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A survey of content-based image retrieval with high-level semantics

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Abstract

In order to improve the retrieval accuracy of content-based image retrieval systems, research focus has been shifted from designing sophisticated low-level feature extraction algorithms to reducing the 'semantic gap' between the visual features and the richness of human semantics. This paper attempts to provide a comprehensive survey of the recent technical achievements in high-level semantic-based image retrieval. Major recent publications are included in this survey covering different aspects of the research in this area, including low-level image feature extraction, similarity measurement, and deriving high-level semantic features. We identify five major categories of the state-of-the-art techniques in narrowing down the 'semantic gap': (1) using object ontology to define high-level concepts; (2) using machine learning methods to associate low-level features with query concepts; (3) using relevance feedback to learn users' intention; (4) generating semantic template to support high-level image retrieval; (5) fusing the evidences from HTML text and the visual content of images for WWW image retrieval. In addition, some other related issues such as image test bed and retrieval performance evaluation are also discussed. Finally, based on existing technology and the demand from real-world applications, a few promising future research directions are suggested.

Keywords: Content-based image retrieval; Semantic gap; High-level semantics; Survey

1. Introduction

With the development of the Internet, and the availability of image capturing devices such as digital cameras, image scanners, the size of digital image collection is increasing rapidly. Efficient image searching, browsing and retrieval tools are required by users from various domains, including remote sensing, fashion, crime prevention, publishing, medicine, architecture, etc. For this purpose, many general-purpose image retrieval systems have been developed. There are two frameworks: text-based and content-based. The text-based approach can be tracked back to 1970s. In such systems, the images are manually annotated by text descriptors, which are then used by a database management system (DBMS) to perform image retrieval. There are two disadvantages with this approach. The first is that a considerable level of human labour is required for manual annotation. The second is the annotation inaccuracy due to the subjectivity of human perception [1,2]. To overcome the above disadvantages in text-based retrieval system, content-based image retrieval (CBIR) was introduced in the early 1980s. In CBIR, images are indexed by their visual content, such as color, texture, shapes. A pioneering work was published by Chang in 1984, in which the author presented a picture indexing and abstraction approach for pictorial database retrieval [3]. The pictorial database consists of picture objects and picture relations. To construct picture indexes, abstraction operations are formulated to perform picture object clustering and classification. In the past decade, a few commercial products and experimental prototype systems have been developed, such as QBIC [4], Photobook [5], Virage [6], VisualSEEK [7], Netra [8], SIMPLIcity [9]. Comprehensive surveys in CBIR can be found in Refs. [10,11].

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1.1. The semantic gap

The fundamental difference between content-based and text-based retrieval systems is that the human interaction is an indispensable part of the latter system. Humans tend to use high-level features (concepts), such as keywords, text descriptors, to interpret images and measure their similarity. While the features automatically extracted using computer vision techniques are mostly low-level features (color, texture, shape, spatial layout, etc.). In general, there is no direct link between the high-level concepts and the low-level features [2].

Though many sophisticated algorithms have been designed to describe color, shape, and texture features, these algorithms cannot adequately model image semantics and have many limitations when dealing with broad content image databases [12]. Extensive experiments on CBIR systems show that low-level contents often fail to describe the high-level semantic concepts in user's mind [13]. Therefore, the performance of CBIR is still far from user's expectations.

In Ref. [1], Eakins mentioned three levels of queries in CBIR.

Level 1: Retrieval by primitive features such as color, texture, shape or the spatial location of image elements. Typical query is query by example, 'find pictures like this'.

Level 2: Retrieval of objects of given type identified by derived features, with some degree of logical inference. For example, 'find a picture of a flower'.

Level 3: Retrieval by abstract attributes, involving a significant amount of high-level reasoning about the purpose of the objects or scenes depicted. This includes retrieval of named events, of pictures with emotional or religious significance, etc. Query example, 'find pictures of a joyful crowd'.

Levels 2 and 3 together are referred to as semantic image retrieval, and the gap between Levels 1 and 2 as the semantic gap [1].

More specifically, the discrepancy between the limited descriptive power of low-level image features and the richness of user semantics, is referred to as the 'semantic gap' [14,15].

Users in Level 1 retrieval are usually required to submit an example image or sketch as query. But what if the user does not have an example image at hand? Semantic image retrieval is more convenient for users as it supports query by keywords or by texture.

Therefore, to support query by high-level concepts, a CBIR systems should provide full support in bridging the 'semantic gap' between numerical image features and the richness of human semantics [13,15].

1.2. High-level semantic-based image retrieval

How do we relate low-level image features to high-level semantics? Our survey shows that the state-of-the-art techniques in reducing the 'semantic gap' include mainly five categories: (1) using object ontology to define high-level concepts, (2) using machine learning tools to associate low-level features with query concepts, (3) introducing relevance feedback (RF) into retrieval loop for continuous learning of users' intention, (4) generating semantic template (ST) to support high-level image retrieval, (5) making use of both the visual content of images and the textual information obtained from the Web for WWW (the Web) image retrieval.

Retrieval at Level 3 is difficult and less common. Possible Level 3 retrieval can be found in domain specific areas such as art museums or newspaper library. Current systems mostly perform retrieval at Level 2. There are three fundamental components in these systems: (1) low-level image feature extraction, (2) similarity measure, (3) 'semantic gap' reduction.

Excellent survey on low-level image feature extraction in CBIR system can be found in Ref. [11]. In this paper, we focus on CBIR with high-level semantics. The rest of the paper is organized as follows. In Section 2, we briefly review various low-level image features used in high-level semantic-based CBIR systems. Image similarity measure is also discussed in Section 2. Section 3 focuses on different methods in narrowing down the 'semantic gap'. In Section 4, test image dataset and performance evaluation (PE) are discussed. Section 5 includes a few other issues related with CBIR systems which are suggested as promising research directions. Finally, Section 6 concludes this paper.

2. Low-level image features

Low-level image feature extraction is the basis of CBIR systems. To performance CBIR, image features can be either extracted from the entire image or from regions. As it has been found that users are usually more interested in specific regions rather than the entire image, most current CBIR systems are region-based. Global feature based retrieval is comparatively simpler. Representation of images at region level is proved to be more close to human perception system [16]. In this paper, we focus on region-based image retrieval (RBIR).

To perform RBIR, the first step is to implement image segmentation. Then, low-level features such as color, texture, shape or spatial location can be extracted from the segmented regions. Similarity between two images is defined based on region features. This section includes a brief description of these three parts focusing on what are used in RBIR system with high-level semantics.

2.1. Image segmentation

Automatic image segmentation is a difficult task. A variety of techniques have been proposed in the past, such as curve evolution [17], energy diffusion [18], and graph partitioning [19]. Many existing segmentation techniques work well for

14 regions 11 regions

Fig. 1. JSEG segmentation results.

images that contain only homogeneous color regions, such as direct clustering methods in color space [20]. These apply to retrieval systems working only with colors [21,22].

However, natural scenes are rich in both color and texture, and a wide range of natural images can be considered as a mosaic of regions with different colors and textures. Texture is an important feature in defining high-level concepts. As stated in Ref. [23], texture is the main difficulty in a segmentation method. Many texture segmentation algorithms require the estimation of texture model parameters which is a very difficult task [23]. ‘JSEG’ segmentation [23] overcomes these problems. Instead of trying to estimate a specific model for texture region, it tests for the homogeneity of a given color-texture pattern. ‘JSEG’ consists of two steps. In the first step, image colors are quantized to several classes. Replacing the image pixels by their corresponding color class labels, we can obtain a class-map of the image. Spatial segmentation is then performed on this class-map which can be viewed as a special type of texture composition. The algorithm produces homogeneous color-texture regions and is used in many systems [16,24,25]. Fig. 1 gives two examples.

Blobworld segmentation [26] is another widely used segmentation algorithm [24,27]. It is obtained by clustering pixels in a joint color-texture-position feature space. Firstly, the joint distribution of color, texture, and position features is modelled with a mixture of Gaussians. Then expectation maximization (EM) algorithm is used to estimate the parameters of the model. The resulting pixel-cluster membership provides a segmentation of the image. The resulted regions correspond roughly to objects.

Some systems design their own segmentations in order to obtain the desired region features during segmentation, be it color, texture, or both [9,28–31]. These algorithms are usually based on k-means clustering of pixel/block features. In Ref. [9], firstly, an image is segmented into small blocks of size $4*4$ from which color and texture feature are extracted. Then k-means clustering is applied to cluster the feature vectors into several classes with each class corresponding to one region. Blocks in same class are classified into same region. A so-called KMCC (k-means with connectivity constraint) is proposed in Ref. [31] to segment objects from images. It is extended from the k-means algorithm. In this algorithm, the spatial proximity of each region is taken into account by defining a new center for the k-means algorithm and by integrating the k-means with a component labelling procedure.

The use of segmentation algorithm depends on the requirements of the system and the data set used. It is hard to judge which algorithm is the best. For example, JSEG provides color-texture homogeneous regions, while KMCC intends to obtain objects which are usually not homogeneous. Compared with JSEG, KMCC is computationally more intensive. JSEG and Blobworld segmentations seem to be the most widely used so far.

2.2. Low-level image features

Many sophisticated feature extraction algorithms have been designed and good surveys are available. Here we focus on the features used in RBIR systems with high-level semantics.

2.2.1. Color feature

Color feature is one of the most widely used features in image retrieval. Colors are defined on a selected color space. Variety of color spaces are available, they often serve for different applications. Description of different color spaces can be found in Ref. [32]. Color spaces shown to be closer to human perception and used widely in RBIR include, RGB, LAB, LUV, HSV (HSL), YCrCb and the hue-min-max-difference (HMMD) [21,25,27,31,33]. Common color features or descriptors in RBIR systems include, color-covariance matrix, color histogram, color moments, and color coherence vector [16,28,34–36]. MPEG-7 has included dominant color, color structure, scalable color, and color layout as color features [37]. In Ref. [38], the authors are interested in objects taken from different point of view and illumination. As the result, a set of viewpoint invariant color features have been computed. The color invariants are constructed on the basis of hue, hue-hue pair and three color features computed from reflection model.

Most of those color features though efficient in describing colors, are not directly related to high-level semantics. For convenient mapping of region color to high-level

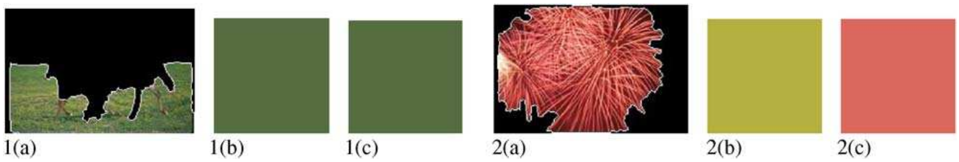

Fig. 2. Average color and dominant color: (a) original region; (b) average color; (c) dominant color.

semantic color names, some systems use the average color of all pixels in a region as its color feature [22,31,39]. Although most segmentation tends to provide homogeneous color regions, due to the inaccuracy of segmentation, average color could be visually different from that of the original region. In Ref. [25], a dominant color in HSV space is defined as the perceptual color of a region. To obtain dominant color, the authors first calculate the HSV space color histogram ($10 * 4 * 4$ bins) of a region and select the bin with maximum size. Then the average HSV value of all the pixels in the selected bin is defined as the dominant color. It is observed that in most cases, average color and dominant color are very similar, as in Fig. 2(1). However, in some cases, they can be visually very different as in Fig. 2(2).

The selection of color features depends on the segmentation results. For instance, if the segmentation provides objects which do not have homogeneous color, obviously average color is not a good choice. It is stated that for more specific applications such as human face database, domain-knowledge can be explored to assign a weight to each pixel in computing the region colors [22].

It should be noted that in most of the CBIR works, the color images are not pre-processed. Since color images are often corrupted with noise due to capturing devices or sensors, it will improve retrieval accuracy significantly if effective filter is applied to remove the color noise. The pre-process can be essential especially when the retrieval results are used for human interpretation. A number of such color filters are available for this purpose [32,40,41].

2.2.2. *Texture feature*

Texture is not so well-defined as color features, some systems do not use texture features [2,21,22,31,42]. However, texture provides important information in image classification as it describes the content of many real-world images such as fruit skin, clouds, trees, bricks, and fabric. Hence, texture is an important feature in defining high-level semantics for image retrieval purpose.

Texture features commonly used in image retrieval systems include spectral features, such as features obtained using Gabor filtering [8] or wavelet transform [9], statistical features characterizing texture in terms of local statistical measures, such as the six Tamura texture features [43], and wold features proposed by Liu et al. [44]. Among the six Tamura features: coarseness, directionality, regularity, contrast, line-likeness, contrast and roughness, the first three are more significant [43]. The other three are related to the first three and do not add much to the effectiveness of texture description. MPEG-7 has employed the regularity, directionality and coarseness as the texture browsing descriptor [33,37]. The wold features of periodicity, randomness and directionality have been proved to work well on Brodatz textures [45].

The limitation of Tamura features is that there was no work at multiple resolutions to account for scale. Wold feature is also affected by image distortions such as scale and orientation variations due to perspective distortion [30]. Though working well on Brodatz textures, these features are proved to be less effective when applied to natural scene image retrieval as texture regions in such images are not so structured and homogeneous [30].

Among the various texture features, Gabor features and wavelet features are widely used for image retrieval and have been reported to well match the results of human vision study [8,9,37]. Gabor filtering and wavelet transform are originally designed for rectangular images. However, regions in RBIR systems are of arbitrary-shapes. How to extract texture features from arbitrary-shaped regions in RBIR systems? In some systems, texture features are obtained based on the texture property of pixels or small blocks contained in the region [8,31]. For example, in Ref. [8], for each region, the mean of the texture features of all the $4*4$ blocks it contains is used as the region feature. The problem of such feature is that they cannot sufficiently describe the texture property of the entire region. An intuitive way to solve this problem is to extend the arbitrary-shaped region into a rectangular area by padding some values outside the boundary and then apply block transforms. However, as regions in real-world images are usually not homogeneous texture, such initial padding will introduce spurious components which do not describe the original region and hence degrade the performance of the texture feature obtained. Still another possible solution is to obtain an inner rectangle (IR) from a region onto which block transforms can be performed to generate coefficients from which texture feature can be calculated. This works well when the region texture is homogeneous and the IR carries enough information to describe the region's texture property. However, image regions in real-world images are usually not homogeneous. In addition, in many cases, we can only obtain an IR covering a small area of the original region. Hence, the texture feature obtained from IR cannot well represent the property of the entire region. To solve this problem, an efficient texture feature extraction algorithm for arbitrary-shaped regions is presented in Ref. [46]. This algorithm extends an arbitrary-shaped region into a rectangle area by initial padding. Then a projection onto convex sets

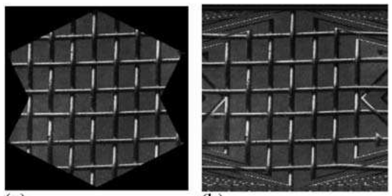

Fig. 3. Arbitrary-shaped region and padded results: (a) original region; (b) mirroring padded result.

(POCS) loop is applied to find a set of coefficients best describing the region by iterative projection between the image domain and its transform domain. Finally, texture features can be extracted from the coefficients obtained. Fig. 3 gives an example of initial padding.

The edge histogram descriptor (EHD) is found to be quite effective for representing natural images [37]. It captures the spatial distribution of edges, somewhat in the same idea as the color layout descriptor. To compute the EHD, a given image is first sub-divided into 4×4 sub-images, and local edge histograms for each of these sub-images is computed. Edges are broadly grouped into five categories: vertical, horizontal, 45°, 135° and neutral. Thus, each local histogram has five bins corresponding to the above five categories. The image partitioned into 16 sub-images results in 80 bins. These bins are non-uniformly quantized using 3 bits/bin, resulting in a descriptor of size 240 bits. But the EHD can be very sensitive to objects or scene distortions.

Huang and Dai have computed the gradient vector from the subband images of a wavelet decomposition as texture feature [47]. The gradient vector is a similar approach to EHD.

2.2.3. Shape

Shape is a fairly well-defined concept. Shape features of general applicability include aspect ratio, circularity, Fourier descriptors, moment invariants, consecutive boundary segments [48], etc.

Shape features are important image features though they have not been widely used in RBIR as color and texture features. Shape features have shown to be useful in many domain specific images such as man-made objects. For color images used in most papers, however, it is difficult to apply shape features compared to color and texture due to the inaccuracy of segmentation. Despite the difficulty, shape features are used in some systems and has shown potential benefit for RBIR. For example, in Ref. [31], simple shape features such as eccentricity and orientation are used. The system in Ref. [34] uses normalized inertia of order 1–3 to describe region shape. In Ref. [28], gross region shape descriptors based on area and second-order moments are used. MPEG-7 has included three shape descriptors for object-based image retrieval, one is the 3-D shape descriptor derived from 3-D meshes of shape surface, one is for region-based shape derived from Zernik moments and the other is for contour-based shape derived from curvature scale space (CSS) [37]. Although the CSS descriptor is invariant to translation, scaling and rotation, it is sensitive to general distortions which can be resulted from objects taken from different point of view. Mokhtarian and Abbasi have extended the CSS descriptor to be robust to affine transform which is a common way to approximate general shape distortions [49].

2.2.4. Spatial location

Besides color and texture, spatial location is also useful in region classification. For example, ‘sky’ and ‘sea’ could have similar color and texture features, but their spatial locations are different with sky usually appears at the top of an image, while sea at the bottom.

Spatial location usually are simply defined as ‘upper, bottom, top’ according to the location of the region in an image [50,51]. In Ref. [8], region centroid and its minimum bounding rectangle are used to provide spatial location information. In Ref. [31], spatial center of a region is used to represent its spatial location.

Relative spatial relationship is more important than absolute spatial location in deriving semantic features. 2D-string [52] and its variants are the most common structure used to represent directional relationships between objects such as ‘left/right’, ‘below/above’. However, such directional relationships alone are not sufficient to represent the semantic content of images ignoring the topological relationships. To better support semantic-based image retrieval, a spatial context modelling algorithm is presented in Ref. [53] which considers six spatial relationships between region pairs: left, right, up, down, touch and front. An interesting method was proposed by Smith et al. [29]. The system uses a composite region template (CRT) to define the spatial arrangement of regions and each semantic class is characterized by the CRTs obtained from a collection of sample images [29].

2.3. Similarity measure

In RBIR systems, image similarity is measured at two levels. The first is region-level. That is to measure the distance between two regions based on their low-level features. The second is at image level. That is to measure the overall similarity of two images which might contain different number of regions.

Most researchers employ the Minkowski-type metric to define region distance. Suppose we have two regions represented by two p dimensional vectors $(x_1, x_2, \ldots, x_p)$, $(y_1, y_2, \ldots, y_p)$, respectively. The Minkowski metric is defined as

$$d(X, Y) = \left(\sum_{i=1}^{p} |x_i - y_i|^r \right)^{1/r}. \quad (1)$$

Particularly, when $r = 2$, it is the well-known Euclidean distance (L_2 distance). When r is 1, it is the Manhattan distance (L_1 distance).

An often-used variant version is the weighted Minkowski distance function which introduces weighting to identify important features

$$d(X, Y) = \left(\sum_{i=1}^{p} w_i |x_i - y_i|^r \right)^{1/r}, \quad (2)$$

where w_i, $i = 1, \ldots, p$ is the weight applied to different features.

Other distances are also used in image retrieval, such as the Canberra distance, angular distance, Czekanowski coefficient [54], inner product, dice coefficient, cosine coefficient and Jaccard coefficient [55].

The overall similarity of two images is more difficult to measure. Basically, there are two ways.

(1) *One-One match*: This means each region in the query image is only allowed to match one region in the target image and vice versa. As in Ref. [56], each query region of the query image is associated to a single 'best match' region in the target image. Then the overall similarity is defined as the weighted sum of the similarity between each query region in the query image and its 'best match' in the target image, while the weight is related to region size.

(2) *Many-Many match*: This means each region in the query image is allowed to match more than one region in the target image and vise versa. A widely used method is the Earth Mover' Distance (EMD) [57]. EMD is a general and flexible metric. It measures the minimal cost required to transform one distribution into another based on a traditional transportation problem from linear optimization, for which efficient algorithms are available. EMD matches perceptual similarity well and can be applied to variable-length representations of distributions, hence it is suitable for image similarity measure in RBIR system [16,57].

Li et al. propose an integrated region matching (IRM) scheme which allows for matching a region of one image to several regions of another image and thus decreases the impact of inaccurate segmentation [34]. In this definition, a matching between any two regions is assigned with a significance credit. This forms a significance matrix between two sets of regions (one set is of the query image, another set is of the target image). The overall similarity of two images is defined based on the significance matrix in a way similar to EMD.

Though Minkowski metric is widely used in current systems to measure region distance, intensive experiments show that it is not very effective in modelling perceptual similarity [58]. How to measure perceptual similarity is still a largely unanswered question. There are some works done in trying to solve this problem. For example, in Ref. [58], a dynamic partial distance function (DPF) is defined, which reduces the dimension of feature vectors by dynamically choosing a smaller amount of dimensions. Let $\delta_i = |x_i - y_i|, i = 1, \ldots, p$, the authors define $\Delta_m = \{m$ smallest δ' s of $(\delta_1, \ldots, \delta_p)\}$. Then DPF is defined as

$$d(m, r) = \left(\sum_{\delta_i \in \Delta_m} \delta_i^r \right)^{1/r}. \quad (3)$$

There are two parameters to be adjusted m and r. Initial experimental results demonstrate that DPF can provide more accurate retrieval results than Minkowski metrics. However, the value of m is data-dependent, this makes the algorithm inflexible. In addition, to be broadly used in image retrieval systems, further study is required to confirm its performance in various applications.

In Ref. [59], a perceptual distance for shape similarity measure is presented. Each shape is characterized with a set of tokens. A metric distance between tokens is first defined then a non-metric distance is defined as the collection of token distance to measure shape similarity. The method can be extended into RBIR by treating image regions as the tokens.

Vasconcelos and Lippman proposed a multiresolution manifold distance (MRMD) for face recognition. In the MRMD, two images to be matched are treated as manifolds, and the distance between the two images are the one which minimizes the error of transforming one manifold into the other. In order to reduce the computation, the images are put into multiresolution analysis. The distance measure is suitable for image alignment applications like face recognition and video scene detection [60].

In Ref. [61], similarity measure between different types of image features is taken as a multilevel decision making process. Images in the database are represented by a number of MPEG-7 color and texture descriptors, these descriptors are put into a hierarchical decision fusion framework using fuzzy logic. The advantage of this similarity measurement is that different types of image features can be combined into an integrated feature. In their later work, the authors have extended the decision fusion framework into a supervised learning framework with RF from users [62].

3. Reducing the 'semantic gap'

The state-of-the-art techniques in reducing the semantic gap can be classified in different ways from different point of view. For example, by considering the application domain, they can be classified as those targeting at artwork retrieval [21], scenery image retrieval [27,28,31], WWW images retrieval [63,64], etc. In this paper, we focus on the techniques used to derive high-level semantics and identify five categories as follows. (1) Using object ontology to define high-level concepts [21,31,65–67]. (2) Using supervised or unsupervised learning methods to associate low-level features with query concepts [2,24,27,28,68]. (3) Introducing RF into retrieval loop for continuous learning of users' intention [16,31,69]. (4) Generating ST to support high-level image retrieval [29,70,71]. (5) Making use of both the textual

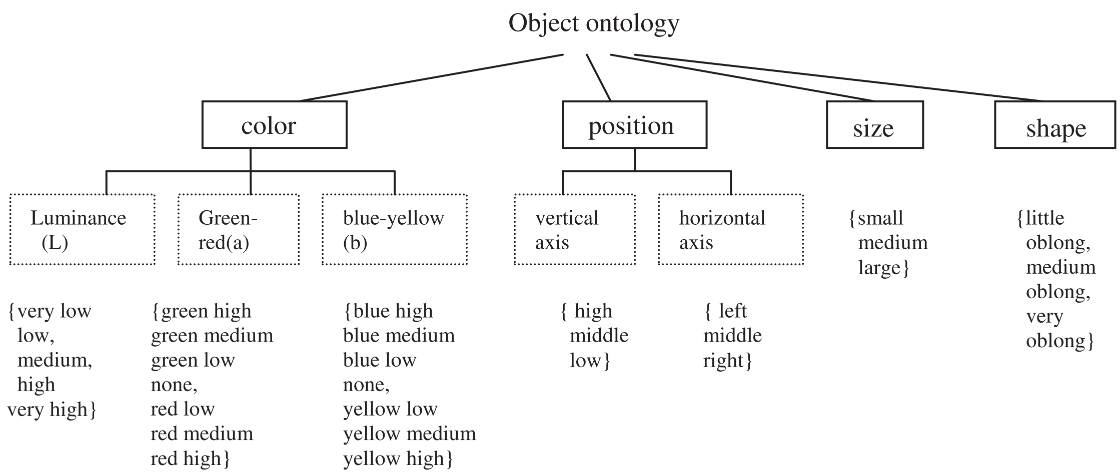

Fig. 4. Object ontology used in Ref. [32].

information obtained from the Web and the visual content of images for Web image retrieval [63,70,72]. Many systems exploit one or more of the above techniques to implement high-level semantic-based image retrieval. For example, (3) is often combined with (1), (2) or (5) [16,31,70,72], (5) is usually combined with the other four techniques [27,63,70].

3.1. Object-ontology

In some cases, semantics can be easily derived from our daily language. For example, sky can be described as 'upper, uniform, and blue region'. In systems using such simple semantics, firstly, different intervals are defined for the low-level image features, with each interval corresponding to an intermediate-level descriptor of images, for example, 'light green, medium green, dark green'. These descriptors form a simple vocabulary, the so-called 'object-ontology' which provides a qualitative definition of high-level query concepts. Database images can be classified into different categories by mapping such descriptors to high-level semantics (keywords) based on our knowledge [31,65–67,73], for example, 'sky' can be defined as region of 'light blue' (color), 'uniform' (texture), and 'upper' (spatial location).

A typical example of such ontology-based system is presented in Ref. [31]. In this system, each region of an image is described by its average color in lab color space, its position in vertical and horizontal axis, its size and shape. The object ontology is shown in Fig. 4.

Quantization of color and texture feature is the key in such systems. To support semantic-based image retrieval, a more effective and widely used way to quantize color information is by color naming. Although millions of colors can be defined in computer system, the colors that can be named by users are limited to about 10–20 [74,75]. Color naming models intend to relate a numerical color space with semantic color names used in natural language. The well-known color naming system is 'CNS' (color naming system) proposed by Berk, Brownston and Kaufman [75]. 'CNS' quantizes HSL space into 627 distinct colors. The basic idea is to quantize the hue value into a set of basic colors. Saturation and luminance are quantized into different bins as adjectives signifying the richness and brightness of the color. The complete set of generic hue names in CNS is *red*, *orange*, *brown*, *yellow*, *green*, *blue* and *purple*, with the addition of achromatic terms *black*, *gray* and *white*, form 10 base colors.

In Ref. [21], 12 hues are defined as fundamental colors, *yellow*, *red*, *green*, *blue*, *orange*, *purple*, and six other colors obtained as the linear combination of them. Then, five levels of luminance and three levels of saturation are identified. This results in 180 reference colors. To relate colors to expression (emotionally) and impression (visually) for painting retrieval, different types of contrasts are defined, light-dark contrast, warm-cold contrast, complementary contrast, etc. For example, colors of yellow, and orange are referred as warm, green and blue are referred as cold. Example query is like this 'find paintings with the following contrasts: light-dark, cold-warm'.

In Ref. [25], the dominant color of a region (in HSV space) is converted to a set of 35 semantic color names as: red, orange, yellow, brown, etc. Semantic color names are related to objects in natural scene images like grass, sky. Example query is 'find images with a sky blue region'. In Ref. [65], based on the author's observation that a small number of colors are usually sufficient to characterize the color information in image region, eight colors are defined based on their RGB values, *red*, *green*, *blue*, *yellow*, *magenta*, *cyan*, *black*, and *white*. These color names are related to objects in natural scenes, for example, white are related to snow, cloud, etc. In this way, the system reduces the 'semantic gap' and supports query by keywords.

Similar to CNS, there is a parallel need for a texture naming system which would standardize the description and representation of textures [76]. However, texture naming is found to be more difficult and so far there is no such a texture naming system available. As a first step towards creating a texture naming system, some researchers try to identify the important features human beings use in texture perception [43,76]. Based on subjective experiment, Rao and Lohse have shown that repetitiveness, directionality and complexity are the three attributes most important to human perception of textures [76]. However, how to obtain these features, and how to map other low-level texture features to these three domains are yet to be further studied [30,76].

Compared with color, texture is not well modelled and understood, much research still needs to be done. Instead of using texture names as keyword for query which is still impossible so far, some researchers quantize perceptual texture features into different intervals and define meaningful texture descriptors. In Refs. [66,67], Tamura features are quantized to different levels as very coarse, medium coarse, fine, very fine; low contrast, high contrast, etc. Combination of such features in logical relationships with *and*, *or* form queries like 'find very fine and low contrast textures'.

For database with specifically collected images, such simple semantics derived based on object-ontology may work fine. However, with large collections of images with various contents, more powerful tools are required to learn the semantics.

3.2. Machine learning

In most cases, to derive high-level semantic features require the use of formal tools such as supervised or unsupervised machine learning techniques [2,28,68,77]. The goal of supervised learning is to predict the value of an outcome measure (for example, semantic category label) based on a set of input measure. In unsupervised learning, there is no outcome measure, and the goal is to describe how the input data are organized or clustered [78].

3.2.1. Supervised learning

Supervised learning such as support vector machine (SVM) [24,27,79], Bayesian classifier [80] are often used to learn high-level concepts from low-level image features.

With strong theoretical foundations available, SVM has been used for object recognition, text classification, etc. and is considered a good candidate for learning in image retrieval system [35,69,81]. SVM is originally designed for binary classification. Assume that we have a set of training data $\{x_1, x_2, \dots, x_n\}$ as vectors in space $X \subseteq R^d$ belonging to two separate classes with their labels $\{y_1, y_2, \dots, y_n\}$ and $y_i \in \{-1, 1\}$. We want to find a hyper-plane to separate the data. Among many possible hyper-planes, the *optimal separating plane* (OSP) is the one which maximizes the margin (the distance between the hyper-plane and the nearest data point of each class). As in Fig. 5, the vectors lying on one side are labelled as -1, and those lying on the other side are labelled as $+1$. '*Support vectors*' refer to the training samples that lie closest to the hyper-plane. To learn multiple

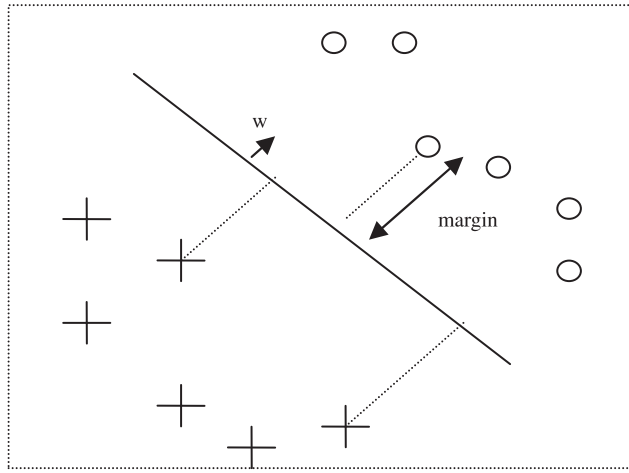

Fig. 5. A simple linear support vector machine.

concepts for image retrieval, a SVM has to be trained for each concept. For example, in Ref. [27], SVM is employed for image annotation. In the training stage, a binary SVM model is trained for each of the 23 selected concepts. In the testing stage, unlabelled regions are fed into all the models, the concept from the model giving the highest positive result is associated with the region.

Another widely used learning method is Bayesian classification [82]. In Ref. [68], using binary Bayesian classifier, high-level concepts of natural scenes are captured from low-level image features. Database images are automatically classified into general types as indoor/outdoor, and the outdoor images are further classified into city/landscape, etc. In Ref. [77], Bayesian network is used for indoor/outdoor image classification.

Other learning techniques such as neural network are also used for concept learning. In Ref. [28], firstly, the author choses 11 categories (concepts): brick, cloud, fur, grass, ice, road, rock, sand, skin, tree, and water. Then a large amount of training data (low-level features of segmented regions) are fed into the neural network classifiers to establish the link between low-level features of an image and its high-level semantics (category labels). A disadvantage of this algorithm is that it requires large amount of training data and is computationally intensive.

In Ref. [24], it is stated that conventional learning algorithms suffer from two problems: (1) a large amount of labelled training samples are needed, and it is very tedious and error-prone to provide such data; (2) the training set is fixed during the learning and application stages. Hence, if the application domain changes, new labelled samples have to be provided to ensure the effectiveness of the classifier. A bootstrapping approach is presented in Ref. [24] to tackle these problems. It starts from a small set of labelled training samples. By using a co-training approach, in which two statistically independent classifiers are used to co-train and co-annotate the unlabelled samples, the algorithm successively annotates a larger set of unlabelled samples. Their experiments show that an improvement of 10% in retrieval accuracy is obtained compared with SVM (400 labelled images for training), with much fewer labelled training samples (only 20 labelled seeds).

Besides the above mentioned algorithms, decision tree (supervised learning) techniques are also used to derive semantic features. Decision tree induction methods such as ID3, C4.5 (improved version of ID3), and CART build up a tree structure by recursively partitioning the input attribute space into a set of non-overlapping spaces [78]. A set of decision rules can be obtained by following the paths from the root of the tree to the leaves. In Ref. [2], the CART decision tree methodology is used to derive decision rules mapping global color distribution (HSV space color histogram) in a given image to textual description (four keywords: Sunset, Marine, Arid images and Nocturne). In Ref. [83], a C4.5 decision tree is built based on a set of images relevant to the query, and then used as a model to classify database images into two classes: relevant and irrelevant. This algorithm is used in the RF loop (will be discussed in Section 3.3) to provide relevant images for the user to label at next iteration. A similar methodology is employed in Ref. [84]. To enhance the performance of RF, the system uses ID3 decision tree to classify the images as relevant/irrelevant based on their color features, instead of directly ranking the images using the modified query obtained in last iteration.

Compared with other learning methods, decision tree learning is conceptually simple, robust with respect to incomplete and noisy input features. In addition, decision tree can be easily translated into a set of rules which can be integrated into an expert system for automatic decision making [78,85]. However, to be used in high-level concepts learning for image retrieval, the underlying problem is the lack of modularity [86,87]. For example, the methods mentioned above use nominal input attributes, but usually low-level image features have continuous values. Though some algorithms [88,89] have been designed to discrete continuous attributes, whether these generally designed algorithms can always provide meaningful splitting of image feature space is a question.

3.2.2. *Unsupervised learning*

Unlike supervised learning in which the presence of the outcome variable guides the learning process, unsupervised learning has no measurements of outcome, the task is rather to find out how the input feature are organized or clustered.

Image clustering is the typical unsupervised learning technique for retrieval purpose. It intends to group a set of image data in a way to maximize the similarity within clusters and minimize the similarity between different clusters. Each resulting cluster is associated with a class label and images in same cluster are supposed to be similar to each other.

The traditional k-means clustering and its variations are often used for image clustering. In Ref. [90], k-means clustering is applied to low-level color features of a set of training images. Then, the statistics measuring the variation with each cluster are used to derive a set of mappings between the low-level features and the optimal textual characterization (keywords) of the corresponding cluster. The mapping rules derived could be used further to index new untagged images added to the database. In Ref. [80], in order to automatically annotate database images for retrieval purpose, the system firstly cluster image regions into region clusters using a variant of k-means clustering called pair-wise constraints k-means (PCK-means) [91]. The number of clusters is empirically set to 300. Then, the posterior probability of every concept (59 concepts are defined for the image database used) given a region is derived using a semi-naïve Bayesian method [80]. Thus, a new image can be annotated by choosing the concepts with highest probabilities.

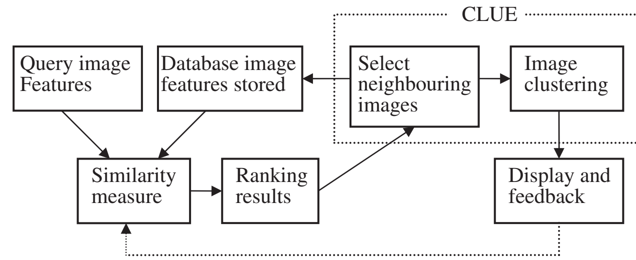

Fig. 6. Image retrieval with CLUE.

Due to the complex distribution of image data (data points are sampled from non-linear manifold), traditional methods such as k-means clustering often cannot well-separate images with different concepts [36]. To handle this problem, a spectral clustering method Normalized cut (NCut) [19] is proposed and has been successfully used in several applications such as image segmentation, image clustering. An extended version of NCut can be found in Ref. [92].

In Ref. [14], a method named 'CLUE' is presented to reduce the 'semantic gap' in CBIR. Unlike other CBIR systems which display the top matched target images to the users, this system attempts to retrieve semantically coherent image clusters. Given a query image, a collection of target images similar to the query are selected as the neighbour of the query. Based on the hypothesis that images of the same semantics tend to be clustered, NCut clustering is used to cluster these target images into different semantic classes. Then the system displays the image clusters and adjusts the model of similarity measure according to user feedbacks. Fig. 6 is the diagram of the system. Though successful in manifold data clustering, NCut cannot produce an explicit mapping function. To deal with new data points, similarities between the new points and all training data have to be measured. The computation of similarities could be very complicated due to the large size of training set [36]. To tackle these problems, in Ref. [36], a locality preserving clustering (LPC) method is proposed for image clustering. LPC can provide an explicit mapping function. Experimental results show that LPC provides retrieval accuracy comparable to that of NCut, but is more computationally efficient. In addition, retrieval result of LPC is proved to be more accurate than that of k-means clustering.

Probabilistic classification based on Bayes theory is among the most powerful clustering tools. The common maximum-a-posteriori or MAP classifier and its variation maximum-likelihood or ML classifier have shown great promise for the CBIR problem [93,94]. However, traditionally it is difficult to apply the classifiers due to the complexity of the MAP similarity function. In Ref. [94], Vasconelos has shown that the similarity function can be computed efficiently when vector quantizers and Gaussian mixtures are used as models for the probability density functions of the image features.

3.2.3. Object recognition techniques for image retrieval

Object recognition in images is an important problem in computer vision with applications in image annotation, surveillance and image retrieval. Supervised or unsupervised object recognition algorithms have been developed recently which can be used for semantic-based image retrieval. For example, in Ref. [95], an unsupervised scale-invariant learning method is presented to learn and recognize object class models from unlabelled and unsegmented cluttered scenes. In this method, objects are modelled as flexible constellations of parts and a probabilistic representation is used for all aspects of the object: shape, appearance, occlusion and relative scale. In recognition, this model is used in a Bayesian manner to classify images. The flexible nature of the model is demonstrated by excellent results over a range of datasets including geometrically constrained classes (such as faces, cars) and flexible objects (such as animals).

It is recognized that most users like to retrieve images based on objects in images. In Ref. [96], the authors developed a new semi-supervised version of the EM algorithm for learning the distributions of the object classes. Images are represented as sets of feature vector of multiple types of abstract regions. Each abstract region is modelled as a mixture of Gaussian distributions over its feature space. As regions used in recognition can come from different segmentation processes, the regions used are referred to as 'abstract region'. A key part of this approach is that it does not need to know the location of objects in each image. The experiments on a set of 860 images demonstrate the efficiency of the approach.

In Ref. [97], a two-phrase generative/discriminative learning approach is proposed that can learn to recognize objects using multiple feature types. The goal of this work is to develop a classification methodology for the automatic classification of outdoor scene images. The generative phrase normalizes the description length of images, which can have an arbitrary number of extracted features of each type. In the discriminative phase, a classifier learns which images, as represented by this fixed-length description, contain the target object. Their experimental results, using color, texture and structure features, show promising retrieval performance on 31 elementary object categories and 20 high-level concepts.

Most current approaches to learn visual object categories require thousands of training images. In addition, most algorithms presented in the literature have been tested on only about 10–20 object categories. In Ref. [98], an incremental Bayesian algorithm was developed to learn generative models of object categories from just a few training images. This method makes use of prior information, assembled from object categories which were previously learnt. A generative probabilistic model is used to represent the shape and appearance of a constellation of features belonging to the object. The parameters of the model are learnt incrementally in a Bayesian manner. The algorithm is tested on images of 101 widely varied object categories including face, laptop, strawberry, zebra, cup, chair, etc.

3.3. Relevance feedback (RF)

Compared with the off-line processing algorithms discussed above, RF is an on-line processing which tries to learn the users' intentions on the fly.

RF is a powerful tool traditionally used in text-based information retrieval systems [99]. It was introduced to CBIR during mid 1990s, with the intention to bring user in the retrieval loop to reduce the 'semantic gap' between what queries represent (low-level features) and what the user thinks. By continuous learning through interaction with end-users, RF has been shown to provide significant performance boost in CBIR systems [100,101].

A typical scenario for RF in CBIR is as below [102]:

(1) The system provides initial retrieval results through query-by-example, sketch, etc.
(2) User judges the above results as to whether and to what degree, they are relevant (positive examples)/irrelevant (negative examples) to the query.
(3) Machine learning algorithm is applied to learn the user' feedback. Then go back to (2).

(2)–(3) are repeated till the user is satisfied with the results. Fig. 7 shows a simple diagram of a CBIR system with RF.

A typical approach in step (3) is to adjust the weights of low-level features to accommodate the users' need (re-weighting). In this way, the burden of specifying the weight is removed from the user. Examples of such systems are in Refs. [16,100]. 'Re-weighting' dynamically updates the weights embedded in the query (not only the weights to different types of features such as color, texture, shape, but also the weights to different components in same feature vector) to model the high-level concepts and perception subjectivity [100].

Another method is called query-point-movement (QPM) [16,103,104]. QPM improves the estimation of the query

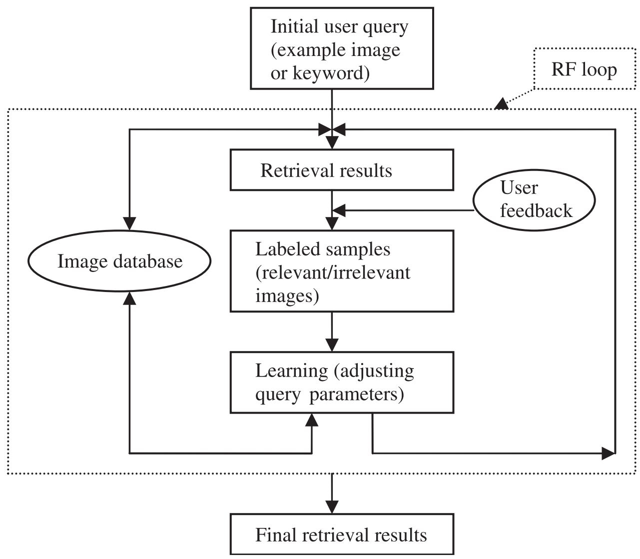

Fig. 7. CBIR with RF.

point by moving it towards the positive examples and away from the negative examples. The technique often used to iteratively improve this estimation is the Rocchio's formula [55,105,106]

$$Q' = \alpha Q + \beta\left(\frac{1}{N_{R'}}\sum_{i\in D'_R} D_i\right) - \gamma\left(\frac{1}{N_{N'}}\sum_{i\in D'_N} D_i\right), \quad (4)$$

where Q and Q' are the original query and updated query, respectively, D'_R and D'_N are the positive and negative samples returned by the user, $N_{R'}$, $N_{N'}$ are the number of samples in D'_R and D'_N, respectively, and α, β, γ are selected constants.

Both query re-weighting and QPM use nearest-neighbour sampling. That is, the system returns top ranked images for the user to examine and then the query is refined based on the user's feedback [35].

Machine learning techniques can be used in step 3 of RF loop as well. SVM is often used to capture the query concept by separating the relevant images from the irrelevant images using a hyper-plane in a projected space [16,31,69]. One advantage of SVM over other learning algorithms lies in its high generalization performance without the need to add a priori knowledge [69]. Another advantage is that it can work for small training sets [69,103]. To effectively use negative and non-labelled samples, and to learn a query concept faster and more accurately, an active learning method named SVMactive is proposed in Ref. [35].

Generally, the labelled samples provided by the user are limited, and such small training data set will result in weak classification of database images (as relevant/irrelevant). In Refs. [107,108], D-EM (Discriminant-EM) is used to boost the classifier learnt from the limited labelled training data. D-EM is an improved version of EM. EM has the disadvantage that a large number of parameters have to be estimated due to the high dimensionality of the generative model used to model data distribution. D-EM alleviates this problem by adding a D-step. The E-step estimates the membership for each unlabelled sample to augment the labelled training set. D-step identifies a mapping such that the data are clustered in the mapped feature space (a discriminating subspace). Based on the augmented data set, M-step estimates the parameters of the generative model in the lower dimensional discriminating space.

In some papers, decision-tree learning methods such as C4.5, ID3 are used in RF loop to classify the database images into two classes (relevant/irrelevant) depending on whether they are similar to the query image [83,84]. Then the relevant images are presented to the user for another round of RF.

There are different methods adopting different assumptions or problem settings, though under the same notion of 'RF'. A more detailed survey can be found in Ref. [102].

Most of the current RF-based systems uses only the low-level image features to estimate the ideal query parameters and do not address the 'semantic' content of images. Such system works well if the feature vectors can well describe the query. However, for specific object that cannot be sufficiently represented by low-level features, these RF systems will not return many relevant results even with a large number of user feedbacks [109]. To address the limitations of such systems, Ref. [109] provides a system named 'iFind' that performs RF on both the low-level feature vectors and the semantic contents of images represented by keywords. Firstly, a semantic network is constructed on top of an image database and a simple machine learning technique is used to learn from user queries and feedbacks to further improve this semantic network. With the semantic network formed on top of the keyword association with the images, the system can accurately derive the image sematic content for retrieval purposes. In this way, semantic and low-level feature-based RF are seamlessly integrated. Experiments on real-world image collections demonstrate its accuracy and effectiveness.

In most of the RF-based systems, the similarity measurement is fixed while the importance or weight of each descriptor is estimated through the RF from users. In contrast to this conventional approach, the Doulamis' have proposed a generalized nonlinear RF algorithm for image retrieval [110]. In this approach, instead of adjusting the degree of importance of each descriptor, the similarity measure itself is estimated through an online learning mechanism. The method is based on a recursive optimal estimation of a nonlinear parametric relation of known functional components. However, due to the problem of optimization itself, the computation can be expensive and the algorithm may be trapped into local minima.

3.4. Semantic template

'ST', though not yet widely used as the above mentioned techniques, is a promising approach in semantic-based image retrieval. ST is a map between high-level concept and low-level visual features. ST is usually defined as the 'representative' feature of a concept calculated from a collection of sample images [29,70]. In some systems, icons or sample images are provided as well for the convenience of user query [111].

In Ref. [111], Chang et al. introduced the idea of semantic visual template (SVT) to link low-level image feature to high-level concepts for video retrieval. A visual template is a set of icons or example scenes/objects denoting a personalized view of concepts such as meetings, sunsets. The feature vectors of these example scenes/objects are extracted for query process. To generate SVTs, the user first defines the template for a specific concept by specifying the objects and their spatial and temporal constraints, the weights assigned to each feature of each object. This initial query scenario is provided to the system. Through the interaction with users, the system finally converges to a small set of exemplar queries that 'best' match (maximize the recall) the concept in the user' mind.

The generation of SVT in Ref. [111] depends on the interaction with the user and requires the user's in-depth understanding of image features. This impedes its application to ordinary users. Compared to this, the system in Ref. [70] generates ST automatically in the process of RF, based on the understanding that RF is a process by which the user embodies the query semantics. Firstly, the user submits a query image with a concept (keyword) representing the image. After several iterations, the system returns some relevant images to the user. The feature centroid of these images are calculated and used as the representation of the query concept. Then the ST is defined as $ST = \{C, F, W\}$ with C the query concept, F the centroid feature obtained, and W being the weight applied to feature vectors. WordNet [112] is used in this system to construct a network of ST. During the retrieval process, once the user submits a query concept (keyword), the system can find a corresponding ST, and use the corresponding F and W to find similar images. The retrieval process is shown in Fig. 8. The user is imperceptible of the template generation, and can use the system even without any knowledge of feature representation.

Another interesting work is presented by Smith and Li in Ref. [29]. They use the so-called CRTs to decode image semantics. The CRTs define the prototypal spatial arrangements of regions in the images. Given a semantic class, a set of sample images are collected. The system firstly segments each image into homogeneous color regions and extracts five region strings by scanning the image vertically. Then, the system consolidates the region strings by counting the frequencies of the CRTs in the set of region strings obtained from all the sample images. Pooling together the CRTs from each semantic class forms a CRT library. Semantic description of unknown images can be generated by matching the arrangements of image regions to the CRTs in the library. The experiments with a set of 10 semantic classes (beach, building, crab, divers, etc.) demonstrate that this method

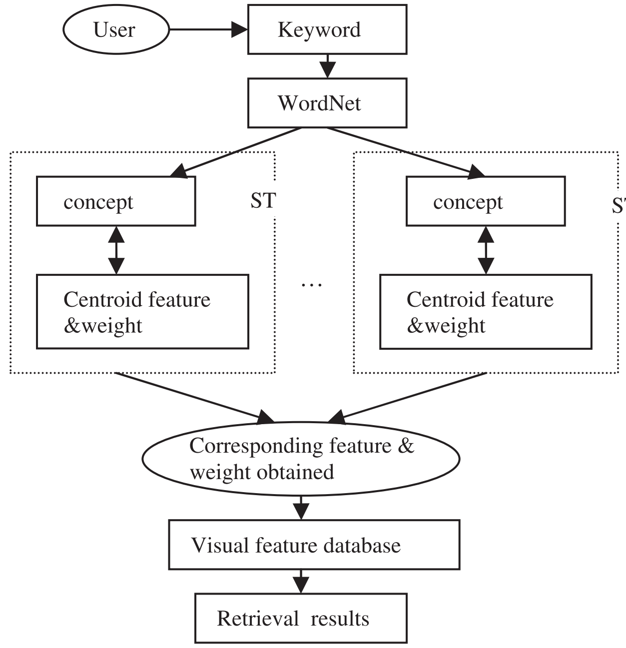

Fig. 8. Image retrieval supported by WordNet and ST.

improves retrieval accuracy compared to traditional methods using color histogram and texture features.

3.5. Web image retrieval

We classify Web image retrieval as one of the state-of-the-art techniques in high-level image retrieval rather than a specific application domain, as it has some technical difference from image retrieval in other applications.

One advantage in Web image retrieval is that some additional information on the Web is available to facilitate semantic-based image retrieval. For example, the URL of image file often has a clear hierarchical structure including some information about the image such as image category. In addition, the HTML document also contains some useful information in image title, ALT-tag, the descriptive text surrounding the image, hyperlinks, etc. However, such information can only annotate images to a certain extend [63,72].

Existing Web image searching such as Google and AltaVista search images based on textual evidences only [63,64]. Though these approaches can find many relevant images, the retrieval precision is poor as they cannot confirm whether the retrieved images really contain the query concepts. The result is that users have to go through the entire list to find the desired images. This is a time-consuming process as the returned results always contain multiple topics which are mixed together. To improve Web image retrieval performance, researchers are making effort to fuse the evidences from textual information and visual image contents.

In Ref. [72], a bootstrapping co-training framework is used to automatically annotate Web images with a given set

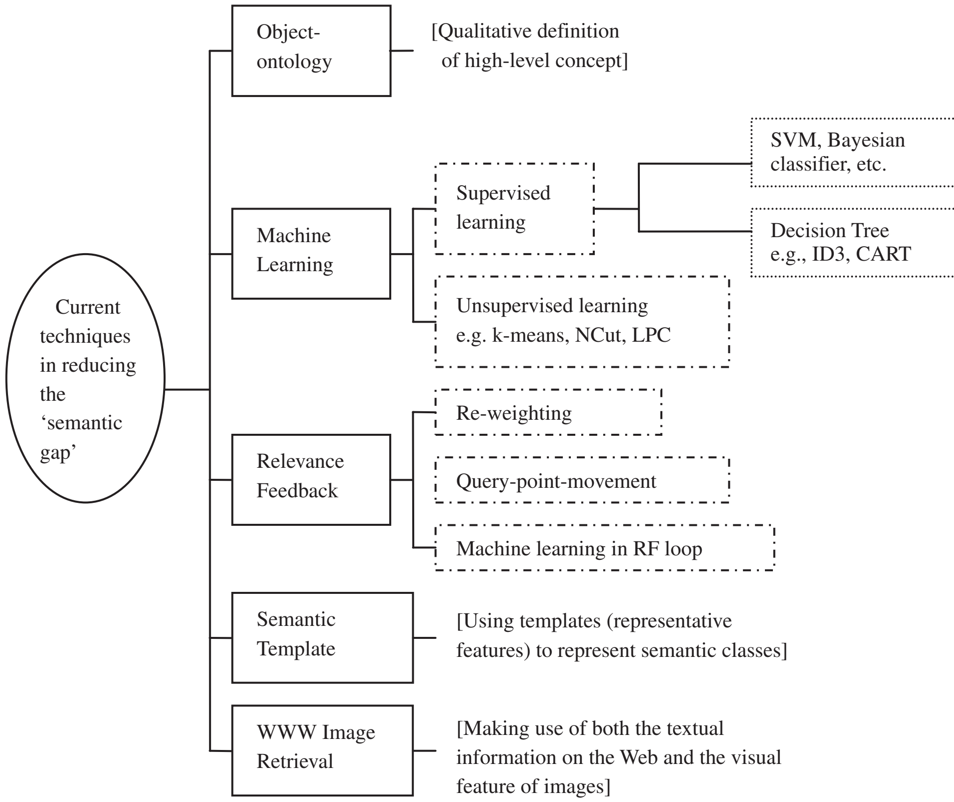

Fig. 9. Summary of the current techniques in reducing the 'semantic gap'.

of concepts for retrieval purpose. The system exploits the evidences from both the HTML text and visual features of images and develops two independent classifiers based on text and visual image features, respectively. The experimental results using a pre-defined set of 15 concepts demonstrate the substantial performance of the system. However, due to the inaccuracy in textural information extraction, the performance for certain concepts is not satisfied.

MSRA (Microsoft Research Asia) is developing a promising system for Web image retrieval [63,64]. The purpose is to cluster the search results of conventional Web image search engines, so that users can find the desired images quickly. Firstly, a intelligent vision-based segmentation algorithm is designed to segment a web-page into blocks. From the block containing the image, the textual and link information of an image can be accurately extracted. Then an image graph is constructed by using block-level link analysis techniques. Hence for each image, three types of representations are obtained, visual feature-based representation, textual feature-based representation and graph-based representation. Initial experimental results show that by combining textual and graph-based representation for image clustering, the system can reveal the semantic structure of the Web images. The search results are clustered into different semantic categories. For each category, several images were selected as representative images, so that the user can quickly understand the main topics of the search results. The images in each category are then reorganized based on their visual features to make the cluster more visually desirable to users. A thorough experimental evaluation needs to be carried out to investigate the robustness of the technique.

3.6. Summary

We have identified five major categories of current techniques used in reducing the 'semantic gap' as summarized in Fig. 9. Ontology-based algorithms are easy to design and are suitable to applications with simple semantic features. However, in most cases, machine learning techniques are required to learn more complex semantics. Due to its simplicity in implementation and the intuitive mapping from low-level features to high-level concepts using decision rules, decision tree is a promising tool for image retrieval if the learning problem can be well modelled. RF has been proved to be effective in boosting image retrieval accuracy. The problem is that most current systems requires about five or even more iterations before it converges to a stable performance level, but users are usually impatient and may give up after two or three tries [16,35,69,109]. Using ST to support image retrieval seems to be a practical and promising way to reduce the 'semantic gap'. Web image retrieval is an active research area, and we look forward to a practical product to be delivered in the near future. Many systems combine one or more of these techniques to implement semantic-based image retrieval. For example, RF is often combined with object-ontology, and machine learning [27,31,70], Web image retrieval systems usually employ one or more of the other four types of techniques [63,72] to derive semantic features.

Besides the major techniques discussed above, there are some other interesting works. For example, in Ref. [34], based on statistical parameters derived from some testing data, the database images are classified into semantic categories, such as texture and non-texture, graph and photograph. In Ref. [113], an image is spectrally separated into different layers, each retaining only pixels in areas with similar 'busyness'. In this way, it associates color features with perceptual meanings. For example, a flat area is very possible to be associated with backgrounds or interior of an object and a busy area may be associated with textured surfaces or object boundaries. The algorithm in Ref. [114] attempts to relate human perception to low-level image features by recognizing the central object of an image as the region with significant color distribution. This is based on the assumption that people tend to locate the most interesting object at the center of the frame when they take a picture.

4. Image database and performance evaluation

There are so far no standard test data and PE model for CBIR systems.

4.1. Image databases

In the surveyed papers, more than half of systems use a subset of Corel image dataset [115] to test retrieval performance, others use either self-collected images or other image sets such as LA resource pictures [116], Kodak database of consumer images [77]. Brodatz textures [45] are widely used in perceptual texture feature studies [30,44,67]. Images collected from Internet serve as another data source especially for systems targeting at Web image retrieval [24,63].

Many researchers tend to use natural scenery images as test bed for semantic extraction as such images are easier to analyse than other images. The reasons are tow-fold. Firstly, the types of objects are limited. Main scenery object types include sky, tree, building, mountain, grass, water, and snow, etc. Secondly, compared with other features of image regions, shape features are less important in analysing scenery images than in other images. Thus we can avoid our weakness in extracting high-level semantics from shape features due to segmentation inaccuracy [50].

Corel image database contains a large amount of images of various contents ranging from animals and outdoor sports to natural sceneries. These images are pre-classified into different categories of size 100 by domain professionals. Some researchers think that Corel image dataset meets all the requirements to evaluate an image retrieval system, because of its large size, heterogeneous content and human annotated ground truth available [101]. But some other researchers consider Corel image database not suitable for CBIR performance evaluation because the associated ground truth (category labels) are often too high-level to be useful in performance analysis [117,118]. Although it is still controversial about Corel images dataset is suitable for CBIR performance evaluation or not, it is so far the most widely used.

In our opinion, Corel image database is good in its large size and various contents available. However, to be used for CBIR performance evaluation, some pre-processing work is necessary for the following two reasons: (1) some images with similar content are divided into different categories. For examples, the images in 'Ballon1' and 'Ballon2' are actually in the same category, same for category 'Cuisine' and 'Cuisines'; (2) some 'category labels' are very abstract and the images within the same category can be largely varied in content. For instance, the category 'Australia' includes pictures of city building, crowds in street, Australian wild animals, etc. Fig. 10 gives a few examples. It is very difficult to measure image similarities within such groups.

Hence, it is appropriate to select a subset of these images as ground truth, or to make some necessary changes in setting group truth data.

Considering the above mentioned problems in Corel image database, in Ref. [119], a new reference data set is presented for evaluating image retrieval algorithms. The authors have collected a large data set of human evaluations of retrieval results, both for query by image example and query by text. The data domain is 16,000 images from the Corel data set. Totally 20,000 query-result pairs were evaluated for query by example image, and 5000 pairs for query by text. The data is claimed to be independent of any particular image retrieval algorithm and can be used to compare many algorithms without further data collection. The data and calibration software are available online at http://kobus.ca/research/data.

For video retrieval, standard test data is available from TREC video retrieval evaluation (TRECVID). The TREC conference series is sponsored mainly by National Institute of Standards and Technology (NIST) to encourage research in information retrieval by providing large test collection, uniform scoring procedures and a forum for organizations interested in comparing their results. In 2001 and 2002, a video 'track' is sponsored for research in automatic segmentation, indexing and content-based retrieval of digital video. From 2003, this track became an independent evaluation workshop two days before TREC conference.

4.2. Vocabulary

To find an 'ideal' vocabulary representing the rich semantics of images is not an easy task. In Ref. [120], psychophysical experiments are conducted to gain insight into the semantic categories that guide the human perception of

Fig. 10. Example corel images from category 'Australia'.

image similarity. By analysing the perceptual data, the most important 20 semantic categories (for example, portraits, crowds, cityscapes) in the perception of image similarity were established. Then 40 low-level features were discovered that best describe each category, such as number of regions, color composition, number of edges, and the presence of central object. In Ref. [121], the authors establish a so-called 'lexical basis functions' which contains 98 words to represent images. In Ref. [112], a 'WordNet' on-line lexical reference system is described. 'WordNet' organizes English words into synonym sets, each representing one underlying lexical concepts. It is a 'dictionary' based on psycholinguistic principles so that searching can be done conceptually instead of alphabetically.

The primary criterion in choosing a set of categories is to ensure that they are sufficiently well-defined in terms of the image descriptors and yet general enough to give meaningful semantic associations [28]. The vocabulary used in a system depends mainly on the image data set used. For natural scenery images, usually the images are classified into about 10–20 categories including water, sky, tree, sand, grass, mountain, snow, etc. For example, in Ref. [28], 11 categories are chosen: brick, cloud, fur, grass, ice, road, rock, sand, skin, tree, and water. In Ref. [116], 10 semantic categories are defined: beach, building, Disneyland, desert, mountain, freeway, downtown, park, people, and unknown. In Ref. [50], the authors discuss the identification of six high-level scenery features: sky, building, tree, water wave, placid water, and ground.

However, for real-world image database retrieval, such small vocabulary is far from enough. It is believed that humans can recognize about 5000–30,000 object categories. Category learning with such large vocabulary is very difficult and much work still remains to be done in this area. In Ref. [98], an incremental Bayesian algorithm is developed to recognize 101 object categories. To our knowledge, this is so far the largest vocabulary set used in object recognition.

4.3. Performance evaluation

Usually precision and recall are used in CBIR system to measure retrieval performance. Precision (Pr) is defined as the ratio of the number of relevant images retrieved (N_r) to the number of total retrieved images K. Recall (Re) is defined as the number of retrieved relevant images N_r over the total number of relevant images available in the database N_t

$$\mathrm{Re} = N_r/N_t, \quad \mathrm{Pr} = N_r/K. \tag{5}$$

It is 'ideal' to have both high Pr and Re. Therefore, instead of using Pr or Re individually, usually a joint Pr(Re) curve is used to characterize the performance of image retrieval system [101].

As recall is often low in color image retrieval system, Pr(Re) curve is less meaningful than it is in text-based retrieval systems. Many researchers are adopting precision-scope curve to evaluate image retrieval performance [122]. Scope(Sc) specifies the number of images returned to the user, that is K in Eq. (5). For a particular scope Sc, Pr(Sc) can be computed as

$$\mathrm{Pr}(Sc) = N_r/Sc. \tag{6}$$

Another performance measure used is the rank (Ra) measure [122–124]. The rank measure is defined as the average rank of the retrieved images. It is clear that the smaller the rank, the better the performance.

While Pr(Sc) only cares if a relevant image is retrieved or not, $Ra(Sc)$ also cares the rank of the retrieved image. Suppose there are two retrieval systems, 'system1' and 'system2'. If $\mathrm{Pr}_1(Sc) > \mathrm{Pr}_2(Sc)$ and $Ra_1(Sc) < Ra_2(Sc)$, then definitely 'system1' is better than 'system2'. However, if $\mathrm{Pr}_1(Sc) > \mathrm{Pr}_2(Sc)$ and $Ra_1(Sc) > Ra_2(Sc)$, we cannot tell which system is better.

5. Research issues

Most of the current image retrieval systems focus on improving the accuracy of retrieval. From system point of view, there are some other issues to be further studied.

5.1. Query language design

Query mechanisms play an important role in bridging the 'semantic gap'. A specialized query language designed for CBIR could provide a means of addressing many of the problems associated with conventional query paradigms such as query-by-example and query-by-sketch. However, there has little recent work addressing this issue [125].

In Ref. [125], the authors argue that "query languages constitute an important avenue for further work in developing CBIR query mechanisms." They design a retrieval language—the OQUEL query language. The retrieval process takes place entirely within the ontology domain and is defined by the syntax and semantics of the query. The format of text queries is highly flexible as the system does not reply on the pre-annotation of images. The vocabulary has 400 words relating to the semantic descriptors (assigned to segmented regions on the basis of low-level features) including synonyms obtained by WordNet [112]. Query example, "some green colored vegetation in the center which is of similar size as blue sky at the top." The OQUEL language supports queries with either simple keyword phrases or complex compound.

In Ref. [51], a natural query language is designed for querying image databases. The vocabulary of the query language is based on the concept of 'semantic indicators' (elementary semantic categories, such as sky, flower), while the syntax captures the basic patterns in human perception of semantic categories (such as 'crowds', 'outdoor scenes') [51]. The language is claimed to be simple yet expressive. It is simple as the words of the language are almost limited to the names of the semantic indicators which are often described with a single word (e.g., snow, mountain). These words can be used to construct sentence expressing an assertion about the image. For instance, "the number of skin regions is greater than 5". During retrieval process, all the database images are tested against the query and only those satisfying the assertion are selected.

In Ref. [126], the authors use sub-image to represent the semantic content of the query in a Search and Retrieve Web (SRW) service for searching databases containing metadata and objects. The semantic content is captured using the multiscale color coherent vector and the texture features computed from wavelet decomposition. The user can use the sub-image query to express 'find a picture with person or object like this', 'find a painting with this class of cracks', etc.

Compared with the other methods in reducing the 'semantic gap', query language is relatively ill-understood and deserves greater attention [125].

5.2. High-dimensional indexing of image features

As the size of image database is increasing rapidly, retrieval speed will be an important factor to be concerned. Hence off-line multi-dimensional image data indexing is more and more necessary. Among the surveyed papers, only a few include multi-dimensional feature indexing as an integrated part of their CBIR systems. For example, in Ref. [127], a k-means clustering algorithm [128] is used to cluster regions according to their features. In Ref. [129], R-tree [130] is used to index MBR (maximum bounding box) of regions.

As the dimensionality of image features are usually high (up to tens or hundreds), traditional indexing algorithms such as k-d-b tree [131], quad-tree [132], and R-tree [130] are not suitable for image feature space indexing, due to the well-known 'curse of dimensionality' problem [133]. That is, the performance of these indexing algorithms degrades as the dimensionality of feature space increases. It is reported that when the dimensionality is above 10, the performance is no better than a simple sequential scan [134]. To relieve this problem, high-dimensional indexing algorithms such as X-tree [135], VA-file [134], and i-Distance [136] have been introduced. However, such algorithms focus only on how to index but not what to index. That is, they are designed without considering the specific properties of image features.

Some effort has been made in designing indexing algorithms specifically for image database. For example, in Ref. [137], a prototype image database system is implemented—the FIDS (Flexible Image Database System) system. In this system, the bare-bones triangle inequality algorithm is used to index image data and to sharply reduce the number of images needed to be directly compared to a query image for a given distance measure. FIDS system allows user great flexibility in run-time to find similar images using complex combinations of many pre-defined distance measures. In Ref. [138], a RBIR system using index is designed. In this system, the regions in the database images are indexed using an algorithm named A_0^{WS} to speed up the evaluation of k-nearest neighbor queries. This algorithm computes the optimal matching between regions in the query image and regions in a database image, so as to maximize the overall similarity score between images.

Further work is still to be done in efficient high-dimensional image feature indexing for real-world image database retrieval.

5.3. Standard DBMS extended for image retrieval

In many image retrieval systems such as Photobook [5], the data and features are typically stored in files addressed by names. When trying to scale up to a large database and a large number of users, this approach is likely to run into data integrity and performance problems. It is clear that when large image database come into view, the connection between CBIR and database management system (DBMS) is inevitable.

QBIC [4] and Virage [6] systems have taken one step beyond the read-only database and extended standard DBMS for image retrieval. In Ref. [139], a relational database system POSTGRES is used for storing and managing digital images and their associated textual data.

Making image retrieval as a plug-in module in an existing DBMS not only solves the image data integrity problem and allows dynamic updates, but also provides natural integration with features derived from other sources [15]. A truly integrated CBIR system would require the integration of content-based similarity, interaction with users, visualization of image database, database management for retrieval relevant images, etc. [15].

5.4. Standard image testbed and performance evaluation model

Though many researchers choose to use Corel images as test data to evaluate their CBIR systems, there is so far no standard test bed and different subsets of Corel images are used in different systems for performance evaluation. In addition, though precision and recall are often used to measure retrieval performance, the queries performed by different researchers are usually different. Hence, it is hard to compare the performance of different CBIR systems.

In Ref. [118], using same subset of Corel images and the same set of performance measures, the authors evaluate the retrieval performance of same CBIR system in different ways, by submitting different query images and by setting different ground truth data. The results show that it is very easy to get different retrieval performance, even with the same image collection, the same CBIR system and the same performance measures. It demonstrated that it is impossible to objectively compare the performances of different CBIR systems unless it is clearly stated which images were used as test data, which were used as queries, and which parameters have been used to measure performance.

Hence, a standard image database with a query set and corresponding performance measure model is highly in need for objective performance evaluation of CBIR systems.

6. Conclusions

Research in content-based image retrieval (CBIR) in the past has been focused on image processing, low-level feature extraction, etc. Extensive experiments on CBIR systems demonstrate that low-level image features cannot always describe high-level semantic concepts in the users' mind. It is believed that CBIR systems should provide maximum support in bridging the 'semantic gap' between low-level visual features and the richness of human semantics.

This paper provides a comprehensive survey of recent work towards narrowing down the 'semantic gap'. We have identified five major categories of state-of-the-art techniques: (1) using object ontology to define high-level concepts; (2) using supervised or unsupervised machine learning methods to associate low-level features with query concepts; (3) introducing relevance feedback into retrieval loop for continuous learning of users' intention; (4) generating semantic template to support high-level image retrieval; (5) making use of the textual information on the Web and the visual content of images for WWW image retrieval. We observe that though significant amount of work has been done in this area, there is so far no generic approach for high-level semantic-based image retrieval. In addition, current systems focus on retrieval at Level 2, and there is yet no good solution for Level 3 retrieval.

Focusing on the differences between CBIR with high-level semantics and traditional systems with low-level features, this paper also provides useful insights into how to obtain salient low-level features to facilitate 'semantic gap' reduction. In addition, current techniques in image similarity measure are described. As conventional Minkowski metric-based similarity measure cannot effectively model human perception, perceptual image similarity measure is to be further studied. Test dataset and performance evaluation of CBIR systems are also discussed. We believe that establishing a standard test set and evaluation model is necessary for objective performance comparison.

Based on the current technologies available and the demand from practical applications, a few open issues are identified from system point of view, including query-language design, integration of image retrieval with database management system, high-dimensional image feature indexing, etc.

To implement a full-fledged image retrieval system with high-level semantics requires the integration of salient low-level feature extraction, effective learning of high-level sematics, friendly user inferface, and efficeint indexing tool. Most systems understandably limit their contributions to one or two of these components. A CBIR framework providing a more balanced view of all the constituent components is in need.

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