USING IMAGE MINING FOR IMAGE RETRIEVAL

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ABSTRACT

In this paper a new method for image retrieval using high level semantic features is proposed. It is based on extraction of low level color, shape and texture characteristics and their conversion into high level semantic features using fuzzy production rules, derived with the help of an image mining technique. Dempster-Shafer theory of evidence is applied to obtain a list of structures containing information for the image high level semantic features. Johannes Itten theory is adopted for acquiring high level color features.

KEY WORDS

Image mining, Semantic features, Multimedia databases

1. INTRODUCTION

More and more audio-visual information is available in digital form, in various places around the world. MPEG-7, formally called "Multimedia Content Description Interface", was created to describe multimedia documents. The most used features for image description are: color, texture, shape and spatial features. Many of the existing image databases allow users to formulate queries by submitting an example image. The system then identifies those stored images whose feature values match those of the query most closely, and displays them. Color features are usually represented as a histogram of intensity of the pixel colors. Same system, such as Color-WISE [1], partitions the image into blocks and each block is indexed by its dominant hue and saturation values. Color and spatial distribution can be also captured by an anglogram data structure [2]. The most used texture features are the Gabor filters [3]. Other texture measurements are: Tamura features, Unser's sum and difference histogram, Galloway's run-length based features, Chen's geometric features, Laine's texture energy. Shape feature techniques are represented from primitive measures such as area and circularity to more sophisticated measures of various moment invariants; and transformation-based

methods ranging from functional transformations such as Fourier descriptors to structural transformations such as chain codes and curvature scale space feature vectors. Spatial features are presented: as a topological set of relations among image-objects; as a vector set of relations, which considers the relevant positions of the image-objects; as a metric set of relations; 2D-strings; geometry-based θR-strings; spatial orientation graphs; quadtree-based spatial arrangements of feature points.

High level image semantic representation techniques are based on the idea of developing a model of each object to be recognized and identifying image regions which might contain examples of the image objects. One early system aimed at tackling this problem is GRIM_DBMS [4]. The system analyzed object drawings, and use grammar structures to derive likely interpretations of the scene. Another technique for scene analysis, using low-frequency image components to train a neural network is presented in [5]. The concept of the semantic visual template is introduced by Chang et al [6]. The user is asked to identify a possible range of color, texture, shape or motion parameters to express his or her query, which is then refined using relevance feedback techniques. When the user is satisfied, the query is given a semantic label (such as "sunset") and stored in a query database for later use. The use of the subjective characteristics of color (such as warm or cold) to allow retrieval of images is described in [7].

Image mining deals with the extraction of knowledge, image data relationship, or other patterns not explicitly stored in the images [8]. It uses methods from computer vision, image processing, image retrieval, data mining, machine learning, database, and artificial intelligence. Rule mining has been applied to large image databases [9, 10, 11]. There are two main approaches. The first approach is to mine from large collections of images alone and the second approach is to mine from the combined collections of images and associated alphanumeric data. [11] presents an image mining algorithm using blob needed to perform the mining of associations within the context of images. [10] uses rule mining to discover associations between structures and functions of human brain. In this paper we use image mining to define rules for converting low level semantic characteristics into high level features.

In this paper a method for image retrieval, based on high level image semantic features is presented. For example "Baroque period", era in the history of the Western arts roughly coinciding with the 17th century can be defined as: "The work that distinguishes the Baroque period is stylistically complex, even contradictory. In general, however, the desire to evoke emotional states by appealing to the senses, often in dramatic ways, underlies its manifestations. Some of the qualities most frequently associated with the Baroque are grandeur, sensuous richness, drama, vitality, movement, tension, emotional exuberance, and a tendency to blur distinctions between the various arts." We try in our search to use such high level terms. The layout of the paper is as follows. In section 2 we explain the image feature extraction mechanism. In section 3 we describe image retrieval based on high level semantic features. In section 4 we detail our experiments, and finally in section 5 the conclusions of this paper are presented.

2. IMAGE FEATURE EXTRACTION MECHANISM

The proposed mechanism transfers low level image characteristics into high level semantic features using fuzzy production rules with degree of recognition and image interpretation, based on the Dempster-Shafer theory of evidence. For the low level image characteristics the following color, shape and texture features are calculated.

2.1. Color characteristics

The color feature extraction procedure includes color image segmentation. For this purpose ideas from the procedure described in [7] are adopted. Fist the standard RGB image is converted as L*u*v* (extended chromaticity) image, where L* is luminance, u* is redness–greenness, and v* is approximately blueness–yellowness [12]. Twelve hues are used as fundamental colors. There are yellow, red, blue, orange, green, purple, and six colors obtained as linear combinations of them. Five levels of luminance and three levels of saturation are identified. This results that every color is transferred into one of 180 references colors. After that clustering in the 3-dimensional feature space is performed using the K-means algorithm [13]. After this step the image is segmented as N regions, every of which is presented in extended chromaticity space.

2.2. Texture characteristics

The Quasi-Gabor filter [14] is explored to present the image texture features. The image is characterized with 42 values by calculation of the energy for each block defined by a combination of one of 6 frequencies (f = 1, 2, 4, 8, 16 and 32) and one of 7 orientations (q = 0°, 36°, 72°, 108°, 144°, 45° and 135°). We take the average value of the magnitude of the filtered image in each block.

2.3. Shape characteristics

For shape representations a procedure based on [15] is adopted. The image is converting into binary. Polygonal approximation that uses straight-line, Bézier curve and B-Spline are applied. As a result the image is presented as a set of straight lines, arcs and curves.

2.4 Multidimensional association-rules mining

For a given image database we construct a database with records containing the following structure: (imageID, C_1, C_2, …, C_n, T_1, T_2, …, T_m, S_1, S_2, …, S_k, F_1, F_2, …, F_l), where imageID is a unique identification of the image; C_1, C_2, …, C_n, are the values of the color characteristics; T_1, T_2, …, T_m, are the values of texture characteristics; S_1, S_2, …, S_k, are the values of shape characteristics; F_1, F_2, …, F_l are the high level semantic features, given by an expert in the field. The mining process is divided into two steps. First we find the frequent multidimensional value combinations and find the corresponding frequent features in the database. The combination of attribute values that occurs two or more times are called multidimensional pattern [16]. For mining such pattern a modified BUC algorithm [17] is used. The second step includes mining the frequent features for each multidimensional pattern. They constitute the obtain rule base set for the high level semantic features.

2.5. Low level feature translation into high level image semantic

The purpose of this phase is to compose more complex image semantic interpretation from the derived through the low-level image analysis features. It is accomplished by applying methods for extracting high level features and recursively applied production rules from a set defined for the correspondent application domain. The rules are defining also the degree of recognition (RD) of a high level semantic feature as a distance between features

implied in the rule and those found in the image. RD is calculated with the help of fuzzy measures. An interference mechanism based on backward chaining tries to derive from the low level features more general features and to give a recognition degree to the features recognized. In this phase a generalized inference mechanism is used. After this step a sequence in the form (1) is obtained:

(1) $O_{1\ 1}(m_{1\ 1}, l_{1\ 1}), ..., O_{1\ S1}(m_{1\ S\ 1}, l_{1\ S\ 1}), ... O_n$
$_{1}(m_{n\ 1}, l_{n\ 1}), ..., O_n\ _{Sn}(m_{n\ S\ n}, l_{n\ S\ n}).$

Such a sequence describes an image with n distinct high level semantic features. The unit O_i $_{j}(m_{i\ j}, l_{i\ j})$ is a semantic representation of the image feature i $(i=1,2, ... ,n)$ in the j-th $(j=1,2, ..., s_j)$ recognition. $m_{i\ j}$ and $l_{i\ j}$ are respectively the RD and the list of attributes of the i-th semantic feature in the j-th recognition. A logic programming language Prolog is chosen to express the feature recognition rules. In this case the Prolog's inference mechanism is used to perform the high level feature recognition.

To reduce the sequence (1) a procedure similar to Barnett's scheme [18], based on the Dempster-Shafer theory of evidence [19] is applied. The results obtained from applying the production rules are converted into a list of new structures containing information for each semantic feature:

(2) $O_{11}([Bel(O_{11}, 1-Bel(not\ O_{11})], l_{11}), ...,$
$O_{1q1}([Bel(O_{1\ q1}, 1-Bel(not\ O_{1\ q1})], l_{1\ q1}), ...,$
$O_{n1}([Bel(O_{n1}, 1-Bel(not\ O_{n1})], l_{n1}), ...,$
$O_{\ q1}([Bel(O_{n\ qn}, 1-Bel(not\ O_{n\ qn})], l_{n\ qn}),$

where $q_i \leq s_i$ $(i=1, 2, ..., n)$.

The function $Bel(Oij, 1-Bel(not\ Oij)]$ is a belief function. In such sequence, features interpretations with low belief are omitted. The belief function $Bel(O_i)$ $(i=1,2, ...,n)$ gives the total amount of belief committed to the features O_i after all evidence bearing on O_i has been pooled. The function Bel provides additional information about O_i, namely $Bel(not\ O_i)$, the extent to which the evidence supports the negation of O_i, i.e. $not\ O_{ij}$.

3. RETRIEVAL BASED ON HIGH LEVEL SEMANTIC FEATURES

In this section we discuss image retrieval based on high level color, texture, shape and semantic features.

3.1. Retrieval by high level color properties

The spatial arrangement of chromatic contents in the image is obtained using the theory formulated by Johannes Itten in 1960 [20]. In this theory, seven types of contrast are defined:

1. Contrast of hue
2. Light-dark contract
3. Cold-warm contrast (Yellow through red–purple give the filing of ''warm'', yellow–green through purple is find as ''cold'')
4. Complementary contrast
5. Simultaneous contrast
6. Contrast of saturation
7. Contrast of extension

Harmony is defined as a combination of colors resulting in a gray mix that generates stability effect onto the human eyes. Non-harmonic combinations are called expressive. Itten's model is adopted for defining fuzzy production rules that are used to translate the low level semantic features into sentences qualifying warmth degree, and contrasts among colors.

3.2. Retrieval by high level texture properties

Transforming the low level texture characteristics into high level semantic features such as texture of wood, rock, wall-paper, etc. is made by calculation the low level texture characteristic of a typical set of corresponding textures and finding the "cluster center" values which is used in the fuzzy production rules.

3.3. Retrieval by high level shape properties

A set of typical shapes characterizing the domain specific objects are defined. Fuzzy production rules are used for calculation similarity between the search shape and given object shape. They are obtained after image mining.

3.4. Retrieval by high level semantic features

A set of high level semantic features which are defining in the image mining process are used. They combine high level color, texture and shape properties and high level semantic features defined by the expert during the image mining.

4. THE EXPERIMENTS

The proposed method is in process of realization in a system named "Flint". In our experiments we use an image database with images from Bulgaria. After low level image properties extraction image mining was made for obtaining associate rules, describing the high level image semantic features.

Figure 1. Sea, sky images with a regain with worm color

Figure 2. House images

In our example for the query "Find a sea or sky images with a regain with worm color" the following images are retrieved (Figure 1.) The result from the query "Find a house images" is given in the Figure 2. In the first query we use color description to find images with color regions satisfy worm contract and textures of sea and sky. In the second query we use shape descriptors for the house forms.
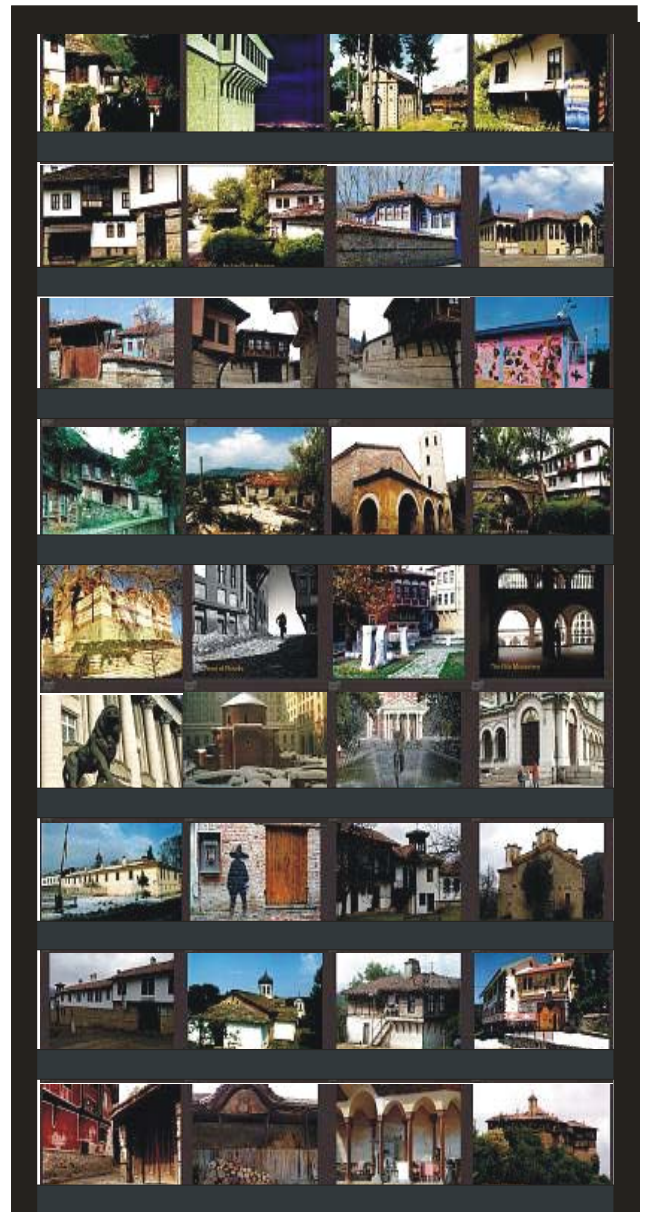
5. CONCLUSIONS

The main advantage of the proposed method is the possibility of retrieval using high level image semantic features. After the full system realization we will be able to obtain statistic characteristics about the usefulness of the suggested method.

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