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Visual Ontology Construction for Digitized Art Image Retrieval

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Abstract Current investigations on visual information retrieval are generally content-based methods. The significant difference between similarity in low-level features and similarity in high-level semantic meanings is still a major challenge in the area of image retrieval. In this work, a scheme for constructing visual ontology to retrieve art images is proposed. The proposed ontology describes images in various aspects, including type & style, objects and global perceptual effects. Concepts in the ontology could be automatically derived. Various art image classification methods are employed based on low-level image features. Non-objective semantics are introduced, and how to express these semantics is given. The proposed ontology scheme could make users more naturally find visual information and thus narrows the "semantic gap". Experimental implementation demonstrates its good potential for retrieving art images in a human-centered manner.

Keywords ontology design, image/video retrieval, image database

1 Introduction

With the advances of multimedia technology, digital acquisition of information have become increasingly popular in recent years. This has attracted significant research efforts in providing tools for effective retrieval and management of visual data. Content-based and semantic-sensitive image analysis and retrieval have been an active research area in the last few years. Prior studies on content-based visual information retrieval such as QBIC[1], VisualSeek[2], and Blobworld[3] are mainly based on the low-level features as color, texture, and shape for general or specific image retrieval task. The advantage of this approach is that it is easy and fairly direct to extract these features; and it is also convenient to design similarity measures of these features. However, low-level features used by current content-based image retrieval systems are hard to be interpreted into high-level concepts that are easily comprehended by human. This is commonly referred to as "Semantic Gap". Some semantic-sensitive image retrieval techniques use relevance feedback method to narrow the gap[4]. Some use pattern recognition techniques[5] to identify or classify between semantic concepts such as nude pictures[6], or indoor *vs.* outdoor images[7] etc.; some use machine learning techniques to learn grouped concepts to facilitate image retrieval[8–10]. But the above-mentioned methods are limited. They may suit for specific applications or presupposed image dataset. In traditional approaches, keyword based method is used for indexing and retrieving images. Unfortunately, this method is rather tedious for textual annotation and subjective, and different users may have different interpretations on the same image.

Above all, current techniques on the topic of image retrieval still could not meet human's demands on image access. The aim of research on this topic is to make users more conveniently and more naturally find the image content they need. From the above analysis, it is hard to achieve this aim by content-based, semantic extraction or keyword-based method separately. From an investigation on how people organize and retrieve images[11], users prefer searching image collection rather than just browsing through it. Besides they like looking for a specific image they have remembered or they just need. Ontology is an important discipline that has the huge potential to improve information organization, management and understanding. How to automatically understand and index images by exploring the potential of semantic of them is a problem to be considered. According to Gruber[12], ontology is the term referring to the shared understanding of some domains of interest, which is often conceived as a set of classes (concepts), relations, functions, axioms, and instances. Ontology is playing a more and more important role in textual analysis and information exchange between different domains. In fact, image retrieval taking advantage of concept hierarchy or ontology is recently proposed, and semantic concept of images may come from automatic machine learning, or manual annotation methods. These methods could establish implicit or explicit relations of different concepts, and make users more naturally obtain images they want to find. More and more researchers are investigating on this topic.

In [13–15], the authors discussed the problem of image annotation based on ontology to facilitate keyword based image retrieval. Hyvönen *et al.*[16] used the image database of university museum to demonstrate how

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ontology could be of some help in querying images. In [17], Soo *et al.* proposed a system of retrieving historical images based on a sharable domain ontology and thesaurus. Wielinga *et al.*[18] described a case study to construct ontology for antique furniture using ATT[19]. The authors of [20] implemented an ontology based image retrieval and recommendation browser Ontogator. Mezaris *et al.*[21] presented an image retrieval methodology such that low-level features are extracted and mapped to intermediate level descriptors called object ontology that is used for the high-level concept queries. In [22], the system used a neural network to identify objects that were fed into the domain-dependent ontology for classification of images. Although the abovementioned studies are ontology-based, they are rather limited, as some are just using ontology to help manually annotating images; and some are using simple ontology to help indexing images. Besides, the area of digitized art images has not been explored in the aspect of ontology-based image retrieval.

At present, more and more digitalized art images are exhibited and sold through the World Wide Web. It is becoming possible to analyze and spread art works at a larger scale. Museums are constructing digital archives of art paintings and preserve the original artifacts. Artists attempt to exhibit and sell their productions on the Internet. Effective indexing, browsing and retrieving digitized art images are important not only for computer scientists and art communities, but also for common art fans. Organization of and query on digitized art images are an important research topic. The DELOS-NSF[23] working group discusses problems of retrieving art images and bridging the semantic gap, and it points out that this area is still in the early stages of research. Li and Wang[24] used multi-resolution HMM method to characterize different painting styles. [25] and [26] gave techniques to identify Canvas and Traditional Chinese Painting images from general images respectively. Bimbo *et al.*[27] investigated on retrieving painting images using color semantics derived from the Itten color sphere. Other ongoing projects in the domain of art images include Artiste and SCULPTEUR.

In this paper, the authors constructed a visual ontology for art images, which include three basic artwork types: painting, art photo and computer generated art graphic. The constructed ontology includes various kinds of concepts that allow users to query visual information through various aspects. Concepts in the ontology could be automatically obtained through image processing and pattern classification techniques. The aim of our method is to make users more naturally find the image information and to narrow the "semantic gap". Conveniently indexing structure and enhanced retrieval performance are achieved.

The organization of this paper is as follows: Section 2 introduces the proposed ontology; Section 3 discusses algorithms of image segmentation and semantic extraction; system architecture and evaluation are introduced in Section 4; and Section 5 gives a short discussion and concludes the paper.

2 Proposed Visual Ontology

Ontology is a specification of conceptualization. It consists of concept hierarchy, concept properties and relations between concepts in a topic area. There are two basic types of ontology: upper ontology and domain ontology. The domain-dependent ontology defines the fine-grained concepts and allows determining specific relationships between concepts in a given area. The constructed ontology is a domain ontology oriented to retrieving digitalized art images.

The proposed art image ontology is presented in Fig.1. It describes the digital art images (DAI) in two aspects: type & style and semantic. Three basic types of DAI are considered: painting; computer generated graphics (CGG) and art photo (AP). Paintings consist of three types: oil painting (OP), traditional Chinese painting (TCP) and watercolor painting. Each of these images may include various style categories. Canvas oil painting includes abstract and realistic styles. Traditional Chinese painting is generally classified into two styles: Xieyi (freehand strokes) and Gongbi (skilled brush). TCP could also be classified into Zhongtang (placed in the center of the living room), Tiaofu (accompanied with couplet) and Shanmian (painted on the shape of Chinese fan).

There are two aspects of semantic descriptions of digitalized art images in the ontology: concrete semantic and non-objective semantic. Concrete semantic includes scene, objects, as well as phenomenon or action. The sub-ontology of concrete semantic is constructed under the framework of the Suggested Upper Merged Ontology (SUMO)[28]. The goal of SUMO is to develop a standard upper ontology that will promote data interoperability, information search and retrieval, and natural language processing. Specific domain ontologies could be constructed based on SUMO. Only the physical part of SUMO is employed as the upper structure of concrete semantic concept hierarchy of digitalized art images.

Non-objective semantics refer to perceptual effects of images; which play a special role in art images. Artists use perceptual semantics such as hue, warmth, contrast to express their feelings and emotions. These semantics are independent of concrete objects or scenes that appear on the art images. In Fig.2, the two oil paintings are both portraits of human, while the psychological effect is rather different: one is cold and the other is relatively warm. Concrete and non-objective semantics are two different aspects to express the meaning of an image especially in the art area. Artists use their brush to paint objects on canvas and in the meantime, generate a global perceptual effect to express their feelings. In fact, non-objective semantics are more closely related to the low level features of images, and the authors try to use quantitative analysis method to compute non-objective semantics.

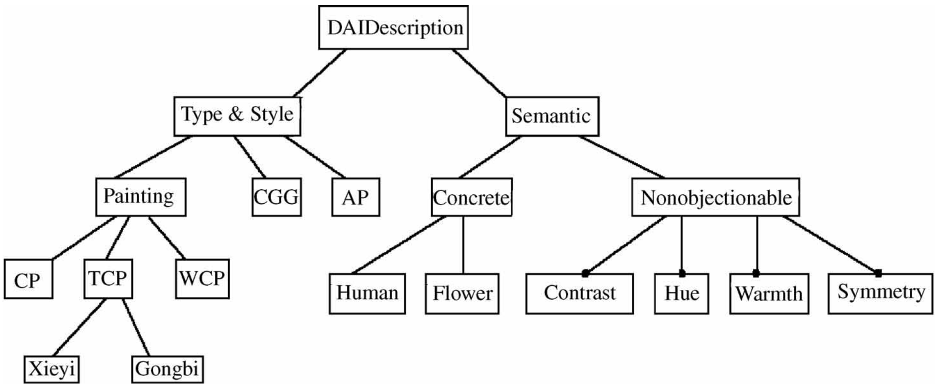

Fig.1. Structure of proposed visual ontology.

Fig.2. Examples of art images: Portraits of human.

Hue, saturation, and luminance are basic tools that artists use to create their paintings, which are also the fundamental elements to produce image features such as: histogram, co-concurrent matrix and wavelet etc. Other non-objective semantics such as warmth, contrast and symmetry could be derived from the pixel information of the images. Fig.3 gives the detailed illustration of the non-objective semantics that we use in the art visual ontology.

3 Algorithms of Image Classification and Semantic Extraction

Semantic concepts of images in the database are derived from various ways including semantic classification, object recognition, and automatic non-objective concept annotation methods. One art image may contain multiple concepts in various aspects. In the following, automatic concept extraction and classification method will be discussed in detail.

There are mainly three parts of art image classification algorithms in the system: detecting oil paintings; detecting traditional Chinese paintings and detecting computer generated art images (art graphics). The role of these classification methods is to differentiate man-made artworks from those photographed by cameras.

To identify oil painting, edge features are employed and the classifier is a neural network[19]. Canny edge detector is used to the RGB color channel and the intensity channel, and two types of edge pixels are used to derive features for differentiating oil paintings. A decision tree method combined with support vector machines (SVM) is used to classify traditional Chinese paintings[26]. The features used are color histogram on Ohta color spaces, color coherence vector and autocorrelation texture features. The authors also developed an algorithm that use newly proposed edge-size histogram (ESH) feature and autocorrelation texture features to categorize TCP images into Gongbi and Xieyi paintings[29]. To compute ESH feature, image should first be resized to have the same number of pixels. We use HSL color space to represent images in the implementation. It could be observed that Gongbi images generally have more detailed edges

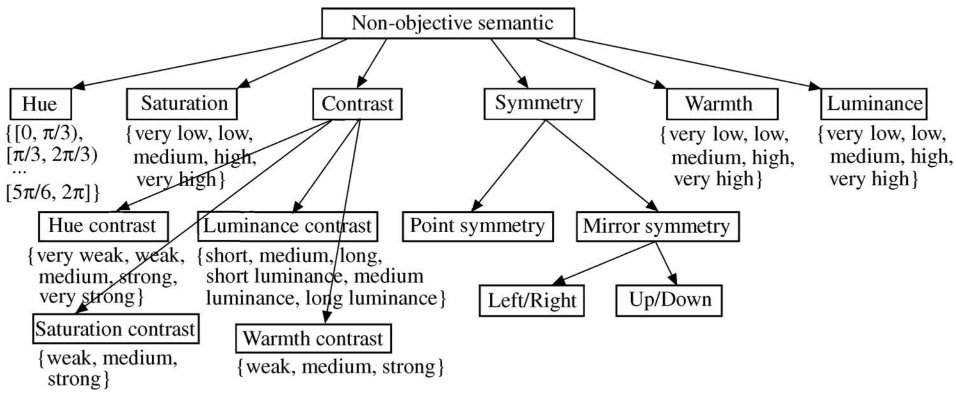

Fig.3. Non-objective semantics in visual art ontology.

than Xieyi images. This is because the former is characterized by simple and bold strokes intended to represent the exaggerated likenesses of the objects, while the latter is characterized by fine brushwork and close attention to details. Some simple features are used to classify graphic art images such as total number of different colors, fraction of pixels having the prevalent color, farthest neighbor metric[30] and spatial gray level dependence texture features[31]. Object detection is another way to establish the connection between the raw image data and its semantic content. A common way to detect object is to shift a search window over an input image and categorize the object in the window with a classifier. At present, objects that are detected in the system include face, text, flower etc. More object detection algorithms will be established in the system by the authors.

Non-objective semantics include hue, saturation, luminance, warmth, contrast, and symmetry. An image G is first segmented into s regions $\{R_1, R_2, \ldots, R_s\}$ using a density-based clustering method[32]. Let $p(p_x, p_y)$ be the pixel of the image, and $N(R_i)$ be the total number of pixels in region R_i. The pixel intensity components of p in the HSL color space are $I_H(p), I_S(p), I_L(p)$. The first three descriptors of region (R_i) are defined as: $D_x^{R_i} = \frac{\sum_{p\in R_i} I_x(p)}{N(R_i)}$, $x \in \{H, S, L\}$. Thus the hue, saturation and luminance descriptors of image G are determined as $D_x^G = \frac{\sum_{i=1}^{s} p_i D_x^{R_i}}{s}$, $x \in \{H, S, L\}$, and p_i is the weight parameter for the region. The hue descriptor is evaluated with six levels and the other two descriptors are evaluated with five levels as illustrated in Fig.3. The warmth value of a pixel could be derived from its hue and luminance values and warmth descriptor of an image could be computed in a similar way. The contrast descriptor is determined by different types of contrasts between regions. There are four types of contrast: hue, luminance, saturation, and warmth. Let $d(R_i, R_j)$ denote the distance between regions R_i and R_j. The distance between regions could be described as follows: if R_1 and R_2 are adjacent, then $d(R_1, R_2)$ is 1; and if R_2 and R_3 are adjacent and R_1 and R_3 are not adjacent, then $d(R_1, R_3)$ is 2. The contrast between two regions is defined as: $C_x^{R_i,R_j} = \frac{pr_{i,j} \bullet |p_i D_x^{R_i} - p_j D_x^{R_j}|}{d(R_i,R_j)}$, $x \in \{H, S, L, W\}$. Here $|p_i D_x^{R_i} - p_j D_x^{R_j}|$ have different definitions for different types of contrast. The whole contrast descriptor of the image could be computed as:

$$CD_x^G = \frac{\sum_{i=1}^{s}\sum_{j=1}^{s} C_x^{R_i,R_j}}{s^2}, \quad x \in \{H, S, L, W\}.$$

Different types of symmetry of an image are decided by comparing various parts of the image. For example, an image has the property of global up/down symmetry if the feature distance of the upper-part and the lower part of the image is below a threshold. More complex symmetry type could be computed in a similar way.

4 System Architecture and Evaluation

When users propose a query, the retrieval engine centralizes and processes information from the query, the related ontology concept and the art image database to generate the retrieved result. The query concept is extended to related concepts using visual ontology under the user's request. The retrieval engine will fetch all images related with these concepts, and the similarity match algorithm ranks these images according to the closeness with the input query. Fig.4 is the architecture of the art image retrieval system based on the constructed ontology.

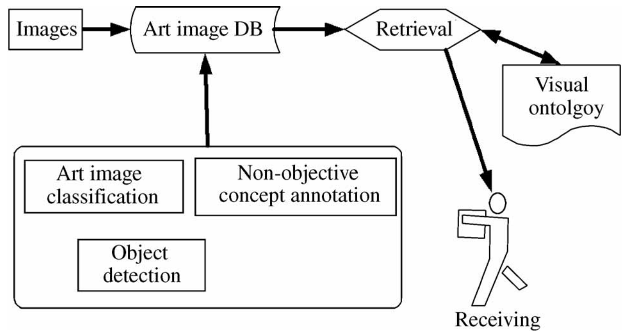

Fig.4. System architecture of ontology based art image retrieval.

The system includes two main parts: automatic semantic concept extraction and image retrieval. As described before, image classification, object detection and non-objective semantic extraction techniques are used. In this section, we will give some typical experimental results on traditional Chinese painting detection and categorization, face detection and non-objective semantic extraction.

1,254 TCP images from various sources and 2,660 general photos are used in TCP classification. High classification rate is achieved by using the combined classifier of C4.5 and SVM. The whole algorithm has only 35 (2.79%) errors on the TCP database, and 6.16% false classification rate on the 2,660 general-image test set. It gives us better performance than any single classifier along (Table 1).

Table 1. Results of TCP Image Classification

(a) Classification rate on TCP test dataset

C45 AutoCor	SVM Histo	SVM CCV	Final classifier
87.74%	94.5%	91.01%	97.21%

(b) False classification rate on general images

C45 AutoCor	SVM Histo	SVM CCV	Final classifier
14.9%	5.3%	7.62%	6.16%

To categorize TCP images into Gongbi and Xieyi, image database including 3,688 Chinese painting images is used that consists of 1,799 Gongbi paintings and 1,889 Xieyi paintings. Then detection precisions are described as:

$$P(G) = \text{Precision (Gongbi)}$$

$$P(X) = \text{Precision (Xieyi)}$$
$$P(O) = \text{Precision (Overall)}.$$

Table 2 shows the classification results of our method. The combined features of edge-size histogram (ESH) and autocorrelation (AC) give us better performance than one feature alone. The final overall classification accuracy of 94.6098% is achieved.

Table 2. Results of Categorization of Gongbi and Xieyi (%)

	ESH	AC	ESH+AC
$P(G)$	85.2854	77.2686	95.5553
$P(X)$	79.2523	78.9172	93.6644
$P(O)$	82.2689	78.0929	94.6098

Miao's method[33] is used to detect faces in art images. Detection rate of frontal face on four types of art images is 86.3%.

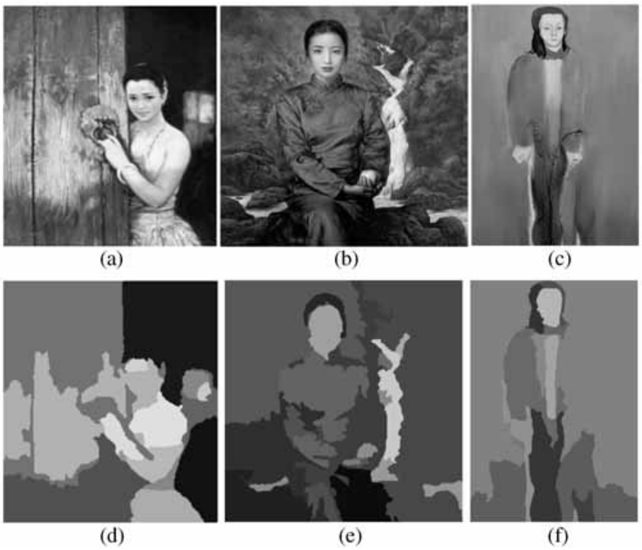

Fig.5. Example of image segmentation results.

Table 3. Non-Objective Semantics of Figs.5(a)–5(c)

	Fig.5(a)	Fig.5(b)	Fig.5(c)
Hue	$[1.3\pi, 1.6\pi]$	$[\pi, 4\pi/3]$	$[2\pi/3, \pi]$
Saturation	High	Medium	Very Low
Luminance	High	Medium	Low
Warmth	Very High	Low	Very Low
Hue Cont.	Very Strong	Strong	Weak
Sat. Cont.	Strong	Medium	Weak
Lum. Cont.	Strong	Medium Luminance	Short
Warm Cont.	Weak	Medium	Weak
L/R Symmetry			Yes

To compute non-objective semantics of art images, density-based clustering segmentation method is employed. Fig.5 gives segmentation results. Then methods described in Section 3 are used to extract non-objective semantics. As an example, Table 3 gives these examples of Figs.5(a), 5(b), and 5(c). The automatically extracted concepts are fed into the database accompanied with the images. Users could query the art images from various aspects: type & style, concrete semantics and non-objective semantics. In fact, different aspects of concept may be inter-correlated, for example mountain and water normally occur in the traditional Chinese paintings. Images related with the user's request are taken out and displayed in order of closeness to the request. In practical applications, end users could identify an image for some categories or compose a complex query, and the system returns all similar images above a threshold based on the ontological description of the images.

Some experiments are conducted to compare the performances between the proposed method and traditional content-based methods whose features include color histogram and textures. The evaluation is made by the precisions on four semantic categories: (Cate. A) TCP of Gongbi; (Cate. B) TCP of Xieyi with high saturation; (Cate. C) OP with short luminance contrast and (Cate. D) CGG with caption text. We use 3,600 images as the retrieval dataset, which include 400 images for each category, and other 2,000 images are taken to have other semantic meanings. Input of our method is semantic keywords, and precisions are computed on retrieved top 50 and 100 images, which are shown in Table 4. Traditional content-based techniques accept only queries by examples, thus we select 5 images as the retrieval sample for each category and compute their average performance, and the retrieval results are shown in Table 5. It could be found that our method performs much better than content-based method.

Table 4. Retrieval Results of the Proposed Method (%)

	Cate. A	Cate. B	Cate. C	Cate. D
Top 50	98	92	86	94
Top 100	94	90	89	91

Table 5. Retrieval Results of Content-Based Method (%)

	Cate. A	Cate. B	Cate. C	Cate. D
Top 50	84.4	65.2	79.2	59.6
Top 100	79.8	63.2	72.4	54

5 Discussion and Conclusion

In this paper, we propose a scheme to construct visual ontology for retrieving art images. The proposed ontology accompanied with the retrieval scheme satisfies users' demand by organizing and querying art images through high-level concepts. These concepts are derived through automatic extraction techniques, thus avoiding the tediousness and subjectivity of manual annotation method. It can be noted that some automatic extraction methods need improving, and more object detection algorithms will be established with progresses of image processing and machine learning techniques.

The studies of [11] reveal that content-based query method is the last choice of users. They will only turn to use it if there is no other way. This method normally needs a query example, while in most cases users only have a vague image of what it looks like. Besides, the query results do not directly reflect users' desire. Ontology includes concept collections and specifies interrelationships among concepts. It helps to extract semantic meanings from images, and facilitate retrieval in a convenient way, thus bridging the semantic gap. In our experimentation, users could conveniently formulate a query in various aspects to get the artworks they need, compared with other systems. And the feedback from some human subjects that have used the system is satisfactory.

This paper first introduces non-objective semantics. They are important aspects to describe an image especially in art area. Although this kind of semantic is independent of concrete things in the image, it does express some kind of thought and feeling. It will be of some help in art image retrieval for artists as well as for common users.

Further studies include establishing more image classification and object detection techniques, and identification of high-level emotional concept of more complex non-objective semantics is also desired. The authors are also investigating other domain ontology for specified kinds of multimedia information such as sports.

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