Emotion-Based Textile Indexing Using Neural Networks

Na Yeon Kim, Yunhee Shin, and Eun Yi Kim*

Department of Internet and Multimedia Engineering, Konkuk Univ., Korea
{yeon0830,ninharsa,eykim}@konkuk.ac.kr

Abstract. This paper proposes a neural network based approach for emotion based textile indexing. Generally, the human emotion can be affected by some physical features such as color, texture, pattern, and so on. In the previous work, we investigated the correlation between the human emotion and color or texture. Here, we aim at investigating the correlation between the emotion and pattern, and developing the textile indexing system using the pattern information. Therefore, the survey is first conducted to investigate the correlation between the emotion and the pattern. The result shows that a human emotion is deeply affected by the certain pattern. Based on that result, an automatic indexing system is developed. The proposed system is composed of feature extraction and classification. To describe the pattern information in the textiles, the wavelet transform is used. And the neural network is used as the classifier. To assess the validity of the proposed method, it was applied to recognize the human emotions in 100 textiles, and then our system produced the accuracy of 90%. This result confirmed that our system has the potential to be applied for various applications such as textile industry and e-business.

Keywords: Emotion recognition, neural networks, pattern recognition, feature extraction, wavelet transform.

1 Introduction

For a given product or object, predicting human emotions is very important in many business, scientific and engineering applications. In particular, the emotion-based textile indexing has been considerable attention, as it can be applicable to the E-business and furthermore help pattern designer. In current, the textiles are manually annotated by human experts in the current, which cause a huge amount of time and effort. To reduce the cost and time, automatic indexing system should be developed to classify the textiles based on the emotional features. However, it is difficult to directly predict the human emotion from the textiles, due to the ambiguity of human emotion. For example, when seeing the images in Fig. 1, some may feel 'romantic' and some may tells that it is dynamic.

Therefore, it is an important issue to find the correlation between the human emotion and physical features such as color, texture and shape information included

* Corresponding author: Tel.: +82–2–450–4135, Fax: +82-2-450-4135.

J. Jacko (Ed.): Human-Computer Interaction, Part III, HCII 2007, LNCS 4552, pp. 349–357, 2007.

Fig. 1. Examples of textile images

in the textile images. Related to this issues, some works have been investigated [1-3]. Kobayashi have investigated how the color and patterns affect human emotion based on the survey. Although they showed the correlation between some physical features and human emotions, they did not provide the automated system to extract the physical features from the textiles and analyze the features. In the previous work, we developed the automatic indexing system using color and textures [3]. The system works well on classifying the textiles for some emotions, however it has limitation to be generally used for all the emotion groups of Kobayashi.

Here, we aim at investigating the correlation between the emotion and pattern, and developing the textile indexing system using the pattern information. Therefore, the survey is first conducted to investigate the correlation between the emotion and the pattern. The result indicates that the human emotions are deeply dependent on the patterns included in the textile. Therefore, the pattern recognition system using traditional machine learning is used for developing automatic indexing system. The proposed system is composed of feature extraction and classification. To describe the pattern information in the textiles, the wavelet transform is used. And the neural network is used as the classifier.

To assess the validity of the proposed method, it was applied to recognize the human emotions in 100 textiles, and then our system produced the accuracy of 90%. This result confirmed that our system has the potential to be applied for various applications such as textile industry and e-business.

This paper is organized as follows. Section 2 shows the data collection and analysis for investigating the correlation between the emotion and the pattern. And the proposed indexing system is described in Section 3. Section 4 shows experimental results, and the conclusion are followed.

2 Data Collection and Analysis

In this work, our goal is to investigate how the pattern information in textiles affects human emotions, and developing the textile indexing system based on the results. For this, the survey is first conducted. The process is performed by two steps: data collection and data analysis.

From the Pattern-Book [1], we collected 220 textile images, and then, classify them into nine groups according to their pattern. In the results, textile images are classified

[1] Meller, Susan, "Textile designs : 200 years of European and American patterns for printed fabrics organized by motif, style, color, layout", Harry N. Abrams, 1991.

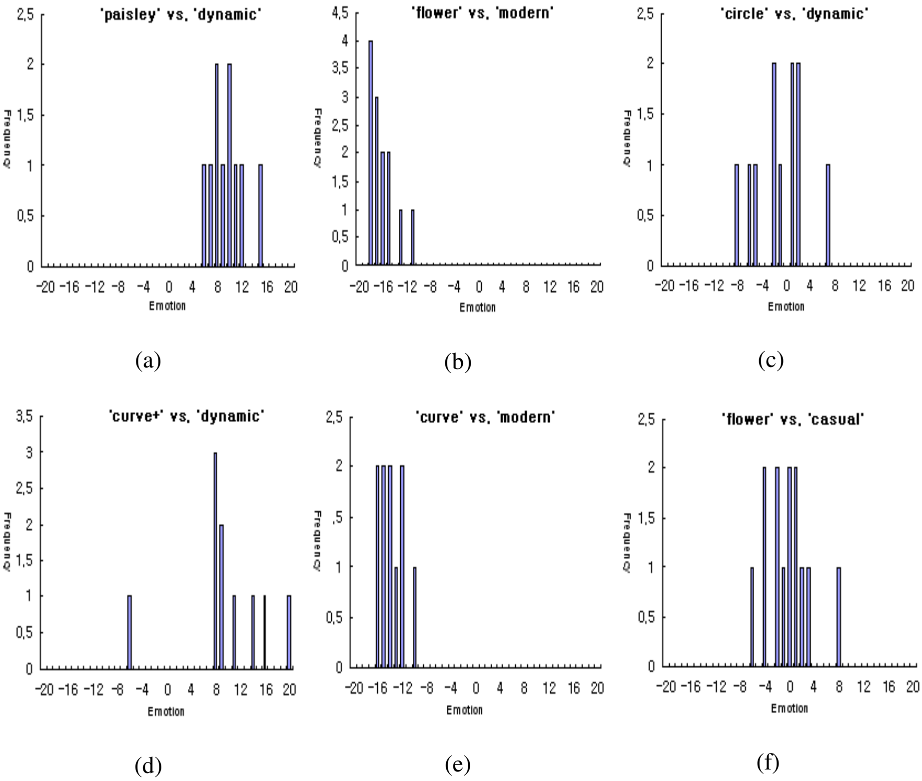

Fig. 2. The histograms to show the correlation of a pattern and an emotion: (a) paisley vs. dynamic (b) flower vs. modern (c) circle vs. dynamic (d) curve vs. dynamic (e) curve vs. modern (f) flower vs. casual

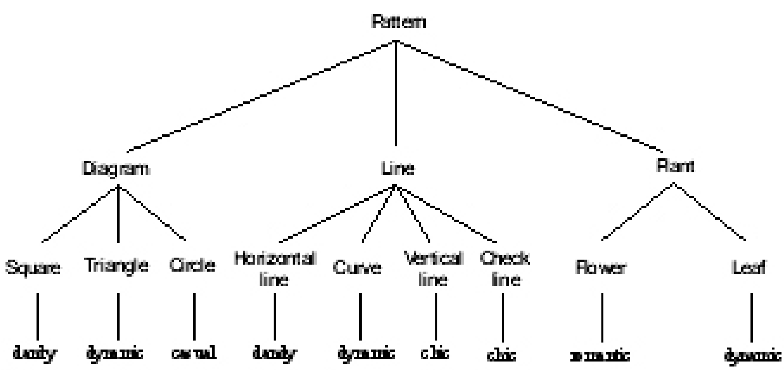

Fig. 3. A graph structure representing the correlation of pattern and emotion

9-type groups as “square”, “triangle”, “circle”, “horizontal line”, “vertical line”, “check”, “curve”, “flower”, and “leaf”.

Our indexing system uses ten pairs of adverse emotional features expressed as adjective words: {romantic/unromantic, clear/unclear, natural/unnatural, casual/uncasual, elegant/inelegant, chic/unchic, dynamic/static, classic/nonclassic, dandy/nondandy, modern/nonmodern}. These features are proposed by Kobayashi [1].

The survey about the classified textile images is conducted on 20 peoples, for total 220 images.

The pollee rated 10 emotions to -1, 0, 1 each textile image, where -1 represents opposite emotion, 1 represents positive emotion, and 0 represents unrelated between the pattern and emotion in textile images. For values obtained each textile, these summed each textile based on investigation results. Thus, each textile has integer value from -20 to 20 for each emotion.

After survey, the data analysis process is performed. For the data analysis, we used the histogram that describes correlation between one pattern and one emotion. Fig. 2 shows some examples of histograms, where the horizontal axis is emotion value, and the vertical axis is frequency of pollee’s response for each emotion value. Here the distribution of a histogram is represented as one value out of (+), (-), and 0. The (-) represents that the pattern makes feel opposite to the emotion. On the other hand, (+) represents that the pattern makes feel positive to the emotion. And 0 represents that there have no relationships between the emotion and the corresponding pattern. Some examples are shown in Fig. 2. Fig. 2(a) shows the histogram for the ‘dynamic’ emotion and ‘paisley’ pattern, where the distribution is inclined toward the direction of the (+). This tells us that the ‘paisley’ pattern affects the ‘dynamic’ emotion. On the contrary, in Fig. 2(b), the histogram is leaned to the direction of (-). This shows that ‘flower’ pattern makes feel opposite emotion to ‘modern’. And a histogram is distributed around 0 as shown in Fig. 2(c), then, it shows that there have no relationships between the emotion and the corresponding pattern.

Through these analyses, we find the fact that the human emotions are deeply dependent on the patterns included in the textile. Fig. 3 illustrates these correlations between the pattern and emotion as tree graph. As shown in Fig. 3, each pattern has the specific emotion. In the case of ‘square’ and ‘horizontal line’, they present ‘dandy’ emotion, while ‘triangle’, ‘curve’, and ‘leaf’ patterns present ‘dynamic’ emotion.

3 Proposed Method

In the previous section, we show that the human emotions are deeply dependent on the patterns included in the textile. Therefore, we try to build emotion-based textile indexing system through the pattern recognition system using traditional machine learning. Here, the neural network is adapted. The proposed system is composed of feature extraction and classification. To describe the pattern information in the textiles, the wavelet transform is used. And the neural network is used as the classifier.

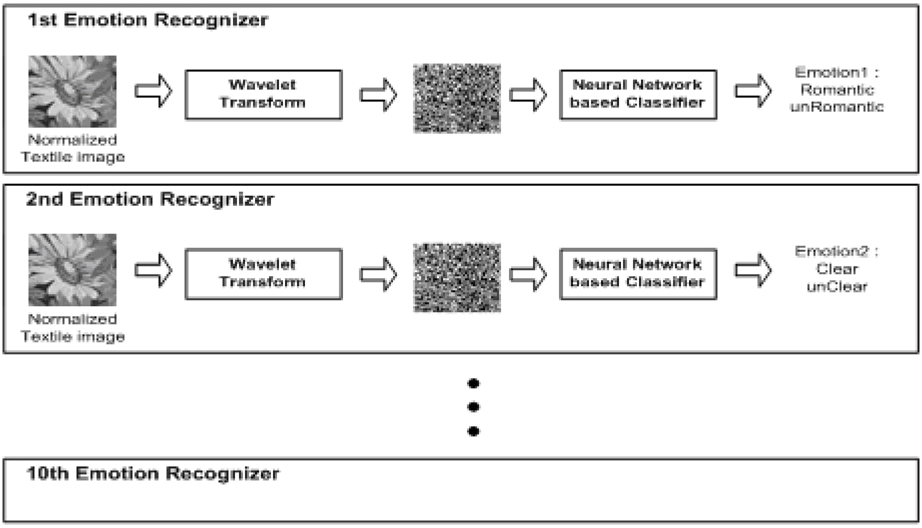

Fig. 4. The NN-based recognizer for a specific emotion

Fig. 4 shows the outline of the proposed system, where it is composed of 10 NN-based systems to recognize the respective human emotions. Each recognizer classifies textile image according to correlation of inputted image.

3.1 Feature Extraction

Generally, a pattern can be described as a combination of texture, edge, and color. Therefore, we use a wavelet transform. The wavelet transform provides successive approximations to the image by down-sampling and have the ability to detect edges during the high-pass filtering. The wavelet transform decomposes to 4 sub-blocks as LL, LH, HL, and HH as shown in Fig. 5 [4]. LL is involving the textual content, while the other sub-blocks are involving edge information for vertical, horizontal and diagonal orientations.

In our method, the LL level is again decomposed into 4 sub-blocks using wavelet transform. This process is iterated 6 times, so that 24 sub-blocks are created. Then, from each block the following parameters are calculated.

$$M(I) = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} I(i,j) \tag{1}$$

$$\mu_2(I) = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (I(i,j) - M(I))^2 \tag{2}$$

$$\mu_3(I) = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (I(i,j) - M(I))^3 \tag{3}$$

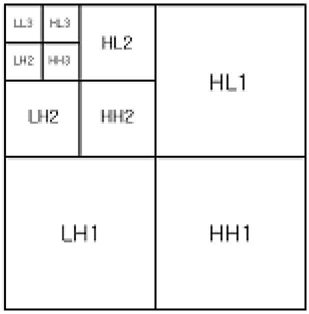

Fig. 5. The wavelet transformed results of a 2-D image

Given *NxN* image, Eq. (1) represents average value, and Eqs. (2) and (3) represent momentum each 2 and 3 dimension. Due to created total 24 sub-blocks after 6-levels wavelet transform, 72 parameters are created. These are used as the input of the classifier that recognizes the pattern information in some textiles.

3.2 NN Based Recognizer

In this paper, the proposed system uses multilayer perceptron (MLP) as a classifier [5-7]. The network is composed of input layer, hidden layer, and output layer. The adjacent layers are fully connected. We use NNs composed of total 72 input nodes and 1 output node from 24 sub-blocks obtained by 6-level wavelet transform. And the number of hidden nodes is determined by the experiment.

Our system uses pattern *(I, d)*, to train the network where *I* is textile image, and *d* is emotion value manually labeled in the textile image. The NNs are trained using the back-propagation algorithm (BP). The input layer receives the wavelet transformed values of 64 x 64 textile image. The output value of hidden node is obtained from the dot product of the vector of input values and the vector of the weights connected to the hidden node. It is then presented with the output nodes. The weights are adjusted by training with a back-propagation algorithm in order to minimize the sum of squared error during the training session.

The output value of NNs is normalized to 0~1. And if the output value is bigger than 0.5, the system decides that the image includes the corresponding emotion. Otherwise, the system decides the opposite emotion or nothing.

4 Experimental Results

To assess the validity of the proposed method, the proposed indexing system has been tested with 220 captured textile images. For the respective textile images, twenty peoples were selected to manually annotate according to the emotions that they feels from the images. Then 120 images of 220 collected images were used for training the NNs and the others were used for test. In this work, the parameters of NN were fixed as follows: error rate is fixed to 0.02, momentum to 0.5, and iteration to 5000.

Fig. 6 illustrates the classified results by the proposed system. Figs. 6(a) and (b) show examples of the classified results as emotion ‘chic’ and ‘unchic’ respectively. As can shown Fig. 6(a), the emotion of ‘chic’ is labeled at the textiles with patterns of ‘vertical line’ and ‘check line’, while the emotion of ‘unchic’ is labeled at the textiles with patterns of ‘geometries’ in Fig. 6(b). And Figs. 6(c) and (d) show examples of the classified results as emotion ‘dandy’ and ‘non-dandy’ respectively. As can shown Fig. 6(c), the emotion of ‘dandy’ is labeled at the textiles with patterns of ‘horizontal line’ and ‘square’, on the other hands, the emotion of ‘non-dandy’ is labeled at the textiles with patterns of ‘curve’ and ‘geometries of curve type’ in Fig. 6(d).

These results prove that the correlation between emotion and pattern described in Fig. 3 is true. Also, these show that our NN-based recognizer is successfully worked.

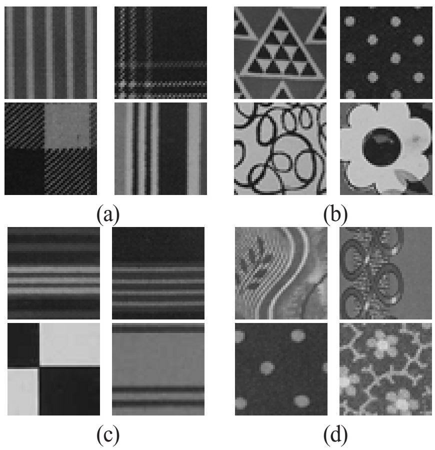

Fig. 6. The examples of emotion recognition results: (a) The emotion of 'chic’, (b) The emotion of ‘unchic’, (c) The emotion of ‘dandy’, (d) The emotion of ‘non-dandy’

The performance of the proposed system is summarized in Table 1. For analysis of performance two measures are used such as precision and recall. These are defined as follows.

$$precision(\%)= \frac{\#\ of\ correctly\ detected\ textile\ image}{\#\ of\ detected\ textile\ image} \times 100 \tag{4}$$

$$recall(\%)= \frac{\#\ of\ correctly\ detected\ textile\ image}{\#\ of\ textile\ image} \times 100 \tag{5}$$

The proposed system shows the precision of 98% and the recall of 90% on average. This result confirmed that our system has the potential to be applied for various applications such as textile industry and e-business.

Table 1. The performance analysis of the proposed recognition system (%)

	Wavelet Transform	
	recall	precision
ROMANTIC	79	100
CLEAR	86	100
NATURAL	86	100
CASUAL	79	100
ELEGANT	100	100
CHIC	100	100
DYNAMIC	86	100
CLASSIC	100	100
DANDY	100	100
MODERN	86	78
AVERAGE	90	98

5 Conclusion

In this paper, a new emotion based indexing system was developed that label each textile using the pattern information in textiles. Our system is component two modules: feature extraction and classification. To describe the pattern information in the textiles, the wavelet transform was used. And the neural network was used as the classifier.

To assess the validity of the proposed method, it was applied to recognize the human emotions in 100 textiles, and then our system produced the precision of 98% and the recall of 90%. This result confirmed that our system has the potential to be applied for various applications such as textile industry and e-business.

Acknowledgments. This work was supported by the Technology Infrastructure Foundation Program funded by the Ministry of Commerce, Industry and Energy, South Korea.

References

1. Shigenobu Kobayashi, COLOR IMAGE SCALE, Kodansha (1991)
2. Soen, T., Shimada, T., Akita, M.: Obgective Evaluation of Color Design, Color Res. Appl., vol. 12, pp. 187–194 (1987)
3. Kim, E.Y., Kim, S.-j., Koo, H.-j., Jeong, K., Kim, J.-i.: Emotion-based Textile Indexing using Colors and Texture. In: Wang, L., Jin, Y. (eds.) FSKD 2005. LNCS (LNAI), vol. 3613, pp. 1077–1080. Springer, Heidelberg (2005)

4. Li, H., Doermann, D., Kia, O.: Automatic Text Detection and Tracking in Digital Video, IEEE Transactions on Image Processing, vol. 9(1) (January 2000)
5. Haykin, S.: Neural Networks a comprehensive foundation, 2nd edn., Prentice Hall, Englewood Cliffs, pp.10-13, pp.156-173 (1999)
6. Bauer, H.-U., Geisel, T.: Dynamics of signal processing in feedback multilayer perceptrons. In: Proc. Int. Joint Conf. Neural Networks, pp. 131-136 (1990)
7. Brown, M., An, P.C., Harris, C.J., Wang, H.: How biased is your multi-layer perceptron?, in World Congr. Neural Networks, pp. 507-511 (1993)