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Medical Image Classification: A Comparison of Various Handcrafted Features

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Abstract

This paper compares different feature extraction techniques exploited by various researchers for medical image classification and retrieval. They are categorized into three groups; (i) feature extraction techniques used for shape, (ii) feature extraction techniques used for texture and (iii) local patch based representation such as bag of visual words. The main aim of this work is to determine the capabilities and the challenges of medical images handcrafted feature extraction techniques as well as to see how best to improve the efficiency and accuracy of medical image classification and retrieval. It focused centrally on the analysis of the most commonly used shape and texture feature extraction techniques applied on medical images. Bag of visual words which is a type of local patch based method was also analysed. The limitations of these techniques are discussed as presented in the paper reviewed. We summarized with some conclusions and a recommendation for future exploits

Keywords: *Bag of visual words, Classification, Feature extraction, Medical image, X-ray.*

1 Introduction

Medical imaging has become an essential area in the effective delivery of modern health care. The continuous usage of medical images has led to the development of image databases consisting of different image modalities. This image database is essential for evidence based diagnosis, for teaching and research purposes.

Retrieving images from medical image databases can be difficult because of the increasing number and variety of images captured from medical equipment in various hospitals. Hence, there is a need for an efficient and effective method of classifying, indexing and retrieving required images of similar characteristic from several collections in the database [1]. Image classification is the bedrock for accurate image retrieval; it involves the assignment of images into their pre-defined categories [1] – [2]. Classification of images is essential in medical image database because of the different image modalities such as x-rays images, computed tomography images, magnetic resonance imaging etc. present in the database. The retrieval process can be difficult if these different image modalities are not properly classified. Hence, image classification has become a crucial task in the content-based image retrieval system (CBIR) [3] - [4]. CBIR is a computer system technique which focuses on the usage of visual contents to locate and retrieve images from a large database of digital images. The task of medical image classification involves two steps, these are training and testing. The first step is training and involves the extraction of visual features from a set of images called training set. The extracted training features and associated ground truth labels are supplied into a classifier to generate a classification model which is used for the classification task. The trained classifier or generated classification model is then saved for use in the next step.

Testing is the second step and it involves the performance evaluation of the generated model using another set of images known as test set. Test features are extracted from the test set like in the training step. However, labels are no longer supplied into the trained classifier for the classification task. The trained classifier output labels are compared with the ground truth labels of the test set and performance measures such as classification rate or accuracy are computed. In image classification task, the determination of the image visual features that can best be extracted for its representation is the uttermost importance. A proper representation of image is essential for high classification accuracy. This paper focuses on the comparison of various shape and texture feature extraction techniques applied on medical images for the purpose of classification and retrieval. It also examines bags of visual words representation technique and highlights their limitations. The commonly used shape and texture feature extraction techniques were reviewed and compared as well as their respective applications to both classification and retrieval of medical images. Bag of visual words method was also examined followed by a brief conclusion.

2 Shape Extraction Techniques

Shape feature describes many pathologies of the image. It is one of the low-level features apart from colour and texture [2]. Low-level features express the content of the image and based on the values of the pixels, information is compressed. Shape deals with the measurement of similarity between the represented feature shapes [3]. It is a primitive feature and very important visual feature used to describe image content. Though the task of measuring the similarity between shapes can be challenging, shape remains an important feature in image representation. There are two main methods or categories in shape description namely region-based and contour-based. While the whole area of an object is used for shape description in a region-based method, only the information available in the object boundary or contour is used for the Contour-based method [4]. There are various shape feature extraction techniques that have been used by various researchers, the most commonly used of them are: Edge Detection, Fourier Descriptors, Zernike Moments (ZM), wavelet transform [8]-[10]. These techniques were studied looking critically at their uniqueness. Fig. 1 shows the summary of comparison between the commonly used shape feature extraction techniques.

Techniques	*Easy computation*	*Robustness to noise*	*Compactness*	*Easy Normalization*	*Expressiveness*	*Rotation Invariance*	*Translation Invariance*	*Scale Invariance*	*Multi-resolution*	*Stability*	*Spatial localization*	*Information Perversion*	*Easy matching process*
Fourier Descriptors	√	√	√	√								√	
ZM		√			√	√							
IM			√			√	√						
Wavelet Transform		√				√			√	√	√		√

Fig. 1. Summary of comparison between some commonly used shape feature extraction techniques

2.1 The application of shape feature extraction techniques in medical image processing

An innovative partial shape matching (PSM) was presented for the purpose of spine X-ray retrieval with the application of dynamic programming by Xu, X. et al [9]. The proposed method was seen as an improved version of the previous corner-guided dynamic programming (DP) [11]. The research work introduced a shape representation technique that employed the use a multiple open triangle and uses a corner-guided PSM method. From the research work, corner-guided PSM was effectively used to retrieve spine X-ray images because of its invariant nature to scaling, translation, rotation and selection.

The lowest precision from the ten queries picked during the system performance evaluation is above 85% which is higher than that of corner-guided Procrustes distance [12] and the traditional DP. Though the method performed better than the traditional dynamic programming approach, corner-guided PSM is limited in terms of processing speed. The implementation can be done on a more competent software design other than MATLAB used in the research to increase the speed. Also, the user is limited in knowledge of retrieval results whenever there is a change in weights of the merging cost.

A similar work was done using canny edge operator to extract shape information in medical X-ray images [5]. The operator was used to generate histogram of images which were inputted into the Support Vector Machine (SVM) [13]-[14]. The researchers used canny edge detection on a collection of 5,000 real time images where 10 tests were conducted for the retrieval performance testing. The performance was impressive with a precision of 60% and recall of 100%. Fig. 2 shows the classification results of some of the shape feature extraction techniques employed by various authors.

Technique	Author	Classification rate (%)
Edge Detection	Xiaoqian Xu et al., 2008.	85.00
	Ramamurthy & Chandran, 2011	60.00
Fourier Descriptors	Rajaei et al., 2015	95.81
	Raju, J. and C. K. Modi	66.67
	Oberoi, A. and M. Singh	80.00
Zernike Moments	Fesharaki, N. J. and H. Pourghassem	82.80
	Calebi, M. E. and Aslandogan Y. A.	64.00

Fig 2: Classification results of some of the shape feature extraction techniques used by various authors.

The description of the shape feature of X-ray images based on the computation and the extraction of the distance and the orientation features was the research task of [15]. The orientation features were gotten from the centroid points of the image boundary. The shape feature was extracted with the use of a symbolic representation generated by a symbolic classifier. The researchers proposed a model that uses symbolic representation and symbolic classifier in the classification of medical X-ray images. Skeleton end points were fed into the Fast Fourier Transform (FFT) function for the derivation of end points shape characteristics. A shape feature vector that describes the total number of the extracted features was obtained. The proposed classifier was trained on the extracted features and the experimental result showed a great improvement. The classification accuracy was 95.81% which was the highest compared to other existing techniques as analyzed in the research.

The classification of 4,937 medical X-ray images into 28 categories was carried out by [16]. After the application of adaptive histogram equalization and median filter as pre-processing steps, shape based features were extracted. Fourier descriptor was extracted in combination with invariant moments [17] and Zernike moments [18]. A feature vector of 263 was organized for each image. The total accuracy was 82.87% and the value of determination function of respective class was acquired based on the Bayesian rule. The research work was similar to that of [19]. It focused on the application of Fourier Descriptor to extract shape feature from dental X-ray images. The overall percentage of image ranked in the top 5 out of the retrieved images from 25 images in a database was only 40%. The method was ineffective on the area of two images with the same shape properties when mean square error was applied for query-database matching.

In a research work, Zernike moments was extracted and combined with Fourier Descriptor and Invariant Moment (IM) for the task of shape feature extraction in X-ray images [16]. The paper used Bayesian rule [20], a feature based classification technique to classify the X-ray images. The classification rate was about 82.87% at the highest for a total of 4,937 medical X-ray images classified into 28 classes.

3 Texture Extraction Techniques

Texture can be explained as the surfaces structure formed by the repetition of a unique element on other elements in various spatial positions. X-ray images can be segmented into region of interest using texture feature because of its strong capacity to describe a region which in turn assists in the image retrieval process [21]. Some commonly used image texture extraction techniques include: Grey level Co-Occurrence Matrix (GLCM), Local Binary Pattern (LBP), Gabor filters, Wavelet transform [22]-[28]. We examined the peculiarity of the techniques in terms of Robustness, compactness etc. Fig. 3 shows the comparison of some of the commonly used texture extraction techniques.

Techniques	*Homogeneity*	*Orientation Selectivity*	*Flexibility*	*Robustness*	*Compactness*	*Rotation Invariance*	*Optimal localization*	*Stability*	*Spatial localization*	*Information Perversion*	*Easy matching process*
GLCM	√		√	√	√						
LBP				√							
Gabor Filter		√	√				√		√		
Edge Detection			√							√	

Fig. 3. Summary of comparison between some commonly used texture feature extraction techniques

3.1 The application of texture feature extraction techniques in medical image processing

In a research that focused on the Dental X-rays Images based on multiple features, GLCM was employed among other extraction techniques for the retrieval of dental X-ray images. The GLCM features were computed which includes contrast, correlation, energy, homogeneity etc. The research also employed the used of Fourier descriptors for feature extraction. The combination of these two techniques formed the feature vector which consists of 14 features. The dataset contains a total of 25 images and the experimental result shows that the retrieval rate is 36% with the use of Euclidean distance while the precision accuracy is 56.25%. This is relatively low compared to the combination of GLCM and Fourier descriptors methods which is 40% and 66.67% for retrieval and precision rate respectively [19].

A study was aimed at the investigation of texture parameters on ultrasound images focusing on breast tumour [29]. The region of interest was discovered by calculating five parameters from GLCM, the procedure was repeated for the rest internal region to make a total of 20 parameters. There was an assessment on the linear discriminant analysis which was employed on more than four parameters. GLCM produced the contrast over the region of interest discovered to have the most relevant individual parameter. A classification of up to 80% accuracy was obtained for breast tumour when the contrast and maximum value from GLCM and complexity curve [30] respectively were taken together. It was discovered from the research work that GLCM assist to extract parameters from the internal region which performs better than those parameters extracted from the region of interest [29].

A research work proposed the use of local binary pattern and wavelet coefficients in the classification of X-ray bones images [31]. It adopted two types of algorithms namely the Trous [32] and the Mallat algorithms [33] for the wavelet function and with the application of LBP descriptors, the resultant images produced are of one dimensional horizontal and vertical projections. The LBP application involves two processes which are the comparison of the LBP histograms and the derivation of statistical measures. The aim was to distinguish between two different populations which are the osteoporotic patients and the control subjects. KNN classifier was used together with the Euclidean distance for the validation purpose. The classification accuracy was 92.3% for 1D and 53.8% for 2D using Mallat algorithms and 94.9% for 1D and 87.2% for 2D using Trous algorithms. The overall result shows that the combination of wavelet decomposition and LBP descriptors helped greatly to improve classification accuracy in bone radiograph using the 1D projection.

A texture based research on medical image indexing and retrieval majorly applicable to cardiac image was conducted by Glatard, T. et al. [6]. Gabor filter was used to extract texture feature from the images and the Euclidean distance was used for the similarity measurement. The accuracy of the retrieval procedure was quantified by comparing the ground truth (know vertical position of the slices) with the computed results. A total number of 170 3D MRI images were used for the experiment. The result of the evaluation shows an impressive result above 80% in the retrieval of cardiac MRI images [34]. Classification results of some of the texture feature extraction techniques used by various authors are summarized in Fig. 4.

Technique	Author	Classification rate (%)
GLCM	Raju & Modi, 2011	40.00
	Alvarenga et al., 2007	80.00
LBP	Ko, Kim, & Nam, 2011.	93.10
	Houam, Hafiane, Boukrouche, Lespessailles, & Jennane, 2012.	94.90
	Reza Zare, Chaw Seng, & Mueen, 2013.	90.70
Wavelet Decomposition	Guler, I. et al.	73.40
	Weng, Z. et al.	97.15

Fig 4: Classification results of some of the texture feature extraction techniques used by various authors.

To solve the problem of noise and the loosing of weak edge information encountered by the out-of-date Canny edge detection algorithms, Weibin and his

group [35] conducted a research. The usage of gravitational field intensity was introduced in their research in replacement of the previous image gradient employed by Canny edge detection algorithms. They adopted the use of two methods of selecting adaptive threshold which considers the magnitude of the image gradient mean and standard deviation. MATLAB [36] was used for the performance test for both out-of-date Canny edge algorithms and the proposed improved Canny algorithm. The experimental detail shows that the improved algorithm was more robust to noise and useful edge information can be preserved.
The application of wavelet analysis for feature extraction and classification of Mammograms was explored by [37]. It focused on improving the detection of breast cancer in mammograms. The wavelet transform was used for the image enhancement and for the extraction of features. The classification stage involved a built classifier called Adaptive Neuro-fuzzy Inference System (ANFIS) [37]. ANFIS classifier was used for the classification of normal and abnormal mammograms. The method as shown in the study was able to effectively detect and classify the abnormalities found in digital mammogram. The system evaluation was carried out using the Mammographic Image Analysis Society (MIAS) dataset [38] and the result showed an average percentage of 73.4% (normal 73% and abnormal 75%) within a scale of 2 and 4 [37]- [40].

4 Bag of Visual Words (BoVW)

BoVW is a type of local patch-based image representation. BoVW has recently been exploited by researchers in an attempt to solve the problem of image classification [41]-[58]. It is a type of local patch-based image representation technique. BoVW involves the feature extraction for local image descriptor and converting it for final image representation. BoVW is used to detect local interest point with a task of getting specific invariant areas and points from images. BoVW model for image representation treats image as a document and is represented by the use of distinct keywords. BoVW basically involves three steps which are (i) The detection and extraction of the local feature (ii) The construction of the codebook (iii) The histogram image representation [21].

In BoVW, an image is usually represented in the feature vector by the count of visual word. It provides image representation with the use of quantized appearance of the local patches histogram [52].The application of BoVW methods to a whole image classification performs well and its robustness against features spatial translation is of great advantage [59].

4.1 The application of Bag of Visual words technique in medical image Processing

The use of bag of visual words to explore various parameters effect on system performance was conducted by a group of researchers [52]. The point of interest was detected by a fixed size sampling of rectangular patches [60] around each pixel and feature descriptors were used to represent the patches. A regular grip was used to extract the patches. The patches were normalized by dividing the subtracted mean grey level by its standard deviation. A total of 10,677 images were trained on an SVM classifier while the testing dataset consist of 2000 separate set of images. The model was able to distinguish between two different cases when applied to categorize chest X-ray images pathological level. The works evaluated SIFT using a normalized raw data and from the report generated, it produced a supreme performance on two different medical datasets.

Another research was conducted using BoVW model to analyse images [53], there was an extraction of local patches which are of different sizes. The local patches were formed from different positions and resized to mutual dimension after which there was a uniform quantization of the feature space. Each dimension of the feature space was quantized and sparse histogram was used to represent the image [53]. Fig. 5 shows the classification results of some BoVW techniques used by various author.

Technique	Author	Classification rate (%)
BoVW	Zare, et al.	90.00
	Yang, et al.	90.00
	Srinivas, et al.	87.50
	Avni, et al.	88.20

Fig 5: Classification results of some BoVW techniques used by various author.

Similarly, [54] carried out a research work for automatic X-ray images classification using annotation. The experiment conducted focused on the categories of image class with higher percentage of inter-class similarity and intra-class variability. The percentage of these image classes are below 80% mainly from the arm sub-region of the body. With the proposed annotation module in the research framework, the classification algorithm was more effective since a good annotation performance aids classification performance.

The combination of the three annotation techniques (binary classification, using top similar image and PLSA) produced a set of key words which contain the combined keywords for the sub-body region respectively. The result of the experiment, compared with other techniques as discussed in the research work, shows a great improvement on the entire database. The combination of the local histograms produced the image final feature.

In a recent development, a research was carried out to alleviate the ambiguity problem associated with bag of visual words [21]. The research employed the use of Probabilistic Latent Semantic Analysis (PLSA) proposed by Hofmann [7] and discriminative SVM classifier for medical X-ray classification. The researchers carried out a series of experiments using ImageCLEF 2007 [62], a medical dataset containing 11,000 X-ray images from about 116 categories and the performance of the classification algorithm was evaluated. The classification accuracy rate was 92.5% obtained from the entire dataset. The result is higher than the 90% classification accuracy obtained with the employment of bags of words. PLSA has lots of applications especially in the area of information retrieval, machine learning, and natural language processing [61]. Despite the advantages of using bag of words as a feature extraction technique as stated above, there are some challenges associated with it. First is the determination of codebook size or how many code blocks are needed for image contents representation. There is a challenge in the selection of codebook size when employing the technique of BoVW. Choosing a word from the dictionary most similar to the patch created during quantization can be difficult if the patch size is too large. The visual dictionary also known as codebook is constructed with the aim of identifying a set of visual patterns reflecting the contents of image collection. As much as it is advisable for it to be larger than some pixels across, it should not be too large to avoid quantization problem [52], [63].

Secondly, the patches created during the point of interest detection needs to be represented using feature descriptor. The selection of what type of descriptor to be used for best performance is an issue in BoVW. We have robust feature detection methods like SIFT, SURF, and PCA [64]. These methods need to be carefully evaluated and selecting the best for a particular task can be demanding especially in terms of speed, illumination changes and invariance.

Thirdly, during the codebook generation, there is a problem that tend to make same visual words to represent images that are not similar and not from the same body region. Also, it is discovered that different visual words tend to represent image from the same body region which should not be so. This visual similarity and visual variation problem as it were with most of the handcrafted features discussed above is also a challenge in BoVW [21].

5 Conclusion

This work is a useful contribution to the development of an effective classification model and a much more accurate retrieval system for medical images. It will assist in choosing the most efficient way of extracting visual feature for image representation. In most of the literature reviewed, there is a common challenge of image misclassification in the similar image regions. This is due to high inter-class similarity and the intra-class variability that exists among images especially those from bigger number of sub-regions. This makes some images to remain misclassified and thus affect the accuracy of the retrieval system.

Image features can be extracted either by handcrafted methods as analysed in this work or by the employment of most recent approach like Convolutional Neural Network. Despite the use of a recent handcrafted method such as bag of visual words to increase the accuracy of classification and retrieval, the problem of intra-class variability still remains unresolved.

From the comparison of the shape feature extraction techniques, it can be deduced that the edge detection technique outperformed the rest producing the highest classification percentage of 95.81%. For the texture extraction techniques, wavelet decomposition generated 97.15% as the highest among other techniques. Also, the bag of visual words techniques was able to classify the medical X-ray images with an average of 80% accuracy.

Imbalanced number of training images, intra-class variability and visual similarity associated with the handcrafted methods can be reduced to the barest minimum by developing an automatic classification system capable of extracting from the available data, the most discriminative information. The extracted discriminative features should be potent enough to present the best representation of the image.

Therefore, it is worth mentioning that the application of a machine learning method like deep learning algorithms should be considered in the quest for efficient and accurate medical image classification and retrieval system. Deep learning architectures such as Convolutional Neural Networks (CNNs) should be explored for feature extraction in medical image classification task.

Furthermore, a multimodal approach that combines two deep learning architectures such as Recurrent Neural networks (RNNs) with CNNs can also be considered as the combination of both networks can effectively analyse the textual and visual feature of label images respectively.

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