Texture Analysis and Description in Linguistic Terms[1]

Hsin-Chih Lin[2], Chih-Yi Chiu[3], and Shi-Nine Yang[3]

***Abstract* - A new approach for analyzing and describing textures in linguistic terms is proposed in this study. The proposed approach consists of three major phases, including texture analysis, fuzzy clustering, and texture description. In the texture analysis phase, six Tamura features, including coarseness, contrast, directionality, line-likeness, regularity, and roughness, are extracted from each texture image in the database. The six features are visually meaningful and easily interpreted through textual concepts. In the fuzzy clustering phase, a term set on each Tamura feature is generated through a fuzzy clustering algorithm so that degrees of appearance for the feature can be interpreted as five linguistic terms. In the texture description phase, the generated six term sets are used to interpret an unknown texture as linguistic terms. In this study, Tamura features and linguistic terms support texture manipulations at various semantic levels. That is, Tamura features characterize low-level statistical properties of textures, whereas linguistic terms characterize high-level textual concepts. Moreover, the generated term set formulates a mapping of low-level properties into high-level concepts; it bridges the semantic gap between the two levels. Experimental results reveal the effectiveness of the proposed approach.**

***Index terms* - texture analysis and description, linguistic term, term set, Tamura features, fuzzy clustering.**

I. INTRODUCTION

The world is rich in textures. However, no generally agreed definition of textures exists despite their importance and ubiquity in digital images [1-5]. Textures are defined depending upon the specific application. Although texture analysis has been studied for several decades, results obtained to date are unsatisfactory. Many researchers keep on active in the design of texture analysis techniques. Detail studies on texture analysis can be referred to [3, 4].

Texture analysis can be studied on three levels: statistical, structural, and spectral. On the statistical level, the texture is defined as a set of statistics extracted from local regions. On the structural level, the texture is defined as primitives and their placement rules. On the spectral level, the texture is defined as a set of coefficients in the transform domain. Although the above approaches perform well in texture identification, classification, and segmentation, the approaches for analyzing textures may not agree with the way humans evaluate textures due to the following reasons:

Semantic gap: The semantic gap is due to the lack of consistence between features extracted from a texture image and user's interpretation for the same image. The gap exists between low-level properties and high-level concepts.

Human perception subjectivity: Different users, or the same user under different circumstances, may interpret the same texture differently. Moreover, the way users interpret the similarity of textures may be quite different. The subjectivity exists in each level.

Analyzing textures at the high semantic level, e.g. textual concepts, may be promising to tackle the above problems. Textual concepts are the most natural ways of human communications; they play an important role in eliminating the perception subjectivity in our daily lives. Moreover, textual concepts of textures yield more informative and reliable interpretations. Therefore, approaches for texture manipulations through textual concepts are desired.

A new approach for analyzing and describing textures in linguistic terms, i.e., textual concepts, is proposed in this study. The proposed approach includes three major phases, including texture analysis, fuzzy clustering, and texture description, as shown in Fig. 1. An overview of the proposed approach is given as follows.

Texture Analysis: This phase is to extract Tamura features [5] that capture statistical properties for a texture image. Tamura features are visually meaningful and easily

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2. Lin, the corresponding author, is with the Department of Information Management, Chang Jung Christian University, Tainan, Taiwan 711, R.O.C. Email: hclin@mail.cju.edu.tw
3. Chiu and Yang are with the Department of Computer Science, National Tsing Hua University, Hsinchu, Taiwan 300, R.O.C. E-mail: {cychiu, snyang@cs.nthu.edu.tw}

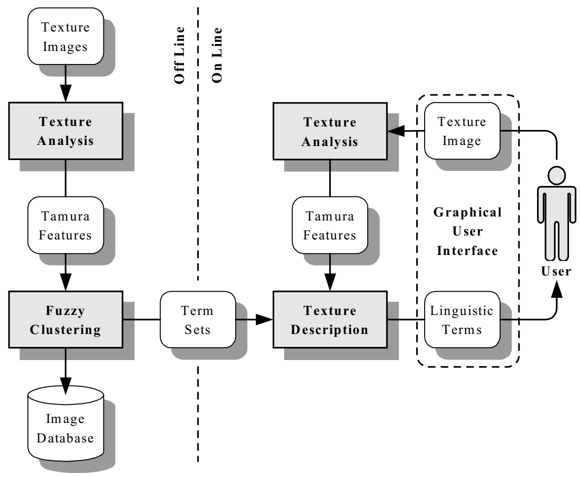

Fig. 1. Block diagram of the proposed approach.

interpreted through textual concepts; they characterize low-level statistical properties of textures.

Fuzzy Clustering: A term set on each Tamura feature is generated through a fuzzy clustering algorithm so that degrees of appearance for the feature can be interpreted as five linguistic terms. Linguistic terms characterize high-level textual concepts of textures; and further, the generated term set formulates a mapping of low-level statistical properties (i.e., Tamura features) into high-level textual concepts (i.e., linguistic terms).

Image Database: Each texture image, together with its Tamura features and linguistic terms, is organized and stored in an image database for further applications, such as texture description, indexing, and retrieval. The generated term sets are also stored in the database.

Texture Description: In this phase, a user can choose a texture image through a graphical user interface to interpret the image as linguistic terms, that is, as degrees of appearance for each Tamura feature. Moreover, the membership value of a Tamura feature in a linguistic term determines the availability of the term for the feature.

In this study, Tamura features and linguistic terms support texture manipulations at various semantic levels. The generated term set bridges the semantic gap between levels. Experimental results reveal the effectiveness of the proposed approach.

The rest of this paper is organized as follows. Section 2 describes the texture analysis phase. Section 3 describes the fuzzy clustering phase. Section 4 describes the texture description phase. Section 5 reports on experimental results. Conclusions and further research are given in the last section.

II. Texture Analysis

The goal of texture analysis is to extract features that capture textural properties for a texture image. In this study, six Tamura features, including coarseness, contrast, directionality, line-likeness, regularity, and roughness, are extracted from each texture image in the database. The six features characterize low-level statistical properties of textures; they are visually meaningful and easily interpreted through textual concepts. That's why Tamura features are used in this study. Detailed discussions about Tamura features can be referred to [5]. We summarize their properties and computations as follows [4-5].

Coarseness: Coarseness is the most fundamental feature in analyzing textures. This feature refers to the size and number of texture primitives; its value can be used as the scale factor when other texture features are extracted. A coarse texture contains a small number of large primitives, while a fine texture contains a large number of small primitives. Coarseness (f_{crs}) can be computed as follows [5].

$$f_{crs} = \frac{1}{n^2}\sum_{i}^{n}\sum_{j}^{n} 2^k\, p(i,j)\ ,$$

where $n \times n$ denotes the image size, the sum is carried out for every pixel $p(i,j)$ and k is obtained as the value which maximizes the differences of the moving averages $\sum_i \sum_j (p(i,j)/2^{2k})$, taken over a $2^k \times 2^k$ neighborhood, along the horizontal and vertical directions.

Contrast: Contrast stands for image quality in the narrow sense. This feature refers the difference in intensity between neighboring pixels. A texture of high contrast has large difference in intensity between neighboring pixels, while a texture of low contrast has small difference. Contrast (f_{con}) can be computed as follows [5].

$$f_{con} = \frac{\sigma}{(\mu_4 / \sigma^4)^{1/4}}\ ,$$

where σ is the image standard deviation and μ_4 is fourth moment of the image.

Directionality: Directionality is a global property over the given region. This feature refers the shape of texture primitives and their placement rule. A directional texture has one or more recognizable orientation of primitives. Directionality (f_{dir}) can be computed as follows [5].

$$f_{dir} = 1 - r \cdot n_p \cdot \sum_{p}^{n_p} \sum_{\phi \in w_p} (\phi - \phi_p)^2 \cdot H_D(\phi),$$

where H_D is the local direction histogram, n_p is the number of peaks of H_D, ϕ_p is the p-th peak position of H_D, w_p is the range of p-th peak between valleys, r is a normalizing factor, and ϕ is the quantized direction code.

Line-likeness: Line-likeness refers only the shape of texture primitives. A line-like texture has straight or wave-like primitives whose orientation may not be fixed. Often the line-like texture is simultaneously directional. Line-likeness (f_{lin}) can be computed as follows [5].

$$f_{lin} = \sum_{i}^{n} \sum_{j}^{n} P_{Dd}(i,j) \cos\left[(i-j)\frac{2\pi}{n}\right] \Big/ \sum_{i}^{n} \sum_{j}^{n} P_{Dd}(i,j),$$

where $P_{Dd}(i,j)$ is the $n \times n$ local direction co-occurrence matrix of points at a distance d.

Regularity: Regularity refers to variations of the texture-primitive placement. A regular texture (e.g., chessboard, textile, and wallpaper) is composed of identical or similar primitives, which are regularly or almost regularly arranged. An irregular texture (e.g., grassy field and cloud) is composed of various primitives, which are irregularly or randomly arranged [4]. Regularity (f_{reg}) can be computed as follows [5].

$$f_{reg} = 1 - r(\sigma_{crs} + \sigma_{con} + \sigma_{dir} + \sigma_{lin}),$$

where r is a normalizing factor and σ_{xxx} means the standard deviation of f_{xxx}.

Roughness: Roughness refers tactile variations of physical surface. A rough texture contains angular primitives, while a smooth texture contains rounded blurred primitives. Roughness (f_{rgh}) can be computed as follows [5].

$$f_{rgh} = f_{crs} + f_{con}.$$

Tamura *et al.* [5] reported that coarseness, contrast, and directionality achieve successful correspondences with psychological measurements. However, line-likeness, regularity, and roughness need further improvement due to their discrepancies with psychological measurements. In this study, coarseness, contrast, and directionality are regarded as major features; whereas line-likeness, regularity, and roughness are complements of the first three features. Although the use of Tamura features is straightforward, we will show in the experiments that Tamura features are effective in texture description.

III. FUZZY CLUSTERING

The goal of fuzzy clustering is to partition texture images (in the database) into fuzzy classes so that the term set on each Tamura feature can be automatically generated. The term set plays an important role in this study; it formulates a mapping of low-level statistical properties (i.e., Tamura features) into high-level textual concepts (i.e., linguistic terms). In fuzzy logic applications, choosing membership functions to reflect the data distribution is the first and an essential step; the choice may be achieved by using unsupervised or supervised learning algorithms [6, 7]. In this study, a term set on each Tamura feature is generated through an unsupervised fuzzy clustering algorithm so that degrees of appearance for the feature can be interpreted as five linguistic terms. For example, linguistic terms for coarseness can be interpreted as "very fine," "fine," "medium coarse," "coarse," and "very coarse." Linguistic terms for other Tamura features can be interpreted likewise. Table 1 summaries linguistic terms for the six Tamura features. The degree of appearance increases from left to right in this table. The proposed algorithm is presented as follows.

Table 1. Linguistic terms for the six Tamura features.

Tamura Features	Linguistic Terms				
Coarseness	very fine	fine	medium coarse	coarse	very coarse
Contrast	very low on contrast	low on contrast	medium on contrast	high on contrast	very high on contrast
Directionality	very non-directional	non-directional	medium directional	directional	very directional
Line-likeness	very blob-like	blob-like	medium line-like	line-like	very line-like
Regularity	very irregular	irregular	medium regular	regular	very regular
Roughness	very smooth	smooth	medium rough	rough	very rough

Algorithm 1. Fuzzy Clustering.

Input. Data sequence $x_1, x_2, \cdots, x_n$, where x_i denotes a Tamura feature over the *i*-th texture image and *n* is the number of texture images.

Output. Five membership functions of the Tamura feature, i.e., a term set on the feature.

Step 1. Let $c_0 = \min\{x_1, x_2, \cdots, x_n\}$ and $c_6 = \max\{x_1, x_2, \cdots, x_n\}$. Compute $c_1, c_2, \cdots, c_5$ using as follows:

$$c_j = c_0 + \frac{j \cdot (c_6 - c_0)}{6}.$$

Initialize membership functions as Fig. 2, in which $c_1, c_2, \cdots, c_5$ denote class centers of the initial fuzzy partition.

Step 2. Set $U = 0$. For each datum x_i, update the element u_{ij} using the following rules, where u_{ij}, $1 \le i \le n$ and $1 \le j \le 5$, is the membership value that the *i*-th pattern belongs to the *j*-th linguistic term.

Rule 1. If $x_i \le c_1$, $u_{i,1} = 1$ and $u_{i,k \ne 1} = 0$.

Rule 2. If $x_i > c_5$, $u_{i,k \ne 5} = 0$ and $u_{i,5} = 1$.

Rule 3. If $c_j < x_i \le c_{j+1}$, compute

$$u_{i,j} = \frac{c_{j+1} - x_i}{c_{j+1} - c_j},\ u_{i,j+1} = 1 - u_{i,j},\ \text{and}\ u_{i,k \ne j,j+1} = 0.$$

Step 3. Compute $c_1, c_2, \cdots, c_5$ using the following equation:

$$c_j = \frac{\sum_{i=1}^{n} u_{ij} x_i}{\sum_{i=1}^{n} u_{ij}}$$

If $c_1, c_2, \cdots, c_5$ are unchanged, the algorithm stops; otherwise go to Step 2.

Stop.

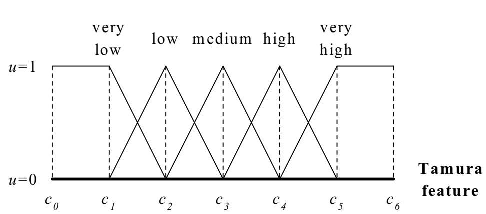

Fig. 2. Initial membership functions of a Tamura feature.

In the proposed algorithm, each linguistic term is a fuzzy set and represented as a triangular membership function. In Step 1, five evenly distributed triangular membership functions are chosen as an initial fuzzy partition, as shown in Fig. 2. In Step 2, each element in *U*, i.e., u_{ij}, is updated according to the three rules. In Step 3, the class centers, i.e., $c_1, c_2, \cdots, c_5$, are recomputed to reflect new data distribution. If the class centers are unchanged, Algorithm 1 ends and the five membership functions are regarded as the representative ones. A representative term set is thus generated.

IV. Texture Description

The goal of texture description is to interpret an unknown textures as linguistic terms, that is, as degrees of appearance for each Tamura feature. Moreover, membership value of a Tamura feature in a linguistic term determines the availability of the term for the feature. In this study, a user can choose a texture image through the graphical user interface to interpret the image. The six Tamura features are first extracted from the texture image. For each Tamura feature, membership values of the five linguistic terms are computed by using the term set generated in the fuzzy clustering phase. The most feasible term to interpret the degree of appearance for the Tamura feature is the one with the largest membership value. This value determines the availability of the linguistic term for the Tamura feature; it is very useful in further applications, e.g., texture-based image indexing and retrieval. The effectiveness of the proposed approach will be demonstrated through examples in our experiments.

V. Experimental Results

The proposed approach is implemented in Matlab script on a PC with an AMD K7 Athlon 650 CPU, 128MB RAM, and Microsoft Windows 98SE. The program is written in Matlab script. The database contains 1570 $192 \times 128 \times 24b$ texture images; these images are transformed to gray-level images before extracting Tamura features. The average time required to extract the six Tamura features from a texture image is about 1.86s. Fig. 3 shows term sets (generated in the fuzzy clustering phase) on the six Tamura features. These term sets are used to interpret an unknown texture in linguistic terms.

To evaluate performance of the proposed approach, a great number of texture images are tested in our experiments. Fig. 4 shows eight texture description examples. Figs. 4(a)-4(d) show four Brodatz textures [8]; Figs. 4(e)-4(h) show four Corel textures in the database. The average time required to interpret a texture image is less than 2s (including the texture-analysis time). We expect that an even better execution time, if the Matlab script is replaced by native C code.

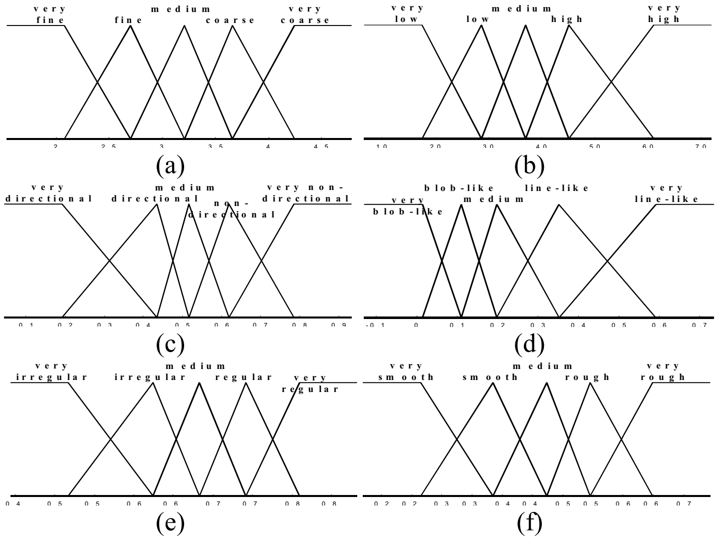

Fig. 3. Generated term sets on the six Tamura features: (a) coarseness; (b) contrast; (c) directionality; (d) line- likeness; (e) regularity; (f) roughness.

VI. Conclusions and Further Research

A new approach to analyzing and describing textures in linguistic terms is proposed in this study. The six Tamura features are shown visually meaningful and easily interpreted through textual concepts. The generated term set well formulates a mapping of low-level statistical properties (i.e., Tamura features) into high-level textual concepts (i.e., linguistic terms). Therefore, a texture image can be analyzed and described in linguistic terms. The proposed approach has been tested on various textures with good results. Experimental results reveal effectiveness of the proposed approach.

Advantages of using linguistic terms in texture manipulations include high intuition and natural interpretation for humans. Thus, using linguistic terms to index and retrieve textures from a large image repertory is a promising and challenging direction for research. Moreover, the generated term sets can be fine-tuned to model the human perception subjectivity through gradient descent algorithms or neural network approaches.

VII. References

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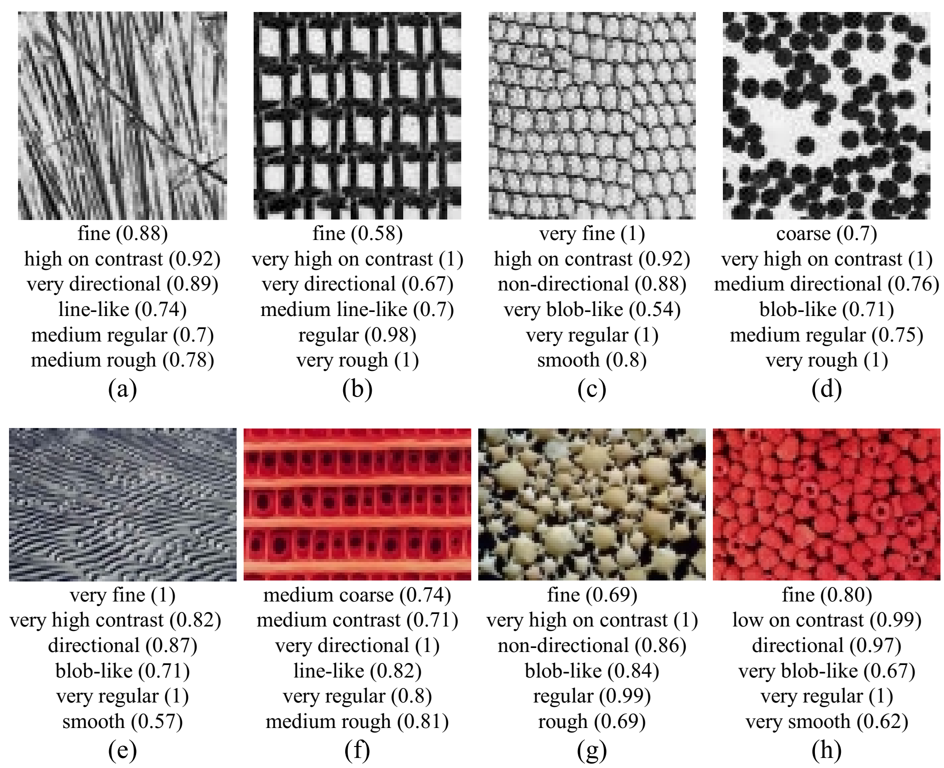

Fig. 4. Texture description examples.