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Modeling the Relationship Between Texture Semantics and Textile Images

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Abstract: Texture semantics, which is the kind of feelings that the texture feature of an image would arouse in people, is important in texture analysis. In this study, we study the relationship between texture semantics and textile images, and propose a novel parametric mapping model to predict texture semantics from textile images. To represent rich texture semantics and enable it to participate in computation, 2D continuous semantic space, where the axes correspond to hard-soft and warm-cool, is first adopted to quantitatively describe texture semantics. Then texture features of textile images are extracted using Gabor decomposition. Finally, the mapping model between texture features and texture semantics in the semantic space is built using three different methods: linear regression, k-nearest neighbor (KNN) and Multi-layered Perceptron (MLP). The performance of the proposed mapping model is evaluated with a dataset of 1352 textile images. The results confirm that the mapping model is effective and especially KNN and MLP reach the good performance. We further apply the mapping model to two applications: automatic textile image annotation with texture semantics and textile image search based on texture semantics. The subjective experimental results are consistent with human perception, which verifies the effectiveness of the proposed mapping model. The proposed model and its applications can be applied to various automation systems in commercial textile industry.

Key words: Image search, mapping model, textile images, texture semantics, semantic space

INTRODUCTION

Textiles are flexible materials made from fibers or other extended linear materials, such as thread or yarn, and commonly used for clothing, containers, coverings, art, industrial and scientific processes (Shin *et al.*, 2010). The image of textiles is an important feature of the textiles. To get an appropriate textile image is a pressing need to textile design, and a search tool would be a great help in this process.

Recently, the focus of Content-Based Image Retrieval (CBIR) has been on semantics (Datta *et al*., 2008). In particular, the high-level perception of images, which is the kind of feelings (e.g., emotions) an image arouse in people, has been considered in image analysis, annotation and retrieval, especially for textile images (Shin *et al*., 2010; Datta *et al*., 2006). For example, when searching a "bed sheet" image, users prefer the queries like "romantic", "classic", etc. Figure 1 shows a semantic level of textile images.Texture features are intended to capture the granularity and repetitive patterns of surfaces in an image (Shin *et al*., 2010). For textile images, the texture features are especially important. Although images provide color, shape information besides texture, this paper only focuses on the semantics hidden in texture features. The purpose of this paper is modeling the relationship between textile images and high-level semantic concepts, denoted as *texture semantics*, such as "romantic", "quiet", etc. Texture semantics shows the kind of feelings that the texture feature of an image would arouse in people.

In researches of texture semantics in textile images, most researchers focus on semantic categories. Shin *et al*. (2010) adopt eight categories (romantic, natural, casual, elegant, chic, classic, dandy and modern) (Shin *et al*., 2010). Kim *et al*. (2005) use six pairs of adverse semantic features: {weak/strong, sober/gay, dark/light, dismal/cheerful, warm/cool, soft/hard} (Kim *et al*., 2005). Kim *et al*. (2005) use ten pairs of adverse semantic features: {romantic/unromantic, clear/unclear, natural/unnatural, casual/uncasual, elegant/inelegant, chic/unchic, dynamic/static, classic/nonclassic, dandy/nondandy, modern/nonmodern} (Kim *et al*., 2007). However, the rich semantic information in images doesn't

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High-level semantics (the terms of human perception)	romantic	classic
Textile patterns (the terms representing features)	Small flower, free curve line, thin	Strong line, thick
Images		

Fig. 1: The semantic level of textile images

limit to a few specific categories. In order to represent the rich semantic information, the 2D continuous semantic space with the axes corresponding to the scales hard-soft and warm-cool is adopted to quantitatively characterize the texture semantics (Kobayashi, 1992). Thus, the texture semantics can be described by a two-dimension semantic vector in the semantic space. This semantic space has been widely used in art and design (Kobayashi, 1992; Kobayashi, 1991; Solli, 2010).

To bridge the gap between texture features and their texture semantics in the semantic space, our work uses machine learning techniques based on Shigenobu Kobayashi's research (Kobayashi, 1991), in which about 50 textile images are placed in the semantic space. However, it is far from enough to train a mapping model between texture features and texture semantics in the semantic space using only these few images.

Accordingly, this study proposes the following approach in modeling the relationship between texture semantics and textile images. First, a dataset with 1352 textile images which are manually annotated with semantic vectors in the semantic space is constructed. Then, texture features are extracted from textile images by Gabor decomposition. The mapping model for predicting texture semantics in the semantic space, representing by semantic vectors, from textile images is finally built using three different methods: linear regression, k-nearest neighbor (KNN) and Multi-Layered Perceptron (MLP).

The proposed mapping model is evaluated using 10-folder cross-validation, and an acceptable average prediction error indicates the mapping model is effective. To further evaluate the effectiveness of the proposed mapping model, we apply it to two applications: automatic textile image annotation with texture semantics and textile image search based on texture semantics. The texture semantics for automatic annotation is represented by adjectives, such as "romantic", "graceful", "classic", etc, since description of images by words is more intuitive than using semantic vectors. The subjective evaluation verifies the annotations are consistent with human perception of images. Based on the mapping model and the automatic textile image annotation, a textile image search system with multiple input modes is established, whose queries can be semantic vectors, adjectives and textile images.

In summary, the key contributions of this paper include: By using the continuous semantic space, we enable texture semantics to be directly applied in computation and can represent rich texture semantics. Here, *rich* means texture semantics is quantitatively described by the continuous semantic space and not limited to specific categories.

A novel mapping model between texture features and texture semantics in the semantic space (semantic vectors) is proposed, which enables prediction of texture semantics from textile images.

We apply the proposed mapping model to two applications: automatic textile image annotation and textile image search. The subjective experimental results show the effectiveness of the mapping model and its application.

The objective of this study is to model the relationship between texture semantics and textile images. The study also aims to enable texture semantics to be directly applied in computation and represent rich texture semantics by describing texture semantics in continuous semantic space. The study proposes a mapping model between texture features and texture semantics, and the mapping model is proved effective by two applications: automatic textile image annotation and textile image search.

PRELIMINARIES

The present goal is to model the relationship between texture semantics and textile images. The texture semantics is represented by two-dimension vectors $s = (s_1, s_2)^T$ in the continuous semantic space with the axes

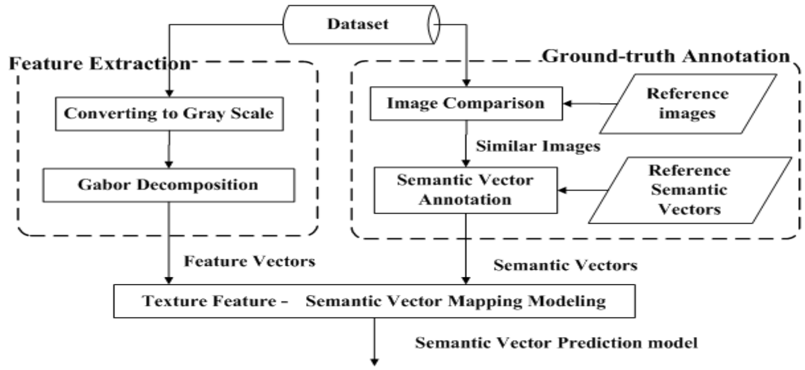

Fig. 2: The proposed framework for modeling the relationship between texture semantics and textile images

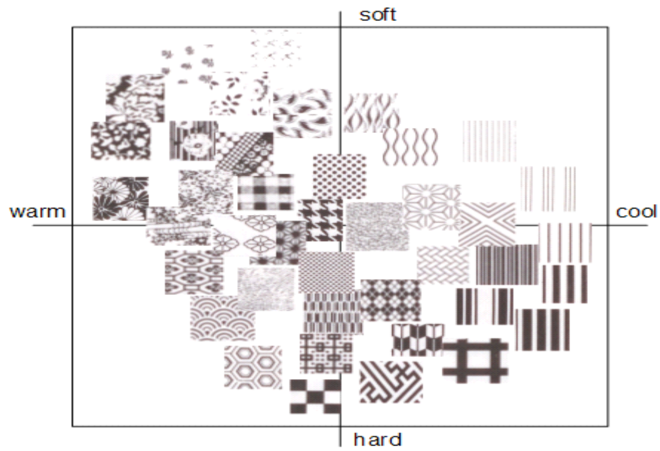

Fig. 3: Reference images placed in the 2D semantic space

corresponding to the scales hard-soft and warm-cool. The framework of the modeling process is described as follows and illustrated in Fig. 2. Ground-truth annotation. Construct a dataset of textile images and annotate each image in the dataset with a semantic vector $s = (s_1, s_2)^T$, $s\, S \in S$, , where S is the semantic space.Feature extraction. Extract a feature vector for each image m in the dataset, $\beta^{(m)} \in \Omega$, where Ω is the feature space. The feature vector is extracted using Gabor decomposition in this paper.

Texture feature-semantic vector mapping modeling. Construct a mapping model P ($P: \Omega \rightarrow S$) using the feature vectors and semantic annotation of images. In this paper, linear regression, KNN and MLP are used to build the model.

2D continuous semantic space: The 2D continuous semantic space, where the axes correspond to hard-soft and warm-cool, is widely used in describing high-level semantic concepts of images (Solli, 2010). A total of 180 adjectives, such as “romantic”, “quiet”, etc., are placed in the semantic space (Kobayashi, 1992).

About 50 textile images are placed in this semantic space in (Kobayashi, 1991). Figure. 3, which is modified from a figure in (Kobayashi, 1991), illustrates some typical images selected from (Kobayashi, 1991) placed in the 2D semantic space. These typical images will be used as reference images in ground-truth annotation.From an aesthetics point of view, the specific patterns such as flowers make people feel warm. In contrast, the abstract patterns such as lines make people feel cool. The thin and sparse patterns such as dots and small flowers make people feel soft. In contrast, the thick and dense patterns such as plaid make people feel hard.

Dataset: For a complete evaluation of the proposed texture feature-semantic vector mapping model, a dataset with the ground-truth is needed. Also, the images in Kobayashi’s research (Kobayashi, 1991) are too few to train the mapping model. Therefore, a larger set of textile images must be obtained and annotated with semantic vectors for the purpose of training and evaluation.In this study, we collect a variety of textile images from the Internet by querying several image search engines. We use queries such as “ fabric texture”, “plaid” , “stripe

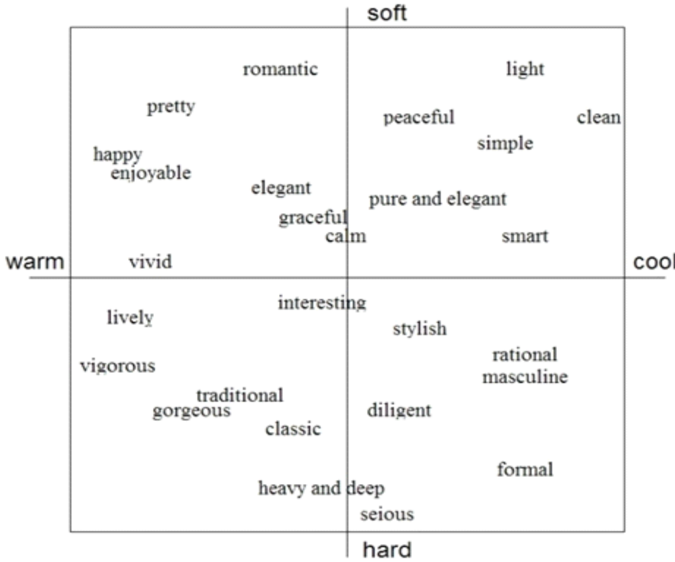

Fig. 4: Adjectives placed in the 2D semantic space

pattern", etc. Search engines typically limit the number of images retrieved (a few hundred to a thousand) and the search results which are textile images are few (a tenth of total). Therefore, to obtain more images, we expand the query set by translating the queries into another language (Chinese) (Fergus *et al*., 2005). After selecting textile images from the search results, the dataset contains 1352 textile images in all.

Ground-truth annotation: The purpose of ground-truth annotation here is to annotate the dataset with semantic vectors in the semantic space, represented by $s = (s_1, s_2)T$, where, $s_1, s_2 \in [-1, +1]$. The annotated dataset will be used in both training and evaluation.

Three university students, whose major is art and design, were invited to the annotation task. They are familiar with the 2D semantic space and the textile pattern and well-trained in perception annotations. Due to subjectivity and ambiguity of human perception of images, it is difficult to manually annotate a textile image with semantic vector directly. So the annotation of textile images is done as follows: (1) Quantify each dimension of the semantic space to the range [-1, +1] and assign a semantic vector $s = (s_1, s_2)^T$ to each of the reference images in Fig. 3. (2) The annotators compare each image in the dataset with the reference images to get the most similar image. Since each of the reference images have typical texture pattern and the difference between each other is great, in most cases the results are consistent among the three annotators. If not, they discuss to obtain a good consensus. (3) Assign the semantic vector of the image to be annotated with that of the most similar reference image.

Modeling the relationship between texture semantic and textile images: In this section, we first present how texture features are extracted and then propose a mapping model between texture features and semantic vectors, using linear regression, KNN and MLP.

Feature extraction: The texture feature of an image *m* is represented by a feature vector $\beta^{(m)}$. The process of feature extraction is as follows. First, an image is converted to gray scale. Then, the texture feature of the image is extracted by Gabor decomposition.

In pattern retrieval, Gabor features have been proved to be able to get excellent performance (Manjunath and Ma, 1996; Daugman, 1988). The texture feature extraction based on Gabor decomposition from (Ma and Manjunath, 1999) is given below. First, a prototype Gabor filter is defined as:

$$h(x,y) = \left(\frac{1}{2\pi\sigma x\sigma y}\right) \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right].\exp[2\pi jWx] \tag{1}$$

A bank of Gabor filters can be generated by dilating and rotating the function (1):

$$h_{i,j}(x,y) = a^{-i}h(x',y'), i, j = \text{int}\,eger \tag{2}$$

$$x' = a^{-i}(x\cos\theta + y\sin\theta) \tag{3}$$

$$y' = a^{-i}(-x\sin\theta + y\cos\theta) \tag{4}$$

where, $\theta = j\pi/K$ and K is the total number of orientations, a^{-1} is the scale factor to ensure the equal energy among different filters. The Gabor filters are used to detect scale- and orientation-tunable edge and line (bar), and the statistics of the detected features can be used to characterize the underlying texture information. Given an image, Gabor decomposition is obtained by:

$$O_{i,j}(x,y) = I(x,y) \otimes h_{i,j}(x,y) \quad (5)$$

φ means the 2D convolution of the image and a Gabor filter. A texture feature can be represented by the mean and standard deviation of the amplitude information:

$$\mu_{ij} = \int\int |o_{i,j}(x,y)| dxdy \quad (6)$$

$$\sigma_{ij} = \sqrt{\int\int (|o_{i,j}(x,y)| - \mu_{ij})^2 dxdy} \quad (7)$$

$$\beta = (\mu_{00}, \sigma_{00}, \mu_{01}, ..., \mu_{(s-1)(k-1)})^T \quad (8)$$

Four different scales, S = 4, and six orientations, K = 6, are used in this paper. So β is a feature vector of length 48. In addition, we consider feature space reduction to improve computation efficiency using a Principal Component Analysis (PCA) (Belhumeur *et al*., 1997). The distance between two images *m* and *n* in the feature space (original or reduced) is defined as (Manjunath and Ma, 1996):

$$d(m,n) = \sum_i \left| \frac{\beta_i^{(m)} - \beta_i^{(n)}}{\alpha(\beta_i)} \right| \quad (9)$$

where, $\beta^{(m)}$ and $\beta^{(n)}$ are the feature vectors of images *m* and *n*, respectively. $\alpha(\beta_i)$ is the standard deviation of the respective features over the entire dataset, which is used to normalize the feature components.

Texture feature–semantic vector mapping modeling: This step aims at building the mapping model between texture features and semantic vectors to predict texture semantics for a given textile image, represented by semantic vectors $s = (s_1, s_2)^T$. Three methods: linear regression, KNN and MLP are applied to build the mapping model. The reason for choosing these three methods is because they are mostly used in semantic prediction and have been shown practical (Shin *et al*., 2010).

Linear regression: Linear regression algorithm is the simplest method to model the mapping, which is defined as:

$$s = A\beta + b \quad (10)$$

where, s is the semantic vector $(s_1, s_2)^T$, which is the output of the mapping model, β is the texture feature vector, A is the transform matrix and b is the offset vector. The Least Square (LS) algorithm is adopted to get the vectors A and b using the dataset, and then s can be calculated by Eq. (10) for a given textile image.

KNN: The *k*-Nearest Neighbor (KNN) method finds the k closest neighbors of a query in the feature space and assigns the properties of these neighbors to the query (Villegas and Paredes, 2011). In our case, the properties are the values of semantic vectors, and these are averaged to get the final semantic vector for a query.

The distance defined in Eq. (9) is used to measure the distance between two feature vectors. And the parameter *k* is determined based on the experiments.

MLP: MLP (Multi-Layered Perceptron) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output (Shin *et al*., 2010; 2008). In our case, the network is composed of one input layer, one hidden layer, and one output layer. The attributes of the input neurons is texture features, and the attributes of the output layer is semantic vectors in the semantic space. We use back-propagation algorithm to adjust the weights in order to minimize the sum of squared error in the training stage. We also test various numbers of neurons in the hidden layer between 10 and 100 using the dataset, and MLP with 50 hidden neurons produces the highest performance.

APPLICATIONS

In order to demonstrate the effectiveness of the proposed mapping model, we apply it to two applications: automatic textile image annotation with texture semantics and textile image search based on texture semantics.

Automatic textile image annotation: For a more intuitive view of image annotation, some adjectives, such as "romantic", "elegant", etc, are selected as the image label. In this study, the image labels are selected from (Kobayashi, 1992), in which 180 adjectives are placed in the semantic space. The predicted semantic vectors by the proposed mapping model can be converted to words by finding nearest adjectives to the semantic vector.

Before the automatic annotation, each of the adjectives is manually annotated with a semantic vector $s = (s_1, s_2)^T$, where $s_1, s_2 \in [-1, +1]$, as no quantified value is given in (Kobayashi, 1992). Figure 4 illustrates some of the adjectives placed in the 2D semantic space, in which also shows how the placement of the adjectives are expressed in (Kobayashi, 1992). The three university

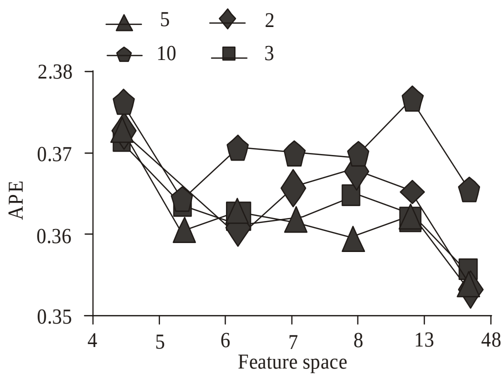

Fig.5: The prediction results of KNN, dot (2), rectangle (3), triangle (5) and Asterisk (10) represent k = 2, 3, 5, 10, respectively

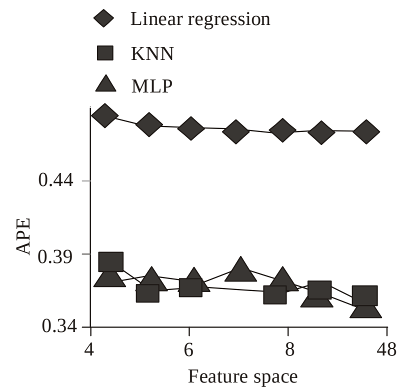

Fig. 6: The prediction results of three methods, KNN with K = 5 and MLP with 50 hidden neurons, respectively

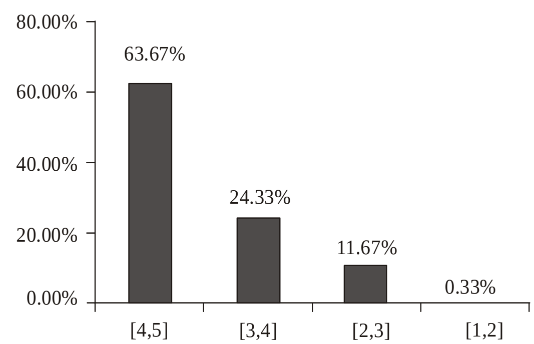

Fig. 7: The MOS evaluation result

students, who participate in the ground-truth annotation, assign each of the 180 adjectives by a semantic vector according to the placement of the 180 adjectives in the 2D semantic space (Kobayashi, 1992). Average value is used to merge the three annotation values.

For a given textile image, the process of automatic annotation is as follows. Texture feature is first extracted by Gabor decomposition. Then, the semantic vector is obtained by the mapping model. Finally, the distances between the 180 adjectives and the image are calculated based on the semantic vectors using Euclidean distance. The adjectives are ranked in ascending order of the distances and a set of m top ranking adjectives $D = \{d_1, d_2, \ldots, d_m\}$ is selected as the label of the image.

In (Kobayashi, 1992), the 180 words are grouped into 15 categories: romantic, pretty, natural, casual, clear, elegant, cool-casual, dynamic, gorgeous, chic, ethnic, classic, modern, dandy and formal. While some researches use some of the categories to annotate images (Shin *et al*., 2010; Kim *et al*., 2007), we use all of the 180 words to enrich the word pool of annotation. Furthermore, any words can be used as labels based on the proposed framework of the automatic textile image annotation, as long as the word is projected to the semantic space.

Textile image search: Based on the proposed mapping model and the application of the automatic textile image annotation, we provide a textile image search framework, whose queries can be semantic vectors and adjectives, respectively.

The preparations for searching by semantic vectors are constructing an image database and annotating it with semantic vectors, either manually or automatically by utilizing the proposed mapping model. Then the search process is accomplished by retrieving images that are nearest with the query semantic vector in the 2D continuous semantic space using Euclidean distance. The search results are ranked in ascending order of the distances. The preparations for searching by adjectives are constructing an image database and annotating it with adjectives using the proposed framework of automatic textile image annotation. Then the search process is finding images which are labeled with the query word. The search results are unordered.

In addition, to meet the demand of Content-Based Image Retrieval (CBIR), we also implement search by query textile image, which is also a need for the commercial textile industry, image retrieval, etc. Searching by query images is retrieving similar images which are nearest with the query image based on the measurement of texture feature space.

In this paper, based on the above mentioned search framework, we establish a textile image search system whose queries can be semantic vectors, adjectives and textile images. The database for the system is the dataset, which contains 1352 textile images and is manually annotated with the semantic vectors in the semantic space. And each image in the database is label with three adjectives of the 180 adjectives using the method presented in the application of automatic textile image search. The adjectives in our system are limited to the 180

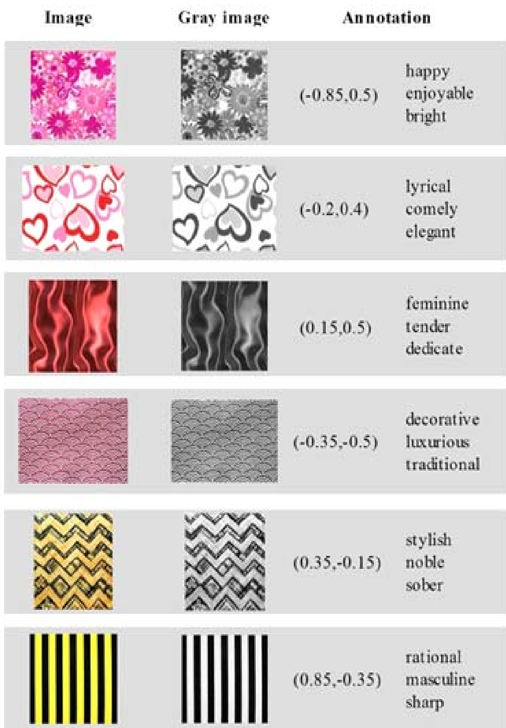

Fig. 8: Images are labeled with semantic vectors in the semantic space and three adjectives

words in (Kobayashi, 1992). However, the word pool can be expanded easily by labeling (manually or automatically) more words with semantic vectors. Some search results are demonstrated in the next section.

EXPERIMENTS AND RESULTS

To evaluate the effectiveness of the proposed method, we conduct two experiments. An objective experiment is to examine the prediction accuracy of the proposed texture feature–semantic vector mapping model. A subjective experiment is to test whether the results of the automatic textile image annotation are consistent with human perception of images, which also verifies the consistency between predicted semantic vectors and human perception. Some examples of predicted semantic vectors and annotations with adjectives are demonstrated at the end of this study.

Evaluation on texture feature-semantic vector mapping model: The mapping model between texture features and semantic vectors is built by three different methods: linear regression, KNN and MLP. The dataset with ground-truth annotation is used to train and test the mapping model. 10-fold cross validation (9 for training and 1 for testing) is used. The Average Prediction Error (APE) is used to measure the performance. Small APE corresponds to high performance. The definition of APE

$$APE = \frac{\sum_{i=1}^{N} \sqrt{(p_{i,1}-s_{i,1})^2+(p_{i,1}-s_{i,2})^2}^2}{N} \tag{11}$$

where ($p_{i,1}$, $p_{i,2}$) and ($s_{i,1}$, $s_{i,2}$) are the prediction result and manual annotation result of the *i*th image, and N is the size of the dataset.In most cases, the performance is also affected by the size of feature space. A feature space with high dimension may contain redundant information and increase the calculation complexity, while that with too low dimension after feature space reduction may lose useful information and increase prediction error. Principal Component Analysis (PCA) (Belhumeur *et al*., 1997) is used for feature space reduction. Here we select 4, 5, 6, 7, 8, and 13 as the size (R) of the reduced feature space, the accumulated energy for each R is 97.43, 98.52, 98.91, 99.34, 99.61 and 99.96%, respectively.

Figure 5 shows a performance comparison by KNN with different k. The KNN with $k = 5$ produces the highest overall performance. When inspecting the respective performance with respect to the size of the feature space, the original feature space performs best. So $k = 5$ is the optimal configuration of KNN in our case.

Figure 6 shows a performance comparison of the three prediction methods with different sizes of feature space, where KNN and MLP use the optimal configurations. Linear regression performs worst while KNN and MLP perform almost the same. Considering the size of the feature space, all the three methods perform best with the original feature space (R = 48). The Average Prediction Error (APE) of KNN and MLP with the original feature space (R = 48) is about 0.35. Because of the fuzziness of human understanding of texture semantics and the ambiguity of discerning difference of textile patterns, the average prediction error (APE) of 0.35 is acceptable.Also, when considering the speed of the three prediction methods for predicting semantic vectors for images, linear regression is the fastest, followed by MLP and KNN. And the speed of KNN is determined by the size of the database, used for predicting semantic vectors from images. With the entire dataset of 1352 textile images as the database, running on a PC with Quad CPU at 3.00 GHz and 4.00GB RAM running Windows7, for the task of predicting semantic vector for one textile image, the linear regression took almost 0s, the KNN with $k = 5$ took 20 ms, and the MLP with 50 hidden neurons took 13 ms, with the original feature space (R = 48).

Evaluation on automatic textile image annotation: To evaluate whether the automatic annotations are consistent with human perception, a subjective experiment of MOS (mean opinion score) evaluation is conducted.

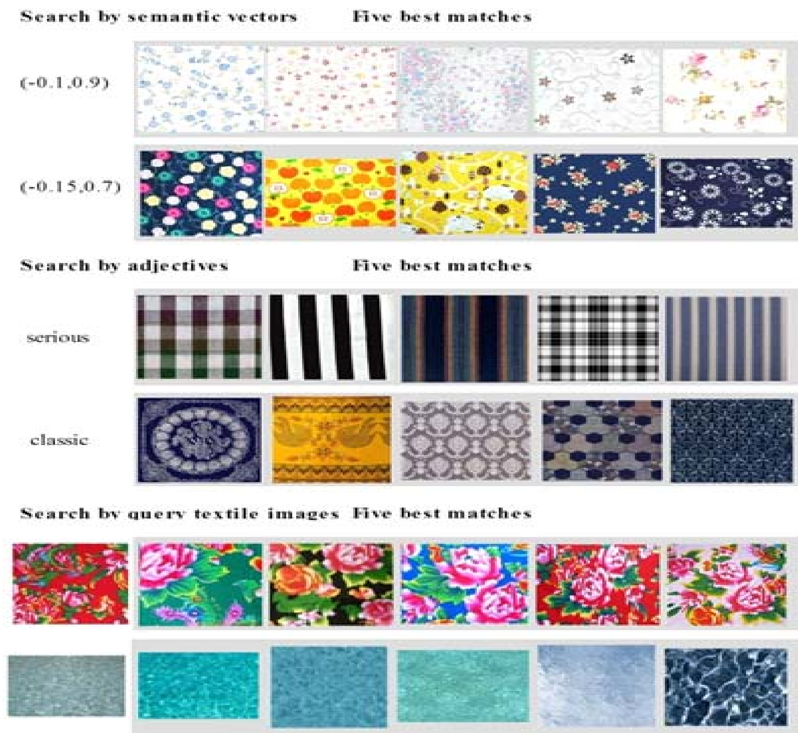

Fig. 9: Image search examples based on semantic vectors, adjectives and query textile images

Participant: Ten university students (2 females and 8 males) with normal visual acuity participate in this experiment. They are all novel to the test.

Stimuli and procedure: Ten textile images, which are downloaded from the Internet and not in the dataset, are automatically annotated by the application of automatic textile image annotation, using the entire dataset of 1352 images for training. Each image is annotated with three words with top ranking and totally 30 image-word pairs are collected. For the evaluation, the images were converted to gray scale to avoid the effects of colors in semantic judgment. The 30 image-word pairs are displayed randomly. Each word is scored with any real number from 1 to 5 according to how well it can describe the image:

- The word perfectly describe the image
- The word fully describe the image
- The word can describe the image
- The relationship between the word and the image is not apparent
- The word is not related to the image

All participants complete the 30 trials in this experiment.

RESULTS AND DISCUSSION

The MOS evaluation result is shown in Fig. 7, which describe the percentage of the different selected score ranges. The MOS average score is 3.7 and the percentage of the selected scores between 3 and 5 is 88%. This result shows that the selected words properly describe images, which indicates that the predicted semantic vectors by the mapping model are consistent with human perception of images. Furthermore, the good results confirm that the mapping model can be utilized in automatic annotation for textile images.

Demonstrations: Figure 8 shows a few results of the automatic textile image annotation. Each image is labeled the two levels of semantic abstraction: a semantic vector and three adjectives with top ranking. Figure 9 illustrates a few search results of the textile image search system. The queries are semantic vectors, adjectives and query images.

CONCLUSION

In this study, we study the relationship between texture semantics and textile images. The texture semantics is quantified by the semantic vectors in the 2D continuous semantic space, which enables the texture semantics to be directly applied in computation, and also enriches the description of textile images compared with categorical approaches. Texture features are extracted by Gabor decomposition. We propose a novel mapping model between texture features and semantic vectors to predict texture semantics from textile images. The performance of the proposed mapping model is evaluated with a dataset of 1352 textile images while the results indicate the mapping model is effective, and KNN and MLP reach the good performance. We further apply the mapping model to two applications: automatic textile image annotation with texture semantics and textile image search based on texture semantics. The subjective experiment shows the results are consistent with human perception of images, which also confirms the effectiveness of the proposed mapping model. As regards to future work, we will explore the relationship between textile images and semantics not limited to texture, and it would include other features, such as color, shape. Another potential issue is adding more adjectives to the automatic annotation system for textile images to enrich the word pool of annotation and collecting more textile images to enlarge the data base of the textile image search system.

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