An Ontology-based Approach to Retrieve Digitized Art Images

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Abstract

Although much progress has been made, current low-level based visual information retrieval technology does not allow users to formulate queries through high-level semantics. More and more digitized art images appear on the Internet, and techniques need to be established on how to organize and retrieve them. In this work, a framework for retrieving art images using an ontology-based method is introduced. The proposed ontology describes images in various aspects. Non-objectionable semantics are first introduced, and how to express these semantics is given. Concepts in the ontology could be automatically derived. The retrieval scheme makes users more naturally find visual information and experimental implementation demonstrates good potential on retrieving art images in a human-centered manner.

1. Introduction

The emergence of multimedia technology and rapidly expanding image and video collections on the internet have attracted significant research efforts in providing tools for effective retrieval and management of visual data. Content-based and semantic-sensitive image analysis and retrieval has been an active research area in the last few years. Content-based method use low-level features such as color, texture and shape to represent image content. The advantage of this method is that it is easy and fairly direct to extract these features and convenient to design similarity measures of these features. The drawback of the current content-based image retrieval systems is that low-features used by them always could not be interpreted to high-level concepts that are commonly comprehended by human. This matter is always called "Semantic Gap". Some semantic-sensitive image retrieval techniques use relevance feedback to narrow the gap; some use pattern recognition techniques to identify or classify between semantic concepts such as human face, nude pictures; indoor& outdoor *etc.*; some use machine learning techniques to learn grouped concept to facilitate image retrieval. The above methods is rather limited, they may suit for specific applications or presupposed image dataset. In traditional approaches, keyword based method are used for indexing and retrieving images. Unfortunately, this method is rather tedious for textual annotation and subjective, different users may have different interpretations on a same image.

The aim of research on image retrieval 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. Ontology is an important discipline that has the huge potential to improve information organization, management and understanding. According to Gruber [1], 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 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 computer vision methods, and manual annotation. This method 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.

Aslandogan *etc.* [2] use WordNet, an electronic lexical system for query and database expansion. They propose a concept normalization formula, and an object significance to improve retrieval effectiveness. In [3], Yang *etc.* propose a thesaurus-aided approach to facilitate semantics-based access to images. They also utilize WordNet to interactively construct a dynamic semantic hierarchy to support flexible browsing. Benitez and Chang [4] present new methods to automatically extract semantic concepts by differentiating the senses of words using WordNet for extracting semantic knowledge from annotated images. In [5][6][7][8], the authors discuss the problem of image annotation based on ontology to

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facilitate keyword based image retrieval. Hyvonen etc. [9] use the image database of university Museum to demonstrate how ontology could be of some help in querying images. In [10, 11], the authors propose a system of retrieving images on historical images based on a sharable domain ontology and thesaurus. Wielinga *etc.* [12] describe a case study to construct an ontology for antique furniture using ATT [13]. The authors in [14] implemented an ontology based image retrieval and recommendation browser Ontogator. Mazaris *etc.* [15] present an image retrieval methodology 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 [16], the system uses a neural network to identify objects that are fed into the domain-dependent ontology for classification of images.

At present, more and more digitized 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. Organization and query on digitized art images in an important research topic. The DELOS-NSF [17] working group discusses problems of retrieving art images and bridging the semantic gap, and points out that this area is still in the early stages of research. Li and Wang [18] use multi-resolution HMM method to characterize different painting styles. References [19] and [20] give techniques to identify Canvas and Traditional Chinese Painting images respectively. A.D. Bimbo *etc.* [21] investigate on the problem of retrieval painting images using color semantics derived from the Itten color sphere. Systems involving processing art images include MARS [22] and Picasso [23].

In this paper, the authors constructed an ontology on art images, which include four types artworks: oil painting, traditional Chinese painting, art photo and computer generated art graphic. The constructed ontology includes various kinds of concepts that make users query visual information through various aspects. Image could be automatically annotated with concepts in the ontology through image processing and pattern classification techniques. The aim of our method is to make users more naturally find the image information and to bridge 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 explains the system architecture; experimental implementation is introduced in section 4; and section 5 gives a short discussion and concludes the paper.

2. The Proposed 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 retrieve digitized 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. Four basic types of DAI are considered: oil painting (OP); traditional Chinese Painting (TCP); computer generated graphics (CGG) and art photo (AP). 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).

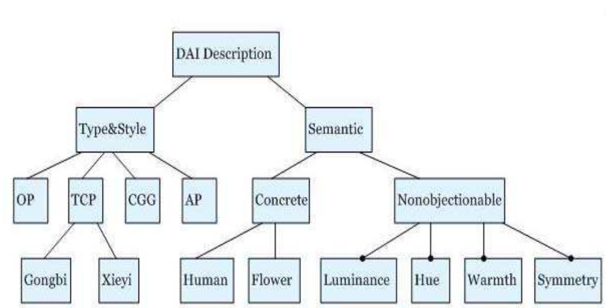

Figure 1. Structure of proposed ontology

(a) (b)

Figure 2. Examples of art images: bird on the flower

There are two aspects of semantic descriptions of digitized art images in the ontology: concrete semantic and non-objectionable semantic. Concrete semantic includes general/specific scene; general/specific objects; and general/specific phenomenon or action. General objects (scene, phenomenon) is that commonsense knowledge is necessary to recognize them, such as an apple, beach, or raining. While recognizing specific concrete semantics relies on known facts, and is usually objective. General Semantic of two pictures of Fig.2 (a) and (b) is the same: bird on the flower, while the specific

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flower is different: water lily and peony respectively. Numerous objects and scenes could appear on the art images. The sub-ontology of concrete semantic is constructed under the framework of the Suggested Upper Merged Ontology (SUMO) [24]. 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. Figure 3 is the basic structure of SUMO. Only physical part of the SUMO is employed as the upper structure of concrete semantic concept hierarchy of digitized art images may consists with this part.

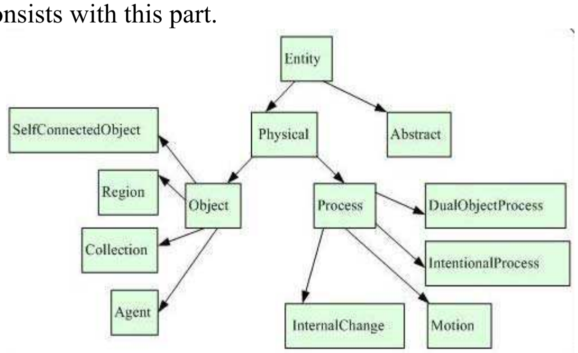
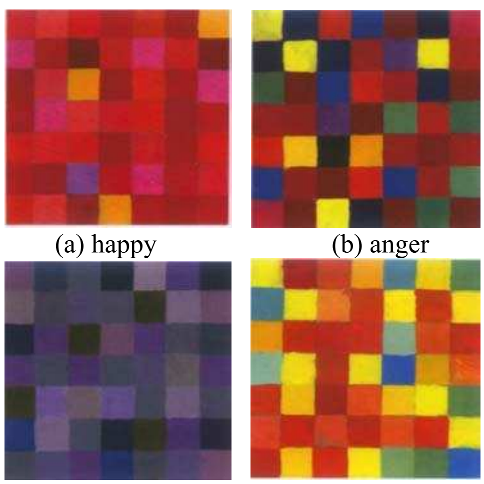


Figure 3. Basic structure of SUMO



(a) happy (b) anger

(c) sad (d) joy

Figure 4. Different feelings expressed by art images

Perceptual effect takes 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 Figure 2, the two traditional Chinese paintings have the same objects: bird and flower, while the psychological effect to the user is rather different: one is cold and the other is relatively warm. This kind of perceptual effect is called non-objectionable semantics in this paper. In the authors mind, concrete and non-objectionable semantics are two different aspects to express the meaning of the images especially in the art area. Artists use their brush to paint objects on the canvas and in the mean time, generate the global perceptual effect to express the feelings. In Fig.4, four basic emotional feelings of human beings could be expressed by art images. In fact, non-objectionable semantics are more closely related to the low level features of images. Hue, saturation, and luminance are basic tools that artists used to create their paintings, which are also the fundamental elements that produce image features such as: histogram, co-concurrent matrix and wavelet *etc.* Other non-objectionable semantics such as warmth, contrast and symmetry could be derived from the pixel information of the images. Figure 5 gives the detailed illustration of the non-objectionable semantics that we used in the art visual ontology.

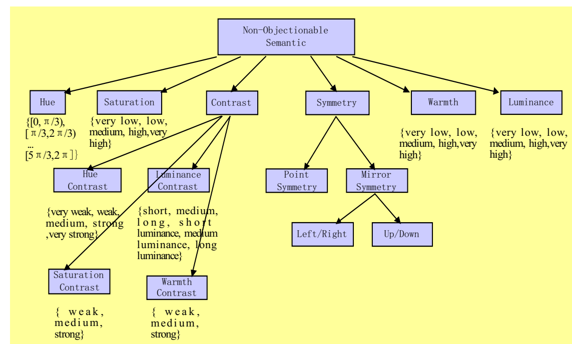


Figure 5. Non-objectionable semantics in visual art ontology

Concepts in ontologies are connected by relationships. Basic relations used in our ontology include Instance-of and Is-A. The concept "Instance of" is used to show membership. Concept "human" is an instance of "concrete semantic". "Is a "relation is used to represent concept inclusion, for example, "Xieyi" is a sub-concept of "TCP". These two relations linked nearly all the concepts to generate the concept hierarchy. Other relations may also be used in our ontology especially in the concrete semantic part. All these relations are used to make users more conveniently retrieval image information they need.

3. System Architecture

Figure 6 is the system architecture of the art image retrieval based on the constructed ontology. Semantic concepts of images in the database are derived from various ways including semantic classification, object recognition, non-objectionable concept annotation. One art image may contain multiple concepts in various aspects. When users propose a query, the retrieval engine centralizes and processes information from the query, 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 ranked these images according to the closeness with the input query. In the following, automatic concept extraction method will be discussed in detail.

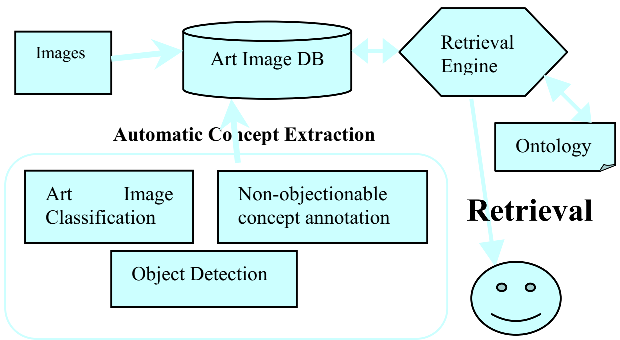


Figure 6. System architecture of ontology based art image retrieval

There are mainly three part of art image classification in the system: detecting oil painting; 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 that photographed by cameras. To identify oil painting, edge features is employed and the classifier is neural network [19]. Canny edge detector is used to the RGB color channel and the intensity channel, and two types of edge pixels are determined as follows:

$$E_g = \frac{\#\text{ pixels : intensity, not color edge}}{\text{total number of edge pixels}}$$

$$E_c = \frac{\#\text{ pixels : color, not intensity edge}}{\text{total number of edge pixels}}$$

Then E_g, E_c, $e_{c\backslash g} = \dfrac{|\{E_c \setminus E_g\}|}{|\{E_c \cup E_g\}|}$, and $e_{g\backslash c} = \dfrac{|\{E_g \setminus E_c\}|}{|\{E_c \cup E_g\}|}$ are used as features to differentiate oil paintings. We use a decision tree combined with SVM method to classify traditional Chinese paintings [20]. The features that are used are color histogram on Ohta color spaces; color coherence vector and autocorrelation texture features. The author developed an algorithm that use edge and texture features to categorize TCP images into Gongbi and Xieyi [25]. Some simple features are used to classify graphic art such as total number of different colors, fraction of pixels have the prevalent color, farthest neighbor metric [26] and spatial gray level dependence texture features [27].

Object detection is another way to establish the connection between the raw image data and its semantic contents. 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 detected in the system include face, text, flower etc. More objects detection algorithms will be established in the system by authors.

Non-objectionable semantics include hue, saturation, luminance, warmth, contrast, and symmetry. The image G is first segmented into s regions $\{R_1, R_2, \ldots R_s\}$ using a density-based clustering method [28]. 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 is $I_H(p)$, $I_S(p)$, $I_L(p)$. The first three descriptors of region (R_i) are defined as: $D_x^{Ri} = \dfrac{\sum_{p\in Ri} I_x(p)}{N(R_i)}$, $x \in \{H, S, L\}$. Thus the hue, saturation and luminance descriptor of image G is determined as $D_x^G = \dfrac{\sum_{i=1}^{s} p_i D_x^{Ri}}{s}$, $x \in \{H, S, L\}$, 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.5. The warmth value of a pixel could be derived from its the hue and luminance. Orange is the warmest color and sky blue is the coolest one. The warmth descriptor of an image could be computed in the same way as hue, saturation and luminance, which is also evaluated by five levels.

The contrast descriptor is determined by different type of contrasts between regions. There are four types of contrast: hue, luminance, saturation and warmth. Let $d(R_i, R_j)$ denote the distance of region 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_2, and R_3 are not adjacent, then $d(R_1, R_3)$ is 2. The contrast between two regions is defined as:

$$C_x^{Ri,Rj} = \frac{pr_{i,j} \bullet |p_i D_x^{Ri} - p_j D_x^{Rj}|}{d(R_i, R_j)}, \quad x \in \{H, S, L, W\}.$$

Here $|p_i D_x^{Ri} - p_j D_x^{Rj}|$ have different definitions for different types of contrast. Let difference between D_H^{Ri} and D_H^{Rj} is denoted as $D_H^{Ri,Rj}$, Then for hue:

$$|p_i D_H^{Ri} - p_j D_H^{Rj}| = \begin{cases} 0, & \text{if } D_H^{Ri,Rj} < 15^\circ \\ 1, & \text{if } 15^\circ \le D_H^{Ri,Rj} < 30^\circ \\ 2, & \text{if } 30^\circ \le D_H^{Ri,Rj} < 60^\circ \\ 3, & \text{if } 60^\circ \le D_H^{Ri,Rj} < 120^\circ \\ 4, & \text{if } 120^\circ \le D_H^{Ri,Rj} < 165^\circ \\ 5, & \text{if } 165^\circ \le D_H^{Ri,Rj} \end{cases}$$

Other types of $\left| p_i D_x^{Ri} - p_j D_x^{Rj} \right|$ could be defined in a similar way, the detailed description of them are not given here for limitation of the paper length. The whole contrast descriptor of the image could be computed as

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

Different types of symmetry of an image are decided by comparing various part 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. Implementation

The system includes two main parts: automatically semantic concepts extraction and image retrieval. As described before, image classification, object detection and non-objectionable semantic extraction techniques are used. To save space, we briefly give some experimental results on traditional Chinese painting classification, face detection and non-objectionable semantic extraction.

1254 TCP images from various sources and 2660 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 makes only 35(2.79%) errors on the TCP database, and 6.16% false classification rate on the 2660 general-image test set. It gives us better performance than any single classifier along (Table 1).

Table 1. Result of TCP image classification

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

(a) Classification rate on TCP test dataset

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

(b) False classification rate on general images

Miao's method [29] is used to detecting faces in art images. Detection rate of frontal face on the four types of art images is 86.3%. Figure 7 gives some detection examples.

(a) (b) (c)

(d) (e) (f)

Figure 7. Some face detection examples

(a) (b) (c)

Figure 8. Segmentation results of Fig.7 (a)(b)(c)

To compute non-objectionable semantics of art images, density-based clustering segmentation method is employed. Figure 8 gives segmentation results of original images in figure 7. Then methods described in section 3 are used to extract non-objectionable semantics. As an example, Table 2 gives these examples of figure 7 (a) (b) (c).

Table 2. Non-objectionable Semantics of Fig.7 (a)(b)(c)

	Fig.7 (a)	Fig.7 (b)	Fig.7 (c)
Hue	[4π/3,5π/3]	[π,4π/3]	[2π/3, π]
Saturation	High	Medium	Very Low
Luminance	High	Medium	Low
Warmth	Very High	Low	Very Low
Hue contrast.	Very Strong	Strong	Weak
Saturation contrast	Strong	Medium	Weak
Luminance contrast	Strong	Medium Luminance	Short
Warmth contrast	Weak	Medium	Weak
Left/Right symmetry			Yes

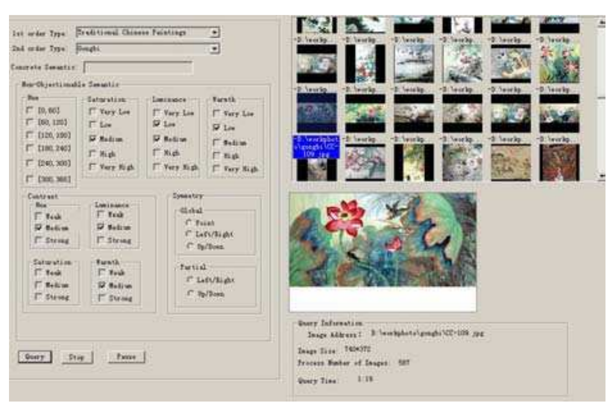


Figure 9. The retrieval system interface

The automatically extracted concepts are fed into the database accompanied with the images. The dataset consists of about 10500 images including the four types of art works from various sources. Users could query the art images from various aspects: type & style, concrete semantics and non-objectionable semantics. In fact different aspects of concept may be inter-correlated, such as mountain & water are normally occurred in the traditional Chinese paintings. Images related with the user's request are taken out and displayed in order of closeness to the request. Figure 9 is the system interface.

5. Discussions and Conclusion

From an investigation on how people organize and retrieve images [30], 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. The proposed ontology based retrieval scheme satisfied users demand by organizing and querying art images through high-level concepts. These concepts are derived through automatically extraction techniques, thus avoiding the tediousness and subjectivity of manually annotation method. It will be noted that some automatically extraction method need improving, and more object detection algorithms will be established with computer vision and image-processing techniques progresses.

The investigation reveals that content-based query method is the users last choice; 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 and the feedback from some human subjects that have used the system is satisfactory.

This paper first introduces non-objectionable 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 works include establishing more image classification and object detection techniques and identification of high-level emotional concept of non-objectionable semantics as showed in figure 4. Evaluation of retrieval performance of our scheme needs further investigation.

6. Acknowledgments

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