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Medical Image Retrieval Based On Edge Histogram Descriptor

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ABSTRACT: *One of the primary tools used by physicians is the comparison of previous and current medical images associated with pathologic conditions. As the amount of pictorial information stored in both local and public medical databases is growing.Per day about 7, 27, 00,000 number of images are loaded into GOOGLE data base. So, efficient image indexing and retrieval became a necessity.* ***E****dge* ***H****istogram* ***D****escriptor describes edge distribution with a histogram based on local edge distribution in an image. EHD describes the distribution of non-directional edges and non-edge cases as well as four directional edges, the edge extraction scheme should be based on the image-block as a basic unit for edge extraction rather than on the pixel. That is, to extract directional edge features, we need to define small square image-blocks in each image. Specifically, we divide the image space into square image-blocks and then extract the edge information from them. A simple method to extract an edge feature in the image-block is to apply digital filters in the spatial domain.*

I. INTRODUCTION

The histogram is the most commonly used structure to represent any global feature composition of an image. It is invariant to image translation and rotation, and normalizing the histogram leads to scale invariance. Exploiting the above properties, the histogram is very useful for indexing and retrieving images [1], [2].
Edges in images constitute an important feature to represent their content. Also, human eyes are sensitive to edge features for image perception. One way of representing such an important edge feature is to use a histogram. An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image. It is a unique feature for images, which cannot be duplicated by a colour histogram or the homogeneous texture features. To represent this unique feature, there is a descriptor for edge distribution in the image. This Edge Histogram Descriptor (EHD) proposed for medical image retrieval expresses only the edge distribution in the image. That is, since it is important to keep the size of the descriptor as compact as possible for Efficient storage of the metadata, the normative medical image edge histogram is designed to contain only 80 bins describing the local edge distribution. These 80 histogram bins are the only standardized semantics for the image EHD. However, using the local histogram bins only may not be sufficient to represent global features of the edge distribution. Thus, to improve the retrieval performance, we need global edge distribution as well. This paper describes how to generate the edge histograms from the histogram bins. Then, the histogram bins are used to evaluate the similarities between images..We begin in Section II with the existing techniques, definition of the standardized semantics of the EHD. The algorithms for EHD extraction and matching, which are non-normative parts of the standard, are then discussed in Sections III . Experimental results with different medical grey images are shown in Section IV,In this section we discuss about the performance comparison of medical images based on precision rate . Finally, we conclude the paper in Section.

II. EXISTING TECHNIQUES:

There are many techniques used to retrieve images. Some of them are bi-orthogonal wavelet filter based mean and variance, texture based image retrieval, text based image retrieval.
Text based image retrieval:
In this we have to write the text about the image to be search for.
For example:

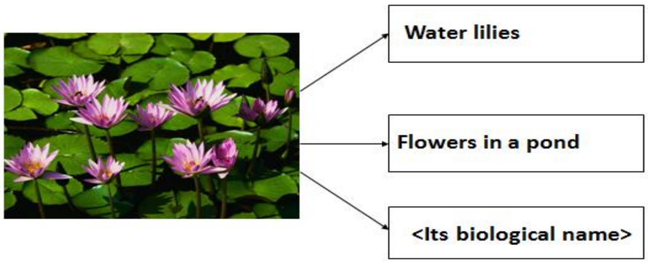


Fig 1: text based image retrieval

Bi-orthogonal wavelet filter based mean and variance: In this we calculate mean and variance for query and database images. By comparing mean of both database and query images, we can retrieve images from database and is done by:

$$\mathbf{dis_{mean}(P_1, P2)} = \left| \frac{P_{1,pp} \cdot P_1.SV - P_{2,pp} \cdot P_2.SV}{P_1 \cdot SV + P_2 \cdot SV} \right|$$

Texture based image retrieval:

In this we had calculated some texture properties for an image. They are:

a. energy
b. correlation
c. entropy
d. homogeneity

III. DEFINITION AND SEMANTICS OF THE EHD

The EHD basically represents the distribution of 5 types of edges in each local area called a sub-image. As shown in Fig. 1, the sub-image is defined by dividing the image space into 4×4 non-overlapping blocks. Thus, the image partition always yields 16 equal-sized sub-images regardless of the size of the original image. To characterize the sub-image, we then generate a histogram of edge distribution for each sub-image. Edges in the sub-images are categorized into 5 types: vertical, horizontal, 45-degree diagonal, 135-degree diagonal, and non-directional edges (Fig. 2). Thus, the histogram for each sub-image represents the relative frequency of occurrence of the 5 types of edges in the corresponding sub-image. As a result, as shown in Fig. 3, each local histogram contains 5 bins. Each bin corresponds to one of 5 edge types. Since there are 16 sub-images in the image, a total of 5×16=80 histogram bins is required, (Fig. 4). Note that each of the 80-histogram bins has its own semantics in terms of location and edge type. For example, the bin for the horizontal type edge in the sub-image located at (0,0) in Fig. 1 carries the information of the relative population of the horizontal edges in the top-left local region of the image.

The semantics of the 1-D histogram bins form the normative part of the standard descriptor. Specifically, starting from the sub-image at (0,0) and ending at (3,3), 16 sub-images are visited in the raster scan order and corresponding local histogram bins are arranged accordingly. Within each sub-image, the edge types are arranged in the following order: vertical, horizontal, 45-degree diagonal, 135-degree diagonal, and non- directional.

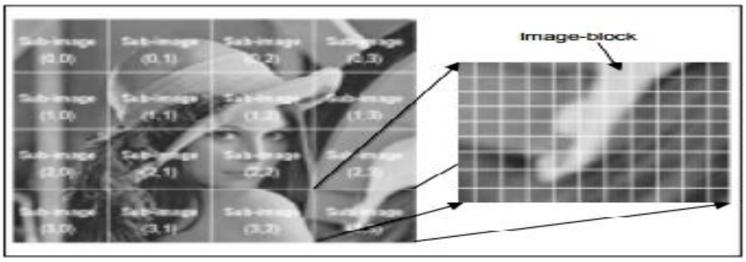


FIG:-1 Definition of sub-image and image-block.

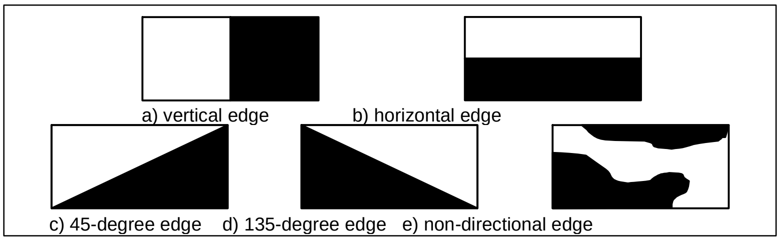


Fig. 2. Five types of edges.

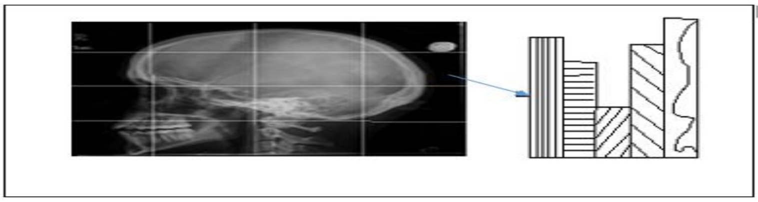


Fig. 3. Five types of edge bins for each sub-image.

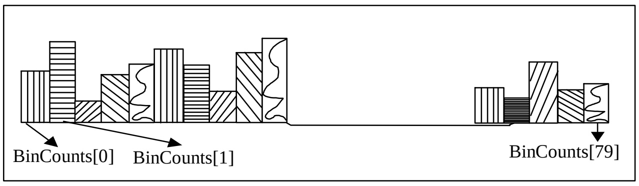


Fig. 4. 1-D array of 80 bins of EHD.

Table 1 summarizes the complete semantics for the EHD with 80 histogram bins. Of course, each histogram bin value should be normalized and quantized. For normalization, the number of edge occurrences for each bin is divided by the total number of image-blocks in the sub-image.The image-block is a basic unit for extracting the edge information. That is, for each image-block, we determine whether there is at least an edge and which edge is predominant. When an edge exists, the predominant edge type among the 5 edge categories is also determined. Then, the histogram value of the corresponding edge bin increases by one. Otherwise, for the monotone region in the image, the image-block contains no edge.

Table 1. Semantics of local edge bins.

Histogram bins	Semantics
Bin Counts[0]	Vertical edge of sub-image at (0,0)
Bin Counts[1]	Horizontal edge of sub-image at (0,0)
Bin Counts[2]	45-degree edge of sub-image at (0,0)
Bin Counts[3]	135-degree edge of sub-image at (0,0)
Bin Counts[4]	Non-directional edge of sub-image at (0,0)
Bin Counts[5]	Vertical edge of sub-image at (0,1)
:	:
Bin Counts[74]	Non-directional edge of sub-image at (3,2)
Bin Counts[75]	Vertical edge of sub-image at (3,3)
Bin Counts[76]	Horizontal edge of sub-image at (3,3)
Bin Counts[77]	45-degree edge of sub-image at (3,3)
Bin Counts[78]	135-degree edge of sub-image at (3,3)
Bin Counts[79]	Non-directional edge of sub-image at (3,3)

In this case, that particular image-block does not contribute to any of the 5 edge bins. Consequently, each image-block is classified into one of the 5 types of edge blocks or a non-edge block. Although the non-edge blocks do not contribute to any histogram bins, each histogram bin value is normalized by the total number of image-blocks including the non-edge blocks. This implies that the summation of all histogram bin values for each sub-image is less than or equal to 1. This, in turn, implies that the information regarding non-edge distribution in the sub- image (smoothness) is also indirectly considered in the EHD.

EHD EXTRACTION: Since the EHD describes the distribution of non-directional edges and non-edge cases as well as four directional edges, the edge extraction scheme should be based on the image-block as a basic unit for edge extraction rather than on the pixel. That is, to extract directional edge features, we need to define small square image-blocks in each sub-image as shown in Fig. 1. Specifically, we divide the image space into non-overlapping square image-blocks and then extract the edge information from them. Note that, regardless of the image size, we divide the image space into a fixed number of image-blocks. The purpose of fixing the number of image-blocks is to cope with the different sizes (resolutions) of the images. That is, by fixing the number-of-image blocks, the size of the image-block be- comes variable and is proportional to the size of the whole image. The size of the image-block is assumed to be a multiple of 2. Thus, it is sometimes necessary to ignore the outmost pixels in the image to satisfy that condition. A simple method to extract an edge feature in the image-block is to apply digital filters in the spatial domain. To this end, we first divide the image-block into four sub-blocks as (Fig. 5). Then, by assigning labels for four sub-blocks from 0 to 3, we can represent the average grey levels for four sub-blocks at (i,j)th image-block as $a_0(i,j)$, $a_1(i,j)$, $a_2(i,j)$, and $a_3(i,j)$, respectively. Also, we can represent the filter coefficients for vertical, horizontal, 45-degree diagonal, 135-degree diagonal, and non-directional edges as $f_v(k)$, $f_h(k)$, $f_{d-45}(k)$, $f_{d-135}(k)$, and $f_{nd}(k)$, respectively, where $k=0,\ldots,3$ represents the location of the sub-blocks. Now, the respective edge magnitudes $m_v(i,j)$, $m_h(i,j)$, $m_{d-45}(i,j)$, $m_{d-135}(i,j)$, and $m_{nd}(i,j)$ for the (i,j)th image-block can be obtained as follows:

$$m_v(i,j)=\left|\sum_{k=0}^{3} a_k(i,j) \times f_v(k)\right| \quad (1)$$

$$m_h(i,j)=\left|\sum_{k=0}^{3} a_k(i,j) \times f_h(k)\right| \quad (2)$$

$$m_{d-45}(i,j)=\left|\sum_{k=0}^{3} a_k(i,j) \times f_{d-45}(k)\right| \quad (3)$$

$$\mathbf{m_{d\text{-}135}(i,j)=\left|\sum_{k=0}^{3} a_k(i,j) \times f_{d\text{-}135}(k)\right|} \qquad \textbf{(4)}$$

$$\mathbf{m_{nd}(i,j)=\left|\sum_{k=0}^{3} a_k(i,j) \times f_{nd}(k)\right|} \qquad \textbf{(5)}$$

If the maximum value among 5 edge strengths obtained from (1) to (5) is greater than a threshold (T_{edge}) as in (6), then the image-block is considered to have the corresponding edge in it. Otherwise, the image-block contains no edge.

$$\mathbf{\max\{m_v(i,j),m_h(i,j),m_{d\text{-}45}(i,j),m_{d\text{-}35}(i,j),m_{nd}(i,j)\}>T_{edge}} \qquad \textbf{(6)}$$

In Document [1], a set of filter coefficients, depicted in Fig. 5, is recommended. Note that the filter coefficients in Fig. 5, especially the non-directional edge filter, appear somewhat heuristic. In fact, the non-directional edges by definition do not have any specific directionality. So, it is hard to find filter coefficients that are applicable for all types of non-directional edges.

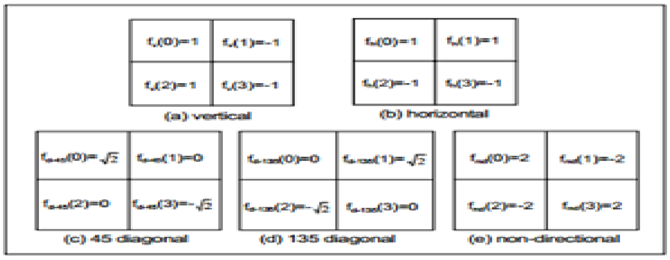
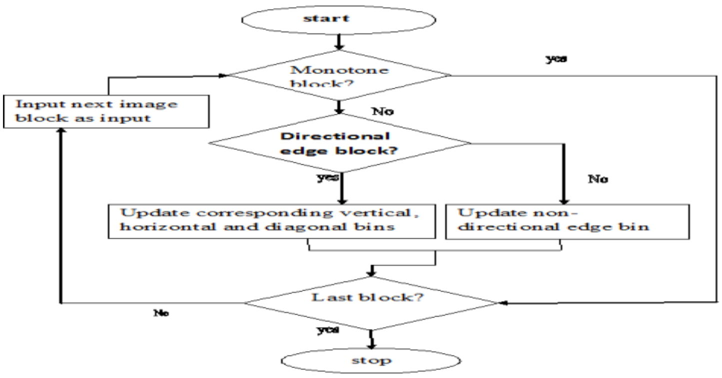


Fig. 5. Filter coefficients for edge detection.

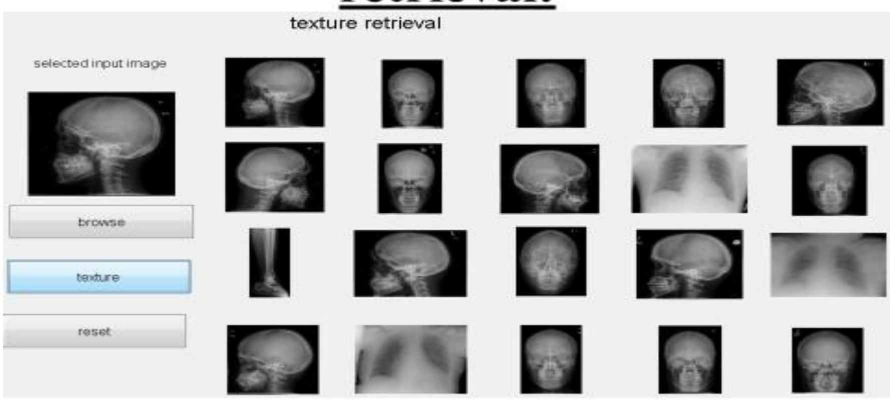
To avoid this problem, we can first check whether the image-block can be classified into one of a monotone block and four directional edge blocks. If the image-block does not belong to any of the monotone or four directional edge blocks, then we classify it as a non-directional block. The flow chart of this method is shown in Fig. 7. Another edge ex traction method that follows this flow chart can be found in [4]. Here, the edge classification is based on the model-fitting criterion.

FLOWCHART:

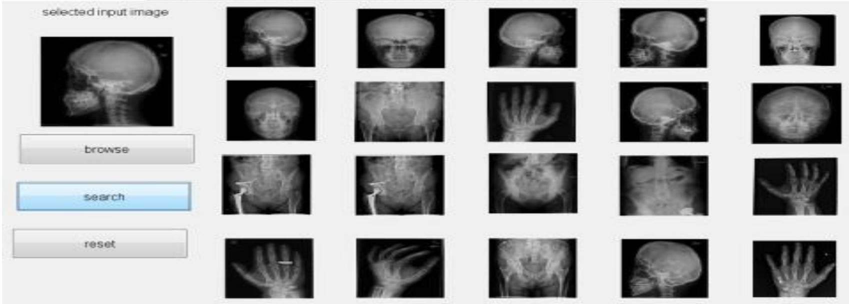


EXPERIMENTALRESULTS

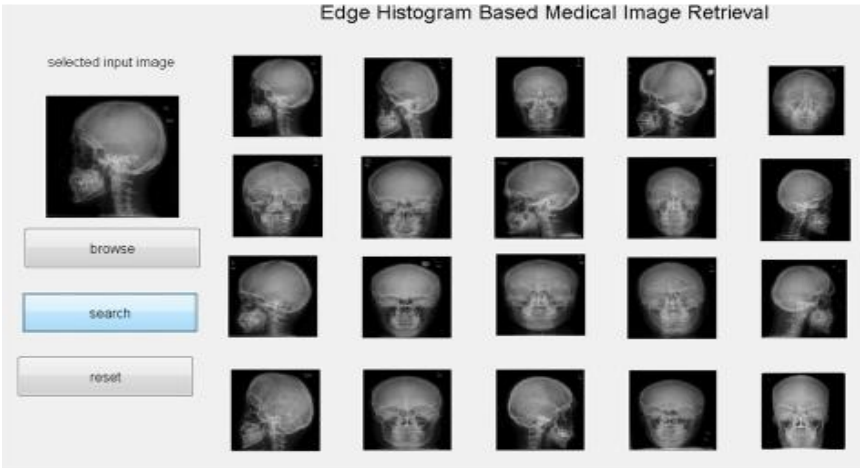
By using texture based image retrieval:



By using biorthogonal wavelet filter mean and variance:

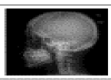
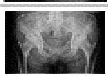
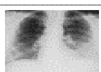


Based on EHD:



PERFORMANCE COMPARISION:

Performance comparision between various techniques for various images:

IMAGE	MEAN/VARIANCE	TEXTURE RETRIEVAL	EDGE HISTOGRAM DESCRIPTOR
	50%	70%	93%
	40%	65%	80%
	45%	60%	90%
	50%	65%	80%
	45%	45%	60%

PRECISION RATE:
Precision rate = Tp/(Tp+Fp)
Recall rate =Tp/(Tp+Fn)
Tp=true positives
Fp=false positives
Fn=false negatives

IV. CONCLUSION

Our proposed technique is compared with the existing techniques in terms of **precision rate.** From the results obtained it is clear that the bi-orthogonal wavelet based mean and variance image retrieval has poor precision rate when compared with texture based image retrieval. Also texture based image retrieval has relatively less precision rate when compared with our proposed technique ie. Image retrieval based on Edge Histogram Descriptor.From this we conclude that our proposed technique is better suited for medical image retrieval.

V. ACKNOWLEDGMENT

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REFERENCES

[1]. M.J. Swain and D.H. Ballard, "Color Indexing," Int. J. of Computer Vision, vol.7-1, 1991, pp. 11-32.
[2]. A.K. Jain and A. Vailaya, "Image Retrieval Using Color and Shape," Pattern Recognition, vol. 29, no. 8, 1966, pp. 1233-1244.
[3]. Wickerhauser, Adapted Wavelet Analysis from Theory to Software,AK Peters, Boston, 1994, pp. 213-214, 237, 273-274, 387.
[4]. J. Bradley, C. Brislawn, and T. Hopper, "The FBI Wavelet/Scalar Quantization Stand ard for Gray -scale Fingerprint Image Compression," tech.Report LA-UR-93-1659, Los Alamos Nat'l Lab, Los Alamos,N.M. 1993.
[5]. J. Gobeill, H. Müller, P. Ruch, Translation by Text Categorization: Medical Image Retrieval in ImageCLEFmed 2006, Springer Lecture in Computer Science (LNCS 4730), pages 706-710, 2007.
[6]. G. Salton and C. Buckley, Term weighting approaches in automatic text retrieval, Information Processing and Management, 24(5):513--523, 1988