

Raport Badawczy
Research Report

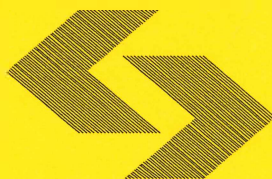
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**Content-based
image retrieval
tools and techniques**

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Content-Based
Image Retrieval
Tools and Techniques

In the beginning was an image.

To my mother
who inspired me
to develop intellectually

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2 The Concept of the Content-Based Image Retrieval

2.1 Introduction

Image retrieval is part of pattern recognition which, generally speaking, is a branch of data mining. The algorithms, tools and techniques applied to the process of image search and retrieval come, nevertheless, from different areas of data mining, for example, statistics, computer vision, signal processing, image processing itself. This is due to the fact that multimedia databases cover text, audio, video and image data.

The construction process of a content-based image retrieval (CBIR) system is, by its nature, very challenging because it needs to connect three intrinsic tasks: (i) how to mathematically describe an image so that we can compare two or more images, (ii) how to find similarity or dissimilarity between images described in an abstract way, (iii) how to attribute image description in the semantic meaning.

In order to live up to this expectations, each CBIR system has to consist of mandatory components, such as: an image repository (mostly a DB), an image processing module for extracting global or local image features, a search engine which indexes images and finds the similarity between them, and an interface for visual interaction with the user. In modern systems these components can possess many auxiliary elements which increase their effectiveness.

The story of a scientific approach to image retrieval began in the early 1980s, but the forerunner of content-based image retrieval (CBIR) was Toshikazu Kato [14], who, in 1992, entitled his article 'Database architecture for content-based image retrieval'; formally introducing this term into image processing. His concept connected the query by example with its description by the user. Thanks to this, the graphical features from the image were connected with a visual semantic concept expressed by the user.

Another milestone was the entire issue of *IEEE Computer* in September 1995, focused exclusively on the latest developments in image retrieval where Gudivada and Raghavan [15] introduced the general concept of CBIR systems and the important research areas, Flickner et al. [16] presented QBIC (Query by Image

Content) architecture and a data model for images and videos, Ogle and Stonebraker [17] applied the relational database management system to image retrieval from the State of California Department of Water Resources, Srihari [9] proposed a new approach to face recognition based on annotated photographs, taking into account spatial, characteristic and contextual constraints, and Metroda and Gary [18] based their system on a similar-shape retrieval method for selected objects.

In spite of its young age, CBIR represents a fully fledged methodology and a dynamic field of research. There is no universal CBIR system because, as we understand it today, it is a technology that helps to organize digital picture collections by their visual content with preliminary attempts at semantic search.

2.2 Main Problems

Perception is a manner of understanding or interpreting an idea, concept or thing. So image perception is the ability to interpret the surrounding visual information. But our interpretation depends on our knowledge and experience. If we do not know something we cannot identify that properly, but we attempt to identify that as something the most similar to a thing well-known to us.

One of the examples of such tricky images is the famous drawing of a young and old woman shown in Fig. 2.1. We present it here in order to draw the reader's attention to the problem that we face when we want to find a proper image.



Fig. 2.1 A young and old woman drawn by an anonymous German postcard designer, 1888.

The main problem which arises with the content-based image retrieval is how to find the semantic information in an image. From the technical point of view, it means that a computer should understand the image in the way a human perceives it. But even so, it is ambiguous, as Fig. 2.1 presents.

The next problem connects closely with annotations, and more generally, with putting a query in a natural or artificial language. First of all, an image is more universal than a word because a graphical object is understandable independently of the user's language. If we ask about a lamp, the system can display all lamps which have been annotated as a lamp. A small sample of the variety of lamps can be seen in Fig. 2.2. It is hardly likely that among these images the user will find that particular one he/she has been looking for. Moreover, if you ask about a lamp in a language other than that of the system, the system will answer that there is no such object or image.

In this situation, it seems natural to design a graphical user interface which enables the user to ask a graphical query. The implementation of this idea is burdened with a whole host of technical problems which are presented in detail in Chapter 8.

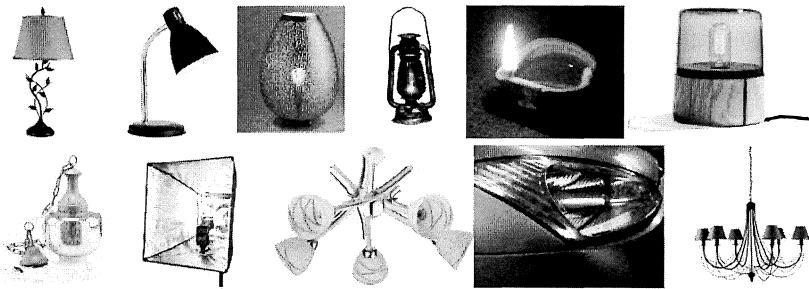


Fig. 2.2 Example of the system answer to a query containing the word 'lamp'.

Additionally, many attempts have been made to present the retrieval results in a proper way. The most classical method is to display retrieved images in order from the most similar to the least or in a 2D window, for example, as it is depicted in Fig. 2.2. A more advanced 3D visualization is shown in Fig. 2.3 and Fig. 2.4.

The last, but not least problem, is 'big data'. It is a dilemma which manifests itself in CBIR in two forms: a huge number of images or objects to search among and a huge size of the images. The best example of the former is Google, which looks through billions of images located on billions of websites. The latter group consists of satellite images and, more and more often, medical ones. We have to remember that satellite images are characterised by not only a great spatial resolution but also a spectral resolution. A spatial resolution is the pixel size of an image represents the size of the area in m^2 or cm^2 . A spectral resolution is defined as the wavelength interval which means the lengths of electromagnetic waves which are registered by satellite sensors. Because of this fact satellite images are so big that handling them is very time consuming.

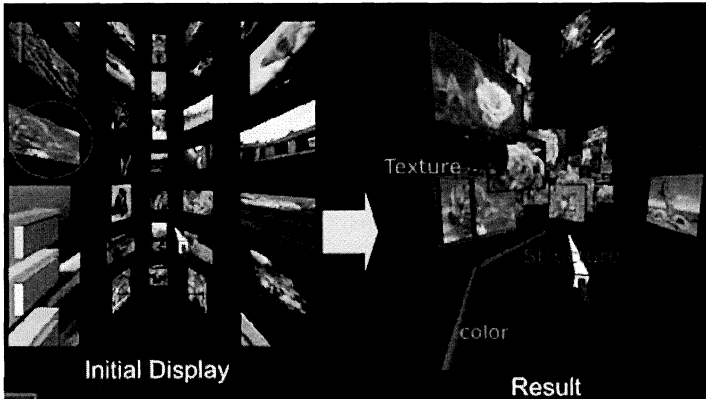


Fig. 2.3 Example of 3D visualization of results obtained from a CBIR system [19].

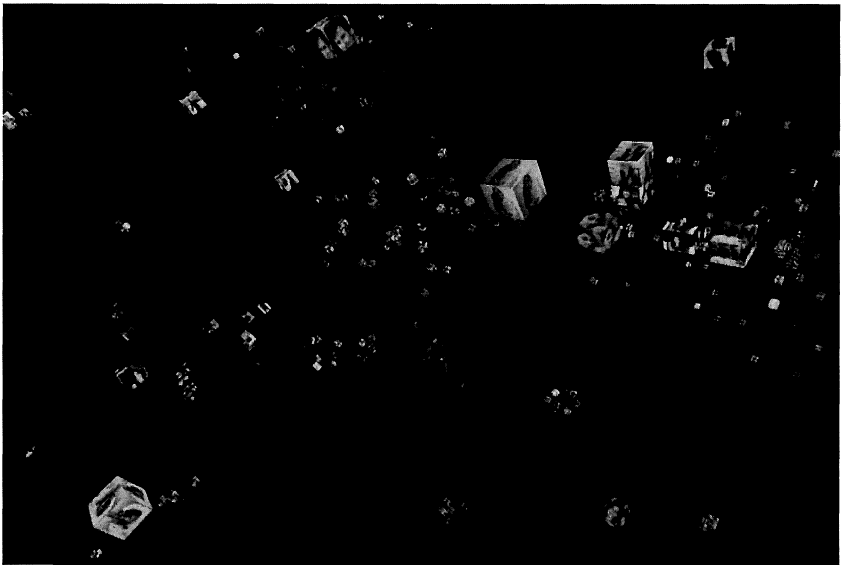


Fig. 2.4 3D visualization of connections between users on Facebook Network FritWork THREE.js created by Saurin Shah [20].

To overcome the above-mentioned obstacles, the CBIR constructors willingly reach over many neighbours search areas, such as discrete mathematics, statistics, stochastics, widely understood data mining and many others.

2.3 Criteria for the Classification of CBIR Systems

CBIR systems have been developed for different kinds of users (see Chapter 10 sect. 3). Below, we would like to present the system aspects which have been taken into account by their creators. According to Chang et al. [21], the classification of CBIR systems can be based on different criteria:

- The level of automation of feature extraction and index generation.** At present, we can observe rapid progress in the automatic low-level feature extraction methods but much slower development of mid-level features, namely, segment extractions [22]. The most state-of-the-art method in this category is the scale-invariant feature transform (SIFT) [23], [24] and its modifications (described in Chapter 3.) which generate a large collection of feature vectors, each of which is invariant to image translation, scaling, and rotation, partially invariant to illumination changes and unaffected by local geometric distortion. Dominant orientations are assigned to localized key-points. Index is generated based on storing SIFT keys and identifying matching keys from the new image. However, object classification remain still a complicated task.

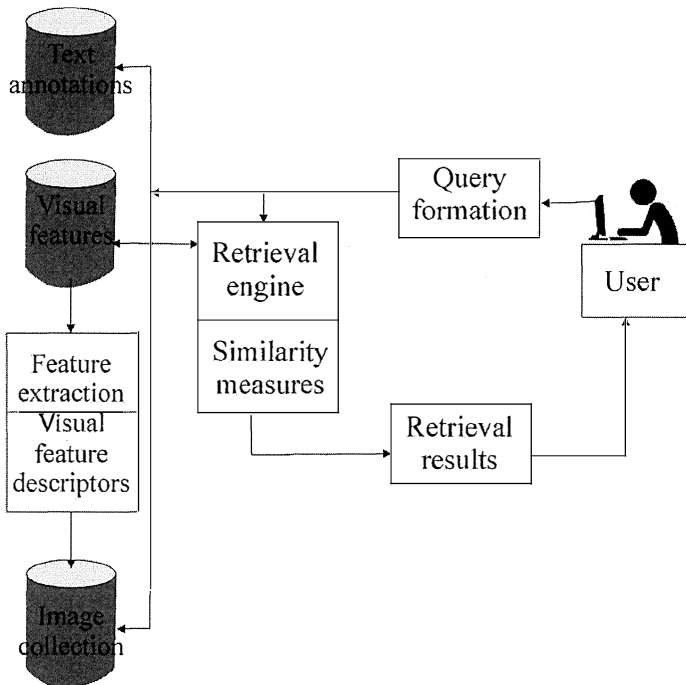


Fig. 2.5 General CBIR architecture.

- **The level of integration of multimedia modalities.** Media modalities cover images, video, films, graphics, multimodal satellite images, text and audio files. The most evident multimedia examples can now be found in medicine [25], where images acquired from different imaging techniques are combined for a 2D or 3D projection. The most dynamic development can be observed in video and film retrieval where particular images or objects need to be traced down or some scenes have to be selected from the whole material. In this area the most rapid achievements are noticeable in news agencies, where there is a continual downpour of new information. Effective retrieval of the relevant fragment of a film is a very challenging task in any news agency's video databases.
- **The level of adaptability to the needs of users and the query.** The most difficult issue in multimedia information retrieval is how to make a query describing the needs of the user. At present, the user requirements are reflected in the query asking methods, which can be generally [26] divided into:
 - Interactive techniques based on feedback information from the user, commonly known as relevance feedback (RF) [27], [28];
 - Automated techniques based on the global information derived from the entire collection;
 - Automated (might also be interactive in some cases) techniques based on local information from the top retrieved results, commonly known as local feedback or collaborative image retrieval (CIR) [29] which is a powerful tool to narrow down the semantic gap between a low- and high-level concept.

In global analysis, all the documents in the collection are indexed. This structure is then used to select additional terms for the query expansion. In local analysis, only the top retrieved documents for a query are examined (usually without any assistance from the user) in order to define the terms for the query expansion as a global relationships [30]. Large modern DBs actively employ user's interaction, namely, relevance feedback by labelling some top similar and dissimilar images as positive and negative samples. Images labelled in this way are incorporated into a training set. A more precisely labelled training set boosts algorithms to build a wider boundary between clusters [31], [32], [33].

- **The level of abstraction.** Among many CBIR systems available on the market, four main approaches to image retrieval can be identified. Firstly, images are determined by text annotations. Secondly, images are retrieved by matching an example based on low-level descriptors, such as colour, texture, shape, etc. [34]. Thirdly, some semantic information is selected from the images analysed to retrieve a similar scene [35], [36], [37]. Fourthly, deep learning is applied based on neural networks.
- **The level of generality of the visual information domain.** Image information depends on the image domain. The most general images are found on the WWW. Medical images are the most varied because a vast array of diagnostic devices generates them, for example, magnetic resonance imaging (MRI), X-ray computer tomography (CT), positron emission tomography (PET) [25],

medical ultrasonography, endoscopy, elastography, tactile imaging, thermography or medical photography. Another example can be satellite images, where a multispectral projection is most frequently used. Users of each domain require different information, which results in different methods of image processing.

- **The level of automation of the database collection.** Different image collections are acquired by means of diverse methods. Automatic acquisition is generally used in monitoring different processes, ranging from biological in microscopic scale [38] through industrial - machine vision [39] - up to geological, visible from satellite in macro scale. Personal images (portraits) are acquired manually unless they are photographed from a CCTV at airports or other monitored objects.

Now, deep learning [40] and convolutional neural networks (CNN) are considered some of the most powerful techniques and they deal with the largest image DBs such as Google's or ImageNet's (described in Chapter 6 sect. 2).

- **The level of information retrieval.** There are two most frequently used measurements, *recall* and *precision*, to evaluate the performance of the retrieval system. For a query q , the database set of images relevant to the query q is denoted as $R(q)$, and the retrieval result of the query q is denoted as $Q(q)$. The precision 2.1 of the retrieval is defined as a fraction of the retrieved images that are indeed relevant to the query:

$$precision = \frac{|Q(q) \cap R(q)|}{|Q(q)|} \quad (2.1)$$

The recall (2.2) is the fraction of relevant images that are successfully returned by the query:

$$recall = \frac{|Q(q) \cap R(q)|}{|R(q)|} \quad (2.2)$$

Usually, precision and recall are only rough descriptions of the performance of the retrieval system because recall tends to increase, while at the same time precision is likely to decrease.

Image and video retrieval is based on how the contents of an image or a chain of images can be represented. The users of a CBIR system have a diversity of goals, in particular, *search by association*, *search for a specific image*, or *category search* [41].

The search by association often implies iterative refinement of the search, the similarity or the examples with which the search was started as the user has only vague aim of an image of interest. Systems in this category typically are highly interactive, where the specification using sketches or example images. The search for a precise copy of the image in mind or for another image of the

same object assumes that the target can be interactively specified as similar to a group of given examples.

For a given query, the system first retrieves a list of images ranked according to a predefined similarity metric. Gradually, the images start to be analysed as a “local concept” space which means that the perceptually and semantically distinguishable colour and texture patches from local image regions in individual images are examined. Then, a similarity can be expressed as a comparison of the query to the whole collection, or only as the local analysis for the correlations between the concepts based on the co-occurrence pattern [30]. Another approach takes into account multi-set data mining and object spatial relationship in a three stage search engine [42].

With the growing amount of images one of the latest developments is the Peer-To-Peer (P2P) CBIR search engine [43]. It has been designed to provide multi-instance query with multi-feature types to effectively reduce network traffic and maintain high retrieval accuracy. These systems have also been designed to provide scalable retrieval among the fully centralized and fully de-centralized database framework, which can adaptively control the query scope and progressively refine the accuracy of retrieved results.

At present, many commercial and academic search engines are offered (a list on the WWW page [44]). The recent progress in image retrieval has been made due to scene understanding [35], [37], [45].

- **The level of visual information compression.** Modern technologies enable us to use visual information, practically, in all user’s front-end equipment. As visual information is very resource consuming, information distribution requires that data transmission is carried out only in a compressed form [46], [47]. Both image compression and transmission have forced the development of many new methods of sending data. Depending on compression rates we divide compression into lossy and lossless. The former, generally, provides higher compression rates, but it is more affected by impairments caused during data transmission on a wireless network, whereas, the latter compression algorithms fully regenerate the original information at the receiver. Some of the commonly used compression standards are JPEG (Joint Photographic Experts Group), GIF (Graphics Interchange Format), and PNG (Portable Network Graphics) [48]. The JPEG 2000 standard was developed using Discrete Wavelet Transformation (DWT) instead of Discrete Cosine Transformation (DCT), which is used for the JPEG codec. As a result, JPEG 2000 offers higher compression rates without introducing the blocky and blurry effects introduced by the original JPEG standard. Furthermore, JPEG 2000 allows progressive downloading of images with different resolution, quality, components, or spatial regions, eliminating the problem of decompression of the entire image before it can be displayed. This feature is particularly useful for Wireless Multimedia Sensor Networks (WMSN).

2.4 The Concept of the Hybrid Semantic System (HSS)

In order to discuss image retrieval, we have to answer some questions, of which the first and foremost is how to define our goal: do we want to construct a new CBIR system from scratch or build it on our existing image collections, for example, art collections, medical images, scientific databases or generally, the World Wide Web. Our objective, in turn, predetermines the kind of queries we wish to put. Once we have answered these fundamental questions, we can start thinking about the construction of an effective system.

CBIR systems developed by universities, government organizations, commercial companies or museums, generally use low-level visual contents of an image, such as colour, shape and texture. The middle-level contents, namely, objects and their spatial relationships, are more powerful on condition that the system can segment and recognize the objects. Different modifications are observed in particular systems, but their basic structure is presented in Fig. 2.5. Here we can see the image collection from which visual features are extracted and saved as a feature bank and additionally, a set of text annotations (optional in some systems). When the user puts a query, the search engine searches the most similar group of images and sends them back to the user as retrieval results.

Our motivation is to approach semantic retrieval as close as possible. We would like to create a CBIR system which includes low- and middle-level features in order to eliminate the 'semantic gap' which has been constantly observed. We expect that the application of global and local features in many variants to a search engine should better emulate human processes of image retrieval based on their content. At the same time we are aware of the fact that CBIR methodologies have some limitations resulting from problems presented in sect 2.2, which is why the undertaken task is particularly challenging.

In order to prepare our CBIR system we had to start from scratch. There was no image collection, only a vague idea of the potential user's needs and a strong determination to prepare a system as automated as possible which would find images according to the user's preference expressed in a graphical form.

We decided at once to start from colour images, as they contain more information than monochromatic ones. In terms of the format, we opted for JPEG because it is the most common image format used in digital cameras and other photographic image capture devices. As for the content, we were interested in architectural images as an additional aid for estate agents in their attempts to find a proper house for their clients.

In general, our system consists of five main blocks (Fig. 2.7): the image pre-processing block [49], the Oracle Database [50], the classification unit [51], the search engine [52] and the graphical user's interface (GUI) [53]. All modules, except the Oracle DBMS, are implemented in Matlab.

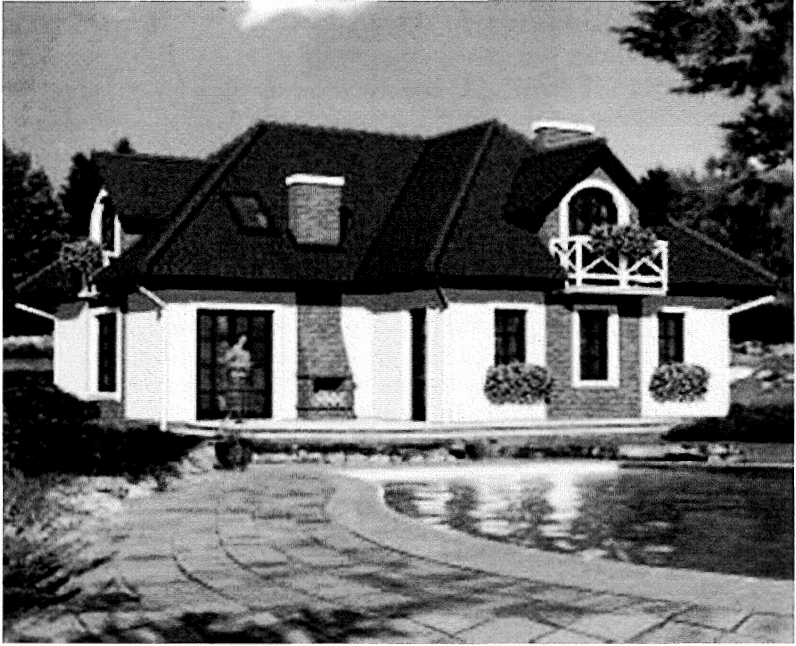


Fig. 2.6 Example of an original image.

In order to have some RGB pictures to start with, we downloaded some relevant images from Google (see Fig. 2.6). In the course of time, we plan to expand the DB content and increase the number of image sources and kinds of formats.

A classical approach to CBIR comprises image feature extraction [54], [55], generally, global features or local features of pixel groups. However, in our system, at the beginning, the new image is segmented, creating a collection of objects. Each object is described by some low-level features according to the algorithm presented in detail in [49].

Whole images, objects and features are stored in the DB, after which the objects are classified in the classifying unit. The classes reflect human understanding of image objects, so it is one of the ways in which we attempt to overcome the 'semantic gap'. For example, a trapezoidal red textured object is classified as a roof, whereas an irregular green polygon is classified as a lawn. Next, the classified objects become obtainable to the user in the graphical user interface (GUI) so that they can construct their queries. In the next stage, the projected query is sent to the search engine which finds the most similar images from the DB.

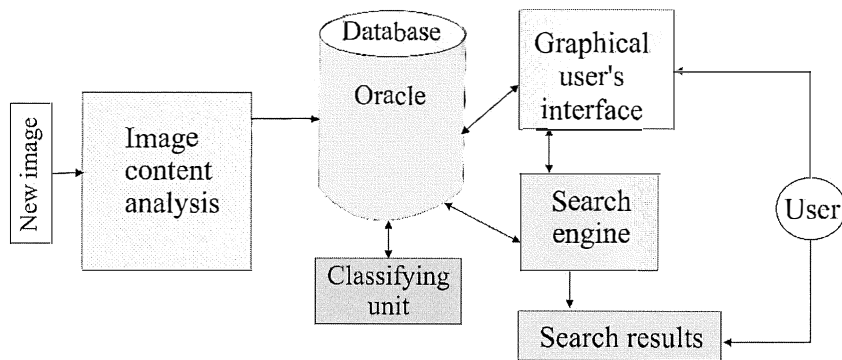


Fig. 2.7 The block diagram of the Hybrid Semantic System.

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