The movement patterns and the experiential components of virtual environments

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Abstract

Human movement in virtual environments (VEs) is a largely unstudied area, and there are no well-established methods of measuring it in VEs. Consequently, it is unclear how movement affects the experiential side of VEs. We introduce a novel method of measuring and modelling human movement. A specific information entropy-based modelling method enabled us to identify different movement patterns and analyse the experiential components related to them. The data was collected by registering the movement patterns of 68 participants who were in a virtual house doing a search task. The experiential side of the VE was measured with the Experimental Virtual Environment Questionnaire (EVEQ). Four movement patterns were identified. In addition, fluent movement in VEs was related to a high sense of presence. Moreover, the participants who moved fluently in the environment assessed their skills high. The results show how movement is related the way in which people experience the VE. The movement analysis method introduced here is applicable to other related research areas as well.

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1. Introduction

Picture yourself driving a bumper car in an amusement park with your friend. Your friend manoeuvres her car with a big smile on her face, while despite your best effort, your car does not move in a direction that you want it to move, making the whole experience unpleasant. The fluency of movement affects how both you and your friend experience the situation. But, how should we study this experience and, especially, how should we study movement? According to Hilgard (1980), experiences should be analysed by considering simultaneously the cognitive (thoughts), emotional (feelings), and conative (motivation) sides of them. The problem with this approach is operationalization of experience and difficulty of conducting experimental research in laboratory conditions on such a complex subject. One solution is the use of virtual environments (VEs) as a research setting.

VEs have high ecological validity when studying human perception (Waller, 2005), motor functions (Zacharias, 2006), or experiences and emotions (Germanchis et al., 2004; Wiederhold and Wiederhold, 2003). It is fairly easy to build realistic yet controllable experimental settings by using VEs. This has led to a large spectrum of applications in different areas, such as using VEs to practise surgical operations (Delp et al., 1997), training astronauts (Loftin and Kenney, 1995), and, in ever growing numbers, in the entertainment industry (Zyda, 2005). However, despite the numerous VE applications, there is relatively little information about the experiential components of VEs. An exception is presence, an illusion of being in a virtual world, which is one of the most commonly used
concepts when studying VEs (Lombard and Ditton, 1997; Sanchez-Vives and Slater, 2005; Schubert et al., 1999; Takatalo et al., 2008; Witmer and Singer, 1998).

Conversely, movement in VE and its effects on subjective experiences is not well studied. The reason for this is simple: there are no well-established methods of measuring movement in VE. However, part of the experiences users attain from VEs could be best explained by their ability (or inability) to move fluently. We introduce a novel information theory-based method of measuring and modelling movement. It allows us to identify and compare different movement patterns, that is, different ways of how users move in VEs, and the background variables related to them. In addition, this entropy-based movement model allows us to make statistical comparisons between movement patterns, which, in turn, enables us to examine the experiential components related to them.

1.1. Movement in virtual environments

Movement in VEs is basically only visual movement which users steer with an interface. In practice, this means that the user is standing still in front of a display device and with the help of control devices the picture, and thereby, the VE around him/her moves. There are numerous interfaces, which are especially developed for VEs. The most common interface for moving is mouse and buttons (Burdea and Coiffet, 2003). Other possible interfaces are, for example, a tracking camera, speech recognition input, and walking on a special treadmill (Hand, 1997). Although steering with a mouse is admittedly far from actual walking, it has been shown that the basic movement strategy in well-built VE is similar to the movement strategy used in natural environment (Zacharias, 2006). Therefore, findings from movement in VE can, with certain restrictions, be generalized to movement in the real environment.

1.1.1. Movement modelling

Movement is a dynamic process, where both the task and the environment where it is done, affect how a person moves. This, in turn, makes mathematical modelling difficult. Partly because of the complexity of it, so far, there have been only a few studies that analyse movement in VEs. These studies have analysed movement in VEs mostly by using qualitative measures (Lathrop and Kaiser, 2005; Ruddle and Jones, 2001). In contrast, there are no well-established methods of measuring which give quantitative information about how users move in VEs, not to mention any standard measures which would allow comparison between previous studies. However, quantitative data is essential to most statistical analysis methods. One way of studying movement quantitatively is the use of distributions that are based on movement speed and rotations (Slater et al., 1998). However, previous research has shown that there are experimental and theoretical limitations when using distributional statistics in movement analysis (Kim et al., 1999). As a solution, information entropy analysis has been suggested as a sound method of movement modelling (Lai et al., 2005).

1.1.2. Information entropy and movement

Entropy is originally a concept of classical thermodynamics, which measures the increase of disorder in a physical system, that is, a change toward thermodynamic equilibrium (Clausius, 1865). Entropy has been applied, for example, in chemistry, statistical mechanics, bioinformatics, and information theory (Settna, 2006). In information theory, entropy measures the amount of information that a data source contains (Weaver, 1963). A data source can be any signal, event, or any other result of measurement, which contains information. When calculating entropy from the measurement, the following rule can be applied: the more often you get a specific result, the less information it gives you. In this case the entropy of the result is also small. To clarify, think of a biased dice which gives you six every time it is cast. In this case the result of a measurement gives you no new information, that is, its uncertainty, and hence entropy, is zero. In contrast, the less frequently you get a specific result, the more information it contains and the bigger the entropy.

In our dice example, this would represent a normal unbiased dice. In other words, the bigger the entropy of the result of measurement, the more randomness and new information it contains. In short, the entropy of the result of measurement tells how much information the result contains. In information theory entropy $H$ is calculated as follows:

$$H(X) = - \sum p(x_i) \log p(x_i)$$

where $X$ indicates the result of measurement, ranging from $x_1$, $x_2$, $x_3$, $x_4$, while the probability of an individual result of measurement $x_i$ is indicated with a $p(x_i)$.

In movement studies entropy measures have been applied only to rather simple tasks, such as muscle control or aiming movements (Lai et al., 2005; Stergiou et al., 2004). Movement in VEs has not been previously studied with entropy measures. What are the advantages of entropy measures then? Entropy measures reveal the regularity and smoothness of the movement, which helps to discriminate, for instance, those who move with a fluctuating speed from those who travel at a steady pace. In addition, the entropy measures are calculated by using the true occurrence of information in the data, unlike many other estimators which make assumptions about the distributional properties of the data. To conclude, by using information entropy it is possible to quantify movement, and thus identify different movement patterns. Furthermore, this approach can be used to show how different movement patterns are related to how users experience the VE.

1.2. Experiences and virtual environments

With the help of modern technology, realistic VEs are easier and cheaper to create than ever before (Lanier,
As VE applications are becoming more popular, there is a growing need to understand what psychologically relevant factors are associated with them. First, it is known that VEs can create a state of presence where a user does not perceive her/his immediate surroundings, but instead feels like being inside the world created by the computer (Lombard and Ditton, 1997; Sanchez-Vives and Slater, 2005). These perceptual and cognitive processes are studied with the concept of presence. This approach emphasizes the active role of perception (Gibson, 1979). Secondly, cognitive and affective factors are studied with the concept of flow, according to which the cognitive evaluation of skills and challenges has an effect on the quality of the affective appraisal of the situation (Csikszentmihalyi, 1975). The study of flow is parallel to the cognitive-motivational theory of emotion as formulated by Lazarus (1991). While the main experiential components that are related to VEs are recognised, the role of movement on these experiences is mainly unknown.

1.2.1. Presence

Presence is a psychological state, which is thought to be a defining factor in what makes VEs unique experiential environments (Sanchez-Vives and Slater, 2005; Schubert et al., 1999). The definition of presence is still a controversial issue, which has led to a wide range of different operationalizations (e.g. Friedman et al., 2006; Sas and O’Hare, 2003; Schuemie et al., 2001). Despite the differences, it is a widely accepted fact that in order to achieve the state of presence, the VE should be immersive and easy to use, so that the user must not consciously pay attention to the equipment she/he is using. That is, the state of presence is defined as a perceptual illusion of non-mediation (Lombard and Ditton, 1997). For example, when playing a driving simulator game the player may feel like really driving a car instead of playing a simulator.

The most common way to measure presence is the use of self-report questionnaires. In practice, a group of component variables is being measured, which when combined tells something about presence. The most salient components of presence are realness and the perceived spatiality of the VE and the possibility to explore it freely (Fontaine, 1992; Lessiter et al., 2001; Schubert et al., 2001; Witmer and Singer, 1998). In addition, the speed and the range of interactivity and the shift of attention to the VE are central components (Lessiter et al., 2001; Schubert et al., 2001; Slater et al., 1998). A common term for all of these components is physical presence. However, why try to maximise presence when designing applications? First of all, high presence is related to pleasant user experience (Novak et al., 2000). Furthermore, high presence is related to better task performance and a smaller number of simulator sickness symptoms (Rice, 1992; Witmer and Singer, 1998). Overall, applications that elicit high presence are more efficient to use and users are keener to use them.

The controllability of the VE and the ease of use are important in order to achieve high presence (Schuemie et al., 2001). If the interface is distracting or it requires a lot of effort to concentrate on the using of VE, it is difficult to be immersed in a virtual world (Lombard and Ditton, 1997). It is reasonable to assume that fluent movement is a prerequisite for a high presence. Previous research has shown that highest presence is achieved when movement in VE is carried out by actual walking by using, for example, a treadmill interface (Usoh et al., 1999). Nevertheless, there is no previous research that addresses how the fluency of the movement affects presence evaluations. All in all, the effects of the control factors and the ease of use on presence have been analysed only on a theoretical level (Novak et al., 2000; Schubert et al., 2001; Witmer and Singer, 1998).

1.2.2. Flow

Flow is a concept that refers to a psychological state of enjoyment and concentration (Csikszentmihalyi, 1975). In addition, in a state of flow a person is fully absorbed into her/his current action and feels motivated, happy, and cognitively efficient. Although originally flow was applied in the analysis of such activities as rock climbing and dancing, later on it has been successfully used when studying computer use (Ghani and Deshpande, 1994), web activities (Chen et al., 1999; Novak et al., 2000), and computer games (Hsu and Lu, 2004; Takatalo et al., 2004). While there is still some debate concerning the definition of flow, it is widely accepted that subjective evaluation of skills and challenges, and a sufficient level of control and playfulness, are the main antecedents of flow (Csikszentmihalyi and Csikszentmihalyi, 1988; Finneran and Zhang, 2005; Novak et al., 2000).

The flow experience itself is a pleasant experience, and hence the action where flow is attained is seen as meaningful, fluent, and efficient. Previous studies concerning the experiential factors of computer use have shown that flow is related to more efficient learning (Hoffman and Novak, 1996), positive affect (Chen et al., 1999; Hoffman and Novak, 1996), and more frequent computer use (Ghani and Deshpande, 1994). It seems that when attained, flow leads to better results, faster learning, and happier users.

Despite the inconsistencies and discrepancies in the definition of flow, there is a strong consensus that skill and challenge and the balance between them is vital in order to experience flow (Finneran and Zhang, 2005). Often the problems with the interface are the main reason that hinders users from experiencing flow in computer settings (Pilke, 2004). In order to be able to move fluently in a VE, the interface cannot be highly distracting. Research-wise, the trouble is the lack of proper objective measuring methods for skills and challenges. This study introduces a novel method of measuring movement, which offers a possibility to use objective evaluation of movement as a skill measure. While skills and challenges are essential to flow, it has been shown that both skills and challenges have to reach a certain level and maintain a balance in order to experience flow (Csikszentmihalyi and Csikszentmihalyi,
Based on this notion, Massimini and Carli (1988) have presented a four-channel flow model (see Fig. 1). According to this model, too easy a task or lack of skills prevents the users from experiencing flow, even though the balance between the skills and challenges would be appropriate. Consequently, it is assumed that fluent movement in VE is related to flow, but only when users evaluate their skills and challenges of the situation as high.

### 1.3. Aim of the study

The aim of this study is to analyse movement in VEs and to examine the role of movement on how users experience VEs. Movement in the VE is modelled by combining traditional movement data, such as the amount of stops, with information-entropy-based measures. With the movement model, we try to identify characteristics of fluent movement and compare fluently moving users with less fluently moving ones. Due to the lack of previous research on the role of movement in VE, this is an exploratory study. Consequently, first it is necessary to find out whether there are movement patterns that can be identified. Secondly, we analyse how different background variables are related to movement patterns. Thirdly, we hypothesize that fluent movement in VEs is related to a high sense of presence. Finally, we expect fluent movement to be related to high evaluations of skill and challenge. In addition, we draw a few tentative conclusions whether our movement modelling method could work as an objective skill measure.

### 2. Methods

#### 2.1. Participants

Volunteers were sought through announcements posted on university mailing lists. In addition, mailing list subscribers were encouraged forwarding the announcement to people who might be interested in participating. The sample consisted of 68 participants, with 43 (63.2%) of them men and 25 (36.8%) women. The mean age of the sample was 28.15 (SD = 5.50), with a range from 18 to 45 years. The majority of the participants were highly educated, with high school degree (n = 32, 47.1%) or a university degree (n = 31, 45.6%). All participants had at least basic skills in using computers. Their weekly computer use ranged from 0 to 60 h per week (M = 28.51, SD = 16.78). Only nine participants (13.2%) had previously used VEs. Twenty-two participants (32.4%) reported never playing computers games, while only three participants (4.4%) reported playing on a daily basis.

#### 2.2. Technology

The experiment took place in the experimental virtual environment (EVE) hosted by Department of Media Technology at the Helsinki University of Technology. EVE is a rear-projection-based virtual reality system, where the user is surrounded by three 3 × 3 m² screens (see Fig. 2a and b). In order to view the environment in 3D, shutter glasses were worn. The participants were able to interact with the environment by a custom-made wand, consisting of a wireless mouse and a magnetic 3D tracker (Laakso, 2001) (see Fig. 2c). For travel technique, we chose throttle and steering-metaphor. In this technique, the user pushes a button in the wand and moves the device in a direction he wishes to move. This results in (continuous) movement to that direction. The distance from the origin

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**Fig. 1.** A four-channel flow model (adapted from Massimini and Carli, 1988).

**Fig. 2.** (a) The stereoscopic images from the projectors are reflected into 3 × 3 m² screens with the help of mirrors, (b) a view of the EVE and (c) the custom-made wand device that was used to move in the VE.
(point where the button was pressed down) determines the speed and releasing the button stops the movement. The rotation is handled by pressing another button and rotating the wand in a desired direction. The rotation angle from the origin determines the rotation speed and releasing the button stops it. The software that we used was a modified version of HCNav by Laakso (2001). The participants heard all the sounds through EVE’s 3D-audio system with a volume of approximately 65 dB. For a more comprehensive description of the software and hardware used, see Jalkanen (2000) and Laakso (2001).

2.3. Test procedure

The procedure started with a rehearsing period. The instructions on how to use the Wand and move in the VE were available to the participants on the test information pages in the Web. In addition, the participants were familiarised with the instructions before entering the EVE. If necessary, the participants were instructed in finding an effective way to move around the EVE. Movement was restricted so that the participants could move only at a horizontal level. The actual task was to go into a virtual five-bedroom house and explore it in order to find objects that do not belong into a normal house. There was only one “wrong” object at each point in time and when it was found the participants were instructed to collide it. The collision made the object disappear and produced a small sound. At the same time, another object turned up somewhere else in the house. In total, there were 11 target objects in EVE. After the participant found all the objects or reached the limit of 15 min the task was aborted. There was no overall collision detection, so the participants were able to move through walls and furniture. However, they were encouraged to avoid it. The idea of the task was to provide the participants a meaningful and quite neutral activity for 10–15 min in EVE. The whole procedure took approximately 20–25 min. Afterwards, the participants were asked to fill in the Experimental Virtual Environment Questionnaire (EVEQ) (Takatalo et al., 2008).

2.4. Movement analysis

The participants’ movement in the VE was recorded on a computer as a two-dimensional \((x, y)\) path (Fig. 3a). The sampling rate for the movement was set on 17 times per second. In order to analyse movement statistically, we needed a way to quantify it. First, we calculated for each participant the total time, the amount of stops, time spent being stationary and mean acceleration. Next, three entropy measures were calculated by using a custom-made algorithm in MatLab R13. We calculated location entropy, the entropy of turning, and speed entropy for each participant individually. All entropy measures were continuous variables.

Location entropy was calculated by dividing the area where the participant was moving in equal sections, which for the sake of clarity are called tiles. Next, we calculated the frequency for how often the participant had visited each tile. Consequently, a 3D histogram was made showing both the movement path of the participant and the number of visits on each tile (Fig. 3b). By using the frequency information, a probability of visit for each tile was calculated, which, in turn, was used to calculate the location entropy. Hence, low location entropy illustrates that the participant has moved most of the time in a fairly limited part of the VE. In contrast, high location entropy shows that the participant has moved evenly in all the parts of the VE.

The entropy of turning was formed by calculating a change in angle for each consecutive point of measurement. Next, a full circle was divided into equal segments (11) and each change in angle was categorised belonging to a segment based on the size of the angle. By this procedure, we were able to calculate the probability for each change in angle, and thereby, to determine the entropy of turning. In

![Fig. 3. (a) Two-dimensional movement path of one participant and (b) movement path of the same participant on a 3D histogram. The height of the histogram illustrates the amount of visits on a certain location.](image-url)
consequence, a low entropy of turning means that the participant has moved by making equal-sized turns, whereas a high entropy of turning shows that the participant has moved by using a whole range of different-sized turns.

Speed entropy was formed by combining the time and location information and calculating the speed for each consecutive point of measurement. Then, the whole range of possible speeds was divided into equal-sized speed intervals (0–1.5 pixels per 0.06 s) and each specific speed measurement was categorised to one of these intervals. Based on this, the probability for each speed interval was calculated, and furthermore the speed entropy was determined. Thus, low speed entropy shows that the participant has moved with a steady pace, while high speed entropy means that the participant has moved with highly variable speed.

In order to find out whether the participants had different movement patterns, a hierarchic cluster analysis was conducted. The entropy of turning, speed entropy, acceleration, the amount of stops, and time spent being stationary were selected as clustering variables. Ward’s method was chosen as a clustering method and squared Euclidean as a distance measure (Ward, 1963). After manual inspection a four-cluster solution was selected. Finally, in order to validate our clustering solution, we randomly split our sample and made a similar cluster analysis separately to both halves. Validation showed that the clustering solution was robust and therefore reasonable to examine more carefully.

### 2.5. Experiential measures

The experiential components of the VE were measured with the EVEQ (Takatalo et al., 2008). EVEQ has been created to evaluate the experiential aspects of the VEs. Later on, EVEQ has been developed to study digital games with it. This EVEQ-GP-questionnaire has been applied in numerous studies, where its reliability and validity have been found solid (Särkelä et al., 2004; Takatalo et al., 2004, 2006). Table 1 summarises the experiential components of the EVEQ that we used in this study.

The experiential components have been divided as part of either a flow or a presence construct (Takatalo et al., 2008). The division has been made with the purpose of making the results easier to interpret. Takatalo et al. (2008) have collected the presence (Lessiter et al., 2001; Lombard and Ditton, 1997; Schubert et al., 1999; Witmer and Singer, 1998) and the flow (Fontaine, 1992; Novak et al., 2000; Lessiter et al., 2001; Witmer and Singer, 1998) components from a number of studies. In reality, the division is not so clear-cut since some of the components (e.g. attention) belong to both flow and presence. A more thorough analysis of the structure of EVEQ and a detailed description of individual components are reported elsewhere (Takatalo et al., 2008).

### Table 1

A short description of the experiential components of the EVEQ and the amount of items that was used to measure the component.

<table>
<thead>
<tr>
<th>1. Flow components</th>
</tr>
</thead>
</table>
| Skill (the perceived level of skill—11 items) | 0.91  
| Challenge (the perceived level of challenge—6 items) | 0.84  
| Control (sense of control over situation—4 items) | 0.82  
| Anxiety (the level of anxiety one felt—7 items) | 0.82  
| Playfulness (how free, flexible, natural, and live one felt—9 items) | 0.85  
| Pleasant (the amount of enjoyment and fun one felt—6 items) | 0.77  
| Valence (was the experience negative or positive—5 items) | 0.86  
| 2. Presence components |  
| Real (the VE was natural, live and vivid—6 items) | 0.83  
| Spatial (spatial awareness of a place, being part of the VE—9 items) | 0.84  
| Attention (concentration on the VE, time distortion—11 items) | 0.90  
| Being there (a feeling that one actually visited a virtual place—5 items) | 0.84  
| Action (objects and things could almost touch me, the VE induced real motion feelings—7 items) | 0.82  
| Arousal (level of arousal evoked by the situation—4 items) | 0.67  
| Interactivity (evaluation of the interaction speed, mapping and range—4 items) | 0.81  
| Exploration (ability to explore the VE—3 items) | 0.74  

The second column indicates the reliability of a component with Cronbach’s alpha.

### 3. Results

#### 3.1. Movement in virtual environments

The cluster analysis revealed four different movement groups in our data. The groups were profiled and named based on the clustering variables and location entropy (Table 2).

To examine the difference between the four movement groups a post-hoc testing was conducted (see Appendix A). For variables with equal variances we used a Tukey post-hoc, and a Games–Howell post-hoc for variables with unequal variances. The confidence interval of post-hoc testing was set on 95%. The fluent movement group had values that were close to the sample mean in all movement variables except the amount of stops and time spent being stationary, which were both quite low. In other words, the participants in group one were moving rather fluently most of the time. Conversely, the participants in the stationary fluent movers group were moving in a very similar way, except that they had more stops and spent more time being stationary in the VE. The first two groups were by far the largest groups in the data. In contrast, the participants in the low control group did lots of different-sized turns and had the greatest variability in their movement speed. Also, they made stops far more often than any other group. Despite the large amount of stops, the participants in group three were almost constantly in motion. Finally, the participants in stationary group did mostly equal-sized turns, had least variability in speed, made lots of stops, and had a high mean acceleration rate. In addition, they spent
Table 2
Four different movement patterns were identified in our data.

<table>
<thead>
<tr>
<th>Movement measures</th>
<th>Groups</th>
<th>df1, df2</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entropy of turning</td>
<td>1 Fluent movers n = 20</td>
<td>2 Stationary fluent movers n = 24</td>
<td>3 Low control n = 10</td>
</tr>
<tr>
<td>Speed entropy</td>
<td>2.76 (0.25)</td>
<td>2.55 (0.13)</td>
<td>3.04 (0.27)</td>
</tr>
<tr>
<td>Amount of stops</td>
<td>54.65 (25.16)</td>
<td>75.75 (22.91)</td>
<td>155.50 (35.02)</td>
</tr>
<tr>
<td>Stationary (%)</td>
<td>23.09 (11.72)</td>
<td>46.21 (4.73)</td>
<td>26.90 (13.05)</td>
</tr>
<tr>
<td>Location entropy</td>
<td>5.54 (0.43)</td>
<td>5.16 (0.22)</td>
<td>5.67 (0.25)</td>
</tr>
</tbody>
</table>

The table shows the cross-tabulation of movement measures (standard deviations in brackets). Location entropy was not used as a clustering variable.  ***p < 0.001, **p < 0.01, *p < 0.05, + p < 0.10,

a Brown–Forsythe test.

b One-way analysis of variance.

Fig. 4. An illustration of differences in movement measures in the four movement patterns which we were able to identify. In the picture, the mean values of each variable are shown. All the variables have been scaled on a commensurate standardized scale.
more time being stationary than participants in other groups. The characteristics and the differences between the groups are illustrated in Fig. 4.

Next, we wanted to examine how the movement patterns are associated with task completion and background variables. The background variables were age, gender, computer experience, average weekly computer usage, and digital gaming experience. The search task was relatively simple, as three-quarters of our participants found at least 10 objects, and half of the participants found all 11 target objects. Movement groups did not differ with respect to the amount of objects found (Kruskal–Wallis, \( \chi^2[3] = 3.85, p = 0.28 \)). In addition, there were only minor differences with respect to background variables. Only average weekly computer usage was related to different movement patterns (one-way ANOVA, \( F[3,63] = 3.50, p < 0.05 \)), so that fluent movers and stationary participants used computers more often than the participants in other two groups. There were no other statistically significant differences between the movement patterns with respect to other background variables.

3.2. Movement and the experiential components of virtual environments

3.2.1. Experiences in all movement groups

After identifying four distinct movement patterns, we examined how they are related to experiential components (Table 3). Furthermore, a Tukey post-hoc testing, with confidence interval set on 95%, was conducted to examine the experimental differences between the movement groups (see Appendix A). First, the fluent movers experienced VE as a realistic and believable space while the low control and the stationary group experienced it as artificial and unconvincing. Furthermore, the participants in the fluent movers group and stationary group assessed themselves as skilled in VE use, while the participants in two other groups did not. In addition, the post-hoc analysis indicated that the participants in the low control group felt more anxiety than other users, although the effect on analysis of variance testing was merely marginally significant. Finally, the fluent movers evaluated the interactivity of the VE as fast and natural but the post-hoc testing failed to identify significant differences between the movement groups.

3.2.2. Experiences in fluent movers and low control groups

Next, we compared the two most diverging groups: the fluent movers and the low control group. This approach allowed us to compare how the fluent movement in VE, or the lack of it, is related to how people experience the VE. The comparison was made by using contrasts in the analysis of variance. The contrast analysis is used for testing specific hypotheses of interest as an alternative to traditional pair-wise comparisons. The results of the contrast analysis are illustrated in Fig. 5.

The low control group differed from the fluent movers with regard to almost all of the experiential components. The using of the VE was easier and more positive

Table 3

Presence and flow components in different movement patterns.

<table>
<thead>
<tr>
<th>Experiential components</th>
<th>Groups</th>
<th>( F(3,64) )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( n = 20 )</td>
<td>( N = 24 )</td>
</tr>
<tr>
<td><strong>Flow components</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Skill</td>
<td>0.26 (0.90)</td>
<td>-0.24 (0.89)</td>
</tr>
<tr>
<td>Challenge</td>
<td>0.04 (1.04)</td>
<td>0.12 (0.88)</td>
</tr>
<tr>
<td>Control</td>
<td>0.20 (0.72)</td>
<td>-0.05 (0.91)</td>
</tr>
<tr>
<td>Anxiety</td>
<td>-0.38 (0.82)</td>
<td>0.04 (0.86)</td>
</tr>
<tr>
<td>Playfulness</td>
<td>0.22 (0.97)</td>
<td>0.06 (0.92)</td>
</tr>
<tr>
<td>Pleasant</td>
<td>0.19 (0.89)</td>
<td>0.05 (1.06)</td>
</tr>
<tr>
<td>Valence</td>
<td>0.31 (0.99)</td>
<td>-0.02 (1.01)</td>
</tr>
<tr>
<td><strong>Presence components</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real</td>
<td>0.47 (0.96)</td>
<td>-0.07 (0.82)</td>
</tr>
<tr>
<td>Spatial</td>
<td>0.27 (1.03)</td>
<td>-0.06 (0.84)</td>
</tr>
<tr>
<td>Attention</td>
<td>0.24 (0.87)</td>
<td>-0.02 (0.95)</td>
</tr>
<tr>
<td>Being there</td>
<td>0.25 (0.92)</td>
<td>0.09 (0.75)</td>
</tr>
<tr>
<td>Action</td>
<td>0.33 (1.03)</td>
<td>-0.10 (0.82)</td>
</tr>
<tr>
<td>Arousal</td>
<td>0.23 (0.67)</td>
<td>-0.01 (0.77)</td>
</tr>
<tr>
<td>Interactivity</td>
<td>0.51 (0.79)</td>
<td>-0.18 (0.96)</td>
</tr>
<tr>
<td>Exploration*</td>
<td>0.14 (1.02)</td>
<td>0.13 (0.75)</td>
</tr>
</tbody>
</table>

The table shows means and standard deviations (in brackets) in each component. In addition the results of the between-group analysis of variance are shown in the table.

***\( p < 0.001 \), **\( p < 0.01 \), *\( p < 0.05 \), +\( p < 0.10 \).

*Brown–Forsythe test.
experience for the fluent movers when compared with the low control participants. A statistically significant or at least marginally significant difference was found on all flow components but challenge. The fluent movers assessed being more skilled and in better control than the low control participants. Furthermore, the fluent movers felt that using the VE was meaningful and pleasant and experienced themselves as playful. In contrast, the participants in the VE was meaningful and pleasant and experienced participants. A statistically significant difference was found on most flow components but challenge. The least marginally significant difference was found on all flow experiential components. The movement analysis that we employed here has not been previously used. In addition, there is no prior in-depth knowledge on the role of movement on the experiential side of VEs.

4. Discussion

The aim of this study was to model and analyse movement in a VE and to examine how different movement patterns are related to experiential components. Although movement is one of the most essential functions of human behaviour, there is no consensus on how to study movement in VEs. In this study, we operationalized movement in the VE by applying information entropy analysis. Hence, we could identify different movement patterns and analyse movement statistically. The analysis revealed connections between movement patterns and experiential components. The movement analysis that we employed here has not been previously used. In addition, there is no prior in-depth knowledge on the role of movement on the experiential side of VEs.

4.1. Movement patterns in VEs

The movement of the participants was modelled by using mean acceleration, the amount of stops, time spent being stationary, and two entropy measures: speed entropy and the entropy of turning. The advantage of entropy measures was that they made statistical movement analysis possible. Moreover, in previous studies it has been shown that entropy provides a more robust way of measuring movement than what distribution-based measures can offer (Kim et al., 1999; Lai et al., 2005). Due to the exploratory nature of this study, the data did not allow us to compare different movement measurement models. Instead, we used a variety of measures and combined them in order to arrive at the most extensive description of movement.

We identified four different movement patterns in our data. Two of the groups were moving fluently most of the time, while the remaining two were not. Another dividing factor was the time being spent stationary. Two of the groups were on a move most of the time, while the other two groups spent most of the time in VE standing still. The movement patterns can be seen to represent different movement strategies, as the participants were doing a search task. Consequently, the participants that spent most of the time standing still might have acted that way because they were searching for the target objects with their gaze rather than by moving. This explanation is supported by previous findings on search strategies (Lathrop and Kaiser, 2005; Ruddle and Jones, 2001). However, the different movement patterns (and search strategies) were equally effective in this study, as most of the participants found all target objects.

Fig. 5. The experiential profiles of the fluent movers and the low control group. The experiential components are roughly classified as a part of a flow or a presence construct.
Next, we analysed how background variables are related to different movement patterns. Weekly computer usage was the only background variable that had statistically significant differences between the movement patterns. The participants in fluent movers group and stationary group used computers more frequently than the participants in two other groups. In consequence, active computer use did not necessarily ensure fluent movement in the VE. The VE used in this study was novel to most participants and using it was different from typical computer use, which is why high computer use did not help users move more fluently. This finding supports the earlier recommendations, which suggests that all users should get structured moving practice before entering a VE (Sayers, 2004). In this study, all participants got such practice session before the task was begun although admittedly this was not sufficient for the participants in the low control group.

### 4.2. Movement patterns and the experiential components of VEs

As was hypothesized, fluent movement in the VE was related to a high sense of presence. Fluently moving users experienced the VE as more realistic environment compared with non-fluently moving ones. In addition, compared with the low control participants, the fluent movers experienced the VE as more presence evoking environment overall. This finding lends support to, and expands, the previous findings in the literature that the ease of use and controllability are related to high presence (Novak et al., 2000; Schubert et al., 2001; Schuemie et al., 2001; Witmer and Singer, 1998). Furthermore, fluent movement in the VE verified that there were no major problems with regard to the interface. Naturally, the connection between fluent movement and high presence would not be possible, if a user had difficulties with the interface (Lombard and Ditton, 1997).

The second hypothesis was that fluent movement is related to users’ evaluations of high skills and challenges. This notion was also partially supported by our data: the participants from both fluent movers and stationary group evaluated themselves as being more skilled than other two movement groups. In addition to high skill evaluation, fluently moving participants felt themselves as playful and thought that the VE was a pleasant environment. Thus, all these components combined suggest that fluently moving participants were in a flow state (Csikszentmihalyi, 1975). However, there were no statistically significant differences in challenge, although the participants in stationary group had a tendency to assess the environment as less challenging compared with the participants in the other groups. Therefore, the participants in the stationary group evaluated as being skilled, but the VE did not seem to be challenging enough for them to achieve a flow state. Instead, they were feeling more or less bored. These findings are in line with the four-channel flow model (Massimini and Carli, 1988).

As a secondary interest, we wanted to examine whether movement modelling would work as an alternative skill measure. Evidently, the low control movement pattern was a clear marker of insufficient skills. This was an important finding, because obviously it is essential to recognise those users who need further practice and guidance in VE use (Sayers, 2004). However, fluent movement in the VE did not necessary mean that the participant evaluated her/his skills as high. For example, the participants in stationary fluent movers group assessed their skills as insufficient, regardless of the fact that their movement was fluent. Furthermore, the movement pattern analysis can be considered as a more objective measure of movement skills than the participants’ subjective evaluation. Consequently, movement fluency could be applied as an alternative skill measure (Finneran and Zhang, 2005).

### 4.3. Limitations and future research

The most evident limitation of this study is that the sample size was rather small. In addition, the search task that we used was easy and resulted in minimal differences in task performance. Admittedly, a bigger sample size would strengthen the reliability of the questionnaire and a harder task would have resulted in clearer differences in task performance. Lately, there have been discussions of the limitations of studying presence with questionnaires (e.g. Slater, 2004). Although some of this discussion has been made in a provocative manner, it has been a necessary reminder that both validity and reliability are essential when using questionnaires. Our EVEQ meets these requirements well and further refinement of the questionnaire is being made (Särkelä et al., 2004; Takatalo et al., 2004, 2006, 2008). The critique can also be pointed on our movement modelling method, particularly since information entropy measures have not been studied sufficiently in complex movement modelling. Nevertheless, this study showed that combining traditional movement data, such as the amount of stops and mean acceleration, with information entropy measures leads to rather simple but extremely multifaceted movement modelling method. However, it is out of the scope of this study to further analyse and compare this modelling method with other possible methods. In the future, there is a clear need for systematic analysis of different measurement models and methods.

Furthermore, in future the movement modelling method introduced in this study could be applied in a number of other research areas which lack a proper movement modelling method. For instance, eye-tracking camera data could easily be quantified with the help of location entropy. In addition, eye-tracking data could help us analyse movement patterns in a VE by comparing, for example, the eye movement paths of the participants who spend most of the time being stationary with those that are constantly on the move. Furthermore, speed entropy and the entropy of turning values of VE users could be registered online and if a certain pre-determined limit...
would be reached the system would notify that additional guidance is probably needed. Alternatively, when aforementioned limits would be reached, the system could start “softening” the steering commands, in order to help users move more fluently. Finally, our movement analysis method could be applied to study movement in computer games, since many games already have a possibility to register player movement in a log file in a similar way as was done in this study.

4.4. Conclusions

To sum up, different movement patterns were related to different experiences. Moreover, the differences were seen on the level of perceptions, cognitions, and affective factors, which are also the fundamental elements of all experiences as such (Hilgard, 1980). The fact that movement patterns were related to presence evaluations is in line with the conception of perception as an active process (Gibson, 1979). After all, all the participants had a similar background (e.g. educational level and age), they were all using the same VE and were all performing the same task. Furthermore, most of them used a VE for the first time. Therefore, the differences in the way that the participants moved had an effect on how they perceived the environment. In addition, part of the users evaluated as having insufficient skills regardless of the fact that they moved fluently, and felt the use of the VE as anxiety provoking. For these users, the cognitive evaluation of skill and challenge level had an effect on the affective appraisal of the situation, which is in line with the propositions about the important role of the cognitive appraisal of the situation on emotion process as suggested in the cognitive-motivational emotion theory (Lazarus, 1991).

In conclusion, there is a growing need to understand what psychologically relevant factors are related to VEs, as they are becoming more and more common. Obviously, room-sized VEs will hardly ever reach average consumer markets, but instead head mounted displays and augmented reality-based VEs are becoming more popular (Lanier, 2016).

Table A1

<table>
<thead>
<tr>
<th>Speed entropy</th>
<th>Amount of stops</th>
<th>Stationary (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subset 1</td>
<td>Subset 2</td>
<td>Subset 3</td>
</tr>
<tr>
<td>Stationary fluent movers</td>
<td>Fluent movers</td>
<td>Stationary fluent movers</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Entropy of turning</th>
<th>Acceleration</th>
<th>Location entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subset 1</td>
<td>Subset 2</td>
<td>Subset 3</td>
</tr>
<tr>
<td>Stationary fluent movers</td>
<td>Fluent movers</td>
<td>Stationary fluent movers</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Real</th>
<th>Anxiety</th>
<th>Skill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subset 1</td>
<td>Subset 2</td>
<td>Subset 1</td>
</tr>
<tr>
<td>Fluent movers</td>
<td>Stationary fluent movers</td>
<td>Low control</td>
</tr>
</tbody>
</table>

a Tukey post-hoc
b Games-Howell post-hoc
2001). While VEs are an interesting research topic as such, one should also keep in mind that the phenomena seen in VE studies cannot and should not be seen as separate from real-world. We do not yet know why some people have more fun in an amusement park than other people do, but if it has anything to do with movement, this study shows that we can measure it and model it.

Acknowledgements

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Appendix A

A post-hoc testing was conducted to examine the differences between the four movement groups. The table shows the subsets that were formed in the post-hoc testing (see Table A1). There is a statistically significant difference between the subsets. Note that two movement groups belonging to a same subset do not necessarily have same mean value.

References


