An Extensive Study of Visual Search Models on Medical Databases

Padmaja Grandhe, Sreenivasa Reddy Edara and Vasumathi Devara

Abstract Due to the rapid growth of medical images, user-specific ROI and object classification are the significant factors in the region-based segmentation instead of a pixel-based segmentation. Manual image annotation, classification, and filtering are not only a difficult task, but also high memory and time usage. In the visual search system, an unknown query image was given as input, relevant visual images with different diagnoses features are retrieved and then used as clinical decisions. The main goal of the visual search engine is to efficiently retrieve user-specific images that are visually identical to a selected ROI query. In this paper, a survey on traditional visual search methods is analyzed in terms of visual features and accuracy are concerned. Based on the survey performed by different visual search systems, the diagnostic efficiency is increased from 30 to 60% for clinical decision.

Keywords SIFT algorithm · Visual search · Classification · Image retrieval

1 Introduction

User Interest in the potential digital images has increased enormously over the past few years with the rapid growth of image database on the Internet. At the same time, demand for tools which can perform search and retrieval of images also has increased. Image retrieval involves retrieving images based on their visual similarity to images or image features provided by a user. Challenges with conventional

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methods of image indexing have lead to the rise of interest in methods for retrieving medical images on the basis of certain features such as texture, color, and shape that are generally referred to as an image retrieval process. Points of interest, which are points on the image that can be uniquely identified, are the most important features due to their robustness. It is usual to associate a scale and a covariant to the point to obtain descriptor invariance. There are two kinds of image retrieval methodologies, namely the text-based methodology and content-based methodology. In the text-based methodology, the images are retrieved through the text that is associated with that image. But this methodology fails in giving the user intent because the text associated with the image may not be relevant. Also, this kind of retrieval requires textual annotations. The subjectivity of the perception and the impreciseness in the annotations may cause mismatches in retrieval processes. Image searching with a specific visual query is one of the advances of the search engines in recent years. Searching for a small region of interest (ROI) in larger images is still a challenging issue. A large number of localization methods have been proposed in the context of detection of objects and recognition of objects in a database; they have not applied in scalable visual search. Traditional methods usually represent an image based on low-level features.

In the Fig. 1, traditional image search query [4, 5, 9, 10] is given input to preprocessing approach. Here, the preprocessing algorithms are used to remove noise or to enhance the brightness of the high resolution spectral images. In the segmentation step, traditional techniques such as K-means, graph-based segmentation, fuzzy-C means are used in [4, 5, 9, 10]. Finally, the number of segmented regions is identified.

CBIR system from a user perspective would find semantically similar images. A set of techniques are used to search the similar images from an image database using image features such as color, shape, and texture. Continuous research on CBIR system expanded its capability to retrieve visual information, images not only

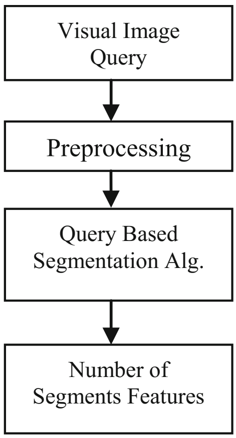

Fig. 1 Traditional visual search using segmentation process

at a conceptual level, but also at the perceptual level using objective measurements of the visual contents.

1.1 Visual CBIR in Medical Domain

As the computer technology is gaining ground in the medical domain, maintenance of digital data that is generated, stored, transmitted, analyzed, and accessed in hospitals has become very complex. In particular, the amount of digital images that are being generated on a daily basis is so huge that it requires some tools to handle data efficiently. The digital images are retrieved using some textual keywords related to the records. Since the current data access techniques are having many limitations, research is being conducted to make medical imaging task easy and efficient. It is proved that visual image search based on image features is more reliable in many cases and visual similarity is easily analyzed than traditional CBIR systems. Also, medical visual characteristics have a strong effect on image diagnosis.

Digital medical image visual search consists of three key steps:

1. Query image features extraction.
2. Analysis of those features for diagnosis.
3. Recommendations for clinical decision making.

2 Related Work

The content-based retrieval systems are improvised in different areas for the better performance.

Johansen Imo, Sebastian Klenk, and Gunther Heidmann worked on **Interactive feature visualization for image retrieval** [4]. The traditional CBIR system is unaware of what features are exactly used and thus fails in analyzing the results. To make it more transparent, image features need to be more visualized for user's selection. They presented a visualization method to extract feature classes such as texture feature and color histogram to evaluate this model.

Manmatha and Ravela [6] implemented similarity of visual appearance. A multiscale vector model is used to filter the query images in the training dataset with linear Gaussian functions at various scales and then computed low-order variations. These differential variations related to feature regions and are compared with those in the training data to find the similarity score for each image.

Gao [3] proposed "**multiple feature-based image retrieval**" model on image color spaces. This system uses color feature by quantifying the color spaces into non-equal intervals using the color histogram. Color histogram is represented by using local patterns. Similarity index is computed between the user query image and the target image in the training using Gaussian normalization on the distance space and feature space.

3 Structure-Based Image Retrieval Models

One of the most important and fastest growing researches in the field of medical is image retrieval with user's interest in content-based image retrieval. The basic idea of the structure-based image retrieval is to find identical images from the training data with the aid of some key features contained in the images. In structure-based image retrieval process [7], image registrations are performed in offline process so that the ROI of the query image was processed immediately. [7]Implemented image retrieval process in both offline and online process. In the online mechanism, user-specific query and the ROI bounding box are used to find the relevant similar images from the database [4, 5, 8–10].

Following two techniques are applied to the given input image to produce the output.

1. Image classification.
2. Global image registration.

3.1 Image Classification

To divide the X-ray images into 5 different classes such as hand, spine, cranium, chest, and negative. They used visual information to classify the images into classes. The main difficulty comes from the visual appearances of object categories. Multiple kernel learning (MKL) is used to detect a combination of the kernels, which differs either in their functionality, visual features, and parameters. Therefore, it is necessary to apply the multiple similarity measures to the available visual features. For instance, in the X-ray feature vector space has a small rectangular region inside the bounding box, this system computes a similarity value for each box of the object recursively.

Let D_b be the kernel base descriptors, and its related distance procedures are $f_1, f_2 .. f_{D_b}$. The descriptors and distance procedures are then kernelised to form base kernels. A novel point can be classified as +1 or −1 by computing Eq. (1).

$$\text{sign}\left(\sum_j \alpha_j y_j k(x, x_j) + b\right) \quad (1)$$

where α_i be the support vector, b is the bounded maximal width. To handle multiclass issues, both one-vs-one and one-vs-all formulations are performed. In one-v-one, region is divided into binary classification and optimal object point is

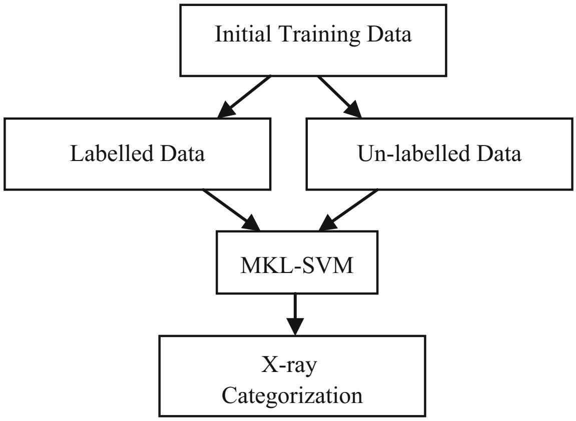

Fig. 2 SVM-MKL image classification

classified by taking majority vote in the classifiers. In one-vs-all, each classifier is learned per class and the optimal point is selected from the hyperplanes. They divided the object's bounding box into a number of rectangular regions and each region used as a feature vector for multiple kernel similarity computation.

As shown in Fig. 2, MKL-SVM based classification is done by using labelled and un-labelled data categories.

3.2 Global Image Registration

Registration is one of the important methods in the area of medical image retrieval for combining multiple image modals, image changes, etc. Image registration is required for fast and efficient image retrieval applications due to the following issues:

- Medical images are heterogeneous and multimodal with temporal features. So, multimodal registration is an integral part of any visual and content-based retrieval application.
- The size of the medical images affects the speed and computational cost for image registration.

Registration is executed using a two-step process. In the first step, points related to current image to the reference image are computed using the block-matching approach. Each block in the current image is compared with the neighborhood of the transformed referenced image. Traditionally, a block matching is computed using normalized cross-correlation and naïve normalization measures.

$$\mathrm{NCC} := (1/N)\sum_{x\in B_r}[B_r(x)-\mu_{B_r}][B_c(x)-\mu_{B_c}]/(\sigma_{B_r}\times\sigma_{B_c})$$

where B_r and B_c are the reference block and current image block, μ and σ are the mean and standard deviation within a block, and N be the size of the block.

Overall Limitations of the Visual and Content-based Search Methods

From this study, it has been depicted that there are many problems which do not have perfect solutions. Some of them are as follows:

- Application of CBIR technique on a large image database containing a wide variety of images result in less accurate results and consume high computation time.
- Traditional CBIR and visual search models heavily depend on segmentation techniques, which are not reliable.
- Problem of accurately representing the user interests in query formulation in ROI (region of interest)-based image retrieval system.
- Problem of considering the relative location of different objects in the query image for increasing the retrieval accuracy while consuming less computation time.
- Traditional local binary pattern (LBP)-based texture descriptors are very useful in analyzing texture of an image. However, there also remain some potential flaws as given below.
- Sensitive to noise magnitude of local difference is not taken and hence unable to represent fine texture details. Global texture properties are not represented.

4 Experimental Results

All experiments are executed with the minimum configurations such as CPU 2.13 GHz, Intel(R) Core(TM)2 4 GB RAM, and Netbeans IDE tool. This framework requires a third-party libraries such as jVisualizer, JAMA, and Apache Math.

Dataset: The dataset contains X-ray images of 5 classes: spine, hand, cranium, chest, and negative taken from the publicly available IRMA dataset [1] (Figs. 3 and 4).

In the results Figs. 5 and 6, it was observed that image orientation and shape are the main problems in the traditional visual search systems (Figs. 7 and 8).

Performance Analysis (Tables 1 and 2).

Fig. 3 User query selection

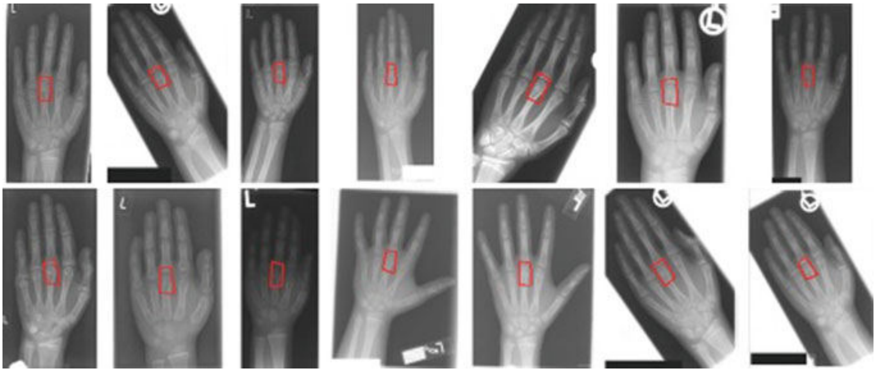

Fig. 4 Top 14 image retrieval results [7]

Fig. 5 User query selection

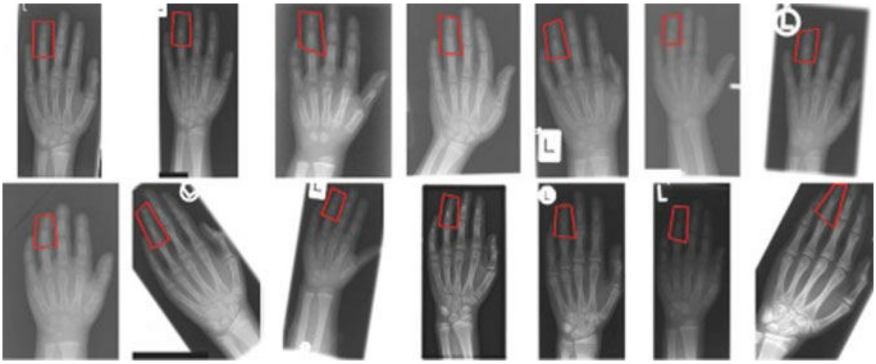

Fig. 6 Top 14 image retrieval results [7]

Fig. 7 User selected query

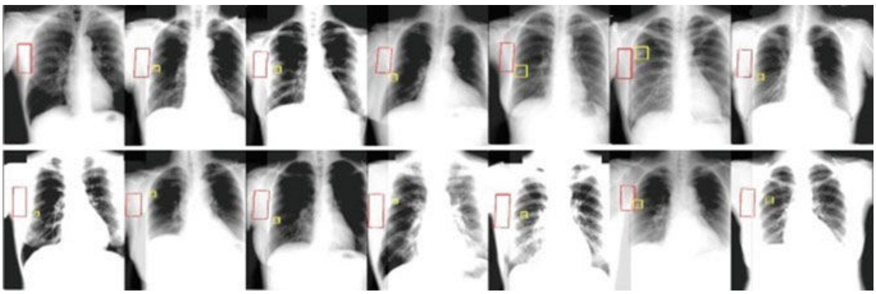

Fig. 8 Lung retrieval results [7]

Table 1 Hand retrieval results using traditional models

Algorithm	Hand1 (Avg. precision)	Hand2 (Avg. precision)	Time (s)
Structure retrieval algorithm	0.85	0.89	10
Local binary pattern	0.814	0.841	16
Region-based algorithm	0.79	0.81	15

Table 2 Lung retrieval results using traditional models

Algorithm	Lung1 (Avg. precision)	Lung2 (Avg. precision)	Time (s)
Structure retrieval algorithm	0.79	0.89	12
Local binary pattern	0.73	0.69	17
Region-based algorithm	0.74	0.77	19

5 Conclusion

The visual captures information in the image database and uses it to improve the performance of user-specific medical image search. Survey of the visual search models on the medical training dataset has proven both advantages and limitations. In the visual search system, an unknown query image was given as input, relevant visual images with different diagnoses features are retrieved and then used as clinical decisions. The main goal of the visual search engine is to efficiently retrieve user-specific images that are visually identical to a selected ROI query. In this paper, a survey on traditional visual search methods is analyzed in terms of visual features and accuracy are concerned. Different image ROI methods along with classification models are explored to highlight the challenges in the visual search process. Based on the survey performed by different visual search systems, the diagnostic efficiency is increased from 30 to 60% for clinical decision.

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