Defects Identification in Textile by Means of Artificial Neural Networks

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Abstract. In this paper we use a neural network approach for defects identification in textile. The images analyzed came from an artificial vision system that we used to acquire and memorize them in bitmap file format. The vision system is made of two grey scale line scan camera arrays and each array is composed of four CCD cameras with a sensor of 2048 pixels. Every single camera has a field of view of 600mm. The big amount of pixels to be studied to determine whether the texture is defective or not, requires the implementation of some encoding technique to reduce the number of the significant elements. The artificial neural networks (ANN) are manipulated to compress a bitmap that may contain several defects in order to represent it with a number of coefficients that is smaller than the total number of pixel but still enough to identify all kinds of defects classified. An error back propagation algorithm is also used to train the neural network. The proposed technique includes, also, steps to break down large images into smaller windows or array and eliminate redundant information.

Keywords: texture defects identification; vision system; artificial neural networks; error back propagation algorithm

1 Introduction

The analysis of images in an artificial vision system is an expensive process. Image compression provides an option for reducing the complexity and the processing time for defects identification. Artificial Neural Networks (ANNs) have been applied to many problems, and have demonstrated their excellence over traditional methods. One example of such application is the compression of images due to their superiority when dealing with noisy or incomplete data. Artificial Neural networks, in fact, seem to be well suited to image compression, as they have the ability to preprocess input

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patterns to produce simpler patterns with fewer components. This compressed information preserves the full information obtained from the external environment. These networks contain at least one hidden layer, with fewer units than the input and output layers. The Neural Network is trained to recreate the input data. Its bottleneck architecture forces the network to project the original data onto a lower dimensional manifold.

There have already been an exhaustive number of published papers showing the application of ANNs to image compression [1-6]. Many different training algorithms and architectures have been used. Some of the more notable in the literature are: nested training algorithms used with symmetrical multilayer neural networks [6], self organizing maps for codebook generation [2], principal component analysis networks [1], back propagation networks [5], and the adaptive principal component extraction algorithm [4]. In particular, the Back Propagation Neural Network Algorithm performs a gradient-descent in the parameters space, minimizing an appropriate error function. The weights update equations minimize this error.

The purpose of this paper is to present a method to identify defects in textile images using the artificial neural network compression approach based on error back propagation algorithm. Starting from the images of textile, acquired by the artificial vision system, we made a classification of defects based on common characteristics and properties, in particular:

- Defects along columns such as contaminations with other materials or wireless
- Defects along raw such as problems in texture in which there are two wire in the same location
- Circular defects in an area of textile with lacerations or hole, such as knots and tears

2 The Vision System

The Vision System implemented for the automatic inspection of textile is constituted of two different arrays of greyscale line scan camera, as described in the introduction.

The first array analyzes structural defects of textile. To emphasize them a backlight source is used. The light source is made by two fluorescent high brightness tubes, while the alimentation is provided by an high frequency generator. The reason behind the choice of the high frequency generator resides in the necessity of producing an intensity of illumination that should be uniform during the acquisition of images.

Thanks to the backlight illumination the detection of holes, lacking wires or two - tired wires is made easier. The system locates those kind of defects because the image will present regions with an high contrast when compared to the background (i.e. darker regions for two-tired wires, lighter for the other defects).

The light system that conditions the image acquisition of the second array of cameras is constituted of direct halogen lamps.

The incident illumination is helpful to analyze dark or thick tissue. This kind of illumination highlights leaning defects like nodes which result emphasized by the edge top light. A panel is interposed between the two benches to prevent light interferences.

For each camera an automatic system that controls and rectifies the Shutter (exposition time length of the camera) is implemented. This control ensures the acquisition of images with a default grey level. The grey level target is 127 on a scale from 0 to 255, in order to guarantee the maximum oscillation range for both white and black spots.

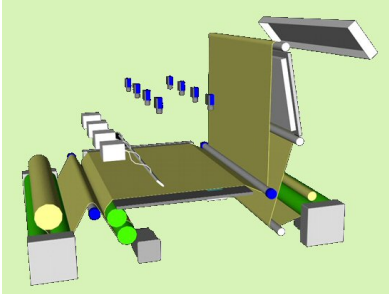


Fig. 1. Representation of the acquisition stage of the prototype

The analysis software is implemented on four Pc platforms equipped with frame-grabber boards. Each Pc drives a couple of cameras and executes the software that performs the defect detection. The results are collected and sent to a supervising platform through an Ethernet network. The supervisor hosts a database where the results of the inspection are stored and controls the motor's speed.

The Vision System receives the acquisition trigger from an encoder that is connected to a motorized roll.

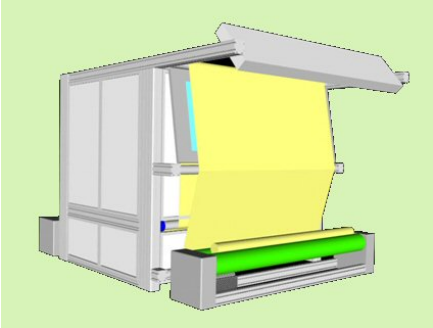


Fig. 2. Schematic representation of the prototype

The mechanic structure of the machine is constituted of a box containing cameras and illumination system, an automatic position system that provides the alignment of the tissue during the wrapping phase and a system of motorized cylinders that are in charge for the unwrap and the subsequent wrap of the tissue.

The movement system is realized using three brushless motors that lead three rolls: one that wraps the tissue, another one that unwraps it and the last one that stretches

the tissue to guarantee the cameras the best acquisitions conditions. For this purpose four load cells are installed to verify the tension of tissues and to avoid folds.

If the image analysis requires long time, the supervisor slows down the progression speed of the tissue.

Before the final wrapping of the tissue, there is a panel where the manual inspection of textile can be performed. This machine's side has been useful during the training time for a real time verification of the results given by the Vision System.

3 Artificial Neural Network Based on Error Back Propagation

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way of the biological nervous systems process information. The key element of this paradigm is the novel structure of the information processing system.

It is composed of a large number of highly interconnected processing elements (neurons) cooperating to solve specific problems. All connections among neurons are characterized by numeric values (weights) that are updated during the training. If we consider n the number of neurons in the input layer, m the number of neurons in the output layer, N_l the number of neurons belonging to the lth layer and $o_k^{(l)}$ be the output of the kth neuron of the lth layer, then the computation performed by each neuron can be expressed as:

$$net_k^{(l)} = \sum_{l=1}^{N_{(l-1)}} w_{kj}^{(l)} o_j^{(l-1)} \tag{1}$$

$$o_k^l = f(net_k^l) \tag{2}$$

where $net_k^{(l)}$ is the weighted sum of the k neurons of the lth layer, $w_{kj}^{(l)}$ is the weight by which the same neuron multiplies the output $o_j^{(l-1)}$ of the jth neuron of the previous layer and f(.) is a nonlinear bounded function, often the sigmoid function. The ANN is trained by a supervised learning process: in the training phase the network processes all the pairs of input-output presented by the user, learning how to associate a particular input to a specific output trying to extend the information acquired also for cases that don't belong to the *training set spectrum*. Any pair of data in the training set is presented to the system a quantity of time determined by the user *a priori*.

For this work an ANN is used to compress a bitmap image in order to represent it with a number of coefficients that is smaller than the total number of pixels to defects identification in textile. The learning step is based on the Error Back Propagation (EBP) algorithm [7].

This algorithm is based on the error correction learning rule. Error propagation consists of two passes through the different layers of the network, a forward pass and a backward pass. In the forward pass the input vector is applied to the network sensory nodes and its effect propagates through the network layer by layer. Finally a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the network are all fixed. In the back pass the synaptic weights are updated sequentially, from the output layer back to the input layer, by propagating an error signal backward along the neural connections (hence the name "back-propagation") according to the gradient-descent learning rule:

$$\Delta w_{ij} = -\gamma \frac{\partial E}{\partial w_{ij}} \quad 0 < \gamma < 1 \tag{3}$$

While using the coefficients obtained from ANN instead of the pixels, we get a very low system computational complexity that allows, in real-time, to identify and to detect the exactly position of a textile problems.

4 Experimental Results

The ANN, using EBP algorithm, extracts, in our work, the main features from the 256x256 pixel images, to store them in a sequence of:

- 256 bits for defects along raw or column;
- 127x127 dimension window for circular defects;

reducing in this way the computational complexity of the problem.

The used neural network, according to the type of defect to analyze and identify, has been designed with different characteristics (in particular as regards the number of input layer - hidden layer - output layer neurons) but the same basic structure, so that it can adapt itself to the nature of the defect.

4.1 Row/Column Defects Detection

The image that represent the portion of textile under test is divided in raw or column representing the input for the network that search for defects along row/columns.

The first ANN layer is formed by 256 neurons which are the rows or columns values (one neuron per pixel); the hidden layer is composed by only 1 neuron (that returns an output value for each row/column with values ranging from zero to one, as depicted in Fig. 3) and the last layer is formed by the same number of neurons of the input layer. The procedure depicted in Fig. 3 has been repeated for all image rows/columns in order to obtain 256 values. In this way it is possible to gain a “strips” image, rebuilt by image coefficient vectors.

The ANN has been trained by using an equal input and output training set and equal only to rows/columns white or black, in order to train the net on the two possible maximum contrasts present in an input image. At the start of training, the error is high, but then it decrease, reaching, at the end of the process, an asintotic value (see the learning curve in Fig. 4).

In the learning phase, the network began to specialize too much on training set but lose generalization.

To test the capacity of generalization of ANN during the training is carried out periodically the classification of a set of samples not belonging to training set (validation set). The trend of learning is shown by two curves, that of the training set and that of validation set (Fig. 5). The stop of the training phase is corresponding to the minimum on the validation set curve.

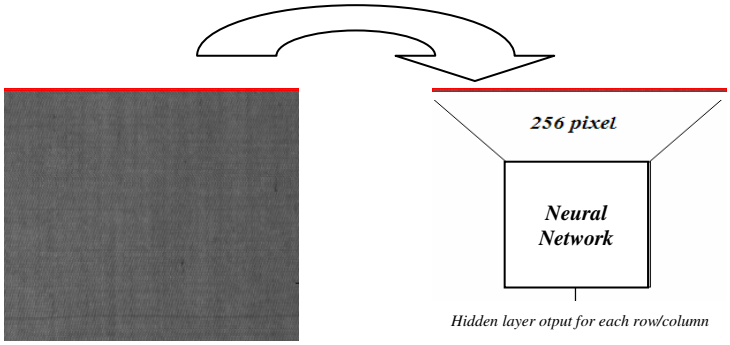


Fig. 3. Schematic representation of the hidden layer output in raw/column defects detection

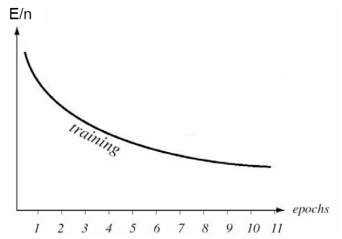


Fig. 4. Learning curve

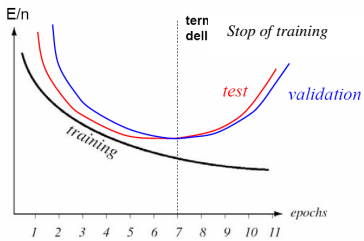
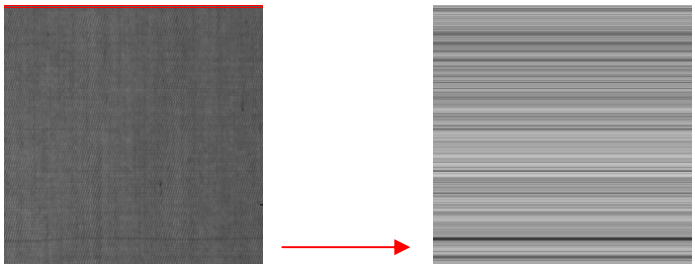


Fig. 5. Learning curve and validation curve

After the training phase, the network is able to work as a pure linear function, where the input of the first layer must be the same of the output of the last layer.

So, for every image we have an array of 256 values that characterize each row/column. The matrix of weights referred to the connections between the inputs and the hidden layer codifies the image bitmap, while the matrix of weights associated to the connections between the hidden layer and the outputs decodes the sequence of bits. At this point, the matrix of weights is stored and finally the ANN is tested with images containing defects that are different from the training set features.

Finally, if we have the image in Fig. 6 (a), the corresponding “strips” image is depicted in Fig. 6 (b). Moreover the results can be graphically valued as in Fig 7, where in 231 and 232 rows there are two crests that identify the most pronounced rows in the original image (see red arrow in Fig. 6 (b)).



(a) (b)

Fig. 6. Original image (*a*). The obtained "strips" image (*b*).

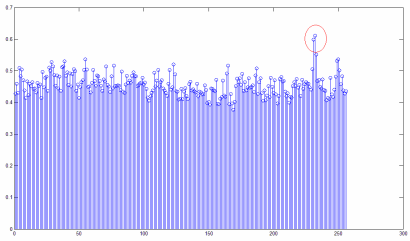


Fig. 7. Chart of the outputs for each row/column

4.2 Circular Defects Detection

In the detection of circular defects, instead, the input of the network is an image sub matrix of 4x4 elements (16 pixel) that scans completely the image with a superimposition of 2 pixel moving in the raw or in the column.

The first ANN layer, in this case, is formed by 16 neurons, which are the values of 4x4 windows (one neuron per pixel); the hidden layer is composed by only 1 neuron (that returns an output value for each sub matrix with values ranging from zero to one as depicted in Fig. 8) and the last layer, even, by 16 neurons.

The steps described in Fig. 8 have been repeated until the entire image has been scanned by windows in order to obtain an 128x128 pixel image of windows, where

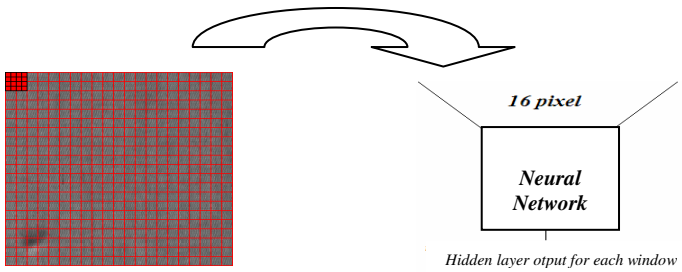
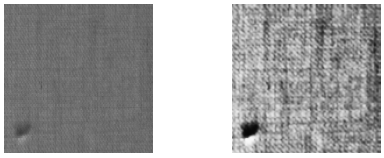
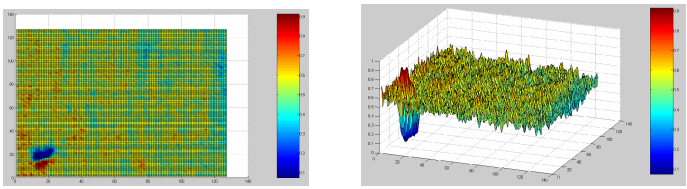


Fig. 8. Schematic representation of the hidden layer output in circular defects detection



(a) (b)

Fig. 9. Original image (*a*). The obtained "windows" image (*b*).



(a) (b)

Fig. 10. 2D chart of the outputs (*a*). 3D chart of the outputs (*b*).

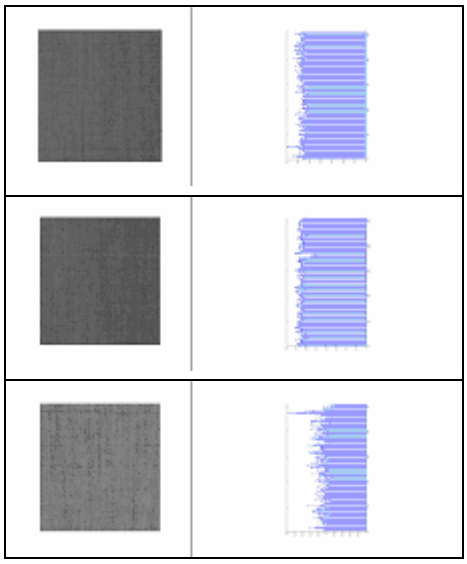


Fig. 11. Examples of row/column defects detection

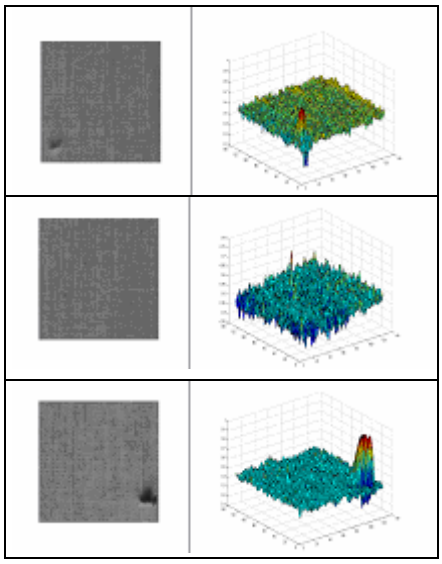


Fig. 12. Examples of circular defects detection

each of them represents the hidden neuron output brightness value of the corresponding window, multiplied by 255. In this way it is possible to gain a "windows" image, rebuilt by image coefficient vectors.

The ANN has been trained using white or black windows in order to train the net with the maximum possible contrast present in an input image. The training phase and the stop of learning process is the same described in the previous subsection. After

the training phase, the compressed image is described by 128x128 bits, that are the outputs of a hidden layer consisting of a sigmoid function processing elements.

Finally, if we have the image in Fig. 9 (a), the corresponding "windows" image is depicted in Fig. 9 (b). Moreover the results can be valued by the two charts in Fig 10 (a) and (b): the points nearer to value one (red points) represent the not homogeneous clearest image parts, while the points nearer to value zero (blue points) represent the not homogeneous darkest image parts (see also Fig. 9 (b)). Others results are depicted in Fig 11. e Fig. 12.

5 Conclusions

In this paper a neural network approach for Row/Column and Circular defects identification in textile has been proposed. An ANN, trained by an error back propagation algorithm, is used to represent the images with a number of coefficients that is smaller than the total number of pixel but enough to identify the defects.

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