did not include some type of prompt-based EMA. We also excluded EMA case studies because of our specific focus on the use of EMA to answer empirically-based research questions.

2.2 Search Strategy

We first aimed to identify all manuscripts arising from appropriate EMA studies by performing literature searches in PubMed, PsycINFO, and ProQuest (Dissertations and Theses) with the following keywords: *ambulatory assessment*, *ecological momentary assessment*, *experience sampling method*, *electronic diary*, *computer-assisted diary*, *electronic momentary assessment*, *ecological validity*, and *hand-held computer*. After removing duplicate references, we performed a computerized search of the resulting abstracts to narrow them down to those based on populations with mood disorders. Abstract search terms included *depression*, *depressive disorder*, *borderline*, *bipolar*, *mood disorder*, and *affective disorder*. All remaining abstracts were manually screened to further identify those which stemmed from studies that fit within our inclusion and exclusion criteria. The full text of each of the remaining manuscripts was then used to determine whether the study from which it arose would be considered appropriate for inclusion. Once the final subset of manuscripts was identified, the full text was again examined to determine which manuscripts stemmed from the same EMA study and which combined data from multiple EMA studies.

Figure 1 summarizes the search strategy and manuscript selection process. Table 1 lists the final 27 studies selected through this selection process. Because each of these 27 studies could generate multiple manuscripts, we refer to them in Table 1 by the by the
first author and year of the earliest manuscript identified through the literature search. Other related manuscripts are displayed in the “References” column.

2.3 Data Collection

The manuscripts referenced in Table 1 and additional author resources (e.g., EMA questionnaires and study protocols) were used to develop a database that included: 1) study design information, such as the sample size, duration of study, number prompts per day, number of questions per prompt, and the type of EMA device used, 2) demographic information for the samples used in each study, such as age and gender, 3) diagnostic groups studied, 4) justification of sampling design, and 5) compliance information, such as missing data and dropout percentages. When collecting the data from studies that also included a randomized trial component, we only included EMA data from the baseline weeks. This was done in an attempt to standardize the studies and also because treatment assignment may impact measures of compliance.

2.4 Data Analysis

We used descriptive statistics to summarize the 27 EMA studies with respect to sampling design and demographic and clinical characteristics of the participants (Aim 1). To explore investigators’ rationale behind EMA study design selection (Aim 2) we first summarized the study design justifications provided in the associated manuscripts. Because only eight of the 27 studies actually provided this explicit justification (see Table 1), we used our observed data to further explore the rationale behind current EMA study design. This involved quantifying observed relationships among study design parameters (the number of days of EMA study, the number of prompts per day, and the number
Table 1. First author and year of the earliest manuscript identified with each study. All other related manuscripts are cited in the “References” column.

<table>
<thead>
<tr>
<th>First Author (Year)</th>
<th>References</th>
<th>First Author (Year)</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Glaser, J.P. (2008)</td>
<td>[41,42]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Reported rationale for study design

of questions per prompt) using scatter plots and Pearson product moment correlations. Because the distributions of these variables were highly skewed, we used the natural log transformation for all plots and calculations.

To investigate the relationships among study design features and compliance (Aim 3), we first needed to select a single compliance measure. After comparing various possibilities, we chose the percentage of unanswered prompts because it was frequently reported and also easily constructed from other types of reported compliance statistics. We calculated the percentage of unanswered prompts ($P$) as the number of unanswered prompts divided by the total number of possible prompts times 100. Some studies reported only $P_1$, the percentage of unanswered prompts based on a subset of $N_1 < N$ compliant participants with fewer than $X\%$ unanswered prompts. Hence, the percentage of unanswered prompts for the $N_2 = N - N_1$ participants, $P_2$, was unknown except for the fact that $X\% < P_2 \leq 100\%$. Because $N_2$ tended to be very small (e.g., one or two participants), we assumed that $P_2$ followed a uniform distribution and let $P_2 = .5 \times (100 - X)$. $P$ was then calculated as a weighted average of the percentages of unanswered prompts prompts for the $N_1$ compliant and $N_2$ noncompliant participants, that is, $P = \frac{1}{N} (P_1 N_1 + P_2 N_2)$.

After calculating the percentage of unanswered prompts ($P$), we used scatter plots and Pearson product moment correlation coefficients to explore its relationships with various study design features. Specifically, we focused on the number of questions per prompt, the number of prompts per day, and the number of days of the EMA study. Because these study design features need to be carefully balanced to reduce participant burden, we also focused on their interactions: questions per day (questions per prompt $\times$ prompts per day), prompts per study (prompts per day $\times$ days of study), and questions per study (questions per prompt $\times$ prompts per day $\times$ days of study). Due to the highly skewed distributions of all variables involved, we used the natural logs of these variables in our plots and calculations.
3 Results

3.1 Aim 1: Summarize the Current State of EMA Research

Study design and demographic characteristics of the of the 27 EMA studies are summarized in Table 2. In general, study participants tended to be female and Caucasian, with a median age of 31. The study design characteristics selected by investigators (e.g., the number of questions per prompts, number of prompts per day, and number of days of EMA) varied widely across the 27 studies, as shown by the minimum and maximum scores in Table 2.

In addition to selecting the number of questions, prompts, and days of EMA, investigators must also choose a method for distributing these prompts throughout the study period. Within each day, the most common method for allocating prompts was random blocking (e.g., divide waking hours into 6 blocks and randomly sample once during each block); this method was used in 10 of the 27 studies (37%). Periodic sampling with random error (e.g., sample every hour plus or minus a randomly drawn number of minutes from a prespecified normal distribution) was the second most common method for allocating EMA prompts, seen in 8 studies (29.6%). Only five (18.5%) studies used random sampling (e.g., randomly select 10 times between the hours of 8:00 am to 10:00 pm) and only four (14.8%) studies used fixed time sampling (e.g., sample every hour on the hour).

The method for distributing prompts throughout the study period must also take into consideration the fact that participants are not able to answer prompts during sleep. Out of 26 studies for which this information was known, 70.1% (n=19) set a fixed daily interval during which prompts could occur (e.g., between the hours of 8:00 am to 10:00 pm for all participants). Other studies set a priori individualized sleep intervals tailored to each participant’s needs (19.2%, n=5) or requested that the participant turn off the device during sleep (7.7%, n=2).

Investigators must also determine which technological device (e.g., hand-held computer, cellular phone, pager) to use to deliver each prompt. A hand-held computer, such as a “personal digital assistant” (PDA) was used in 59.3% of studies (n = 16). The next most frequently used technological device (37%, n=10) was a pager or wristwatch along with a paper-and-pencil diary. One study (3.7%) used a cellular phone.

Patients with depression (major depression, minor depression, or dysthymia) were included in eighteen studies (66.7%), patients with bipolar spectrum disorders were included in five studies (18.5%), and patients with borderline personality disorder were included in 9 (33.3%) studies. Other non-affective clinical groups (e.g., schizophrenia, panic disorder) were included in four (14.8%) studies. Healthy controls were used as a comparison group in 16 (59.3%) of the studies.

3.2 Aim 2: Explore Investigators’ Rationale behind EMA Study Design Decisions

We first searched for explicit study design justifications in the manuscripts stemming from each study. Overall, we identified some type of sampling justification in eight of the 27 studies (29.64%). Two of these eight studies discussed rationale for the days on
Table 2. Demographic, clinical, and study design characteristics from 27 studies.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>N Observed</th>
<th>Mean (SD)</th>
<th>Median (Min, Max)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Age</td>
<td>26</td>
<td>31.69 (11.14)</td>
<td>31.04 (10.01, 62.45)</td>
</tr>
<tr>
<td>% Female</td>
<td>24</td>
<td>79.08 (16.54)</td>
<td>78.10 (50, 100)</td>
</tr>
<tr>
<td>% Caucasian</td>
<td>12</td>
<td>65.61 (23.72)</td>
<td>64.70 (33.33, 100)</td>
</tr>
<tr>
<td>% Higher Education</td>
<td>17*</td>
<td>56.81 (33.39)</td>
<td>64.50 (0, 100)</td>
</tr>
<tr>
<td>% Married or Cohabitating</td>
<td>15*</td>
<td>35.34 (32.00)</td>
<td>26.37 (0, 88.24)</td>
</tr>
<tr>
<td>% Employed (Full- or Part-Time)</td>
<td>12*</td>
<td>37.40 (17.77)</td>
<td>43.24 (0, 55.73)</td>
</tr>
<tr>
<td>Study Design</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample Size at Study Entry</td>
<td>27</td>
<td>78.67 (43.90)</td>
<td>73 (10, 164)</td>
</tr>
<tr>
<td>Days of EMA/ESM</td>
<td>27</td>
<td>9.33 (9.52)</td>
<td>6.79 (1, 42)</td>
</tr>
<tr>
<td>Prompts per Day</td>
<td>27</td>
<td>9.16 (9.63)</td>
<td>8 (1, 54)</td>
</tr>
<tr>
<td>Questions per Prompt</td>
<td>26</td>
<td>25.58 (16.91)</td>
<td>23 (1, 75)</td>
</tr>
<tr>
<td>Percentage of Missed Prompts</td>
<td>22</td>
<td>16.79 (10.40)</td>
<td>12.97 (3, 41.9)</td>
</tr>
</tbody>
</table>

*Among 24 studies with an average participant age > 18

which EMA sampling occurred, citing that “the weekend was chosen because it is the time when adolescents have the greatest amount of free time and control over activities and companions” [21] and “the same weekdays (Tuesday-Thursday) were used to have a homogenous sample of days” [29].

The remaining six of the eight studies provided justification for the timing and/or frequency of prompts within each day. In two different studies, Stetler et al. [56, 57] sampled cortisol levels at the same time as the self-reported EMA. Specific sampling time intervals were chosen because they were previously found to “...adequately capture the diurnal pattern of cortisol secretion without placing undue burden on the participants” [56] and because they were able to “...capture the early morning peak that is part of the diurnal pattern of cortisol secretion” [57]. Ebner-Priemer and Sawitski [14] emphasized that “the temporal dynamics of emotional-cognitive processes are largely unknown”, and thus, their study employed multiple sampling frequencies to investigate this question. Depp et al. [34] cited the “need to balance between ‘coverage’ of affective experiences and subject burden.” Doyle [35] simultaneously employed three different types of recording procedures “to capture mood ratings in close proximity to the behaviors and events of interest...”. Links [44] stated that “random times were used to approximate the daily range of a participant’s affective intensity within the context and flow of the participant’s daily experience.”

Because there were only eight studies for which an explicit sampling design rationale was found, we also explored the observed relationships among the number of days of EMA, the number of prompts per day, and the number of questions per prompt. Because the study design variables were highly skewed, Figure 2 displays the associations among the log-transformed study design variables (henceforth, the reader may assume that all variables discussed are logged transformed). There was a strong negative association between the number of questions per prompt and the number of prompts per day ($r = -0.45, p = .02$). Similarly, there was a strong negative association between the number of prompts per day and the number of days of EMA ($r = -0.41, p = .03$). There
was a strong positive association between the number of questions per prompt and the number of days of EMA ($r = .48$, $p = .01$). The positive association may reflect the fact that more days of EMA leads to fewer prompts per day, which may in turn lead to more questions asked at each prompt. There was no significant association between the number of questions per prompt and the total number of prompts over the entire EMA study.

### 3.3 Aim 3: Investigate Relationships among Study Design Features and Compliance.

Figure 3 illustrates the relationships among the study design features and the percentage of unanswered prompts. The number of questions per prompt and the number of prompts per day were not significantly associated with the percentage of unanswered prompts. After removing the high but valid outlier in the number of prompts per day (estimated 54 prompts per day [36]), there was a strong positive relationship between the percentage of unanswered prompts and the number of prompts per day ($r = .44$, $p=0.05$); however, the removal of this outlier only highlights the potential leverage of the low outliers (1 prompt per day [56, 57]). There were strong and borderline-significant positive relationships between the percentage of unanswered prompts and both the days of EMA and questions per day (questions $\times$ prompts). There were strong and significant positive relationships between the percentage of unanswered prompts and both the total number of prompts (prompts $\times$ days) and the total number of questions (questions $\times$ prompts $\times$ days).
Fig. 3. Scatter plots with least-squares regression lines displaying relationships between the log-transformed study design features and the log percentage of unanswered prompts. Pearson product moment correlation coefficients (r) and associated p-values are also displayed.

4 Discussion

The overall goal of this manuscript is to provide researchers with a comprehensive summary and analysis of current EMA study design methods used in mood disorders research. To attain this goal, we summarized the current state of EMA study design used in mood disorders research, explored the rationale behind the selection of EMA study design features, and investigated the impact of study design on participant compliance.

The results of our comprehensive summary highlight the wide variety of EMA study design methods that are currently used in mood disorders research. This is particularly true regarding the number of questions per prompt, the number of prompts per day, and the number of days of EMA. To a large degree, this variability may be explained by the fact that each study has its own unique goals, participants, and restrictions; thus, each study’s design must be tailored to meet its specific needs. However, insight into this process was only provided to the reader in 8 of the 27 studies we investigated. This lack of detail may pose challenges for newer investigators who may want to enter into EMA research but do not have the experience to make these decisions on their own. It may also lead more experienced EMA researchers to use only one familiar study design, rather than tailoring each study design to match the temporal dynamics of the underlying process of interest.

The lack of explicit detail regarding study design rationale makes it difficult to explore which considerations are most important for EMA investigators. However, the observed negative associations between the number of prompts per day and both the
days of EMA and the questions per prompt suggests that investigators do indeed consider the need to balance these study design features, presumably to reduce participant burden.

Our investigation of the relationships among study design features and participant compliance showed that the number of study days may have a bigger impact on compliance than either the number of prompts per day or the number of questions per prompt. Not surprisingly, the strongest observed relationship showed a positive association between the total number of questions asked during the study (questions × prompts × days) and the percentage of unanswered prompts. Although these relationships may not be unexpected, their quantification is an important first step towards developing a set of study design guidelines for future EMA research.

Although care was taken to avoid potential biases and when developing the data base, analyzing the data, and interpreting the results, there are limitations that must be considered. One such limitation stems from the fact that our primary unit of analysis was the study. As such, features of each study often had to be identified through manuscripts and by discussion with the actual study investigators. When investigators could not be reached, the full scope of the original EMA study was not always evident; this could lead to errors in the data base due to a lack of full study descriptions in these manuscripts. However, the fact that these study design features were not immediately evident from the manuscripts highlights the need for a more standardized approach to developing and reporting EMA studies.

4.1 Future Directions

When designing EMA studies, two critical considerations are to obtain quality EMA data at the frequency necessary for modeling underlying dynamic processes and to use a sampling scheme that will not result in undue participant burden [14]. These considerations are often at odds with one another, and thus, pose challenges for EMA researchers. Furthermore, the “underlying temporal dynamics” of mood disorders are still largely unknown [14], making it difficult to select the appropriate sampling frequency even without participant constraints.

To overcome these challenges, it will be important to address three areas of EMA research: 1) monitor and standardize current sampling methods 2) evaluate whether current EMA sampling methods work actually work as intended (i.e., capture true underlying processes), and 3) develop new EMA sampling methods that can balance the need to effectively capture these processes while considering participant burden. The research presented herein is aimed at addressing the first area of research. We are currently working to address areas two and three so that future EMA investigators can have the tools they need to answer the critical EMA-related questions, both in the field of mood disorders specifically and in the broader fields of mental and physical health research.

References


Managing Data in Help4Mood

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http://www.help4mood.info

Abstract. Help4Mood is a system that supports the treatment of people with major depression through collecting a wealth of cognitive, psychomotor, and motor data, which can then be summarised and analysed further. Data is stored in functional units that correspond to treatment relevant entities using a custom XML DTD. As far as possible, observations and findings are coded using SNOMED CT to ensure interoperability with other applications such as Electronic Health Records.

1 Help4Mood—Avatar-Based Support for People with Major Depression

Depression is the main cause of disability worldwide [1]. It is characterised by a persistent and intense change of mood which affects behaviour, cognition, and physiology.

There are various forms of depression [2]. Here, we focus on major unipolar depression, which is mostly treated in the community. The core symptoms are persistent low mood and loss of interest. Figure 1 summarises the definitive diagnostic criteria for an episode of major depression, which includes activity and sleep symptoms.

As the DSM-IV definition suggests, depression also greatly affects psychomotor function [3, 4]. Two types of major depression can be distinguished, a melancholic form where patients’ movements are significantly slowed down, and a non-melancholic form, where movements are not affected or agitated. Slowed movements are reflected in both gross motor function, such as gait, and fine motor function, such as movement initiation and reaction times. They also contribute to a reduced speech rate and a flat intonation [5, 6].

At the moment, recovery is monitored infrequently through self-reported patient questionnaires that require the person with depression to remember over a period of time that can be as long as two weeks (e.g., PHQ-9 [7]). Those self-reports can be unreliable, especially if the patient is not keeping regular notes or a diary.

The Help4Mood system is intended to support the treatment of people with major unipolar depression in the community. In addition to monitoring through questionnaires and sensors, the patient interacts with Help4Mood through an avatar interface. Help4Mood consists of three components, a personal monitoring system, a virtual agent, which implements the avatar interface, and a decision support system.
A. Five (or more) of the following symptoms have been present during the same 2-week period and represent a change from previous functioning; at least one of the symptoms is either (1) depressed mood or (2) loss of interest or pleasure:

(1) depressed mood most of the day, nearly every day, as indicated by either subjective report (e.g., feels sad or empty) or observation made by others (e.g., appears tearful).

(2) markedly diminished interest or pleasure in all, or almost all, activities most of the day, nearly every day (as indicated by either subjective account or observation made by others).

(3) significant weight loss when not dieting or weight gain (e.g., a change of more than 5% of body weight in a month), or decrease or increase in appetite nearly every day.

(4) insomnia or hypersomnia nearly every day.

(5) psychomotor agitation or retardation nearly every day (observable by others, not merely subjective feelings of restlessness or being slowed down).

(6) fatigue or loss of energy nearly every day.

(7) feelings of worthlessness or excessive or inappropriate guilt (which may be delusional) nearly every day (not merely self-reproach or guilt about being sick).

(8) diminished ability to think or concentrate, or indecisiveness, nearly every day (either by subjective account or as observed by others).

(9) recurrent thoughts of death (not just fear of dying), recurrent suicidal ideation without a specific plan, or a suicide attempt or a specific plan for committing suicide.

B. The symptoms do not meet criteria for a Mixed Episode.

C. The symptoms cause clinically significant distress or impairment in social, occupational, or other important areas of functioning.

D. The symptoms are not due to the direct physiological effects of a substance (e.g., a drug of abuse, a medication) or a general medical condition (e.g., hypothyroidism).

E. The symptoms are not better accounted for by Bereavement, i.e., after the loss of a loved one, the symptoms persist for longer than two months or are characterised by marked functional impairment, morbid preoccupation with worthlessness, suicidal ideation, psychotic symptoms, or psychomotor retardation.

**Fig. 1.** DSM-IV criteria for major depressive episode.

The sensors of the personal monitoring system assess sleep and activity patterns using sleep sensors and a wrist actigraph. The virtual agent asks questions, sets tasks, and summarises the results of each session. Some of these tasks will yield cognitive data, such as relevant negative automatic thoughts, others are designed to capture relevant neuropsychomotor symptoms of depression, such as speech changes and slowed reaction times [3]. The decision support system plans and controls sessions with the virtual agent and converts data about the patient’s sleep, motor, speech, and other psychomotor patterns into graphical, textual, and conceptual summaries that can be communicated to clinicians, patients, and electronic health records.

In this paper, we describe our approach to data management in Help4Mood. We focus on the high-level data structures that form the basis for communicating with clinicians, patients, and other stakeholders; the personal monitoring system and the virtual
agent have internal structures for storing the fine-grained, detailed data which is analysed by the decision support system. The basic elements of the high-level Help4Mood data structures are described in Section 2. Provisions for interoperability are outlined in Section 4, and future work plans are summarised in Section 5.

2 Overview of Help4Mood

Help4Mood is structured around patients’ sessions with the Virtual Agent. Ideally, patients interact with their Virtual Agent daily. While content and length of a session can be varied depending on the patient’s current mood and stamina, a default session consists of five parts: welcome and daily mood check, diary, documenting negative thoughts, speech task / game, summary feedback and closing.

The daily mood check is a validated four-item questionnaire, the CES-VAS-VA [8]. In the diary entries, patients reflect on a specific prompt. These entries are stored internally in the VA; patients will be able to discard them or save them for rereading. All that is stored for the DSS is their length. Next, patients document negative thoughts relating to this diary entry, and Help4Mood provides guidance for challenging these thoughts. Then, patients perform a speech task or a cognitive game. Finally, the session is briefly summarised in a final screen, and the virtual agent bids the patient goodbye.

While sleep data is collected every night, the wrist actigraph will only be worn for 72 hours at a time. Sessions with the virtual agent can include summaries of activity and sleep patterns. In addition to the daily mood check, patients fill in a formal screening questionnaire, the PHQ-9 [7], every fortnight; this task is added to the session at the appropriate time.

3 Core Data Structures

All data structures are described using XML. We chose this solution over a relational database, because Help4Mood has a highly modular architecture, and almost all inter- and intra-module communication is based on XML. Elements are extensively cross-indexed to ensure flexible access to data.

The XML elements that are used to store relevant data are summarised in Table 1. They fall into four main categories, high-level tracking of patient and Help4Mood use, storing monitoring results, managing the interaction between patient and virtual agent, and storing the data collected during the interaction. Each set of elements is briefly explained below.

High Level Tracking. The three high-level tracking elements summarise relevant information about the patient and system usage and store the regular reports generated by the system. Patient information includes basic demographics (occupation, gender, age) as well as current depression scores. As for reports, only official reports that are sent to the clinicians and can be discussed in patient/clinician meetings are stored. The feedback given to the patient at the end of each session is not saved, because it can be reconstructed deterministically from the data collected in each session.
Table 1. Basic Elements of the Help4Mood data structure. Each one is defined using XML.

<table>
<thead>
<tr>
<th>Element</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>High-Level Tracking of Patient and Help4Mood Usage</strong></td>
<td></td>
</tr>
<tr>
<td>User Model</td>
<td>high-level summary of information about the patient</td>
</tr>
<tr>
<td>Adherence</td>
<td>adherence of patient to Help4Mood; can refer to sessions, tasks, and monitoring schedules</td>
</tr>
<tr>
<td>Report</td>
<td>summary report generated for clinician</td>
</tr>
<tr>
<td><strong>Managing the Results of Monitoring</strong></td>
<td></td>
</tr>
<tr>
<td>Monitor Data</td>
<td>set of measures that are collected during a session</td>
</tr>
<tr>
<td>Measure</td>
<td>high-level measure computed from a given set of monitoring data</td>
</tr>
<tr>
<td>Score</td>
<td>score on a standardised questionnaire</td>
</tr>
<tr>
<td><strong>Managing the Interaction with the Virtual Agent</strong></td>
<td></td>
</tr>
<tr>
<td>Session</td>
<td>content and results of a session with the Virtual Agent</td>
</tr>
<tr>
<td>Event</td>
<td>event triggered by the decision support system during a session</td>
</tr>
<tr>
<td>Task</td>
<td>task that is performed by the patient during a specific session</td>
</tr>
<tr>
<td>Emotion</td>
<td>emotion used by virtual agent while patient performs task</td>
</tr>
<tr>
<td><strong>Storing Information Collected During Interaction with the Virtual Agent</strong></td>
<td></td>
</tr>
<tr>
<td>Diary</td>
<td>information related to diary entries</td>
</tr>
<tr>
<td>Speech</td>
<td>changes in relevant speech parameters</td>
</tr>
<tr>
<td>Games</td>
<td>changes in reaction times and scores</td>
</tr>
<tr>
<td>Negative Thought</td>
<td>frequency of specific negative automatic thoughts</td>
</tr>
</tbody>
</table>

**Monitoring.** The next two elements are used to describe high-level monitoring data. While the measure element covers specific analysis results, the monitoring data element collects a set of measures obtained during a given session.

**Managing the Interaction with the Virtual Agent.** The Decision Support System controls the Virtual Agent’s interaction with the user through events (event element). Events are triggered when their preconditions are fulfilled. They are implemented as interaction tasks (task element). Each task is associated with an emotion (emotion element) that controls the affective behaviour of the Virtual Agent.

The sequence of of events and task/emotion pairs that occurred during a session and the data that was generated during a session is stored in a session element for easy reference.

Table 2 shows the structure of an event element. Each event is linked to a session, a patient, and a specific time within the session. A range of auxiliary elements is used to specify events. Descriptors link Events to a formal code that describes the underlying procedure and can be exported to external systems (c.f. Table 3). Preconditions and postconditions are described using condition elements that consist of ⟨Property, Operator, Value⟩-tuples (c.f. Table 4).

**Data Collected During Interaction.** During most tasks, the system collects rich information about the patient’s cognition and current psychomotor functioning. Relevant high-level data is encoded in the diary, speech, games, and negative thought elements.
Table 2. The Event class.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>⟨Type⟩</td>
<td>{1,2,3,4}</td>
<td>Event type as classified by data source</td>
</tr>
<tr>
<td>⟨Session⟩</td>
<td>timestamp</td>
<td>Session ID</td>
</tr>
<tr>
<td>⟨Patient⟩</td>
<td>alphanumerical code</td>
<td>Patient ID</td>
</tr>
<tr>
<td>⟨Description⟩</td>
<td>descriptor</td>
<td>Formal description of the event</td>
</tr>
<tr>
<td>⟨Generated⟩</td>
<td>timestamp</td>
<td>time at which the event was generated</td>
</tr>
<tr>
<td>⟨Preconditions⟩</td>
<td>list of conditions</td>
<td>pre-conditions that trigger the event.</td>
</tr>
<tr>
<td>⟨Postconditions⟩</td>
<td>list of conditions</td>
<td>findings or observable entities</td>
</tr>
</tbody>
</table>

Table 3. Structure of Descriptors.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Values</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>⟨Code⟩</td>
<td>9-digit integer</td>
<td>Numerical identifier. If the attribute is a concept taken form the SNOMED-CT classification, the code is its corresponding ID</td>
</tr>
<tr>
<td>⟨Snomed⟩</td>
<td>Yes/No</td>
<td>Yes if the attribute is a SNOMED-CT concept, otherwise no</td>
</tr>
<tr>
<td>⟨Name⟩</td>
<td>String</td>
<td>SNOMED-CT description if attribute is a SNOMED-CT concept, otherwise internal description</td>
</tr>
</tbody>
</table>

Table 4. Structure of Conditions.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>⟨Property⟩</td>
<td>Descriptor</td>
<td>Property or action in the VA’s world that is tested in the precondition.</td>
</tr>
<tr>
<td>⟨Operator⟩</td>
<td>&lt;, &gt;, =, !=</td>
<td>A string that specifies the operator used to determine the truth value of the condition. The first two operators are defined for numerical values, the last two are defined for numerical and strong values</td>
</tr>
<tr>
<td>⟨Value⟩</td>
<td>descriptor</td>
<td>Value used to compare the property to.</td>
</tr>
</tbody>
</table>

4 Communication and Interoperability

4.1 Clinician

Clinicians can access a patient’s history through a web interface to a special clinician-side version of the decision support system, which generates textual and graphic summaries to support treatment planning. In addition, Help4Mood generates a regular report for each patient / clinician meeting. All relevant health care professionals as well as the patient can see this report; clinician and patient may discuss specific findings when they meet.

4.2 Patient

The patient receives textual and / or graphical summaries at the end of each session that are generated dynamically. The Virtual Agent stores detailed information about
performance on speech tasks and games which can be exported for further refinement of measures. Patients can choose to save their diary entries for later perusal. The entries themselves are not passed on to the clinician. Patients will be made aware that diary entries are private every time they use the system. In addition to their diary entries, patients have access to the shared reports, which are stored patient-side.

4.3 EHR Integration

As far as possible, we use the international Core Release of SNOMED CT [9] to describe our findings and observations. SNOMED CT is a highly complex, extendable clinical vocabulary that can be integrated with standards such as HL7 [10], which Help4Mood will support.

Most of the SNOMED-CT concepts used in Help4Mood come from the Clinical Finding hierarchy. Clinical findings are the outcome of assessments, observations, or judgements. For example, if the sleep sensor data indicate that the patient tossed and turned frequently at night, this can be encoded as the Clinical Finding “restless sleep”.

Other concepts are Procedures, i.e., activities that occur at a specific time and involve the patient. Procedures include education and administration activities. For example, showing the patient a list of activities that were identified as comforting could be a procedure. Another example of a procedure would be guiding the patient through a relaxation exercise.

Most of the relevant information about a patient’s social context is modelled using concepts from the Social Context hierarchy, such as occupation. A question or a procedure that produces a result is an Observable Entity. For example, “gender” is an observable entity, while “female gender” is a finding. Questionnaire scores are modelled as observable entities; the associated finding is their interpretation.

The questionnaire instruments themselves are part of yet another hierarchy, Staging and Scales. For example, the Beck Depression Inventory [11] When extending Help4Mood to provide medication education, we may also include concepts from the hierarchy Pharmaceutical/biological product, which correspond to the type of medication being given.

We defined our own codes only if the relevant findings, observable entities, or procedures were not included in SNOMED-CT. In all cases, these codes are linked to a parent concept in SNOMED-CT. For example, unlike the Beck Depression Inventory, neither of our depression measures are modelled explicitly in SNOMED-CT. Therefore, we assigned the resulting scores system-specific codes and linked them to relevant parent concepts. Hence, the PHQ-9 score is an Observable Entity which is in an is-a relation with the SNOMED CT concept Mental state, behaviour / psychosocial function observable.

If necessary, relevant data is mapped onto SNOMED CT categories by the Decision Support System. While information such as questionnaire scores can be stored more or less directly, concepts such as “restless sleep” will be derived from sensor data using validated algorithms.
Table 5. Anchoring New Concepts in SNOMED-CT.

<table>
<thead>
<tr>
<th>SNOMED CT Type</th>
<th>SNOMED CT Concept Code</th>
<th>Description</th>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Procedure</td>
<td>999991011</td>
<td>Assessment using CES-D-VAS-VS</td>
<td>445536008</td>
<td>Assessment using assessment scale</td>
</tr>
<tr>
<td>Observable Entity</td>
<td>999991012</td>
<td>CES-D-VAS-VS score</td>
<td>363870007</td>
<td>Mental state, behavior / psychosocial function observable (observable entity)</td>
</tr>
<tr>
<td>Procedure</td>
<td>999991021</td>
<td>Assessment using PHQ-9</td>
<td>445536008</td>
<td>Assessment using assessment scale</td>
</tr>
<tr>
<td>Observable Entity</td>
<td>999991022</td>
<td>PHQ-9 score</td>
<td>363870007</td>
<td>Mental state, behavior / psychosocial function observable (observable entity)</td>
</tr>
<tr>
<td>Finding</td>
<td>999992011</td>
<td>Change of Score on Cognitive Game SIMON</td>
<td>248536006</td>
<td>Finding of functional performance and activity</td>
</tr>
</tbody>
</table>

5 Future Work

The data management approach outlined here provides a detailed, systematic representation of all of the relevant high-level information that Help4Mood collects about a patient with major unipolar depression. It was designed for easy maintenance and maximum interoperability with EHRs.

We are currently implementing the first version of Help4Mood based on the data structures outlined in this paper. In future versions, we plan to add HL7 integration, refine the elements and clinical vocabulary described here to provide a more detailed ontology for interoperability, and extend Help4Mood with reminder functionality and patient education through tailored health information presentation.

References


An Event-driven Psychophysiological Assessment for Health Care

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Abstract. Computerized experience-sampling method comprising a mobile-based system that collects psychophysiological data appears to be a very promising assessment approach to investigate the real-time fluctuation of experience in daily life in order to detect stressful events. At this purpose, we developed PsychLog (http://sourceforge.net/projects/psychlog/) a free open-source mobile experience sampling platform that allows psychophysiological data to be collected, aggregated, visualized and collated into reports. Results showed a good classification of relaxing and stressful events, defining the two groups with psychological analysis and verifying the discrimination with physiological measures. Our innovative approach offers to researchers and clinicians new effective opportunities to assess and treat psychological stress in daily-life environments.

1 Introduction

Assessing and monitoring emotional, cognitive and behavioral dimensions of human experience, both in laboratory and in natural setting, has a crucial role in research and treatment of psychological stress. According to Cohen and Colleagues [1] “Psychological Stress” occurs when an individual perceives that environmental demands tax his/her adaptive capacity. In this perspective, stressful daily experiences could be conceptualized as a continuous person-environment transaction [2]; [3]. Every day, in fact, individuals are continually invited to deal with several situations or circumstances (for example, being fired from work or having trouble with parents or partner) that provoke anxiety and psychological discomfort. In this perspective [1-3], a stressful event [4]; [5] occurs when a person isn’t able to effectively cope with a challenge that is perceived to exceed his/her skills. Physiological measures can also give further information to a psychological definition of stress, but there are still few studies, above all in everyday situations, considering the relation between these two dimensions. To accurately analyze real-time interaction between environmental demands and individual adaptive capacity and to precisely detect stressful events during the daily life situations, it is fundamental to use a real-time multimodal assessment. As underlined by Ebner-Priemer and Trull [6], different terms have been used to refers to real-time assessment of psychophysiological data: Ambulatory
Assessment [7-9], Ecological Momentary Assessment [10], Experience Sampling Method [11], Real-Time Data Capture [12], and Day Reconstruction Method [13]. These assessment methodologies, although arose from different research paradigms, have in common the continuous recording of psychological and physiological data or indices of behavior, cognition or emotions in the daily life of subjects. Barrett and Barrett [14] effectively defined real-time assessment procedure as a "window into a daily life" since participants provide self-reports of their momentary thoughts, feelings and behavior across a wide range of daily situations in ecological contexts.

Recent progress in biosensor technology and, on the other hand, the incredible diffusion of mobile electronic devices have lead to ubiquitous and unobtrusive recorder systems that allow naturalistic and multimodal assessment [14-18].

Computerized experience sampling method comprising a mobile-based system that collects psychophysiological data appears to be a very promising assessment approach to investigate the real-time fluctuation of experience in everyday life in order to detect stressful events. At this purpose, we developed PsychLog (http://sourceforge.net/projects/psychlog/) a free open-source mobile experience sampling platform that allows psychophysiological data to be collected, aggregated, visualized and collated into reports [19]. Our smartphone-based system collects physiological data from a wireless wearable electrocardiogram equipped with a three-axial accelerometer. Moreover, the application allows administering self-report questionnaires [20] to collect and investigate participants’ feedback on their daily life experience in its various cognitive, affective and motivational dimensions. In particular, in this study we proposed and tested the use of PsychLog [19]: (1) to investigate the fluctuation of experience during a week of observation; (2) to detect, on the basis of psychophysiological real-time assessment, stressful events that normally occur during daily activities and situations; (3) to compare the psychophysiological data between stressful events and relaxing events occurring in everyday contexts.

2 Materials and Methods

2.1 Tools

In our study we used PsychLog (http://sourceforge.net/projects/psychlog/), a mobile experience sampling platform that allows the collection of psychological, physiological and activity information in naturalistic settings [19]. The system consists of three main modules. The survey manager module allows configuring, managing and administering self-report questionnaires. The sensing/computing module allows continuously monitoring heart rate and activity data acquired from a wireless electrocardiogram (ECG) equipped with a three-axis accelerometer. The wearable sensor platform (Shimmer Research™) includes a board that allows the transduction, the amplification and the pre-processing of raw sensor signals, and a Bluetooth transmitter to wirelessly send the processed data. Sensed data are transmitted to the mobile phone Bluetooth receiver and gathered by the PsychLog computing module, which stores and process the signals for the extraction of relevant features. ECG and accelerometer sampling intervals (epochs) can be fully tailored to
the study’s design. During each epoch, signals are sampled at 250 Hz and filtered to eliminate common noise sources using Notch filter at 0 Hz and low pass at 35 Hz and analogue-to-digital converted with 12-bit accuracy in the ±3 V range. The application extracts QRS peaks through a dedicated algorithm and R-R intervals [21]; [22]. The visualization module allows plotting in real time ECG and acceleration graphs on the mobile phone’s screen. Psychological and physiological data are stored on the mobile phone’s internal memory, in separate files, for off-line analysis. Data are stored as .dat (supported by most data analysis programs), .txt and .csv format.

In this study, we used standard smartphone (Samsung Omnia II i8000) equipped with 32 bit CPU, ARM 11 RISC processor (cache 16KB) 667 MHz, RAM 256 MB, 1500 mAh Lithium ion battery, running the operative system Windows mobile 6.5

2.2 Experimental Design

Participants were six healthy subjects (2 males and 4 females, mean age 23) recruited through opportunistic sampling. Participants filled a questionnaire assessing factors that might interfere with the psychophysiological measures being assessed (i.e. caffeine consumption, smoking, alcohol consumption, exercise, hours of sleep, disease states, medications). Written informed consent was obtained from all subjects matching inclusion criteria (age between 18-65 years, generally healthy, absence of major medical conditions, completion of informed consent).

Participants were provided with a short briefing about the goal of the experiment and filled the informed consent. Then, they were provided with the mobile phone with pre-installed PsychLog application, the wearable ECG and accelerometer sensor and a user manual including experimental instructions. Subjects were asked to wear biosensor for one week of observation. PsychLog was pre-programmed to beep randomly 5 times a day each day (between 10 AM and 10 PM) to elicit at least 35 experience samples over the 7-days assessment period. At the end of the experiment, participants returned both the phone and the sensors to the laboratory staff. After filling a short usability questionnaire, participants were debriefed and thanked for their participation.

2.3 Psychological Assessment

Psychological stress was measured by using a digitalized version of an ESM survey adapted from that used by Jacobs and Colleagues [19]; [20] for studying the immediate effects of stressors on mood. The self-assessment questionnaire included open-ended and closed-ended questions investigating thoughts, current context (activity, people, location, etc.), appraisals of the ongoing situation, and mood. All self-assessments were rated on 7-point Likert scales. Following the procedure suggested by Jacobs and Colleagues [20], three different scales were computed in order to identify the stressful qualities of daily life experiences. Ongoing Activity-Related Stress (ARS) was defined as the mean score of the two items “I would rather be doing something else” and “This activity requires effort” (Cronbach’s alpha = 0.699). To evaluate social stress, participants rated the social context on two 7-point Likert scales “I don’t like the present company” and “I would rather be alone”; the
Social Stress scale (SS) resulted from the mean of these ratings (Cronbach’s alpha = 0.497). For Event-Related Stress (ERS), subjects reported the most important event that had happened since the previous beep. Subjects then rated this event on a 7-point scale (from 3 very unpleasant to 3 very pleasant, with 0 indicating a neutral event). All positive responses were recoded as 0, and the negative responses were recoded so that higher scores were associated with more unpleasant and potentially stressful events (0 neutral, 3 very unpleasant). In addition to those scales (not included in the original survey), we introduced an item asked participant to rate the perceived level of stress (STRESS) on a 10-point Likert scale. In particular, to rate the gap between challenge and skills, we introduced two specific items: (1) an item assessing the perceived level of ongoing challenge (CHALLENGE) on 7-point Likert; (2) an item evaluating the perceived level of skills (SKILLS) on 7-point Likert.

2.4 Cardiovascular and Activity Indexes

Cardiovascular activity is monitored to evaluate both voluntary and autonomic effect of respiration on heart rate, analyzing R-R interval from electrocardiogram. Furthermore standard HRV spectral methods indexes and similar have been used to evaluate the autonomic nervous system response [23].

From ECG each QRS complex is detected, and the normal-to-normal (NN) intervals (all intervals between adjacent QRS complexes resulting from sinus node depolarizations) are determined to derive the most common temporal measures, including RMSSD, the square root of the mean squared differences of successive NN intervals, and NN50, the number of interval differences of successive NN intervals greater than 50 ms [23]. In general, RMSSD are estimate of short-term components of heart rate variability. This experiment aimed at testing the feasibility of monitoring concurrent stress and physiological arousal within subjects’ typical daily environments and activities. Previous works have shown that psychological stress is associated with an increase in sympathetic cardiac control, a decrease in parasympathetic control, or both [21]; [22]. Associated with these reactions is a frequently reported increase in low frequency (LF, range between 0.04-0.15 Hz) or very low frequency (VLF, < 0.04 Hz) HRV, and decrease in high frequency (HF, 0.15–0.50 Hz) power. HF power is reported to reflect parasympathetic modulation of RR intervals related to respiration, whereas the LF component is an index of modulation of RR intervals by sympathetic and parasympathetic activity (in particular baroreflex activity) [21-23]. Furthermore, stressors are often accompanied by an increase in the LF/HF ratio (a measure used to estimate sympathovagal balance, which is the autonomic state resulting from the sympathetic and parasympathetic influences) [23]. Although the time domain methods, especially RMSSD method, can be used to investigate recordings of short durations, the frequency methods are usually able to provide results that are more easily interpretable in terms of physiological regulations [23].

Spectral analysis has been be performed by means of autoregressive (AR) spectral methods with custom software. The AR spectral decomposition procedure has been applied to calculate the power of the oscillations embedded in the series. The rhythms have been classified as very low frequency (VLF, <0.04 Hz), low-frequency (LF, from 0.04 to 0.15 Hz) and high frequency (HF, from 0.15 to 0.5 Hz) oscillations. The
power has been expressed in absolute (LF_{RR} and HF_{RR}) and in normalized units. For example, RR series: LF_{nu} and HF_{nu} as 100 * LF_{RR} / (\sigma^2_{RR} - VLF_{RR}) and 100 * HF_{RR} / (\sigma^2_{RR} - VLF_{RR}), where \sigma^2_{RR} represents the RR variance and VLF_{RR} represents the VLF power expressed in absolute units [21-23]. ECG biosensors used by PsychLog application have also an integrated three-axial accelerometer. SMA index [24]; [25] has been calculated in order to establish when subject was not in movement. In this way we calculated ECG indexes, avoiding the periods in which the subject was running, walking, or also moving too much. Signal-magnitude area (SMA): It is calculated according to

\[
SMA = \sum_{i=1}^{n} (|x(i)|) + (|y(i)|) + (|z(i)|)
\]

where \(x(i), y(i),\) and \(z(i)\) indicate the acceleration signal along the \(x\)-axis, \(y\)-axis, and \(z\)-axis, respectively.

Fig. 1. Mean and variance values of SMA index related to the previous five minutes of activity.

2.5 Data Analysis

In order to detect both stressful and relaxing events, Activity-Related Stress Scale (ARS), Social Stress Scale (SS), Perceived Stress Scale (STRESS), Challenge Scale (CHALLENGE) and Skill Scale (SKILLS) were within-subjects standardized. Event-Related Stress Scale wasn’t standardized so it was classified as follows: 0 = no stress; 1 = low stress; 2 = medium stress; 3 = high stress.

We proposed the following classification to define stressful and relaxing events:
Table 1. Classification of relaxing and stressful events.

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>STRESS</strong></td>
<td></td>
</tr>
<tr>
<td>Zscore(STRESS)</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>Zscore(ARS)</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>Zscore(SS)</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>EVS</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>Zscore(CHALLENGE) &amp; Zscore(SKILLS)</td>
<td>&gt; 1 &amp; &lt; -1</td>
</tr>
<tr>
<td>Zscore(STRESS)</td>
<td>&lt; -1</td>
</tr>
<tr>
<td>Zscore(ARS)</td>
<td>&lt; -1</td>
</tr>
<tr>
<td>Zscore(SS)</td>
<td>&lt; -1</td>
</tr>
<tr>
<td>EVS</td>
<td>= 0</td>
</tr>
<tr>
<td>Zscore (CHALLENGE) &amp; Zscore (SKILLS)</td>
<td>&lt; -1 &amp; &gt; 1</td>
</tr>
</tbody>
</table>

Hierarchical structure of the experiment data makes traditional forms of analysis unsuitable. Subjects are measured at many time points during each day, across seven days. Traditional repeated-measures designs require the same number of observations for each subject and no missing data. Moreover, also other dependencies existing in the data can be taken into account. Because the ESM entries are nested within seven days within participants, we estimated the psychophysiological indexes on events (Relax or Stress), with hierarchical linear analysis, an alternative to multiple regression suitable for our nested data. We referred to two levels in the model: beep-level and subject-level. Our model was based on binary logistic, specifying Binomial as the distribution and Logit \((f(x) = \log(x / (1-x)))\) as the link function. Using a mixed hierarchical model we inferred the dichotomised event (Relax or Stress) on the basis of physiological parameters. In this sense we used these indexes to predict relax or stress condition indicated by subjects. The analysis aimed at finding statistically significant parameter for the estimation of a model designed to predict relaxing and stressful events. More, a linear discriminant analysis (LDA) has been used to verify if a set of physiological measures (RMSSD, NN50, and HF Power) was able to discriminate between the two groups (Relax and Stress).

3 Results

The six participants completed a total of 213 ESM reports. Aggregated over participants’ means, mean Perceived Stress was 2.99 (S.D. = 1.50), mean Activity-Related Stress was 3.35 (S.D. = 0.72), mean Social Stress was 3.34 (S.D. = 1.40), mean Challenge was 2.99 (S.D. = 1.92), mean Skills was 4.58 (S.D. = 1.86), and frequencies for Event-Related Stress was: 88% no stress, 4.2% low stress, 3.1% medium stress, and 4.7% high stress. A total of 31 events (14.55 % of total events) have been identified, 18 relax events (8.45 %) and 13 stress events (6.10 %) among the six subjects. For each one of these events we calculated two temporal HRV
indexes, namely RMSSD and NN50, and one spectral HRV index, i.e. HF power.

In Table 2, means and standard deviations are reported per each index on the basis of events’ group (Relax or Stress). As explained in data analysis, we estimated the psychophysiological indexes on events (Relax or Stress), with hierarchical logistic analysis. Results show, a statistical significant hierarchical regression model for RMSSD (Beta: 1.177; St. Dev.: .5839; p < .044), and a quasi statistical significant for HF power (Beta: .888; St. Dev.: .4612; p < .055). The RMSSD method is preferred to NN50 because it has better statistical properties [23].

### Table 2. Group Statistics.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Valid N (listwise)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RELAX</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zscore(RMSSD)</td>
<td>.2175527</td>
<td>.78903922</td>
<td>18</td>
</tr>
<tr>
<td>Zscore(NN50)</td>
<td>.3686125</td>
<td>.80597461</td>
<td>18</td>
</tr>
<tr>
<td>Zscore(HF_power)</td>
<td>.4263368</td>
<td>.81428263</td>
<td>18</td>
</tr>
<tr>
<td><strong>STRESS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zscore(RMSSD)</td>
<td>-.4225023</td>
<td>.73893069</td>
<td>13</td>
</tr>
<tr>
<td>Zscore(NN50)</td>
<td>-.5293378</td>
<td>.62354657</td>
<td>13</td>
</tr>
<tr>
<td>Zscore(HF_power)</td>
<td>-.5657602</td>
<td>.57913531</td>
<td>13</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zscore(RMSSD)</td>
<td>-.0508575</td>
<td>.82114721</td>
<td>31</td>
</tr>
<tr>
<td>Zscore(NN50)</td>
<td>-.0079473</td>
<td>.85235392</td>
<td>31</td>
</tr>
<tr>
<td>Zscore(HF_power)</td>
<td>.0102961</td>
<td>.87036922</td>
<td>31</td>
</tr>
</tbody>
</table>

A linear discriminant analysis (LDA) has been used to verify if the physiological indexes (RMSSD, NN50, and HF Power) were able to discriminate between the two groups (Relax and Stress) defined on the basis of the questionnaires, as above defined. Tests of equality of group means are showed in table 3. More, results showed a 0.622 Wilks' Lambda (Chi-square: 13.070, df: 3, p < .005) with 77.4% of original grouped cases correctly classified (see table 4).

### Table 3. Tests of equality of group means.

<table>
<thead>
<tr>
<th></th>
<th>Wilks’ Lambda</th>
<th>F</th>
<th>df1</th>
<th>df2</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zscore(RMSSD)</td>
<td>0.847</td>
<td>5.233</td>
<td>1</td>
<td>29</td>
<td>0.03</td>
</tr>
<tr>
<td>Zscore(NN50)</td>
<td>0.721</td>
<td>11.236</td>
<td>1</td>
<td>29</td>
<td>0.002</td>
</tr>
<tr>
<td>Zscore(HF_power)</td>
<td>0.673</td>
<td>14.085</td>
<td>1</td>
<td>29</td>
<td>0.001</td>
</tr>
</tbody>
</table>

### Table 4. Classification Results. Overall, 77.4% of original grouped cases correctly classified.

<table>
<thead>
<tr>
<th></th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original</strong></td>
<td></td>
</tr>
<tr>
<td>Condition</td>
<td>Relax</td>
</tr>
<tr>
<td>Relax</td>
<td>72.2 %</td>
</tr>
<tr>
<td>Stress</td>
<td>15.4 %</td>
</tr>
</tbody>
</table>
4 Discussions and Conclusions

Recent progress in the sophistication and feasibility of biosensor technology and the remarkable spread of mobile electronic devices have lead to ubiquitous and unobtrusive recorder systems that allow naturalistic and multimodal assessment of psychophysiological parameters [14-16]. Since psychological stress could be defined as a continuous person-environment transaction [1-3], this integrated and mobile assessment offers the opportunity to analyze the real-time interaction between challenges and skills occurring in daily life situations. In this study, we proposed and tested the use of PsychLog [19] a free open-source mobile experience sampling platform, aggregated, visualized and collated into reports, to investigate the fluctuation of subjects’ experience [11] and to detect, on the basis of psychophysiological real-time assessment, stressful events that normally occur during daily activities and situations. Analysis has been set selecting two events groups (Relax and Stress) on the basis of psychological questionnaires. Then, a hierarchical logistic analysis and a discriminant analysis between the two groups, showed that physiological measures have been able to predict the groups selected on psychological basis. These results seem to indicate that a relation between physiological patterns and psychological behavior exists. Being true these results, we would be able to predict particular events on physiological basis, i.e. without having to ask subjects about their own states. Although more psychometric work is needed to validate our innovative approach, it offers to researchers and clinicians new effective opportunities to assess and treat psychological stress in daily-life environments. The advantages in using a mobile psychophysiological stress assessment are potentially several: (a) it is possible to evaluate the continuous fluctuation of the quality of experience in ecological contexts; (b) it is possible to schedule the timing and the modality of psychophysiological monitoring; (c) it allows a multimodal assessment; (d) it permits the detection of stressful events in daily life; and (e) it provides the opportunity of giving immediate, graphical and user-friendly feedback. As a consequence of the detection of a stressful event, PsychLog will be able to give the chance to deliver real-time and effective Ecological Momentary Interventions [26]; [27] to provide real-time support in the natural context, when they are most needed.

Acknowledgements

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21. Magagnin, V., Mauri, M., Cipresso, P., Mainardi, L., Brown, E. N., Cerutti, S., Villamira, M., Barbieri, R.: Heart rate variability and respiratory sinus arrhythmia assessment of
Abstract. Within the field of biosignal acquisition and processing, there is a growing need for combining multiple modalities. Clinical psychology is an area where this is often the case, and one example are the studies where heart rate and electrodermal activity need to be acquired simultaneously. Both of these parameters are typically measured in distinct anatomical regions (the former at the chest, and the later at the hand level), which raises wearability issues as in some cases two independent devices are used; finger clip sensors already enable heart rate measurement at the hand level, however they can be limiting for free living and quality of life activities. In this paper we perform a study and evaluation of an experimental blood volume pulse sensor, to assess the feasibility of measuring the heart rate at the hand palms, and thus enabling the design of more convenient systems for multimodal data acquisition.

1 Introduction

Blood Volume Pulse (BVP) sensors are a commonly used method for assessing the cardiovascular activity at the arterial level [1]. Their operating principle is based on photoplethysmography, that is, by externally applying a light source in the visible or invisible wavelengths to the tissues, and measuring the amount of light that reaches a photodetector [2]. The detector can be positioned to measure either by reflection or transmission; as the heart pumps blood through the arteries, and subsequently through the peripheral vessels, the translucency of the vessels changes due to the increased blood volume, modifying the way that the emitted light is reflected or transmitted to the photodetector [3]. The typical output of the sensor is then a signal where each cardiac cycle is expressed as a pulse wave (Figure 1(a)).

In this paper we present a study and evaluation of a palmar BVP sensor for heart rate measurement, designed to be integrated in multimodal systems for biosignal acquisition at the hand level. The studied arrangement further expands the current state-of-the-art in the field by improving wearability aspects. Unlike existing systems, taking into account that the sensor is placed at the hand palm, no additional volume is moved on to the fingers, enabling the wearer to make normal use of the hand. Experimental results have shown a good correlation between the measurements taken at the hand palm and at the fingertip, validating the palmar placement as an adequate alternative to
standard approaches. The remainder of the paper describes the motivation for our work in Section 2, presents the materials and methods in Section 3, and highlights the results and conclusions in Sections 4 and 5 respectively.

2 Motivation

The heart rate has become a widespread biosignal measurement for self-management and assessment, with extensive application in a variety of contexts such as clinical diagnosis, sports activities, and affective computing, among others [4–6]. Chest straps have risen as a standard for unobtrusive data acquisition, and although these form factors are concealed by the clothing and thus, discrete for regular use, a growing number of applications require the measurement of multiple parameters simultaneously. This is the case of clinical psychology [7, 8], where besides the heart rate and derived information, electrodermal activity is also used as a psychological or physiological arousal indicator. As electrodermal activity is more noticeable at the hand palms and fingers, several usability difficulties arise when both parameters need to be measured simultaneously, since two independent devices are generally required.

Due to the close relation between BVP signals and the cardiac activity, the heart rate is one of the parameters generally extracted from the collected data. Furthermore, BVP sensors can be applied to any place in the body irrigated by blood vessels, particularly in peripheral areas, making it an appealing alternative to the more intrusive chest mounted apparatuses. The most common placement is at the fingertip [9] (Figure 1(b)); however, for long term or continuous use, this anatomic placement limits the regular activities of its wearer as the fingers play a fundamental role in most daily tasks. Furthermore, for patients with schizophrenia, psychosis, autism, among other, to place biomedical sensors at the finger is hard to the medical staff, because these patients have high movements and tendency to remove the finger clip. Thus, a BVP glove can overcome some of these issues, since the patient wears a glove, which is hard to remove and it as not being subject to the fingers movements.

From BVP signal, Heart Rate (HR) and RR intervals can be extracted, allowing the Heart Rate Variability (HRV) analysis in terms of time and frequency domains. HRV is
widely related to the mental diseases, since it can provide information about the emotional state of the patient, by its correlation with the automatic heart modulation being a powerful tool for clinical use. For example, the HRV spectral analysis reveals that the vagal activity is the major contribution to the high frequencies component. Furthermore, it is also argued that the low frequency (LF) and high frequency (HF) ratio reflects the sympathovagal balance or the sympathetic modulation. These parameters are very important since some authors defend that there is a significant increase of LF band and significant increment of the HR for panic disorders patients and significant lower values of R-R intervals and HF peak of spectral analysis in depressive patients than in the health people.

In addition to the HR and HRV analysis, the BVP sensor can be updated with other emitter, becomes in an oximetry sensor, which allows to measure both HR and oximetry parameters. BVP sensor can also be combined with an ECG sensor and through the Pulse Transient Time (PPT) technique allowing to measure the blood pressure.

Thus, sensors designed for other areas such as the earlobe can also be found, nonetheless, the placement at the hand level is particularly advantageous for the design of multimodal measurement units, as it enables the combination of BVP signals with other parameters (e.g. electrodermal activity).

3 Methodology

Our work targeted the comparison of heart rate measurements taken at the hand palm and at the fingertip, aiming at the feasibility evaluation of palmar sensors for that purpose. We used a set of two BVP sensors, a standard transmissive sensor placed at the tip of the ring finger, and an experimental reflective sensor in a side-by-side, dual-emitter, single detector configuration (Figure 2(a)), placed at the base of the hypothenar eminence, near the point where it meets the wrist (Figure 2(b)). This palmar location was identified as the least affected area within hand whenever finger movements occur. The palm sensor was compared with a finger tip since this last one is considered the gold standard to measure heart rate based on PPG technique for clinical practice. Furthermore, the finger tip used as standard it was also validated by [10], which compared the HR and HRV extracted from the finger tip sensor and ECG sensor. The authors have shown a strong positive association between all the parameters calculated using the finger BVP and ECG signals.

A bioPLUX research wireless biosignal acquisition unit was used for data acquisition, enabling synchronous sampling and real-time transmission of the collected data to a base station. For the measurements at the fingertip, a bvpPLUX sensor was used; for the experimental palmar sensor, the base circuitry of a bvpPLUX was used but the emitter/detector arrangement was adapted according to what previously described. Raw sensor data was acquired with 1000Hz sampling rate and 12-bit resolution; through off-line signal processing, we computed the heart rate information and performed statistical analysis of the results. Figure 3 depicts an example of the raw signals obtained with each of the sensors.
Fig. 2. Blood Volume Pulse (BVP) sensor and placement at the hand palm.

Fig. 3. Palmar and fingerprint BVP signal.

4 Results

Experimental evaluation was performed on a group of 10 healthy subjects, composed by 5 males and 5 females, with an average age of $26 \pm 3$ years, and quietly sat in order to avoid movement artifacts. We intend to validate the palm position with the finger and so no movement artifact must be in the signal. These artifacts mask the BVP signals, not allowing to visualize the raw BVP signal and extract the cardiac and signal parameters. Data was acquired at rest for a period of 5 minutes, and analysed with respect to the accuracy of heart rate calculation (HR), signal-to-noise ratio (SNR), and root mean square (RMS). Table 1 outlines the main results; which revealed a very strong positive association between the measurements obtained by both sensors.

The heart rate exhibits a coefficient of determination $R^2 > 98\%$, and a $p-value > 0.05$, showing that the outcomes are not statistically different. The measurement divergence between both sensors is $1bpm$ at most, as shown by the average heart rate difference of $0.25bpm \pm 0.45$. Another interesting finding is a pulse latency between
Table 1. Fingertip and hand palm BVP sensors comparison.

<table>
<thead>
<tr>
<th></th>
<th>Fingertip M ± SD</th>
<th>Hand Palm M ± SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>HR (bpm)</td>
<td>70.13 ± 10.51</td>
<td>70.38 ± 10.07</td>
</tr>
<tr>
<td>SNR (dB)</td>
<td>132.70 ± 61.43</td>
<td>173.30 ± 60.21</td>
</tr>
<tr>
<td>RMS (V)</td>
<td>0.22 ± 0.12</td>
<td>0.07 ± 0.05</td>
</tr>
</tbody>
</table>

The heart rate is one of the most widely adopted biomedical indicators in use to date, and state-of-the-art research has focused on finding wearable and easy to use acquisition methods applicable in free living and quality of life activities. While chest straps currently provide a convenient acquisition possibilities, with a very high level of discretion, a problem arises in applications that require the combination of heart rate with other indicators that need to be measured in body areas other than the chest.

Clinical psychology is one such area, where measurements as the electrophysiological activity (typically measured at the hand palms or fingers), also provide important psychophysiological information. Blood Volume Pulse (BVP) sensors, stand as alternative method for heart rate assessment at the hand level, however current measurement approaches greatly limit the subjects normal activities, as they require the sensor to be clipped to a finger. In our work, we further extend the stat-of-the-art in the field, by evaluating the feasibility of using the BVP for heart rate assessment at the palmar level, thus enabling the design of more integrated and practical multimodal measurement systems.

Results obtained from real-world data have revealed a high correlation between measurements taken at the hand palm and at the standard finger tip location ($R^2 > 98\%$), as shown also by the average divergence of 0.25 bpm. Another interesting finding was a latency between the palmar and finger BVP pulses; this, together with further validation on a larger set of test subjects will be the focus of future work within our group and in daily-use condition. This will allow to lead filter studies in order to understand how to remove the movement artifacts into the BVP signal and, consequently, to improve the feasibility of the measures. Furthermore, usability and hygiene conditions will be also evaluated, which will enable to make adjustment in the glove and become it more comfortable and usable for clinical practice.

Acknowledgements

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"ICT4Depression" project (ref. 248778), and by the Fundação para a Ciência e Tecnologia (FCT) under the grant SFRH/BD/65248/2009, whose support the authors gratefully acknowledge.

References

Localized Electroencephalography Sensor and Detection of Evoked Potentials

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Abstract. The limitations of current electroencephalographs are unanimous and relate primarily to its low spatial density and assembly complexity for certain applications. In this paper, we introduce an innovative technique, capable to answer to some challenges created by those limitations. A localized, miniaturized and user-friendly electroencephalography (EEG) sensor was developed for signal acquisition in a bipolar montage, to be placed anywhere on the scalp. The low consumption, small size and high spatial resolution, compared with the standard systems, are the main features of the EEG sensor presented. With this sensor we acquired and analyzed spontaneous EEG activity and auditory evoked potentials which are relevant for the cognitive activity analysis. The developed sensor is an important unobtrusive tool for applications of mental health evaluation.

1 Introduction

Electroencephalography (EEG) is a clinical tool with high functional relevance in the diagnosis of various diseases. Despite its wide use and good temporal resolution, the EEG has some clinical and research limitations comparing to other techniques. Its limitations are unanimous and relate often to low density spatial records and the sheer assembly complexity for certain applications (typically 19 electrodes over the scalp), which causes a lengthy experiment preparation and a discomfort to the subject.

Various solutions in order to overcome those technical limitations have been explored, like the study of high density EEG [1][2] and the EEG integration with different acquisition techniques, such as the EEG-fRMN [3], however non of those solutions answer to the lack of ergonomics in current systems and there are vast applications for which a smaller and localized tool would be useful.

The EEG is typically described in terms of rhythmic or spontaneous activity, which is composed by rhythms which refer to the subject’s condition, and transients or evoked potentials that reflects the brain response to a stimulus.

An evoked potential is an electrical potential recorded from the nervous system after a stimulus. After the application of a stimulus, a specific neuron population activates simultaneously or sequentially, creating evoked potentials that can be measured at the scalp. Evoked potentials amplitudes tend to be low comparing to spontaneous potentials, ranging from less than a microvolt to a few microvolts [4][5]. To resolve these
low-amplitude potentials, the stimulus should be repeated 50 to 200 times and a sig-
nal averaging should be performed. This procedure distinguishes the evoked potentials
from the noise provoked by the spontaneous potentials which are stimulus independent
[6].

The depolarization of a stimuli response can be positive (e.g. P300) or negative
(e.g. N200) and with varied latency. The potentials are gradually more complex with
the increasing latency from stimulus to response. Therefore, the potentials with small
latency rely on the physiological perception of stimuli while components with bigger
latency essentially depend on cognitive mechanisms like attention or expectation. The
P300 wave, for example, links mainly to the stimulus classification, while the N200
wave associates with perception and discrimination of a stimulus [7].

In this paper we introduce an innovative technique, capable to answer to some chal-
lenges created by the limitations of current electroencephalographs. A localized, miniaturized and user-friendly EEG sensor was developed for signal acquisition in a bipolar montage anywhere on the scalp. The developed sensor was used to collect and ana-
lyze EEG auditory evoked potentials. The acquisition of evoked potentials allowed us
to visualize and study stimuli such as N100, N200 and P300, relevant markers for the
analysis of cognitive activity.

The low consumption, small size and higher spatial resolution, compared with the
standard systems, represents a solution of high applicability in unobtrusive long-term
cognitive activity monitoring.

2 Localized EEG Development

In this section we describe the steps of the EEG sensor design and development, point-
ing its main characteristics.

2.1 Electronics

The EEG sensor has three channels of acquisition and the signal of each channel is
acquired by two electrodes assembled in a differential configuration which measure the
electrical activity at two nearby points of the cortex. As the signal variation between two
points tend to zero with the proximity, a high amplification is needed for this sensor. Our
sensor has a total gain of 40000, which is four times superior to the gain of common
electroencephalographs, leading to a high sensitivity in the signal acquisition. This high
sensitivity requires an efficient filter chain.

The EEG sensor circuit has three amplification and two filter levels as shown in
Figure 1.

The first amplification stage has a small filtering step to remove the high frequency
noise at the acquisition entrance. This is a radio frequency interference filter (RFI) with
a cut frequency superior to the remainder circuit’s bandwidth. The low-pass and high-
pass filters cancel the high frequency noise and emphasize the frequency band of inter-
est. The cut frequencies of each filter are 0,79Hz (high-pass) and 48,22Hz (low-pass),
which are the standard values for the EEG signal’s bandwidth. Each filter has a real
pole in the cut frequency which gives an attenuation of -3dB for decade. As we have
two high-pass and two low-pass filters, the poles are duple, so the real attenuation is -6dB in relation to the maximum for the two cut frequencies.

The final version of the EEG sensor is a closed loop of three acquisition channels, in which each channel is the circuit described above (and presented in Figure 1).

2.2 Characteristics of the Sensor

The EEG analog to digital conversion and Bluetooth transmission to the computer was performed using a bioPLUX research [8] signal acquisition system, which has a 12 bit ADC and a sampling frequency of 1000 Hz.

The circuit was encapsulated in a structure designed to support all the electronic and enable the contact of the scalp, containing three conductive electrodes. The developed sensor is portable and miniaturized, with 43mm of diameter and 50g of weight. An illustrative photograph of the developed sensor is presented in Figure 2.

The standard procedure for this sensor is to use Ag/AgCl pre-gelled electrodes and a band strap over the sensor to enable an appropriate setting and contact with the scalp. The ground electrode sticked to a bone surface, behing the ear.

3 Acquisition of Evoked Potentials

This section describes the procedure used to induce the evoked potentials and the processing tools needed to visualize those potentials.
3.1 Firmware

The auditory stimuli was generated by a microcontroller which synchronized the signal acquisition with the stimuli application (through headphones), marking the stimuli occurrence in the collected EEG signal. Those markers were different to each stimulus.

The infrequent stimulus had a sound frequency of 1900Hz and the frequent stimulus 900Hz. Both stimuli had an intensity of 81dB and last for 50ms. The stimulus type and frequency are based on a distribution of pseudo-random numbers. The infrequent stimuli occur with 15% of probability, following an uniform distribution of 100 numbers, and the time between stimuli also follows an uniform distribution between 1100ms and 1400ms, to raise the expectation level of the subject.

3.2 Methods

EEG data was recorded from a healthy volunteer with no history of hearing, neurological, learning or stress problems. The subject was sitting in a relaxed state in a quiet environment with minimum distracting elements. The subject was equipped with headphones in mono configuration which received auditory stimuli from the microcontroller and was asked to count the rare sounds that appeared in a series of frequent sounds.

The EEG sensor was positioned at the left occipital region of the head, located near the F3 electrode of the 10-20 EEG standard system [9]. We used AgCl pre-gelled disposable dry detection surfaces fixed with an elastic band strap.

3.3 Signal Processing

After the acquisition procedure, we used Python to visualize and process the EEG data. As the evoked potentials amplitudes tend to be low, a signal processing code was developed to enhance the evoked potentials over the other EEG tracings. The first step was to go through the signal and find the markers left by the microcontroller after a stimulus. The 800ms following the position defined by the marker were saved as infrequent or frequent values, depending on the marker left by the microcontroller.

This process was repeated to each stimulus and the average of each frequent and infrequent vectors was computed.

4 Results

Figure 3 presents the results obtained for 3 tests performed on the subject, who remained with his eyes closed.

In figure 3 a) (first test) we can identify the N200/P300 complex in the infrequent stimuli graphic. This complex begins with a negative depolarization near 200ms, followed by a positive component near 300ms. The noise present in the infrequent stimuli is due to the low repetition rate (19 times). In figure 3 b) is also noticeable the N200/P300 complex in the infrequent records, with a noise level smaller due to the higher number of stimuli. In the third test (figure 3 c) the component P300 appears with much less intensity. The N200 component is still visible in the infrequent waves graphic.
Fig. 3. Subject’s Evoked Potentials: a) first test with 19 infrequent and 751 frequent stimuli; b) second test with 51 infrequent and 1187 frequent stimuli; c) third test with 25 infrequent and 1132 frequent stimuli.

The N100 complex is also noticeable specially in the frequent responses, although with less definition.

5 Discussion and Conclusions

The N100 potential appears with low definition in all tests, which can be explained for the position where the sensor was placed. The F3 site favors the acquisition of N200 and P300 potentials and attenuates the N100 components. The N200/P300 complex emerges in all tests, but in the third the N200 component is much more pronounced than the P300. That happens because in the third test the subject was already accustomed to the task and was performing the test with less expectation than the first times - hence the distinctness of N200 which associates with sound perception over the P300 which mingle with attention and expectations. The habituation factor decreases the impact of the test than when done for the first time.

A prototype version of this sensor was previously presented with the detection of EEG alpha rhythm and processment of its latency [10]. The acquisition of evoked potentials, because of its low amplitude values, represents a more effective valitation to evaluate the high sensibility of the sensor. The development procedure denoted a high efficiency level for this sensor, in accordance with the user-friendly, signal quality and ergonomics requirements, taking into account that the results were achieved directly with the raw signals without any filtering process.

A sensor with this specifications has high applicability in various scenarios, since it could allow to record huge amounts of data related to everyday and ambient assisted living activities. This sensor could also be meaningful for analysis of sleep disorders, as a
sensor like this has minimum influence to the patients sleep given its ergonomics characteristics. Another possible application is the monitoring of epileptic seizures, since these appear uniformly through the brain and its signal can be acquired in any point of the scalp. In a more futuristic view, we can affirm that a localized sensor like the one we present can contribute in areas like brain computer interfaces (BCI). In this field is convenient to monitor a specific brain structure and associate it to an interface control, so our sensor represents a big contribution through its localized acquisition characteristics.

Future Work

In future steps of this project we intend explore and validate the sensor’s capacity to map the cerebral activity.

In order to further reduce external noise, we intend to eliminate the cables that connect the conditioning circuit to the scan and transmission circuit, integrating both components inside the same physical packaging.

We also intend to raise the channels number in the same area of the sensor.

References

A Mobile System for Treatment of Depression

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Abstract. This paper presents a mobile treatment system developed as part of the FP7 ICT4Depression project. The project targets the efficient treatment of minor and major depression. To this end, treatments that have traditionally been administered via relatively simple web-based interfaces, have been translated for use on a smart phone. The delivery of the treatments is supported by an evidence-based approach to patient progression and treatment adherence monitoring. The mobile system consists of a graphical user interface, biomedical sensors to measure the patient’s affective state, a medication adherence system, an activity monitor and a server based reasoning system to combine the various sensor data streams and obtain abstracted information relating to patient status and progression, thereby allowing for appropriate feedback and advice for both patient and medical staff.

1 Introduction

In recent years depression has received significant attention as a disorder with a far-fetched impact on individuals and society as a whole. Studies show that in 2003 the occurrence of major depressive disorder ranged from 3% (in Japan) to 16.9% in the US with most countries showing a prevalence of 8% to 12% [1]. The burden of depression is on the rise and by the year 2030, depression is expected to have the highest disease burden in high income countries. There thus is a real need for effective treatment of depression within the cost constraints of health services.

Treatments have already been adapted for online use to allow for more cost effective treatment and such systems have been shown to be of value [2]. The aim of the ICT4Depression project is to take this approach a step further and provide various treatment modules not only on a personal computer, but also on a mobile phone. The advantages of this approach are that users can be provided with continuous treatment, are free to decide when to interact with the system, can be monitored throughout the day and can effectively include and integrate day-to-day duties and habits in their customized treatment. Of particular interest in this regard is the recent insight that the
inclusion of user specific data in the form of ecological momentary assessments (EMA) is an important goal for future mobile treatment systems [3].

This paper describes the architecture and various sub systems comprising the mobile system used for treatment of depression in the ICT4Depression project.

The mobile system architecture is shown in Fig. 1. For reference, the other components of the ICT4Depression system are shown in the dashed box. The user interacts with the mobile system through a Samsung Galaxy S smart phone. A dedicated graphical user interface presents the user with information on the treatment, allows the user to execute those parts of the treatment that need user input, incorporates a calendar and acts as a sensor data aggregator for the biomedical sensors. These consist of a hand worn device for the measurement of electro-dermal activity (EDA) and blood volume pulse. Whereas the latter yields information on the heart rate, the EDA is an indicator for a wide range of emotional responses, thus providing the system an additional insight in the user’s mental state. The second biomedical sensor is a chest strap that can be worn under normal clothing. The chest strap provides heart rate, respiration rate and an accelerometer that can be used to infer the trunk orientation of the user. The latter data is combined with motion data measured directly on the smart phone to obtain accurate information on patient physical activities.

![Fig. 1. Overview of the ICT4Depression System.](image)

Treatment of depression is normally supported by medication and the adherence to the prescribed medication regimen is often low. For this reason, a smart pill box is used to monitor medication intake. All sensor data is sent to a dedicated server where analysis of the data takes place in a reasoning system that incorporates models of the user and their progression. This system can assess whether the treatment is successful...
and provides the medical staff and user with advice for further treatment. The rest of this paper will discuss the system in more detail. In Section 2 the graphical user interface will be discussed after which the various sensors will be introduced in Section 3. Sections 4 and 5 introduce the reasoning system and server infrastructure respectively and conclusions are presented in Section 6.

2 Graphical User Interface

The patient has access to the ICT4Depression system through a smart phone interface. The interface is developed using html and java scripts, which are stored on the phone such that the application can also be used if there is no connectivity. For conformity in the presentation of the treatment modules to the patient and for ease of treatment module development, a structure of available module screens was developed.

The first category of screens is the navigation screen, which is depicted in Fig. 2. Its primary function is to facilitate navigation through and around the application. Through the use of these screens, patients can access further navigation controls, read module content or undertake module centric activities.

The module content screens, as depicted in Fig. 3, allow the patient to read about the treatments available in the ICT4Depression application.

The third category of screen is the patient input screen, an example of which is shown in Fig. 4. This page type requires interaction between the patient and the module to assist in the patient’s treatment.

A logo is present on every screen which acts as a link that will allow the patient to immediately link back to their home page. Because the patient should be able to return to the source screen, a button with sitemap functionality is integrated into the application. On clicking this button, the patient is able to navigate back to a previous screen. An additional button for inclusion in the ICT4Depression application is the
calendar quick link. This button enables the patient to view, edit and add module activities to their personalised calendar as necessary. Finally an activities quick link was included to enable patients to access their exercises and activities from anywhere within the application.

3 Sensor Systems

One of the innovative aspects of this system is the use of sensors in various ways to elicit information on the user’s well-being and treatment progression. To this end, biomedical sensors are used to measure heart rate, breathing rate and electro-dermal activity, the phone itself is used to measure user physical activity and a medication adherence system monitors the user’s medication intake.

3.1 Biosignal Acquisition System

Two wearable sensor form factors can be used by the patient enabling the measurement of multiple biosignals. The devices are controlled by the mobile phone through an Application Programming Interface (API) and corresponding software development kit (SDK) and are used to sample raw sensor data. The relevant characteristics, like the heart rate [4] or skin resistance changes [5,6] are detected and extracted from the signal. Finally, the resulting data are sent to the mobile phone via the wireless Bluetooth protocol. In the next sections we describe the Chest Strap and Glove prototypes.

3.1.1 Chest Strap

The chest strap, which is shown in Fig. 5 has three embedded sensors and one acquisition system. The sensors are an ECG (Electrocardiography), Respiration sensor and tri-axial accelerometer that are situated in the chest of the wearer. All the embedded electronics are easily removable and reassembled, to allow the wearer to machine-wash the chest band when the need arises.

The chest strap form factor allows an easy and seamless placement of the acquisition system and sensors. In the following pictures, the acquisition system and the...
sensors are embedded inside the textile band. It is slid in the narrow space between two seams. This creates the needed stability to obtain a good respiration signal. The chest band opening that houses the acquisition system and the sensors, is closed by means of a metallic snap or a zipper. The three electrodes of the ECG sensor must be aligned with three small holes in the textile and then the snaps must be closed. This is essential to obtain the ECG signal and it will help also in maintaining the system in its place while in use. The technical specifications are described in Table 1.

### Table 1. Specifications of the chest strap device.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerometer</td>
<td>±5G 3-axis MEMS technology</td>
</tr>
<tr>
<td>Respiration</td>
<td>1 Hz low-pass filter Piezofilm technology</td>
</tr>
<tr>
<td>ECG</td>
<td>Gain 1000 0.05-30 Hz band pass filter 110 dB CMRR &gt; 100 MOhm input impedance</td>
</tr>
</tbody>
</table>

#### 3.1.2 Glove

The glove has two embedded sensors and one acquisition system. The sensors are an EDA (Electro-dermal Activity) and BVP (Blood Volume Pulse) that are situated in the palmar side of the non-dominant hand of the wearer (for this document the left hand is used). All the embedded electronics are easily removable and reassembled, to allow the wearer to machine-wash the glove when the need arises.

The acquisition system and the sensors must be placed in the correct locations before the user puts the glove on. The BVP sensor is passed through a small opening in the textile. This sensor will stay in its place by means of Velcro or a metallic snap. For the EDA sensor, the process is also very simple. The two wires with metallic electrodes must be aligned with the two small holes in the textile and then the snaps must be closed. Fig. 6 depicts the sensor system and placement in the hand. Through the integrated sensors, this system enables us to acquire heart rate and skin conductance response (SCR). The technical specifications are described in Table 2.

### Table 2. Specifications of the glove device.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDA</td>
<td>3 Hz low-pass filter &gt; 1 TOhm input impedance</td>
</tr>
<tr>
<td>BVP</td>
<td>Double emitter/Single detector setup Infrared wavelength range</td>
</tr>
</tbody>
</table>
3.2 Physical Activity Monitor

On the mobile phone the accelerometers are used to obtain a better insight in user physical activity behaviors. Raw acceleration data is used in a physical activity monitoring algorithm to determine periods of lying, sitting, standing, walking, running and energy expenditure. To obtain further insights in the user’s activities, the phone’s GPS is used to obtain a geo-location based perspective on user behavior without continuously tracking the user location. The user defines a list of places in which they perform social and exercise activities. Whenever the GPS indicates that the phone is within a preset distance from any of these points, this is logged and thus an indication of the frequency and duration of time spent in these locations is obtained.

3.3 Medication Adherence System

Sub-optimal adherence to prescribed medicines is frequently the principal obstacle to successful pharmacotherapy in ambulatory patients, especially when unrecognized clinically, as often occurs [7]. Sub-optimal adherence is highly prevalent, associated with poor outcomes of treatments that, when administered correctly, have well-established benefits. For unclear reasons, sub-optimal adherence and its consequences have been a largely neglected aspect of therapeutics. Across all fields of ambulatory pharmacotherapy, a large number of patients do not adhere to effective treatments including circumstances in which life-saving medicines are available for life-threatening diseases.

Electronic monitoring of ambulatory patients’ dosing histories has repeatedly revealed that their drug intake is frequently irregular, spanning a wide spectrum of deviations from the prescribed regimen. It is strongly skewed toward under-dosing, created by delayed and omitted doses, sometimes occurring in multiple, sequential omissions of prescribed doses. Those deviations, in turn, tend to nullify therapeutic actions of the drugs in question, contributing thereby to worsening of disease, and increased health care costs.

Given the clinical and economic impact of non-adherence, urgent actions need to be taken to enhance patient adherence to drug therapies. During the last decade, many interventions have been tested but few of them have addressed simultaneously both the intentional and unintentional aspects of non-adherence to medications [8]; [9]; [10]; [11]. These successful interventions rely on the two principal values of electron-
ic monitoring: first, it provides objective and reliable information on patient’s dosing history, which defines the extent of the exposure to the prescribed medication; second, the dosing history serves as a crucial element of intervention methods to manage adherence to medication [12].

Until recently, those interventions took place at clinical visits, typically every few months, and were corrective by nature. Today, new ICT technologies allow the remote monitoring of patients’ adherence to drug therapies, providing timely information to both caregivers and patients to support effective medication management.

3.3.1 Adherence Monitoring System

The adherence system is depicted in Figure 7. This system covers the chain needed to:

- Monitor adherence data
- Wirelessly transfer adherence data to a dedicated server
- Provide information on adherence to different types of client

The main goal of the adherence monitoring system is to assure the collection of adherence data but, more importantly, to facilitate their integration in external systems. These systems require different levels of integration. Some may simply need a visualization of adherence data while others expect more advanced feedbacks based on the detection of highly contextual adherence issues (e.g., risk of treatment discontinuation in depressed patients, detection of drug holidays in HIV patients). Some systems may push the integration a step further by accessing raw adherence data for pharmacokinetic-pharmacodynamic modeling.

![Adherence Monitoring System Diagram](image)

**Fig. 7.** Adherence monitoring system.

The architecture of the adherence system is based on the following elements:
• The MEMS monitor is a pill container with integrated electronic micro circuitry designed to record the date and time of each opening and closing of the container. It also provides direct basic feedback to the patient through an LCD screen.
• The wireless reader is used to download data from the MEMS monitor and wirelessly transfer these data to the adherence backend.
• The adherence backend stores adherence data and supports their interpretation. This backend can be accessed in a secured way through web-services by different clients.
• Finally, specific components have also been developed to facilitate the integration of adherence data into those clients. An android and a javascript adherence module have been developed.

4 Reasoning System

One of the key elements of the overall system is an intelligent reasoning system to support the patient in a highly personalized manner. The system essentially combines the data that has been obtained from sensors (including the information that the patient has provided to the system, e.g. rating of mood) to an overall picture of how the patient is functioning. Based upon this overall picture, the system can then decide to provide feedback to the patient (in the form of motivational messages or reminders), but the system can also decide to suggest therapeutic changes. Four main parts are distinguished that establish this behavior: (1) a data abstraction component, (2) a virtual patient component, (3) an evaluation component, and (4) a communication component. In Fig. 8 the overall structure of the reasoning system is shown.

On a high level, the reasoning system first abstracts the data to determine the current state of the patient (e.g. how much is the patient involved in the therapy). Besides assessing the actual behavior of the patient, the reasoning system also comprises of a virtual patient that makes predictions about the state of the patient (the component virtual patient) given his/her characteristics (obtained from the sensor data) and the type of therapy. In the evaluation component the current state of the patient is evaluated as well as the therapeutic success. This is performed by analyzing the measured
state itself, but also by comparing these states with the predictions of the virtual patient. Finally, in the component communication generation the evaluation is used to advice a different therapy in case another therapy is expected to be more successful. Furthermore, more instant forms of feedback are generated based upon the sensory data including the sending of reminders, and providing of motivational messages. Below, each of the components is treated in more detail.

4.1 Data Abstraction

In the data abstraction component the idea is to compose an abstract overall picture of the patient. This overall picture indicates the patient state and the trends in the patient state (e.g. the general patient state is good, but the trend is negative) and similar for the therapeutic state (e.g. the involvement is bad, but an increasing trend in involvement can be seen). In order to establish this behavior, a dedicated language to express complex temporal patterns called the Temporal Trace Language (TTL) has been used (cf. [13]). First, the measurements are abstracted in a temporal fashion (e.g. calculating the average mood during a day), thereafter trends are identified in this abstracted data (e.g. the average mood was good during that particular day). Finally, the trends of multiple measurements are aggregated into a single overall patient and therapeutic state, which makes the approach more robust against missing data. In this aggregation, each particular measurement is assigned a certain weight in the overall compilation of the picture.

4.2 Virtual Patient

The second component concerns a so-called virtual patient model. This model is able to make predictions about the development of the patient during a certain therapy. In order to do so, dedicated computational models are present that express the states within the patient (e.g. mood, appraisal) and how these states influence each other. In addition, the therapeutic influence is also modeled. The models incorporated in the virtual patient prediction component are described in more detail in [15,16,17]. As an input for these models, the characteristics for the patient as provided in a questionnaire are used. The output of the prediction is the development of the general patient state and therapeutic development over time given a certain therapy which is followed.

4.3 Evaluation

The evaluation component creates an assessment of the patient by comparing the predictions using the model with the actual state of the patient. In case the patient is significantly underperforming, a process is started to evaluate alternative therapies and see whether these might be more effective. This evaluation again takes place using the virtual patient model, thereby possibly altering the parameters of the model to make sure that the model is an accurate description of the patient. As a result, the component derives whether a therapeutic change should be advised. A more detailed
description of the evaluation process can be found in [14].

4.4 Communication Generation

The final component is the generation of communication to the patient. This communication can either concern information about a therapeutic switch (due to the evaluation made in the previously discussed component), but can also involve motivational messages and reminders. The messages are generated using dedicated rules that express in what situation what information should be communicated to the patient. Note that not only the high level assessment are hereby considered, but also the immediate sensory information, for instance a positive mood rating by the patient could trigger a message expressing that it is good to hear that the patient is feeling well.

5 System Server and Infrastructure

The server main goal is to work as an information repository to be accessed in a web, decentralized and in an interoperable fashion. The current clients are developed within the project consortium, but this architecture allows expandability and openness to new market players.

The repository uses the Microsoft SQL 2008 database management system. To ensure the standard data protection, the database TDE (Transparent Data Encryption) [18] feature was used. For the information exchange the option in use was the Web Service development over the WCF (Windows Communication Foundation) [19] targeting .NET Framework 4. This framework, as other modern frameworks, allows the use of WS (Web Services) standards, which enable the development of service oriented applications. As such, the ICT4Depression is a SOA (Service Oriented Architecture) that relies on WS to send and receive data. The main advantage is the loose coupling between client applications and repository. This implies that any client created on any platform can connect to the ICT4Depression system according to established information access policies, as long as the essential contracts [20] are met. The current client applications are WS client applications, a web client PHP application and a mobile application running on Android. They implement the therapy modules and use XML/JSON over HTTPS to communicate to the server, which implements both the synchronous and asynchronous web method invocation.

![Fig. 9. ICT4D SOA layers.](image)
6 Conclusions

In this paper a mobile system designed for the continuous treatment of depression is presented. The mobile system uses a smart phone to provide the treatment to the user, obtain input from the user and display feedback and advice. Biomedical sensors and the phone itself measure parameters which are linked to emotional markers to obtain further information on the user’s well-being and treatment progression. The user’s adherence to the set medication regimen is monitored using a dedicated medication adherence system. All information is gathered in a server where a reasoning system analyses the data, determines the treatment progression and provides feedback to the user. The system will be tested with real users in 2012.

Acknowledgements

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References


Applicability of Multi-modal Electrophysiological Data Acquisition and Processing to Emotion Recognition

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Abstract. We present an overview and study on the applicability of multimodal electrophysiological data acquisition and processing to emotion recognition. We build on previous work in the field and further explore the emotion elicitation process, by using videos to stimulate emotions in several participants. Electrophysiological data from Electrocardiography (ECG), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Respiration (RESP), Electromyography (EMG), and Peripheral Temperature (SKT) sensors was acquired and used to classify the negative and positive emotions. We evaluate the emotional status identification accuracy both in terms of the target emotions and those reported by the participants, with recognition rates above 70% through Leave One Out Cross Validation (LOOCV) with a k-NN Classifier.

1 Introduction

Over the last years, different authors have studied emotions and their components and concluded about their crucial role in numerous areas of human life such as problem solving, social interaction, decision-making, perception, and motivation, [7]. Emotions are composed of two parts: a psychological and a physiological part. The former is related with the individual cognitive aspect of emotion; the latter has to do with the physiological responses that occur when an individual experiences an emotion. The use of biosignals to study emotions is a growing research field with more and more applications, [15].

In this paper we present an overview and study on the applicability of multimodal electrophysiological data acquisition and processing to emotion recognition. We developed a protocol for emotion elicitation and biosignal acquisition, for which preliminary results were presented in [2]. The rest of the paper is organized as follows: in Section 2 a review of the State-of-the-Art in emotion recognition is given; Section 3 summarizes the methodology and experimental setup proposed in; in Section 4, we evaluate the emotion elicitation procedure, and present the emotion classification results; Section 5 outlines the main conclusions and presents ideas for future work.
Table 1. Summary of emotion recognition studies.

<table>
<thead>
<tr>
<th>Year</th>
<th>Reference</th>
<th>Recognition rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001</td>
<td>[16]</td>
<td>81%</td>
</tr>
<tr>
<td>2004</td>
<td>[13]</td>
<td>61.8%</td>
</tr>
<tr>
<td>2006</td>
<td>[12]</td>
<td>71%</td>
</tr>
<tr>
<td>2009</td>
<td>[10]</td>
<td>86.3%</td>
</tr>
<tr>
<td>2010</td>
<td>[15]</td>
<td>61%</td>
</tr>
<tr>
<td>2011</td>
<td>[2]</td>
<td>30-97.5%</td>
</tr>
</tbody>
</table>

2 State-of-the-art

Emotion recognition using electrophysiological data is one of the branches of the Affective Computing field: a growing research field that merges emotions and computers in many different applications (see [18] and references therein). Table 1 summarizes some results found in State-of-the-Art work for emotion recognition using biosignals. The work by [16] sought the classification of 8 emotions from BVP, RESP, EDA, and EMG data; tests were performed in 1 subject with 81% recognition rates.

In 2004, Haag et al. [11] used Neural Networks (NN) and obtained a classification accuracy ranging from 64% to 97% for two components of emotion (arousal and valence) of 1 subject; the authors used EMG, ECG, RESP, EDA, SKT, and BVP data. By arousal we are referring to the physical arousal response to an emotional stimulus (e.g., a stimulus may provoke excitement and thus high arousal or it may be boring and provoke a low arousal response) and valence indicates whether an emotion is negative, neutral, or positive.

In [13], the authors used data from the ECG, EDA, and SKT to classify 4 emotions of 175 subjects using Support Vector Machines (SVMs); the accuracy was 61.8%. Leon et al. [12] also used NN in the pursuit of distinguishing positive, negative, and neutral emotions of 8 subjects; they used data from the BVP and EDA and had recognition rates of 71%.

In [10], data from EEG, BVP, and EDA was also used to classify 4 emotions of a subject while studying; they applied SVMs and k-Nearest Neighbors (k-NN) obtaining a best result of 86.3%. In 2010, [15] presented an emotion classification framework with Analysis of Variance (ANOVA), Principal Component Analysis (PCA), k-NN, SVM, and NN; an accuracy of 61% was achieved with the use of EMGs and EDA data to classify positive, negative, and neutral emotions of 21 subjects.

Recently, our team proposed a multimodal biosignal (ECG, BVP, EDA, RESP, EMGs, and SKT) sensor data handling for emotion recognition, [2]; we applied k-NN (k=5) to classify positive, negative, neutral, and a mix of different emotions of 20 subjects with recognition rates in the 30-97.5% range.
3 Methodology, Experimental Setup and Data Acquisition

Our team has been researching in Behavioral Biometrics and Affective Computing since 2007 when a project called HiMotion began, [5]. Within that project, a protocol was proposed to monitor Human Computer Interaction and acquire different electrophysiological signals for the study of behavioral biometrics, [3].

Later, in [1] and [2], we build upon the developed tools and results obtained and added an emotion elicitation component so that we could study how biosignals and emotions relate to each other. To elicit emotions, various techniques are available, [1]. We decided to use videos as emotional stimulus as they are easy to use and provide reasonable results, [17], [19]. Based on the experience setup by [17] and [19], we designed a Web application for video visualization.

The experience took the participant through the steps of Figure 3: (a) welcome page; (b) participant information; (c) protocol briefing; (d) light brown screen time
for a period of 30 seconds; (e) full screen video; (f) questionnaire about the emotions felt during the video. Steps (d), (e) and (f) were repeated for a sequence of different videos. Step (c) has the objective of briefing the participant about the experience; step (d) is a 30 second period with no emotional stimulus so that the participant could relax and return to the baseline emotional state after each video; step (f) is a questionnaire used to retrieve the participants opinion about the emotions felt during the video.

The experimental setup and system architecture used is presented in Figure 1: we have a participant interacting with the Web application, with a set of seven biosensors attached to his/her hand, chest and face: Electrocardiography (ECG), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Respiration (RESP), Electromyography (EMG), and Peripheral Temperature (SKT). The biosignals data is acquired using a bioPLUX research, wireless biosignal acquisition unit and corresponding set of sensors [6]; this information is then saved in a database along with information gathered by the Web application.

Synchrony between the biosignal and the Web application data is achieved through the use of a Light Dependent Resistor (LDR). This sensor outputs different values for different light values and so we placed it at the lower left corner of the screen where the color changes from light brown to black when a video is being played (an emotion is being elicited). We have also developed a Python toolbox to process the biosignals and apply feature extraction and classification techniques, [2].

4 Experimental Results

4.1 Emotion Elicitation

Table 2 summarizes the information retrieved by the video questionnaires, described earlier, for all the participants. As in [17], intensity refers to “whether a film receives a high mean report on the target emotion relative to other candidate films”; discreteness is the ratio between the number of participants that felt the target emotion (one point or more than all other emotions) and the total number of participants. We have also asked the users to rate the valence of their emotions in a 0-9 scale (0 stands for very negative emotion and 9 for very positive emotion).

Different conclusions can be drawn from the obtained data. First, we wanted to elicit 8 different emotional states (target emotions) and the participants reported 22 different emotions (see column 2 of Table 2 and Notes 1-4 of Table 4). As we can see, different people have different reactions for the same video as the reported emotions vary within the same film. Also, the target emotion is not achieved for all cases and all individuals. Overall, the Sadness, Disgust, and Amusement videos had the best results as the mean valence reported fell within the expected range (below 5 for the first three cases and above 5 in the last one) and had also higher intensity and discreteness levels. Fear is difficult to elicit, as people tend to reveal anxiety or interest about the situation being presented.
Table 2. Summary of video information and feedback given by the participants.

<table>
<thead>
<tr>
<th>Target Emotion</th>
<th>Reported emotions (Most Common)</th>
<th>Reported valence</th>
<th>Intensity</th>
<th>Discreteness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neutral 1 (60 sec)</td>
<td>Confusion/Boredom</td>
<td>2-4-9</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Neutral 2 (80 sec)</td>
<td>Nothing/Pity/Love/Interest</td>
<td>2-4-9</td>
<td>0.28</td>
<td>0.33</td>
</tr>
<tr>
<td>Sadness 1 (90 sec)</td>
<td>Sadness/Uncomfortable</td>
<td>0-3-7</td>
<td>0.54</td>
<td>0.69</td>
</tr>
<tr>
<td>Sadness 2 (173 sec)</td>
<td>Sadness</td>
<td>0-2-6</td>
<td>0.77</td>
<td>0.89</td>
</tr>
<tr>
<td>Anger 1 (90 sec)</td>
<td>Anger/Disgust</td>
<td>1-3-6</td>
<td>0.39</td>
<td>0.62</td>
</tr>
<tr>
<td>Anger 2 (254 sec)</td>
<td>Anger/Anxiety</td>
<td>0-2-5</td>
<td>0.43</td>
<td>0.56</td>
</tr>
<tr>
<td>Surprise 1 (16 sec)</td>
<td>Anxiety/Interest/Fear</td>
<td>1-4-8</td>
<td>0.09</td>
<td>0.15</td>
</tr>
<tr>
<td>Surprise 2 (47 sec)</td>
<td>Confusion/Fear/Anxiety</td>
<td>1-3-9</td>
<td>0.11</td>
<td>0.22</td>
</tr>
<tr>
<td>Disgust 1 (60 sec)</td>
<td>Disgust</td>
<td>0-2-6</td>
<td>0.83</td>
<td>0.92</td>
</tr>
<tr>
<td>Disgust 2 (65 sec)</td>
<td>Disgust/Interest</td>
<td>0-2-5</td>
<td>0.27</td>
<td>0.33</td>
</tr>
<tr>
<td>Fear 1 (82 sec)</td>
<td>Anxiety/Interest</td>
<td>2-4-6</td>
<td>0.10</td>
<td>0.15</td>
</tr>
<tr>
<td>Fear 2 (207 sec)</td>
<td>Anxiety</td>
<td>0-3-7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Amusement 1 (155 sec)</td>
<td>Amusement/Surprise</td>
<td>3-5-9</td>
<td>0.50</td>
<td>0.69</td>
</tr>
<tr>
<td>Amusement 2 (247 sec)</td>
<td>Amusement</td>
<td>0-6-9</td>
<td>0.65</td>
<td>0.78</td>
</tr>
<tr>
<td>Happiness (87 sec)</td>
<td>Happiness/Amusement</td>
<td>4-6-9</td>
<td>0.56</td>
<td>0.89</td>
</tr>
</tbody>
</table>

4.2 Classification

After the electrophysiological data acquisition, we used our Python toolbox to process the biosignals, extract a set of relevant features, and for classification. Table 3 presents the extracted features for each biosignal. For a list of commonly extracted features in the emotion recognition field refer to [15].

The classification process employed a k-NN (k=5) classifier [20], [21], and to assess how the results would generalize to an independent data set we used the LOOCV technique. The k-NN classifier evaluates the k points closest (k-Nearest Neighbors) to a given input data point, \( x_i \), and outputs a class label, \( c_i \). Each neighbor belongs to a class and \( c_i \) is determined as the most predominant class among them. The k-Nearest Neighbors were found using the Euclidean distance. The LOOCV technique divides data into a test set composed of one sample point and a training set composed of the remaining sample points.

The authors in [2], achieved a classification accuracy ranging from 30% to 97.5% for different scenarios – last line of Table 1. The labels used for classification were the target emotions. However, as we have seen before, the targeted emotions do not
match the emotions reported by the participants in all cases. With that in mind, we applied the same techniques used before but having the classification labels equal the reported emotions. Table 4 shows the results obtained for both cases. As we can observe, the recognition rates are better for the target emotions: it may have to do with the division between positive and negative emotions that sets Amusement, Happiness, Joy, Love, Interest, and Peaceful in the positive emotions group and Anger, Disgust, Anxiety, Fear, Confusion, Embarrassment, Bored, Contempt, Shame, Powerless, Pity, Sadness, Touched, Scared, Surprise, and Unhappiness in the negative emotions group; for a future work, other criterions should be used such as the emotion valence reported by the participants.

Table 3. List of extracted features for each biosignal. $\mu$: mean; $\sigma$: standard deviation; $\sigma^2$: variance; AD: absolute deviation; RMS: Root Mean Square; SCL: Skin Conductivity Level; SCRs: Skin Conductivity Responses; IBI: Inter Beat Interval; RMSSD: Root Mean Sum of Squared Differences.

<table>
<thead>
<tr>
<th>Biosignal</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMG</td>
<td>$\mu, \sigma, \sigma^2, AD, RMS$</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
</tr>
<tr>
<td></td>
<td>Kurtosis</td>
</tr>
<tr>
<td>EDA</td>
<td>$\mu$ of SCL</td>
</tr>
<tr>
<td></td>
<td>$\sigma, \sigma^2, AD$</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
</tr>
<tr>
<td></td>
<td>Kurtosis</td>
</tr>
<tr>
<td></td>
<td>Number of SCRs</td>
</tr>
<tr>
<td></td>
<td>$\mu$ and $\sigma$ of the SCRs amplitudes</td>
</tr>
<tr>
<td></td>
<td>$\mu$ and $\sigma$ of the SCRs rise times</td>
</tr>
<tr>
<td></td>
<td>$\mu$ and $\sigma$ of the SCRs $\frac{1}{2}$ recovery times</td>
</tr>
<tr>
<td>SKT</td>
<td>$\mu, \sigma, \sigma^2, AD$</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
</tr>
<tr>
<td></td>
<td>Kurtosis</td>
</tr>
<tr>
<td>ECG</td>
<td>Heart Rate</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ of IBI</td>
</tr>
<tr>
<td></td>
<td>RMSSD of IBI</td>
</tr>
<tr>
<td></td>
<td>Power Spectrum of IBI</td>
</tr>
<tr>
<td>RESP</td>
<td>$\mu, \sigma, \sigma^2, AD$</td>
</tr>
<tr>
<td></td>
<td>Zero crossings</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
</tr>
<tr>
<td></td>
<td>Kurtosis</td>
</tr>
<tr>
<td>BVP</td>
<td>Envelope</td>
</tr>
<tr>
<td></td>
<td>Heart Rate</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ of IBI</td>
</tr>
<tr>
<td></td>
<td>RMSSD of IBI</td>
</tr>
<tr>
<td></td>
<td>Power Spectrum of IBI</td>
</tr>
</tbody>
</table>
Table 4. Classification results.

<table>
<thead>
<tr>
<th>Labels</th>
<th>Reported Emotions$^1$</th>
<th>Target Emotions$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive (Amusement) vs. Negative (Anger, Disgust, Sadness)</td>
<td>All Positive$^3$ vs. All Negative$^4$</td>
<td>Positive (Amusement, Happiness) vs. Negative (Anger, Disgust, Fear, Sadness, Surprise)</td>
</tr>
<tr>
<td>Accuracy</td>
<td>71.2%</td>
<td>70.7%</td>
</tr>
</tbody>
</table>

Fig. 2. Classification results for Positive vs. Negative emotions: reported emotions (left) and target emotions (right).

5 Discussion and Future Work

In this paper we approached the applicability of multi-modal electrophysiological data acquisition and processing to emotion recognition. We further explored and evaluated the emotion elicitation protocol proposed in [2]: it consists of a Web application for video viewing and the evaluation is based on the feedback given by the participants for each video used. On the one hand, videos for emotions such as the Sadness, Disgust, and Amusement scored the best results; on the other hand eliciting Fear turned out to be more difficult.

We wanted to elicit 8 emotions and the participants reported 22: different people have different reactions to the same emotional stimuli. New emotion classification results are presented based also on the information reported by the participants. Rec-

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1 The set of emotions that the individuals felt (Amusement, Happiness, Joy, Love, Interest, Peaceful, Anger, Disgust, Anxiety, Fear, Confusion, Embarrassment, Bored, Contempt, Shame, Powerless, Pity, Sadness, Touched, Scared, Surprise, Unhappiness)

2 The set of emotions that we wanted to elicit (Neutral, Amusement/Happiness, Anger, Disgust, Sadness, Fear, Surprise)

3 The set of positive emotions (Amusement, Happiness, Joy, Love, Interest, Peaceful)

4 The set of negative emotions (Anger, Disgust, Anxiety, Fear, Confusion, Embarrassment, Bored, Contempt, Shame, Powerless, Pity, Sadness, Touched, Scared, Surprise, Unhappiness)
Ocognition rates above 70% are achieved when classifying positive and negative emotions using LOOCV estimates with a k-NN Classifier. For future work, classification based on criterions such as the emotion valence and arousal will be used; other emotion elicitation techniques such as pictures, sounds, games can also be inserted and tested in the developed Web application; acquiring new electrophysiological data and extend our current database is also a future goal.

Acknowledgements

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Appendix

Web application interface for emotion elicitation.

(a) Start page

Fig. 3. Web application for emotion elicitation using videos.
Fig. 3. Web application for emotion elicitation using videos.(cont.)
Fig. 3. Web application for emotion elicitation using videos. (cont.)
(f) Questionnaire page

**Fig. 3.** Web application for emotion elicitation using videos. (cont.)
Towards Emotion Related Feature Extraction based on Generalized Source-Independent Event Detection

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Abstract. Emotion recognition is of major importance towards the acceptability of Human-Computer Interaction systems, and several approaches to emotion classification using features extracted from biosignals have already been developed. This analysis is, in general, performed on a signal-specific basis, and can bring a significant complexity to those systems. In this paper we propose a signal-independent approach on marking specific signal events. In this preliminary study, the developed algorithm was applied on ECG and EMG signals. Based on a morphological analysis of the signal, the algorithm allows the detection of significant events within those signals. The performance of our algorithm proved to be comparable with that achieved by signal-specific processing techniques on events detection. Since no previous knowledge or signal-specific pre-processing steps are required, the presented approach is particularly interesting for automatic feature extraction in the context of emotion recognition systems.

1 Introduction

The ability to recognize emotion is of upmost importance with the increasing development of intelligent and adaptive computer systems, allowing them to sense and respond appropriately to user’s affective feedback [1]. Emotions are one of the least explored frontiers of intuitive Human-Computer Interaction (HCI) [2], and its understanding is expected to improve the acceptability of those systems. This requires, however, robust emotion recognition systems, capable of guaranteeing acceptable recognition accuracy, and adaptable to practical applications [3].

Emotion recognition systems still present relevant challenges, as it is very hard to uniquely correlate emotion-relevant signal patterns with a certain emotional state. Furthermore, these patterns may widely differ from person to person, and between different situations [3]; there is a lack of ground-truth datasets in order to develop user-independent systems, which would be essential for practical applications [4, 5]. There have been many attempts to built automatic emotion recognition systems [3, 6–9], which mostly rely on supervised pattern classification approaches. However, some of the major problems still verified are the low recognition rates when considering subject-independent classification and generalization to more than one task [10]. A generally...
applicable recognition system, for realistic online applications, would have to automatically select the most significant features and specific classifiers to several data sets obtained from different natural contexts [8].

Emotions are inherently multi-modal, and several studies on their recognition work by fusing features extracted from multiple modalities (facial expression [11], voice [12] or gesture [13] and biosignals). The work around biosignals include the heart rate, skin temperature, electrodermal and electromyographic activity or respiration rate [1, 14]. The areas of speech and face recognition are far more explored, mostly because it is a very hard task to uniquely map physiological patterns onto specific emotional states and some of the sensors used to acquire those biosignals may be sensitive to motion artifacts [6]. However, the size of such sensors is decreasing and this method is considered to be less disturbing than the standard audiovisual techniques [2]. Moreover, biosignals allow us to continuously gather information on the user’s affective state, and should be more robust against possible artifacts of human social masking, since they are directly controlled by the human autonomous nervous system [3, 8].

Feature extraction from biosignals is a complex multivariate task, requiring a broad insight into biological processes related with neuropsychological functions [6]. Standard specific processing techniques in which the results are highly dependent on the input parameters are usually applied, bringing an added complexity to these feature extraction systems. In this paper we propose a signal-independent approach to the detection of specific signal events, in order to accomplish an accurate feature extraction based on the results of a generic algorithm. The performance of the generic events detection approach is also compared with that of signal-specific standard algorithms.

The following section presents a brief description of the biosignals considered in this preliminary approach, as well as the applied signal processing methodologies. The obtained results are presented and discussed in section 3. In the last section some final remarks and future work steps are referred.

2 Materials and Methods

2.1 Biosignals

This subsection introduces the biosignals that were considered in this preliminary study, including the main features usually extracted in the context of emotion classification systems. Those types of signals were selected based on their characteristic waveshapes, in which the events are clearly distinguishable. As such, an intuitive evaluation of the algorithm performance on that signals is accomplished. Furthermore, these signals are strongly related to mental diseases and they are very helpful into infers about the mental health condition of the patients.

With these signals we only intend to exemplify the application of the developed algorithm, since their origin, as respectively described, is not related to the testing protocols usually followed in emotion classification studies [1, 3].

Electrocardiography. The electrocardiogram (ECG) is the recording, on the body surface, of the electrical activity generated by the heart. From the ECG processing one can
extract features as the Heart Rate (HR) and the Heart Rate Variability (HRV). HRV has become the conventionally accepted term to describe variations of both instantaneous heart rate and RR interval. In a continuous ECG record, each QRS complex is detected, and the so-called normal-to-normal (NN) intervals or the instantaneous heart rate is determined. Simple time domain variables that can be calculated include the mean NN interval, the standard deviation of the NN intervals (SDNN) or the mean heart rate. Spectral analysis is also usually performed, since there is a correlation between the relative power of the low frequencies (LF) and high frequencies (HF) ranges and the sympathetic and parasympathetic nervous systems activity. Non-linear methods based on chaos theory and fractal analysis are also used on HRV analysis to better understand the HR fluctuations. The common example of non-linear methods is the Poincaré plot, which reflects the graphical correlation between consecutive RR intervals [15].

Since HRV and the automatic heart modulation are correlated, HRV analysis is a powerful tool for clinical use. The HRV analysis allows a better understanding of the SA node automatic modulation. For example, the spectral analysis reveals that the vagal activity is the major contribution to the high frequencies component. Furthermore, it is also argued that the LF and HF ratio reflects the sympathovagal balance or the sympathetic modulation. These parameters are very important since some authors defend that there is a significant increase of LF band and significant increment of the HR for panic disorders patients and significant lower values of R-R intervals and HF peak of spectral analysis in depressive patients than in the health people. In general, both the HR and the HRV are dependent on the activity level of the autonomic nervous system, which in turn is dependent on emotional stimuli [4]. A low HRV can indicate a state of relaxation, while an increased HRV can be caused by mental stress or frustration [2].

The ECG signals here considered were obtained from a public database (PhysioBank) at PhysioNet library [16]. Those were acquired from healthy people, with normal sinus rhythm, during 4 seconds and at a sampling frequency of 125 Hz. A total of 26 ECG signals was considered.

**Electromyography.** Electromyography (EMG) signal arises from the flow of charged particles across the muscle membrane when its cells are electrically activated. This biosignals can record both voluntary and involuntary muscle activation, in addition to the action potentials produced by external stimulation, such as motor evoked potentials after central or peripheral nerve stimulation [17]. EMG signals have been shown to correlate with negatively valenced emotions [18]. The signals here considered were acquired in the context of a study aiming at accessing the performance of the right leg during the execution of an emergency brake in a car simulator [19]. EMG signals of the Rectus Femoris, Vastus Medialis, Tibialis Anterior and Gastrocnemius muscles were acquired while 3 subjects performed the emergency brake test. From that data set, a total of 40 EMG signals was considered in this study, comprising 10 signals of each considered muscle. Bipolar EMG sensors (emgPLUX) were used to access the muscle activation. The sensors were connected to a wireless acquisition unit, bioPLUX research [20], which performed the acquisition at a sampling frequency of 1000 Hz.
2.2 Generalized Signal Processing Approach

The main features that guided the development of the introduced signal processing methodology have been the signal-independence, implying no specific pre-processing steps. The immunity to noise and artifacts and the simplicity, in order to allow a real-time implementation, were also considered.

The basis of the developed algorithm is the identification of time-domain specific morphological parameters that can clearly distinguish events, such as onset and offset instants and transient waveshapes, within a signal. In practice, after a signal segmentation, these events are computed as the split points for which the absolute values of the difference between the standard deviation of the successive segments are maximized. A further optimization step is then applied through an iterative change of the input parameters of the previously described processing steps. The optimal solution is selected as the one which assures a better fitting of all the signal segments, between the detected events, to linear regressions models.

A detailed description and performance evaluation of this signal processing approach can be found in [21]. This paper extends that events detection approach to application in different biosignals and evaluates its performance by comparison with standard signal-specific algorithms.

2.3 Standard Signal-specific Algorithms

In order to evaluate the performance of the proposed signal processing approach, its results were compared with those from signal-specific standard techniques for EMG onset and ECG waveshape detection.

An adaptation of the QRS complex detector algorithm proposed by Pan and Tompkins [22] was implemented as a standard method for performance evaluation on detecting heartbeats within an ECG signal. ECG signal pre-processing steps included the application of a 2\textsuperscript{nd} order Butterworth lowpass filter with a 30 Hz cutoff frequency, to remove some possible high frequency noise due to electronic devices interference. A 2\textsuperscript{nd} order Butterworth high pass filter with 2 Hz cutoff frequency was also applied to remove some possible baseline fluctuations and other respiration artifacts.

Considering EMG signals, a standard onset detector proposed by Hodges et al.[23] was implemented. This approach implies the EMG signal to be pre-processed in order to reduce the high frequency noise and obtain the signal’s envelope. After subtracting the mean value from the EMG signal and obtaining the rectified wave, a sixth-order digital butterworth filter with 50 Hz cutoff frequency was applied, following the implementation procedure described in [24], completing the envelope detection.

The muscle activity onset was identified as the instant from which the mean of the following $N$ samples from the EMG envelope exceeds the baseline activity level by a specified multiple $h$ of standard deviations. The baseline activity was adaptively determined, at each instant, by averaging $M$ previous signal samples [24]. With a cutoff frequency of 50Hz, the set of criteria \{N=25, h=3\} and \{N=50, h=1\} are those reported as able to identify the EMG onset more accurately [23]. Hodges detector was implemented with both set of parameters, considering the baseline activity level computed from $M=100$ and $M=200$, respectively [24].
3 Results and Discussion

The signal processing methodology described in sub-section 2.2 was applied to the selected raw biosignals. No signal-specific pre-processing steps were applied. Graphic representations exemplifying the obtained results are presented in Figure 1.

![Graphic representations of detected ECG waveshapes and EMG onset and offset points.](image)

**Fig. 1.** Graphic example of: a) detected ECG waveshapes and b) EMG onset and offset points applying the developed events detection algorithm. The events are marked by vertical red marks.

As exemplified in Figure 1a), the developed algorithm allows the ECG waveshape discrimination, from the electrical baseline, detecting two events around it. Choosing one of those instants, parameters such as the HR and the HRV can be easily accessed. Furthermore, this events marking could be used for a further and more complete features extraction based on the waveshape morphology, such as the position of each of the P, Q, R, S and T waves and the respective amplitude. After applying Pan and Tompkins adapted algorithm to ECG signals, the resulting graphics were then visually examined and, for both algorithms, the percentage of detected ECG waveshapes and the number of extra detected events were registered. Table 1 exposes the mean values of those parameters.

<table>
<thead>
<tr>
<th>Events detection algorithm</th>
<th>Pan and Tompkins algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of detected ECG waveshapes</td>
<td>93.84% (± 15.64%)</td>
</tr>
<tr>
<td>Number of extra detections</td>
<td>1.35 (± 1.52)</td>
</tr>
</tbody>
</table>

**Table 1.** Results obtained from the proposed events detection algorithm and from Pan and Tompkins adapted algorithm while performing the ECG signals QRS complex detection. The results follow the format mean(±standard deviation).

These results show that the mean percentage of detected events within a given signal is significant for both algorithm, being slightly bigger for the events detection algorithm proposed in this paper. Considering the number of extra detections, however, this is more significant when considering our events detection algorithm than for Pan and Tompkins adapted algorithm. This extra events detection is mostly due to the detection...
of some pronounced T waves in some signals.

Figure 1b) exemplifies our tool’s ability to accurately mark both onset and offset instants in EMG signals. This is extremely important towards an accurate posterior features extraction, such as the signal amplitude and the duration of each activation. For performance evaluation on onset detection, the results of our approach and those of Hodges detector were compared with those obtained previously by visual inspection. In order to minimize the error from intra-rater variability, results from 3 examiners were considered and averaged, in each signal, to define the “true” onset value. For each signal the difference between the ”true” onset and those detected for each one of the implemented computational methods was computed. In case that a computational method detected no onset time, that was also registered. Table 2 exposes the mean error (considering only the signals for which the onset detection was achieved) and the percentage of missing detections verified for each of compared methods.

Table 2. Results obtained from the proposed events detection algorithm and Hodges detector while performing the EMG signals onset detection. The ”true” onset values were determined by visual inspection. The results follow the format mean(±standard deviation).

<table>
<thead>
<tr>
<th></th>
<th>Hodges detector</th>
<th>Hodges detector</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>{N=25, h=3}</td>
<td>{N=50, h=1}</td>
</tr>
<tr>
<td>Mean error (samples)</td>
<td>-22.94 (± 115.09)</td>
<td>12.65 (± 81.85)</td>
</tr>
<tr>
<td>Percentage of missing detections</td>
<td>0%</td>
<td>100%</td>
</tr>
</tbody>
</table>

These results show that the proposed events detection algorithm achieved a superior, though not significant, absolute mean error than that verified for Hodges detector implemented with the parameter set \{N=50, h=1\}. An high standard deviation value was verified for mean error values of both approaches. Therefore, there is no clear tendency of either the algorithms to perform an early or late onset detection.

Considering the events detection algorithm results, no missing onset detections were verified. Hodges detector implemented with the parameters set \{N=50, h=1\} missed 2 out of 40 onset detections. However, when applied with the criteria \{N=25, h=3\}, no onset was detected applying Hodges algorithm. This clearly exemplifies the sensibility of this single-threshold based algorithm to its input parameters, in agreement with that previously reported in other studies [23, 24].

In general, the algorithm here proposed showed to have a comparable efficiency and higher reliability than that of standard signal events detectors, without the previous knowledge or specific pre-processing steps required in those approaches.

4 Conclusions and Future Work

In this paper we have introduced a generalized approach on biosignals analysis, aiming at an accurate events detection for posterior features extraction. The performance of our algorithm proved to be comparable with that achieved by ECG and EMG signals specific processing techniques on events detection. Since no previous knowledge
or signal-specific processing steps are required, our approach is particularly suited to application in the context of automatic emotion recognition, bringing simplicity and scalability to those systems.

In future work it is our intention to perform its application on a wider range of biosignals used for emotion recognition, such as the electrodermal response and the respiration signals. The integration of the developed algorithm with features classification tools will also provide means to evaluate its performance towards an automatic emotion recognition system, when compared with standard signal-specific features extraction techniques.

Acknowledgements

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References


Brain Computer Interface and Eye-tracking for Neuropsychological Assessment of Executive Functions: A Pilot Study

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Abstract. In this study we explored the use of Brain Computer Interface (BCI) and Eye-Tracking (ET) technology both as augmentative and alternative communication (AAC) tool and to assess cognitive deficits. Specifically, we focused on the possible development of a neuropsychological battery for cognitive assessment based on the integration of BCI and ET tools. To preliminary test this approach we assessed eight healthy subjects with a widespread used cognitive task. AAC and usability of both instruments have also been evaluated with the aim to fine-tune the overall system architecture for clinical use.

1 Introduction

Some of the most consistently reported cognitive changes regards frontal executive functions, e.g. verbal fluency, attention, working memory, planning and abstract reasoning [1-6]. However, the assessment of cognitive impairment still remains a problematic issue in patients, because of the possible presence of severe physical disabilities, including movement impairment, paralysis in the advanced stages and dysarthria, which interfere with the outcome of traditional neuropsychological testing.

New technologies to enable communication have been recently used in several studies; however, a comprehensive battery for cognitive assessment has never been implemented with these promising methodologies. Among these methods, Brain Computer Interface (BCI) and Eye Tracking (ET) are the most promising
technologies. BCI uses neurophysiological signals as input commands to control external devices, while ET allows the measurement of eye position and movements.

To date, no applications have been developed, using ET as a communication device in order to administer traditional cognitive tasks to patients.

The main disadvantage in the use of ET systems is that they require good ocular mobility, and the absence of important visual deficits; the former may be lost or altered in the final stages of disease, and the latter may be present in patients of advanced age, thus forbidding the use of this device. In fact, ET may not be proficiently used in case of poor or lack of eye-motor control, such as in late stages of the disease. In this case there is the need of a more direct interface between voluntary cortex activity and the computer. BCI may offer an interesting answer to this issue with a growing number of different paradigms proposed. The most frequently used is the P300, an event related potential (ERP) elicited by infrequent task stimuli, that occurs 200-700 ms; it is typically recorded over central-parietal scalp locations [8-10] and it can also be used by patients suffering from complete paralysis and impairment in oculo-motor dysfunctions, such as locked-in patients.

It is notable, however, that 20% of subjects are not proficient in using BCI; this phenomenon is called “BCI illiteracy” [11] and it is due to the fact that some users do not produce brain activity detectable at the scalp level, independently from the health conditions: even about 10% of healthy subjects do not produce “usable” P300.

With regard, as an example, to Amyotrophic lateral sclerosis (ALS) patients, studies have shown that some of them produce less typical ERPs than healthy matched subjects [12]; [13]. A previous ERP study in patients with sporadic ALS found that P3a and P3b amplitudes of ALS patients were lower and P3a latencies were significantly longer compared with the controls [14]; ERP recordings in non-demented patients with sporadic ALS also showed prolonged N200 and P300 latencies compared to healthy controls [15]. Ogawa and colleagues [16], by employing neuropsychological measures, event-related potentials (ERPs) and clinical scales, studied a sample of patients with early-stage sporadic ALS. They found that patients with the bulbar-onset type showed marked prolongation of P3 latency compared to patients with the limb-onset type and controls. Furthermore, bulbar functional rating scale correlated with prolonged P3 latency and low P3 amplitude. Additionally, patients with bulbar-onset ALS had consistently poorer cognitive test performance than those with limb-onset ALS [17]. These results represent a challenge for the use of P300 as an input signal in BCIs. Kübler and Birbaumer [7] investigated the relationship between the level of motor and physical impairment and the ability to use brain computer interface by comparing three different BCI systems (P300, SCP and SMRs, i.e. sensorimotor rhythms). They found no continuous decrement in BCI performance with physical decline, even in the completed locked-in state (CLIS) where no communication was possible.

Two important criteria in order to evaluate the feasibility of a BCI system are speed and accuracy [18]. The former is related to the fact that the more rapidly a BCI can be controlled, the greater quantity of information can be produced by the user and the greater the chance for effective communication. Obviously, compared to verbal speech production, communication rate is severely reduced with BCI. With regard to accuracy, it consists of the percentage of correct selections per time interval. A wrong selection could turn into an error in communication, with both practical and psychological consequences for the user. In order to avoid this, the BCI system must
be equipped with options that allow the user to correct wrong selections. A balance
between speed and accuracy should be identified.
A recently funded project, "eBrain: BCI-ET for ALS", [19] aims to evaluate BCI
P300 technique and eye-tracking technology both as AAC systems and as cognitive
assessment tool with ALS patients.

Before beginning the actual testing phase with ALS patients, we performed a pilot
study with healthy subjects to fine-tune the overall project testing setup. Specifically,
a small group of healthy subject was administered a subset of the eBrain designed
sessions to generally assess feasibility, user-friendliness, pleasantness and fatigue.
Emotional aspects related to the experimental setting, as well as its usability, have
been evaluated, too. In this paper we report the results of this pilot study.

2 Materials and Methods

2.1 Subjects

Eight healthy subjects (4 females and 4 males) constituted the participants, ranging in
age between 25 and 39 (M: 31.75, SD: 5.946). They were all volunteers with a
schooling degree ranging from 13 to 24 years of education (M: 19, SD: 4.276). All the
subjects were experienced in the use of PC (50% fair or good and 50% excellent),
some of them (50%) declared to have already used Brain Computer Interface or an
Eye-tracker system, and more than half (62.5%) had already participated into EEG
experiments. Exclusion criteria were related to the states of participants’ cardiac,
optical, mental, and psychological health. Participants were asked not to drink
caffeine or alcohol and not to smoke prior to the experimental test to avoid any effects
of these substances on the central and autonomic nervous system.

2.2 System Setting

Test architecture (Figure 1) was composed of an eye-tracking system, and a BCI
device, both controlled by a laptop PC (HP DV3-4101SL, Hewlett Packard, USA),
connected to an external monitor, meant for the stimuli presentation (Display PC).

The BCI device module consisted of a g.USBAnp biosignal amplifier (Guger
Technologies, Graz, Austria), connected to an active electrodes head cuff
(g.GammaCap, Guger Technologies). 16 EEG channels were used (FZ, C3, C4, CZ,
CPZ, P3, P4, PZ, PO3, PO4, POZ, PO7, PO8, O1, O2, OZ); ground was placed in
FPZ, and reference was located on the left ear lobe.

The eye-tracker was an Eyelink-1000 (SR Research Ltd., Mississauga, Ontario,
Canada), consisting of a high-speed infrared camera and the related illuminator,
positioned just below the Display Monitor.

Tests were administered through two different software: a customized version of
assessment and a suitable custom software, developed within the project for the eye-
tracking evaluation.
2.3 Experimental Procedures

Subjects who met the experimental criteria were enrolled and tested at the Applied Technology for Neuro-Psychology Laboratory, located at the Istituto Auxologico Italiano in Milan. All subjects were required to sign a release form. Since the experiment was constituted by two separated parts, the design was balanced between the subjects. Immediately after the former session, subjects were asked to fulfill the required questionnaires and to rest for 15 minutes.

After a calibration, required by both instruments, the neuropsychologist started the cognitive assessment through a Phonemic Fluency test and a Semantic Fluency test (as described below), adapted to the experimental conditions (see figure 1).

At the end of Eye-tracking session, the subjects had to copy a sentence twice (FIAT ALAN FORD MERCEDES BENZ): the first time using a virtual keyboard (ordered letters in rows from A to Z see figure 2a), the second time using a scrambled keyboard (mixed position of the letters, see figure 2b). The total time of the experiment was about two hours.

Fig. 1. Experimental procedure timeline for both BCI and ET sessions.

2.4 Psychological and Usability Self-report Questionnaires

2.4.1 STAI form Y Questionnaire

The Italian version of the STAI form Y questionnaire was used to assess changes in two different types of anxiety, namely, anxiety detected as the subject's current state (STAI-Y1, i.e. state anxiety) and anxiety detected as a reasonably stable trait of the personality of an individual (STAI-Y2, i.e., trait anxiety). A total of four Self-reported STAI-Y1 were gathered before and after both BCI and Eye-tracking sessions. One self-reported STAI-Y2 was gathered five minute before the experimental session [22].

2.4.2 Self Assessment Manikin (SAM)

The Self Assessment Manikin (SAM) is a non-verbal pictorial assessment technique that directly measures the pleasure, arousal, and dominance associated with subjects' affective reactions [23]; [24]; [25]. A total of four Self-reported SAMs were gathered before and after both BCI and Eye-tracking sessions.
Fig. 2. The used ET Keyboards and the Saccades plotted over them: (a) Standard Virtual Keyboard, (b) Scrambled Keyboard, (c) Saccades on Standard Virtual Keyboard, (d) Saccades on Scrambled Keyboard.

2.5 Usability Inventory Post-test Questionnaire

Since there are no usability validated tests for Eye-tracking and BCI systems, we developed a questionnaire with 19 items based on the literature available [26-29]. Our purpose was to evaluate the instruments' general usability, and the following specific variables: fatigue, screen readability, perceived usefulness, and so on.

2.5.1 Neuropsychological Tests

We used a classic spoken letter-based word generation procedures (Phonemic Fluency), such as the Controlled Oral Word Association test [30-34] and then repeated the procedure with the Category Fluency, also known as Semantic Fluency [30]. These tests have been recognized as the most sensitive tools in detecting cognitive impairments in ALS patients [5].

For both the Semantic and the Phonemic Fluency in the BCI session we used to measure the time taken by the subjects to think the word starting with the given letters: “A” and "H" respectively. A timer was started by the researcher right after the letter was presented to the subject. Then, the timer was stopped when the subjects indicated to be ready to effectively start to write the word with the BCI system. Finally the procedure was repeated for the Semantic Fluency, with the categories "furniture" and "means of transport."

Concerning the Eye-tracking system we used an adapted version of Fluency Index [6] to adjust for eye motor component. Thus the subjects were required to write all the
words starting with a specific letter (“Q” and “Z”) in exactly one minute (generation condition). Then the subjects were asked to copy exactly the same words while a researcher measured the time taken (control condition). The same procedure was repeated for the Semantic Fluency task, with the categories “type of shoes” and “cooking ingredients.”

The difference between the specified time for the generation condition and the time taken for control condition was then calculated and used to determine the Fluency Index, which represented the average time taken to think about each word [6].

3 Results

Data were analyzed with the aid of the statistical software SPSS, version 17 (Statistical Package for the Social Sciences–SPSS for Windows, Chicago, Illinois, USA). Due to the small sample size, nonparametric tests were preferred, even if several measures showed a normal distribution (also according to Kolmogorov-Smirnov test).

In the following paragraphs the main results of this preliminary study are presented.

3.1 Fluency Tests

In BCI session, Phonemic Fluency average time in seconds was 6.42±2.76 and Semantic Fluency average time in seconds was 4.08±1.94. Regarding Eye-tracking session, we used the Fluency Index, as above described. Phonemic Fluency Index was 4.28±5.84 and the Semantic Fluency Index was 3.37±2.58. These data will be used to assess future patients’ performances.

3.2 Behavioral Measures

Wilcoxon Signed Ranks Tests indicated no statistical differences for both the pre-post STAI-Y1 and pre-post SAM scales, indicating that no negative affective state or anxiety have been generated by the performance with BCI or ET. However a small increase in anxiety was detected after the use of BCI.

3.3 Usability

As can be seen in Table 1, subjects recognize both systems as enough usable, but Eye-tracker is perceived as more usable than BCI (statistical significance is calculated with Wilcoxon Signed Ranks Tests).
Table 1. Average values of 7-point Likert scale items of the usability questionnaire.

<table>
<thead>
<tr>
<th>ID</th>
<th>Item</th>
<th>Mean BCI</th>
<th>Mean ET</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>It is easy to use the device</td>
<td>5.25</td>
<td>6.25</td>
<td>.131</td>
</tr>
<tr>
<td>2</td>
<td>The instructions are clear</td>
<td>6.25</td>
<td>6.50</td>
<td>.157</td>
</tr>
<tr>
<td>3</td>
<td>Sometimes I wondered if I was selecting the right letter</td>
<td>2.25</td>
<td>1.75</td>
<td>.336</td>
</tr>
<tr>
<td>4</td>
<td>Letters on the screen are clear and sharp</td>
<td>5.25</td>
<td>6.88</td>
<td>.066</td>
</tr>
<tr>
<td>5</td>
<td>I felt in command of this device when I was using it</td>
<td>5.13</td>
<td>5.38</td>
<td>.916</td>
</tr>
<tr>
<td>6</td>
<td>I properly understood the instructions</td>
<td>6.63</td>
<td>6.63</td>
<td>1.000</td>
</tr>
<tr>
<td>7</td>
<td>Using this device was frustrating</td>
<td>2.38</td>
<td>1.88</td>
<td>.357</td>
</tr>
<tr>
<td>8</td>
<td>I felt tense at times when using this device</td>
<td>2.63</td>
<td>2.50</td>
<td>.931</td>
</tr>
<tr>
<td>9</td>
<td>The device requires too many steps to work</td>
<td>2.00</td>
<td>1.38</td>
<td>.197</td>
</tr>
<tr>
<td>10</td>
<td>New users will find this device easy to use</td>
<td>4.63</td>
<td>6.25</td>
<td>.038</td>
</tr>
<tr>
<td>11</td>
<td>It is easy to make the device do what I want</td>
<td>5.13</td>
<td>5.38</td>
<td>.666</td>
</tr>
<tr>
<td>12</td>
<td>The device did what I expected</td>
<td>5.25</td>
<td>5.63</td>
<td>.732</td>
</tr>
<tr>
<td>13</td>
<td>The device appears to be limited</td>
<td>2.88</td>
<td>2.38</td>
<td>.480</td>
</tr>
<tr>
<td>14</td>
<td>The equipment is comfortable</td>
<td>3.75</td>
<td>4.63</td>
<td>.167</td>
</tr>
<tr>
<td>15</td>
<td>Using the device was demanding and tiring</td>
<td>4.13</td>
<td>2.63</td>
<td>.071</td>
</tr>
<tr>
<td>16</td>
<td>The icon to correct answers was helpful (ET)</td>
<td>-</td>
<td>5.88</td>
<td>-</td>
</tr>
<tr>
<td>17</td>
<td>An initial tutorial on the usage of the device would be helpful</td>
<td>3.25</td>
<td>2.75</td>
<td>.194</td>
</tr>
<tr>
<td>18</td>
<td>Using the device was amusing and exciting</td>
<td>4.25</td>
<td>5.25</td>
<td>.071</td>
</tr>
<tr>
<td>19</td>
<td>I believe that the device is fit to communicate in the presence of disorders that prevent from communicating with the voice</td>
<td>5.13</td>
<td>6.75</td>
<td>.102</td>
</tr>
</tbody>
</table>

3.4 Anxiety Traits and Consequences

No correlations were found between STAI-Y2 and all the Fluency measures, for both the BCI and the Eye-tracking.

On the other hand we found interesting correlation between STAI-Y2 and some items of the usability questionnaire. In particular, the item 15 for the BCI (the instruments has been demanding and tiring) is positive correlated with STAI-Y2 ($r = 0.747$, $p = .033$). In sum, usability is negatively correlated with the trait anxiety level.

3.5 Copying Text using Different Keyboards with ET

The average time to copy the same text with the standard virtual keyboard was $46.09\pm 6.55$. The average time for the same copy with the scrambled keyboard was
60.17±21.23. Wilcoxon Signed Ranks Tests indicated statistical significant differences ($Z = -2.201, p = .028$).

4 Conclusions and Future Work

No studies have been performed so far to evaluate BCI and the eye-tracking system for AAC and cognitive assessment in ALS. Our pilot study provided evidences for the effectiveness and usability of these techniques. Specifically, the BCI/computerized assessment could provide new insight into the understanding of cognitive deficits, when applied to ALS patients, through the integration of multidisciplinary data: neurophysiological, neuropsychological, behavioural and psychological.

The proposed study is characterized by at least two innovative aspects: (1) the comparison between two promising technologies, one already extensively investigated (ET), the other being a very promising candidate (P300 BCI), (2) the adaptation of a computerized verbal fluency task for the neuropsychological assessment of higher order cognitive functions in ALS patients.

Results showed a good usability of both instruments, better for Eye-tracking, but promising for BCI too. Furthermore the strong negative correlation between trait anxiety and perceived usability clearly shows that the higher the subject is anxious, the more the instruments will be perceived as demanding, tiring, and difficult to use. Finally, no affective effects on cognitive performances were revealed by the psychological measures administered.

As expected, BCI calibration was a critical issue. The average score obtained after the calibration process was 89.73%, leading to an accuracy of BCI system during the tests of 81.72% (i.e. 18.28% of errors). However, the 6 subjects that obtained 100% of correct calibration did very few errors in the testing phase. These data suggest that it is crucial to extend the calibration phase in order to reach very high correct ratio (close to 100%).

More, the choice of virtual keyboard used in the task, clearly influences the performances obtained, showing a high potential use of such instruments for the development of novel cognitive tests.

Finally, these preliminary results may have interesting implications for both clinical practice (the availability of an effective tool for neuropsychological evaluation of ALS patients) and ethical issues, the last one arising from a proper assessment of cognitive ability preservation, in particular regarding relevant decisions about medical treatments, economical and end-life issues.

Acknowledgements

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References

SHORT PAPERS
Abstract. In this paper we present a new tool, which enables the study of the dose-response relationship in real time, through the assessment of the level of physical activity using METs, and applicable in exercise therapy. A validation protocol for METs algorithm was performed, and METs values were obtained for various real-world and lifestyle and sporting activities. These values were compared with the results from the state-of-the-art work in the field for the same activities. Results have proven to be accurate, according to the model by Crouter, allowing the assessment of physical activity level. Our tool is intended for practitioners working addressing exercise activities and exercise therapy in a wide range of areas, one of which is psychology. According to the obtained results, the base hardware holds comparable performance with the advantage of being wearable and wireless, and thus convenient to be used on the daily monitoring of the patients daily routines.

1 Introduction

Associated with both morbidity and mortality, depression is a major public health problem throughout the world and is characterized by lowered mood, loss of capacity to experience pleasure, increased sense of worthlessness, fatigue, and preoccupation with death and suicide [1]. Exercise therapy is known to play a major role in the reduction of morbidity and mortality [1]; several studies consistently found relation between physical activity and disorders such as depression [1–5] and it has become generally accepted that regular physical exercise ultimately results in benefits to participants [2, 3]. Evidence of a dose-response relationship between physical activity and protection against symptoms of depression and anxiety has also been documented [4, 6].

Biosignal measurement and analysis stand as an important resource, for practitioners to better support prevention and intervention strategies aimed at decreasing depression and anxiety disorders. Strategies applicable to populations inexpensively and without side effects, are needed, as current estimates point psychological disorders such depression to be the leading burden of disease worldwide by the year 2020 [4]. In this
paper we present a tool capable of monitoring the dose of physical activity in real-time and record data for future analysis. This will allow practitioners to better study the dose-response of physical activity in exercise therapies, and to be used in the future by patients to monitor their activity level. The rest of the paper is organized as follows: Section 2 describes the tool targeted at the study of dose-response relationship between physical activity and depression; Section 3 presents the acquisition system and validation procedures; Section 4 outlines the main results, and Section 5 highlights the overall conclusions.

2 Measuring Physical Activity

Our proposed tool is capable of monitoring and evaluate the level of physical activity based on the metabolic equivalent for task (MET). METs are used to estimate the level of physical activity, and it is defined as the resting metabolic rate, that is, the amount of oxygen consumed at rest. As such, exercise at 2 METs requires twice the resting metabolism, and so on [7]. METs can be computed as a function of the magnitude of the accelerometer signal. For this, a real time bandpass filter was implemented, based on a Infinite Impulse Response model determined for a $2^{nd}$ order Butterworth filter within the $0.25-1.4$ Hz passing band. This filter was used since these frequencies correspond to the range of human activities are performed.

Based on uniaxial Actigraph devices, the input signal corresponds to the acceleration signal in a range of 0.05-2 G, and the output signal to the filtered acceleration signal, which is subsampled at 10 Hz. Then, $counts \times min^{-1}$ and the coefficient of variation of $counts$, $c_v = \frac{\sigma}{\mu}$, are determined each 10 seconds over a period of one minute. For this operation, the range of the accelerometer is divided into levels of 0.001664 g, being each level considered 1 count. The number of $counts$ is determined by how many levels the difference of the magnitude of the acceleration between samples corresponds to during this period [8]. Then the $counts \times min^{-1}$ are converted into METs through a non-linear signal processing algorithm using two regression equations based on the method described by Crouter et al. [9].

The output values presented to the user, in the visual display alongside with the raw data signals, are the METs, as shown in Figure 1. The raw data is represented in a window with a dimensionless auto-scale y-axis. If the user chooses to record the data, the parameters recorded are the $counts \times min^{-1}$ and METs. Table 1 shows the typical classification of the physical activity according with the METs results [10].

<table>
<thead>
<tr>
<th>METs</th>
<th>Activity level</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\leq 3$</td>
<td>Light</td>
</tr>
<tr>
<td>$3 &gt; METs \geq 6$</td>
<td>Moderate</td>
</tr>
<tr>
<td>METs $&gt; 6$</td>
<td>Vigorous</td>
</tr>
</tbody>
</table>
3 Experimental Evaluation

We used a bioPLUX motion data acquisition system [11]. This wireless system is also responsible for the signal’s analog to digital conversion, using a 12 bit ADC, and Bluetooth transmission of data to a computer. This system can acquire data from an integrated 3-axis accelerometer at a maximum sampling rate of 1000 Hz. The bioPLUX allows to visualize the raw signal in real-time and save data in .txt file to post-processing. With this system we can see the METs values in real-time and compare these values with the offline values from the raw data. The comparison between real-time and offline values allowed to validate if the algorithm in real-time are correctly implemented.

To validate the real time algorithm for METs calculation based on the model defined by Crouter [9], a set of various lifestyle and sporting activities were performed. The selected activities were Lying, Standing, Computer work, Filling papers, Ascending/Descending stairs, Slow walk, Brisk walk and Slow run. These activities were selected based on those used by Crouter to validate his model. Each of these activities had a duration of 10 minutes, and were repeated only once producing a total of 60 METs values per repetition, since the algorithm determines the METs each 10 seconds. The mean value and standard deviation of METs per min were calculated to compare with Crouter model results for each activity.

It is intended that this tool is used by practitioners to study the dose-effect in different physical activity levels. The protocol used in these studies must be done by the practitioners according with their knowledge and intended therapeutic model.
4 Results and Discussion

Table 2 shows the mean and standard deviation (SD) METs values obtained by Crouter and by our METs algorithm for each activity [10]. As we can observe, the METs results from our algorithm for Lying, Standing, Computer work and Slow run are equal to those obtained by Crouter. For the Filling papers activity it is possible to verify a difference of 0.07 METs. For the activities of Slow walk, Brisk walk and Ascending/Descending stairs a difference of 0.27, 0.33 and 0.67 METs was found, respectively.

These differences can be explained by the fact that these activities involve free movement and/or depend heavily on the locomotion of the individual. Therefore, more tests must be done, preferably also using a gold standard device, but preliminarily we were able to prove experimentally the correct functioning of the algorithm. The lower values of SD obtained using METs algorithm are justified by the use of only one repetition instead of the fifteen performed by Crouter. The dose-response relationship study results will be obtained in future by practitioners using this tool, and will help to provide a better understanding of this relationship. This fact would be the most helpful for practitioners advising patients about the benefits of physical activity for both somatic and psychologic well-being [1]. Since this tool is already portable, it would be ready for use in the daily life of patients, allowing the real-time adjustment of the exercise therapy.

Table 2. Results from Crouter and METs algorithm.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Crouter METs Mean (SD)</th>
<th>METs alg. Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lying</td>
<td>1.00 (0.00)</td>
<td>1.00 (0.00)</td>
</tr>
<tr>
<td>Standing</td>
<td>1.00 (0.00)</td>
<td>1.00 (0.00)</td>
</tr>
<tr>
<td>Computer work</td>
<td>1.00 (0.00)</td>
<td>1.00 (0.00)</td>
</tr>
<tr>
<td>Filling papers</td>
<td>1.30 (0.67)</td>
<td>1.23 (0.56)</td>
</tr>
<tr>
<td>Slow walk</td>
<td>3.73 (0.42)</td>
<td>3.46 (0.05)</td>
</tr>
<tr>
<td>Brisk walk</td>
<td>4.71 (0.58)</td>
<td>4.38 (0.06)</td>
</tr>
<tr>
<td>Asc./Desc. stairs</td>
<td>6.08 (1.29)</td>
<td>5.41 (1.15)</td>
</tr>
<tr>
<td>Slow run</td>
<td>7.76 (0.96)</td>
<td>7.76 (0.27)</td>
</tr>
</tbody>
</table>

5 Conclusions

In this paper we presented a tool for real time evaluation of physical activity, supported in an inexpensive and miniaturized base hardware device. We were able to validate the METs algorithm for the calculation of physical activity estimates in real-time; experimental results on real-world data enabled us to validate our results and prove the accurate operation of the system as our results are within the confidence intervals of the reference work by Crouter for the same activities. As future work, we will implement this algorithm in Android operation system in order to improve the portability and usability of the system and take advantage of smartphone technology. Our work enables practitioners to better study the dose-response relationship in physical activity, since
it allows the quantification of the activity level, and, use the collected information to better support the evaluation and prescription of exercise therapy based techniques.

Acknowledgements

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Sedentary Work Style and Heart Rate Variability: A Short Term Analysis

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Abstract. Emerging studies suggest that sedentary work style is often associated with deleterious physiological implications, including diabetes, high blood pressure and obesity. However, only few studies linked prolonged periods of sitting with psychological responses thus the implications of sedentary behavior on mental health still remain highly unexplored. In this study, we investigated the relation between sedentary time and Heart Rate Variability (HRV) parameters, which are considered important biological markers of psychological processes including cognitive and emotional aspects. In this manner, we aim to explore factors that may indicate that sedentary behavior causes responses at psychological level. Recent progress in the sophistication and usability of wearable sensors offers the opportunity to continuously record ECG parameters and accelerometer data in daily-life settings, such as at workplace.

1 Introduction

Physical inactivity leads to a number of health complications and various media campaigns are designed to encourage increase in physical activity levels and promote healthy lifestyle. However, a general increase in physical activities is not sufficient to improve health. An important component of physical activity is the work style. In developed economies, knowledge workers typically have a work style that requires sitting for prolonged periods of time. As a number of studies have shown [1]; [10]; [13] sedentary work style leads to an array of health complications, including diabetes, high blood pressure and obesity. The negative effects on health due to sedentary work style occur even if people follow the guidelines on physical activity and lead a healthy lifestyle outside of the workplace [1]; [10]. However, the impact of prolonged periods of sitting on mental health remains a largely unexplored area of research [18].

In this study, we explore how sedentary behavior affects a biological marker that is indicative for processes at physiological (and maybe emotional and cognitive) levels, namely Heart Rate Variability (HRV). Being suitable for a short term analysis of cognitive and emotional responses, HRV might provide cues for the potential
psychological impacts of sedentary behavior thus motivating further investigations in this area.

Wearable devices to measure ECG are readily available and are unobtrusive to use, finding applications beyond health monitoring (for instance sport performance monitoring), therefore becoming a powerful tool for both research and clinical studies [4]. The clinical relevance of HRV was first noted in 1965 [9] and continues to be used today to examine neuropathy in diabetic patients, risk of cardiovascular mortality and a number of other physiological and pathological conditions [4]. On the other hand, recent studies have found strong correlation between HRV and mental stress [7], visual stimulations [3] and mood states [5]; [6]. In addition, the influence of physical activities on HRV has been widely studied, including the effects of habitual physical activity and also HRV analysis during pre-scheduled activities. However, less emphasis has been placed on the physical inactivity, especially in workplace.

2 Background

Heart rate variability represents variations in inter-beat intervals (IBI) and provides a significant measure of physiological and pathological conditions [4], furthermore psychological responses. It mirrors the relationship between sympathetic and parasympathetic branches of autonomic nervous system; the former stimulates organs’ functioning and causes increase in heart rate (HR), while the later inhibits functioning of organs and causes a decrease in heart rate [3]; [15]; [16]. The balance between sympathetic and parasympathetic systems constantly changes when the body attempts to achieve an optimum state corresponding to all internal and external stimuli [2]; [17]. Therefore, HRV is considered a measure of changes in system balance and consequently as a measure of body responses to internal and external provocations [2]; [17].

These studies have demonstrated that lower HRV values often suggest sympathetic dominance, higher stress and negative emotions, according to experiments where subjects were asked to watch horror movies [3] or perform mental tasks [7], [15]. Higher HRV values, to the contrary, indicate domination of parasympathetic system and positive emotions that were typically evoked by watching delightful movies, such as love stories [5] or landscape scenes [3].

3 Materials and Methods

3.1 Classification of Sedentary Time

Accelerometers are widely available in newer generations of smart phones, typically used for their role in user interfaces [14]. They provide an important research tool able to reliably measure and classify a number of physical activities, including walking, jogging, sitting, standing [11], and more complex activities such as estimation of metabolic energy expenditure, sit-to stand transfers, and assessment of balance and intensity of physical activity [12].
For our study, it was important to distinguish only sitting periods from all other physical activities and to provide precise duration and timestamp of each segment. We analyzed acceleration data and calculated standard deviation of resultant accelerations over each one-minute interval [12] - the square roots of the sum of the values of each axis (x, y and z) squared [11]. In most cases it was easy to distinguish periods characterized by very low intensity movements that were considered sedentary periods.

All the activities related to usage of the phone itself, such as making phone calls or sending texts, were also recorded; the accelerometer data for these periods was discarded to avoid confusion with physical activities.

3.2 HRV Measures

In order to acquire HRV, we used Shimmer Wireless ECG sensor [8]; [17], connected with the mobile phone via Bluetooth. Due to limited performance of the mobile device, the maximum ECG sampling rate that it could process (along with the data from other sensors, including accelerometer and location) did not allow us to use frequency domain analysis [4]; [15]; [16]. Therefore, our focus was on time domain analysis of HRV. In order to prevent the sensor battery from running out during subjects’ working time, we recorded ECG data for 1 minute during a time frame of 5 minutes. Before the calculation of time domain measures of HRV took place, all abnormal heart beats and artefacts were removed from consideration; the signal suffered high noise usually when the subject was moving intensively.

In the ECG recordings, each interval between neighboring beats, called NN interval was detected. We analyzed the following measures [4]; [15]; [16]:

SDNN[ms] – Standard deviation of the NN interval, i.e. the square root of variance.
RMSSD[ms] - The square root of the mean squared differences of successive NN intervals.
pNN50[%] – The proportion derived by dividing NN50 by the total number of NN intervals, where NN50 represents the number of interval differences of successive NN intervals greater than 50ms.

4 Experiments and Results

We recruited 6 participants from our research centre (4 males and 2 females), with ages between 26 and 35, with an average age of 29. They were all knowledge workers with no major differences either in the type of job regarding sedentary routines or in the number of working hours. None of the subjects was a cigarette smoker, nor had a chronic disease.

A total of 47 recordings have been collected among the six subjects. Descriptive statistics have been reported in Table 1.

For each one of these recording we calculated three HRV indexes, namely SDNN, RMSSD and pNN50, as before described, and an activity index (NonSedTime) to measure non-sedentary time, that is the percent of time spent in non sedimentary
activities. Since sedentary and non-sedentary time indexes are counter-proportional, selecting one of the two is sufficient to investigate the correlation between sedentary behavior and HRV parameters.

Table 1. Descriptive statistics of activity and HRV indexes, used in our study.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>NonSedTime</td>
<td>47</td>
<td>0.00</td>
<td>46.85</td>
<td>13.38</td>
<td>10.49</td>
</tr>
<tr>
<td>SDNN Mean</td>
<td>47</td>
<td>0.05</td>
<td>0.18</td>
<td>0.09</td>
<td>0.04</td>
</tr>
<tr>
<td>RMSSD Mean</td>
<td>47</td>
<td>0.63</td>
<td>0.87</td>
<td>0.76</td>
<td>0.06</td>
</tr>
<tr>
<td>pNN50 Mean</td>
<td>47</td>
<td>0.25</td>
<td>0.49</td>
<td>0.37</td>
<td>0.06</td>
</tr>
</tbody>
</table>

The analysis (Table 2) showed a positive correlation between non-sedentary time and HRV indexes – SDNN and pNN50 indexes increase as NonSedTime increases and vice versa, i.e. the lower amount of time spent in non-sedentary activities the lower the values of SDNN and pNN50. A lower levels of SDNN and pNN50 is known to be associated with higher stress levels [4]; [15]; [16] and negative emotions [3-7]. Therefore, the results indicate that sedentary workstyle lead the subjects to be more prone to negative emotions and stress, measuring the stress level according to the Task Force of the European Society of Cardiology and the North American Society of Pacing Electrophysiology [4]. However, due to the small sample size of this pilot study, the results should be considered only as an indication for the association between sedentary behavior and psychological processes.

Table 2. Correlation analysis between non-sedentary time and HRV indexes.

<table>
<thead>
<tr>
<th></th>
<th>SDNN Mean</th>
<th>RMSSD Mean</th>
<th>pNN50 Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>NonSedTime</td>
<td>.442**</td>
<td>0.046</td>
<td>0.262**</td>
</tr>
<tr>
<td>SDNN Mean</td>
<td>1</td>
<td>.305*</td>
<td>.740**</td>
</tr>
<tr>
<td>RMSSD Mean</td>
<td>.305*</td>
<td>1</td>
<td>.576**</td>
</tr>
<tr>
<td>pNN50 Mean</td>
<td>.740**</td>
<td>.576**</td>
<td>1</td>
</tr>
</tbody>
</table>

* Correlation is significant at the 0.10 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Table 2 also shows a strong internal coherence for HRV indexes, in fact the correlations between these indexes are always highly statistically significant. This means that the relationship between SDNN, RMSSD, and pNN50 is typically strong, and the phenomena revealed with one of the indexes should also apply for the others, even though it is indirect.

Furthermore, since the recording entries are hierarchical within participants, we estimated, with hierarchical linear regression, the relationship between the non-
Table 3. Hierarchical linear regression.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>B</th>
<th>Std. Error</th>
<th>95% Wald Confidence Interval</th>
<th>Hypothesis Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Lower</td>
<td>Upper</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>.072</td>
<td>.0085</td>
<td>.056</td>
<td>.089</td>
</tr>
<tr>
<td>NonsedTime</td>
<td>.002</td>
<td>.0003</td>
<td>.001</td>
<td>.002</td>
</tr>
<tr>
<td>(Scale)</td>
<td>.001</td>
<td>.0010</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5 Conclusions

Emerging studies suggest that sedentary work style is often associated with deleterious health complications, including diabetes, high blood pressure and obesity [1]; [3]; [5]; [9]; [10]; [11]; [19]. In this study, we aimed to explore the correlation between sedentary time and HRV parameters, which are considered biological markers of both physical and mental health. In particular, recent studies demonstrated that lower HRV values often suggest sympathetic dominance, higher stress and negative emotions [3-7]. Recent progress in the sophistication and usability of wearable biosensors offers the opportunity to continuously record ECG parameters and accelerometer data in daily-life settings, such as at workplace. In this experiment we used a Shimmer Wireless ECG sensor, connected with the mobile phone via Bluetooth, to investigate the correlation between sedentary time and HRV parameters at workplace, thus exploring possible cues for the association between sedentary behavior and psychological processes. Results showed a strong relationship with HRV parameters, in particular with SDNN and pNN50, suitable for a short term analysis. Such evidences suggest the use of wearable devices to measure ECG indexes in naturalistic environment to explore new possibilities to encourage a healthy work style. However, due to the small sample size, these results provide only cues about the examined correlations and we believe that they might motivate for future investigation on the correlation between sedentary time and HRV but also on the impacts of sedentary behavior on psychological response including emotions, stress and the mood.

References

Posters
The Role of Smartphones as an Assistive Aid in Mental Health

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Abstract. Recent developments in wearable sensors and smartphone technology have demonstrated the applicability and viability of such devices to the successful and cost effective treatment of mental illness, particularly depression. This paper describes a software toolkit and physical activity algorithms developed at the University of Limerick that will be used to monitor and assist clinical professionals in analyzing physical activity and physiological data. The resulting information is used in the ICT4Depression project to deduce an individual’s mental state, and progression through mental illness. Two trials were performed to assess the algorithms and the resulting data are discussed.

1 Introduction

Major depression is currently the fourth disorder worldwide in terms of disease burden, and is expected to be the disorder with the highest disease burden in high-income countries by 2030. Current treatment methods can reduce the burden of this disease by approximately one third [1]. ICT4Depression is an FP7 funded project that aims to reduce the disease burden significantly further. To this end the ICT4Depression consortium has set out to develop a system for the provision of online and mobile treatment of depression. Where current methods rely on direct contact with health care professionals or are Internet-based self-help therapies with a low level of interaction with the patient, the ICT4Depression system is a responsive system that allows the patient to receive a highly personalized and interactive treatment and work on their own progress anywhere and anytime.

Fig. 1 presents an overview of the ICT4Depression system. Central to the technology used is a smart phone, which is used to provide treatment to the user. This treatment consists of the provision of self-help modules, the gathering of sensor data (physiological sensors, activity sensors and various user ratings and questionnaires) and the measurement of medication adherence. This information is used in a decision support system to reason about the user’s progression and to advise on further treatment if and when necessary. In addition to being able to interact with the system on the mobile phone, the user has access to a web interface which can be used to provide more extensive feedback to the system and to view information generated by the system on a larger screen.
Sensor information plays an important role in the system as it is used in an innovative way to assess the user’s treatment progression. To this end, heart rate (and variability), breathing rate and trunk acceleration are measured with a chest strap. A glove type sensor is used to measure skin conductance and blood volume pulse with the data analysed for emotive triggers. Using acceleration sensors on the mobile phone the user’s physical activity is recorded. The latter plays an important role as exercise and depression are intricately linked. Various scientific studies have shown the important role physical activity plays in depression and it is widely known that depression tends to result in lower patterns of physical activity. From this perspective, it is interesting to measure the levels of physical activity for patient’s diagnosed with depression to obtain an insight in the disease progression. However, it has also been shown that the reverse is true and that a regime of increased physical activity can be used to reduce the severity of the depression [2]. Several reasons for the positive effect of physical activity on mood and depression have been suggested. First, exercise may act as a diversion from negative thoughts. Second, the mastery of a new skill may be important. Third, social contacts during the activity may act as a working mechanism. And fourth, physical activity may have physiological effects such as changes in endorphin and monoamine levels, or reduction in the levels of the stress hormone cortisol which all may improve mood. Exercise has been found to be effective in the treatment of depression in more than 20 randomized controlled trials [3]. Moreover, Blumenthal reported in 1999 that 16 weeks of group exercise training was as effective as antidepressant treatment with sertraline and that the 10-month relapse rate for the group that performed exercise was 8% whereas this same rate was at 38% for the group treated with Sertraline [4].

In the ICT4Depression system exercise is recognized as a treatment in itself which is normally conducted in parallel to other treatments. This paper discusses how smart phone based sensors are used in the ICT4Depression project for the identification and
monitoring of user physical activities (measured as periods spent lying, sitting, standing, walking, running, cycling and energy expenditure).

2 Physical Activity Monitoring

Physical activity monitoring using accelerometers is a well-established art which has seen a large interest from the research community in the last 20 years. Whereas research has long focused on the use of dedicated sensors rigidly attached to the user’s body, recent efforts have focused on use of the accelerometers available on most modern mobile phones. Due to the high uncertainty as to the exact location and orientation of the device in a realistic setting, physical activity monitoring on mobile phones poses significant challenges. Accelerometers measure acceleration from two sources: the output signal contains both acceleration resulting from user movement and acceleration due to gravitational forces. If the orientation of the device is not known \emph{a priori}, as is the case for a mobile phone, it is difficult to separate the two contributions to the acceleration output signal. For this reason early endeavours with mobile phones focused on step count and energy expenditure measurements [5] as both measures have the advantage that the orientation of the measurement device need not be known. Recent developments in this area of research go a step further and show promising results for sensors which can be attached to the user’s body with more freedom whilst still being able to identify various physical activities [6,7]. The methods used, typically do not explicitly separate gravitational and movement components from the acceleration data. As a result, the wealth of existing algorithms cannot be re-used. The work on mobility monitors described in this paper builds on the results found in the literature, but explicitly attempts to obtain the direction of gravity in device-fixed coordinates, such that a rotation of the measured accelerations (in device-fixed coordinates) can be performed to world-fixed coordinates (with the gravity vector pointing straight down). Where this can be done with sufficient accuracy, existing algorithms can be employed to then obtain accurate insight in specific user activities.

2.1 The PA Monitor

The PA monitor was developed and tested on a Samsung Galaxy S GT-I9000 which integrates Bosch’s SMB 380 TA accelerometer. This digital accelerometer falls into the differential capacitive line, whereby a change in capacitance can be mapped to changes in acceleration, and consumes 290µA while in use. The Samsung uses a 1500mAh battery, with which a mobility monitoring application will run for approximately 6 hours. Output RMS noise from the accelerometer is in the order of 0.5mg/√Hz. Android does not allow developers to specify the sampling rate explicitly. Instead, suggestions are made to the Android platform, such as DELAY_NORMAL, DELAY_UI or DELAY_FASTEST. These determine the priority with which the accelerometer readings are processed but do not guarantee a fixed sampling rate. Using the DELAY_FASTEST attribute on the Samsung provides applications with samples at approximately 90Hz.
2.2 Data Processing

As the sampling frequency of the accelerometer is not constant, raw acceleration data from the phone are first interpolated. A lightweight linear interpolator is used to facilitate any real time requirements. Interpolation facilitates processing further down the chain, since the quantity of samples in the incoming stream becomes fixed, at 120Hz in this case. For the case of linear interpolation, let \( x = \{x_{m+1}, x_{m+2}, \ldots, x_{n-1}\} \) be the vector of missing data points bounded either side by the known points \((x_m, y_m)\) and \((x_n, y_n)\) where \(n>m\). The \(n-m-1\) missing data points can be found using linear interpolation between the two known points:

\[
\forall i \in (m,n) \quad y_i = y_m + \frac{y_n - y_m}{x_n - x_m}(x_i - x_m)
\]

Next, the interpolated stream is median filtered with a 3-point median filter to eliminate any sporadic spikes in the signal. This median filtered stream is then used to fragment the acceleration signal in two using both band pass and low pass filters to give estimated vectors for the dynamic and static (gravitational) components respectively. The static and dynamic acceleration components are then fed into a physical activity state machine algorithm to derive user physical activity.

2.3 Activity Inference

Firstly, the incoming sample stream is converted to a world fixed coordinate system to overcome variations in the input signal due to changes in the phone’s orientation. The transformed stream is given by: \( a_{wf} = a_{df} R \), where \( R \) is the rotation matrix which is derived from the static component of the acceleration signal, and is defined by:

\[
\begin{bmatrix}
1 + (1 - \cos(\varphi)) \cdot (x^2 - 1) & -z \cdot \sin(\varphi) + (1 - \cos(\varphi)) \cdot x \cdot y & y \cdot \sin(\varphi) + (1 - \cos(\varphi)) \cdot x \cdot z \\
z \cdot \sin(\varphi) + (1 + \cos(\varphi)) \cdot x \cdot y & 1 + (1 - \cos(\varphi)) \cdot (y^2 - 1) & -x \cdot \sin(\varphi) + (1 - \cos(\varphi)) \cdot y \cdot z \\
y \cdot \sin(\varphi) + (1 - \cos(\varphi)) \cdot x \cdot z & x \cdot \sin(\varphi) + (1 - \cos(\varphi)) \cdot y \cdot z & 1 + (1 - \cos(\varphi)) \cdot (z^2 - 1)
\end{bmatrix}
\]

Once world-fixed accelerations are available, traditional physical activity algorithms can be used. The first step undertaken to achieve activity recognition involves selecting a heuristic feature set. The features chosen to distinguish between high and low energy activities are one-dimensional counts per minute (CPM) and the coefficient of variation (CV) [8], which give an indication of the energy contained in the acceleration signal and the variation in the latter respectively. Formulae for these can be found in equation 2 and 3.

\[
CPM(k) = \sum_{i=0}^{N-1} \frac{|a_z(k+i)|}{N}
\]

\[
CV(k) = \frac{\text{Standard Dev}(|a_z(k: k+N-1)|)}{\text{mean}(a_z(k: k+N-1))}
\]

where \( a_z \) is the component of the acceleration pointing straight down and \( N \) is the number of samples collected in a 1 minute window starting at time \( k \).

Whereas the CPM is per definition high for high energy activities, the CV is relatively low in these cases. CV tends to be high for sedentary activities as small move-
ments results in the CV increasing significantly. Hence these features are ideal candidates for the classification of high energy versus sedentary activities. Moreover, these features are used to distinguish between varying high energy activities, such as walking, running and cycling.

Further classification of sedentary activities is performed based on the static component of the acceleration signal which indicates the orientation of the device. This information is only useful if one also knows the orientation of the device relative to the orientation of the user. This information is obtained whilst the user is performing dynamic activities (for which activity the orientation of the user’s body is relatively well known) and updated regularly to account for the changing orientation of the phone as it is being used by its owner.

3 Trials Performed

Two separate trials were conducted to assess the performance of the PA monitor. In initial short technical trials the performance of the physical activity algorithms were assessed and trial results were used to fine-tune the algorithms. At present these algorithms are being employed in a larger study which also assesses the mood of the user.

The first trial took part in the University of Limerick, Ireland and entailed the monitoring of prescribed activities organized in a protocol lasting around half an hour. Six healthy individuals (5 males, 1 female) went through a range of activities which can be found in Table 1. The combined mean age of all participants was 30.6 years.

Activities recorded included: sitting, standing, walking at the subject’s comfortable pace on a corridor, cycling on an indoor bike, treadmill walking at 5km/h & 6km/h, jogging at 8km/h, and finally running on a treadmill at 9.6km/h. A total of 327 minutes of data were collected using three Samsung Galaxy S phones per subject,
which included a central controller, and two clients. Each subject was asked to place a phone in their right and left pants pockets. Both phones were controlled remotely via Bluetooth by the central controller. This program could issue commands to the client PA monitors including facilitating a synchronization request between devices. For example, if the individual performs an activity beyond the scope of the trial, the observer could issue a synch request when the subject started the next scripted activity. Both smartphones placed in the subject’s pockets, sent real-time activity information back to the controller. Using Matlab, the data was labeled for each activity performed and processed to obtain a confusion matrix showing the rates of correct and incorrect classification. In case of an incorrect classification, the confusion matrix also indicates which activity was incorrectly inferred by the PA monitor. The obtained confusion matrix, which is depicted in Table 1, shows that correct classification rates lie between 82% and 91% for all activities other than sitting. Sitting is misclassified as lying as for both activities the phone (which is in the pants’ pocket) is in the exact same orientation. This shortcoming can be overcome by also measuring trunk orientation which is measured by the aforementioned sensor for heart rate and breathing rate. Although this feature was beyond the scope of the described trials, use will be made of the trunk orientation in the final ICT4Depression system. The reader should also note that all rows sum to a likelihood of 1, apart from the row describing the Stand activity. This is due to the fact that the algorithms use an extra ‘Transition’ stage which indicates that the state machine is in between two of the listed activities. This only affects the Stand activity and occurred in 9% of the time.

<table>
<thead>
<tr>
<th></th>
<th>Lie</th>
<th>Sit</th>
<th>Stand</th>
<th>Walk</th>
<th>Run</th>
<th>Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lie</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Sit</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Stand</td>
<td>0</td>
<td>0</td>
<td>.91</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Walk</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.86</td>
<td>0.14</td>
<td>0</td>
</tr>
<tr>
<td>Run</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.13</td>
<td>0.85</td>
<td>0.02</td>
</tr>
<tr>
<td>Cycle</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
<td>0.17</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Further trials are currently underway at the VU University, Amsterdam, The Netherlands. The goal of this study was testing the feasibility of wearing the devices (mobile phone plus aforementioned chest strap and wrist strap) for prolonged period of time and the ability to reliably detect the ongoing activity (specifically posture and physical activity) from the sensors. In this study a larger cohort of volunteers are subjected to an hour of scripted activities and consecutively to 23 hours of unscripted activities. Thirty healthy volunteers were recruited for this study, aged 18-25. The scripted activities consist of sitting, standing, lying, walking, cycling and tone avoidance activities (see Figure 3). The tone avoidance task is an experiment in which the user has to react to a visual stimulation by pressing a button as fast as possible. The visual stimulation is presented as a square on a computer screen that can appear in all four corners. The user has to react by pushing a button corresponding with the opposite corner. By doing this in time, the user prevents a loud noise from sounding. This test was used to induce a stress situation in the user, which was measured through the use of heart rate, breathing rate and skin conductance sensors. However, this part of the trial falls outside the scope of this paper. Subjects engage in the scripted activities
under supervision of the experimenter. They subsequently perform 23 hours of daily activities without further instructions. Subjects will be monitored during this time. During this unsupervised period, an iPod will be used by the subjects to fill out a self-report every 30 minutes. They rate how they felt, what they did, where they were and with who and how much time (in %) they spent on lying, sitting, standing, walking and biking.

![Fig. 3. Overview of elements assessed during the trials at the VU University.](image)

Data analysis for these trials so far has focused on the physical activity aspects performed as part of the ‘Regular Daily Activities’ and the ‘Standardized Physical Activities’ as defined in Figure 3. This yields incomplete yet modestly encouraging confusion matrices as depicted below in Table 2 and Table 3. Note that ‘Climbing Stairs’ is not currently identified as a separate category in the physical activity algorithms and that ‘Recovery’ is a period of sitting.

**Table 2. Confusion Matrix for User 03.**

<table>
<thead>
<tr>
<th></th>
<th>Lie</th>
<th>Sit</th>
<th>Stand</th>
<th>Walk</th>
<th>Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sit</td>
<td>0.46</td>
<td>0.47</td>
<td>0.06</td>
<td>0.01</td>
<td>0</td>
</tr>
<tr>
<td>Walk</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
<td>0.98</td>
<td>0.02</td>
</tr>
<tr>
<td>Cycle</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.66</td>
<td>0.34</td>
</tr>
</tbody>
</table>

**Table 3. Confusion Matrix for User 04.**

<table>
<thead>
<tr>
<th></th>
<th>Lie</th>
<th>Sit</th>
<th>Stand</th>
<th>Walk</th>
<th>Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sit</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Walk</td>
<td>0</td>
<td>0</td>
<td>0.98</td>
<td>0.02</td>
<td>0</td>
</tr>
<tr>
<td>Cycle</td>
<td>0</td>
<td>0</td>
<td>0.15</td>
<td>0.85</td>
<td>0</td>
</tr>
</tbody>
</table>

The results in above tables show that the difference between static (lying, sitting, standing) and dynamic activities (walking, cycling) is accurately identified by the algorithms. For user 03, the sitting activity is often confused with standing and lying due to the fact that this particular sitting activity was a Recovery activity which took place while the participant sat on an exercise bike. As the physical activity algorithms
assume that both upper legs are horizontal, the sitting activity on the exercise bike is not identified correctly. The identification of the cycling activity for user 03 shows that further features may be needed to identify the difference between walking and cycling accurately.

For user 04 results show good identification rates. Although sitting and lying are confused 100% of the time, the trunk orientation of the user would give a potentially perfect feature to correctly identify sitting. The identification of static versus dynamic activities is 100% for this participant and the correct identification of walking and cycling 98% and 85% respectively. Similar to user 03, the correct identification of cycling is still rather low whereas the correct identification of walking is similar at 98%, which suggests that the algorithms could be improved by fine-tuning the identification of cycling. As data analysis of these trials is ongoing, more extensive results, also including the other activities performed during the trial, will be published in a subsequent paper.

4 Conclusions

This paper outlines the use of mobile phones in the treatment of depression as a means of communication with the user, presentation of the treatment modules, sensor data gatherer and physical activity monitor in its own right. The focus of this paper was on the latter and two physical activity monitoring trials performed as part of the ICT4Depression project are described. The inherent challenge in measuring physical activity with a sensor whose orientation is not known, is addressed through a data transformation from device-fixed coordinates to world-fixed coordinates through the use of an approximated gravity vector. The world-fixed acceleration signal is then used to apply thresholding based algorithms to the identification of various activities. Preliminary results show that the phone can lead to a reasonable estimate of user activity although it is also clear that further work is needed to obtain accuracies similar to those obtained with traditional sensors.

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in Human-Computer Interaction. Part II: Intelligent and Ubiquitous Interaction Environments. (2009)


Wireless User-computer Interface Platform for Mental Health Improvement through Social Inclusion

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Abstract. Loss of communication due to long-term neurological conditions leads to isolation and loneliness. Individuals in these conditions raise the risk of depression, since they can’t convey their needs and wants and loose their social networks. This paper describes the development of a wireless platform for user-computer interface, targeted at mental health improvement through communication and social inclusion. We describe the proposed approach in the context of an input device based on a single channel electromyographic signal, although the use of other biosignals is discussed to expand users’ possibilities. Users’ needs in terms of user interface implementation are considered, concerning severe speech and physical impairments.

1 Introduction

There are several neurological conditions in which affected individuals dramatically loose generalized motor control (e.g. brainstem stroke, motor neurodegenerative diseases, cerebral palsy, traumatic brain injuries or spinal cord injuries) [1]; [2]; [3].

Severe motor limitations often cause motor speech disorders and consequently severe difficulties in communicating. Communication loss will raise depression factors in user, due to isolation and loneliness [4]; [5]. Moreover it will difficult clinical support, since individuals cannot express symptoms and needs. In these conditions, if there is no effective technology for enabling the user to communicate, communication will be restricted to yes/no answers, which represent a great limitation to several important aspects in a person’s life, as expressing needs and wants, decision making and social closeness[6]; [7]. Recognizing and addressing communication disorders is then of utmost importance.

Concerning communication disorders, access to Information and Communication Technologies (ICT) is important, since it offers means for providing social and emotional support, beyond space and time constraints caused by severe speech and physical impairments [7]; [8].

In this context, the great challenge is finding a user-computer interface that the user can control with autonomy, efficiently and consistently [1]; [9], in spite physical
imPAIRMENTS. Efficient control of a user-computer interface will make possible for the user to break isolation and total dependence through access to the computer (e.g. user could independently control a virtual keyboard to access to the Internet).

Our work presents the development of a wireless platform targeted at mental health improvement through social inclusion. We describe the application of the proposed platform to a single channel user-computer interface, based on electromyographic (EMG) signal control. Important aspects concerning users’ needs and technology development are presented. New possibilities to connect other types of sensors are discussed. The rest of the paper is organized as follows: Section 2 outlines the needs faced by the target user groups; Section 3 describes the proposed approach; and Sections 4 and 5 present the discussion and main conclusions.

2 User Needs

Concerning severely speech and physically impaired (SSPI) users, the following characteristics were considered in implementation of the presented user-computer interface:

(a) Mobility – wireless sensors allow user to be in a comfortable position or move independent from the place where the computer is.

(b) Biofeedback – developed software includes the possibility to go through a training period, where the user can watch and learn to control its own signal (EMG) using biofeedback. In case of individuals in rehabilitation process, this tool is useful for the clinicians to evaluate the best place for the sensors and to explore new muscles.

(c) Personal solution – the user can operate with the system in his/her own personal computer and choose the software that will receive the events from this interface.

(d) Communication – it was developed a specific connection between our platform and a specific software for Augmentative and Alternative Communication (AAC) and Computer Access (©The Grid 2, from Sensory Software), aiming to provide specialized features for user communication.

3 Proposed Platform

3.1 EMG Signal Processing

The electromyographic signal is a record of the electrical activity generated by muscle cells when they are electrically or neurologically activated. For the detection of the EMG natural activation, the signal is usually rectified and filtered to obtain its envelope [10] or processed using statistical based methods [11].

In this work, the EMG data is collected and processed at real time using Python [12] with the NumPy [13] and PyWin [14] packages. The processing procedure consists in removing the sensor offset value and rectifying the result. To extract the signal's envelope, a smoothing filter is applied to the rectified signal.
When the muscle is activated, the amplitude of the EMG envelope increases and if it surpasses a defined threshold, the initial instant of muscular activity is accepted after validating it for sporadic activations - by checking if the end of the activation was at least 100ms after the start of the activation. If accepted, the voluntary activation is converted into a triggering event to control an external predefined software (e.g. a virtual keyboard software). This voluntary activation can be configured as a Windows keyboard event or a software specific event (implemented for ©The Grid 2, Sensory Software), and is sent through Windows Messages [15]. A block diagram representative of the overall communication flow is presented in Figure 1.

3.2 User Interface

A web-based application was developed in order to provide a user-friendly tool to visualize the signals in real time, store the specifications of the software and provide feedback concerning the muscle activations.

The application is independent of the external software to which the signal activation is sent. In the application configurations it is possible to choose the specific software to which events will be sent – keyboard events (e.g. enter or space key) or software-specific events previously registered with Windows Messages.

As the application starts, the signal is graphically displayed on the screen. The threshold that sets the activation level necessary to accept the event is defined after signal calibration. After pressing the calibration button, the subject has to perform a few muscle activations and the threshold is defined as a third part of the maximum contractions' mean value. As the amplitude of the EMG signal may decrease with muscle fatigue for long acquisitions, a slider bar provided in the web interface enables the manual adjustment of the threshold value.

When the muscle is active and surpasses the defined threshold, the event is sent to the external software. To indicate that activation, a visual feedback is shown in the interface. A screenshot of the web interface with the functions here described is presented in Figure 2. This single event will activate a scanning process [1] by which the user can select a virtual key (containing a character, a text message or other types of commands to access to computer) in a virtual keyboard.

4 Discussion

Our work was focused on creating a wireless user-interface platform based on a single-channel biosignal onset detection, which can operate signals from a variety of electrophysiological or biomechanical sources. We presented an embodiment of this
platform that produces the necessary events for manipulating a virtual keyboard. We worked with surface EMG sensors, which can be placed anywhere in the body.

An alternative to the presented EMG sensor, and for detection of specific eye movements, would be an electrooculography (EOG) sensor, which has a higher gain than the EMG sensor and can be suitable for low muscle electrical activity.

A relevant approach would be to combine different miniaturized and unobtrusive sensors to capture and send different types of events. An electroencephalography (EEG) sensor could be used in the occipital region of the head to capture EEG alpha rhythm, which appears after eye closure [16]. The event created through this mechanism could be used for other functions like starting or shutting down the application or switch between menus.

Tests are being made in real scenarios with SSPI users. This will be important to solve real problems arising from user-computer interaction.

5 Conclusions

Accessibility to ICT is important to SSPI individuals since it breaks isolation and restores the ability to communicate, which has a major impact on mental health of the users. Access to a computer may allow these individuals, not just to express needs and wants, but also to restore social roles and access to assisted living services.

A wireless platform and user-computer interface was developed taking into account users needs, in the context of severe motor limitations. We described an application of the proposed approach to the use of EMG sensors, which allow users to control the computer using minimal muscle movements. Connection to a specific software for AAC and Computer Access was considered in this work, fulfilling users’ specific needs for Communication. Future work will focus on real-world validation of our system both with EMG, and other biosignals, which can be seamlessly introduced in our platform to expand users’ possibilities.
By opening a way to ICT, our work can be helpful in sustaining and expanding social networks, reducing isolation then challenging multiple mental health factors affecting the target user groups.

References

Author Index

Araújo, T. .......... 41
Azevedo, L. .......... 114
Baldus, G. .......... 25
Canento, F. ......... 59
Carelli, L. .......... 79
Carter, M. .......... 3
Cipresso, P. ....... 25, 79, 96
Corda, D. .......... 25, 96
Fred, A. ........... 59
Gaggioli, A. ....... 25, 96
Gamboa, H. ....... 35, 41, 71, 91
Guiry, J. .......... 105
Hastie, H. .......... 17
Henriques, M. ...... 47
Hilst, P. .......... 105
Hoogendoorn, M. .. 47
Iyengar, S. ....... 3
Klein, M. .......... 47
Londral, A. ....... 114
Ludolph, A. ....... 79
Lulé, D. .......... 79
Marques, C. ...... 71
Martínez-Miranda, J. 17
Matheson, C. ...... 17
Matic, A. .......... 96
Mayora, O. ....... 96
McGovern, E. ...... 47
Meriggi, P. ....... 79
Nelson, J. ....... 47, 105
Nunes, N. ....... 41, 114
Osmani, V. ....... 96
Pioggia, G. ...... 25
Poletti, B. ....... 79
Popleteev, A. ...... 96
Quintão, C. ...... 41
Riper, H. ....... 105
Riva, G. .......... 25, 79, 96
Santinha, J. ....... 91
Santos, R. ....... 71
Serino, S. ....... 25, 96
Silani, V. ....... 79
Silva, H. .... 35, 47, 59, 71, 91, 114
Solca, F. .......... 79
Sousa, J. .... 35, 71, 91
Tartarisco, G. .... 25
Tousset, E. ...... 47
Ven, P. .......... 47, 105
Wallace, M. ...... 3
Warmerdam, L. .. 105
Wolters, M. ...... 17