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1-D Spectral Contour Coding For Content-Based Medical Image Retrieval

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Abstract: *In the process of medical image retrieval, the representing features define the retrieval accuracy. The representing features are described by various definitions, one is the shape. The shape representation of an observation made reveals various effects in the observing individual. In this paper to improve the accuracy of shape based feature extraction and retrieval is developed. This paper presents a new modified approach for shape feature representation in a 1-D representation and decomposition for a closed bounding region extraction for contour coding. This coding develops a new retrieval system for shape based retrieval system.*
Keyword: *Medical image retrieval, contour coding, 1-D representation, spectral coding.*

I. Introduction

In the process of medical diagnosis automated image retrievals are very demanding. With the low time consuming process for diagnosis such systems are in greater demand. However in such system the dependency of total reliable diagnosis is still a open question. In various areas of applications where proper retrievation is required, such system could not reflect the accurate observation due to lack in content definition or feature extraction techniques. Where in past, various methods were developed to achieve these objectives, the approach still needs an improvement to achieve proper feature definition and estimation. In various descriptive feature shape is considered to be one important feature as describing feature for image retrieval. In recent past to achieve shape representation contour coding have emerged. Themethods of the contour-based are mainly chain code [1].Polygonal approximation, Fourier descriptors [2, 3], waveletdescriptors, scale space [4, 5], and so forth. And some ofthe region-based methods are mainly geometric momentinvariants, orthogonal moments [6, 7], and so on.In terms of contour-based image retrieval, distancehistogram [8] is a method commonly applied for shapedescription, but it cannot reflect the spatial distribution ofcontour pixels and different shapes may be with the samedistance histogram. Shape descriptors based on scale space are also often used for image retrieval and have a good performance of antinoise. In [4, 5], the method of retrieving image by using curvature scale space descriptor is applied. Curvature scale space descriptor is a closed contour descriptor used by MPEG-7 standard image database and has performance of translation, rotation, and scale invariance, as well as relatively stronger noise immunity. In [11], a contour-based image retrieval algorithm is proposed. It firstly evolves the image contour and then the descriptor is constructed by using distance histogram between the evolutionary contour and the skeleton. The descriptor has comparatively stronger noise immunity but does not reflect the spatial distribution feature of contour points. To achieve the objective in this paper the contour coding is presented in a 1-D coding format to reduce the computational overhead and improve the retrieval accuracy. The rest of the paper outlines the contour coding approach, the curvature scale coding for image retrieval and the proposed 1-D coding, with a experimental analysis.

II. Shape descriptor-Contour coding

Contours are defined as the bounding regions of an image. Contour defines the shape, region and edge region in images. The process of edge estimation by edge operators were analyzed in previous section. It is observed that during compression as image is processed in blocks, blocking artifacts are generated. These artifacts are been minimized by tracing the edge regions, so as the edge artifacts are nullified. In previous section it is seen that working over edge with filtration reduces the visual artifacts. However the system overhead due to edge estimation and filtration process has not been considered. The edge estimated and processed in such system are lost at the bounding region in a block due to lossy compression and because of block processing. Where as in a contour it is estimated in a continuous tracing over the image, hence such coding is more informative for region description than the edge descriptor.

Fig1: (a) Original image sample, (b) Extracted Edge region using canny operator, (c) Extracted contour region.

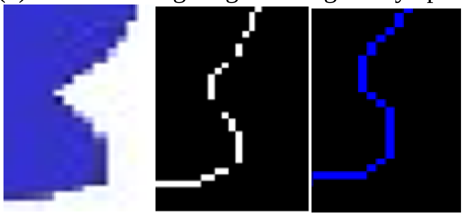

Fig 2: (a) enlarged section of the original sample, (b) Estimated edge of the region, (c) Estimated contour region

Figure1 illustrates the extracted bounding region for the given image sample. Figure1 (b) shows the extracted edge region using canny operator and Figure2(c) shows the extracted contour for the same image. Figure2 illustrates the enlarge version of figure1. It is observed from Figure2 (b) that the bounding region obtained by the edge estimation operator result in disjoints due to loss of information. While the bounding region derived by contour estimation results in a continuous bounding region. This estimation results in higher edge preserving, results in minimization of visual artifacts.

a) Contour Evolution

Contour is defined as outermost continuous bounding region of a given image. For the detection of contour evaluation all the true corners should be detected and no false corners should be detected. All the corner points should be located for proper continuity. The contour evaluator must be effective in Estimating the true edges under different noise levels for robust contour estimation. For the estimation of the contour region an 8-region neighborhood-growing algorithm is used as illustrated below.

b) 8-Region Neighborhood growing algorithm

1. Find outermost initial pixel of an edge by vertical or horizontal scanning for obtained edge information.
2. The obtained initial pixel is taken as reference and is termed as seed pixel.
3. Taking seed pixel as starting co-ordinate, find eight adjacent neighbors of it tracing in anti-clock wise direction.
4. The possible tracing order is as shown in figure 3.
5. If the obtained seed coordinate is taken as (x,y) then the scanning order is, [1. (x+1, y), 2. (x+1, y+1), 3. (x,y+1), 4. (x-1, y+1), 5. (x-1, y), 6. (x-1, y-1), 7. (x,y-1), 8. (x+1, y-1)].
6. In case of the current pixel is found to be the next adjacent neighbor, update-the current pixel as new seed pixel and repeat step 3,4 and 5 Recursively until the Initial seed pixel is reached.

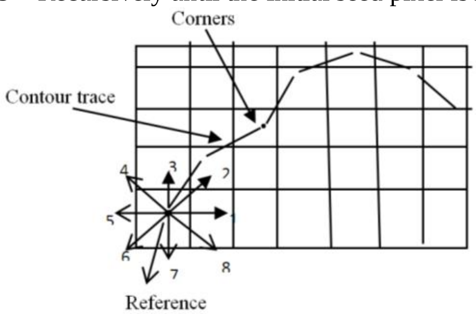

Fig3: probable scanning order for 8-Region neighborhood-growing algorithm

The tracing order is coded for path tracing in frame formation, wherein the tracing orientation is given values defined by,

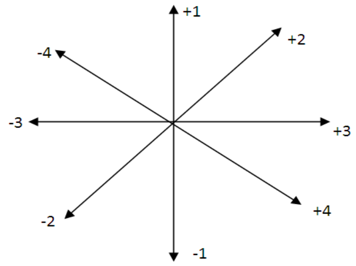

Fig4: Issued Orientation weight value for contour tracing

This contours defines the bounding region of the image and used as a shape representing feature for processing sample. To describe the feature description in a medical sample a level set active contour model is presented as outlined below.

III. Level Set Active Contour Model [1]

Active contour model (ACM) is one of the most successful methods which have been used extensively in image segmentation. Geometric active contour (GAC) model is one of most popular and powerful edge-based models. It utilizes image gradient to construct an edge stopping function (ESF) to stop the contour evolution on object boundary. Let Ω be a bounded open set and C(s) parameterized by arc-length s, an initial contour in Ω . Given an input image I(x,y). However, it is usually unreasonable in medical region representation because internal distributions of lesions are complex as a result of different pathological changes. While compared to intensity distributions of objects, intensity distributions of backgrounds are consistent statistically. Thus only background information to delimitate Region is used. A Gamma distribution to fit the background distribution is adapted. A two-parameter distribution is more flexible to adapt the probability density function to a range wide of database compared to a one-parameter model such as the Rayleigh distribution or the Poisson distribution. The Gamma model issued for the region fitting problem to extract the region where the Gamma probability function is defined as:

$$P(I(x,y)) = I(x,y)^{\kappa-1}\frac{e^{-I(x,y)/\theta}}{\theta^{k}\Gamma(\kappa)}, I(x,y) > 0, \theta > 0, \kappa > 0$$

Where κ is the shape factor, θ is the scale factor. We could get the two parameters of the gamma distribution by using the maximum likelihood estimates (MLE). The MLE is used to extract the region of interest by the selection of contour region and probabilistic convergence of the same to extract the region. To the extracted region a curvature scale representation result in feature extraction.

To evaluate the contour plane for the obtained contour of given image following approach is made, For a given contour co-ordinates (x (u), y(u)) the contour plane of the given contour is given by,

$$\mathrm{k}\,(\mathrm{u}) = \frac{\mathrm{x}'(\mathrm{u}) * \mathrm{y}''(\mathrm{u}) - \mathrm{y}'(\mathrm{u}) * \mathrm{x}''(\mathrm{u})}{[(\mathrm{x}'(\mathrm{u}))\text{^}2 + (\mathrm{y}'(\mathrm{u}))\text{^}2]\text{^}(3/2)]}$$

Where (x', y') are first derivative of given contour co-ordinates and (x'', y'') are the double derivative of x and y.

For the obtained contour plane, 1-D contour is obtained by applying smoothening operation to reduce the noise in bounding contours. The smoothening is continued by incrementing the Gaussian value (σ) on the obtained contour until no noise exist. A contour is a set of points whose position vectors are the values of a continuous, vector-valued function. It can be represented by the parametric vector equation, $\mathrm{r}(\mathrm{u}) = (\mathrm{x}(\mathrm{u}), \mathrm{y}(\mathrm{u}))$

The function r (u) is a parametric representation of the contour. Planar contour has an infinite number of distinct parametric representations. A parametric representation in which the parameter is the arc length 's' is called a natural parameterization of the contour.

IV. 1-D Spectral Contour Coding (1-DSCC)

It is observed that although the normalized arc length parameter on the original contour r**,** the parameter u is not, in general, the normalized arc length parameter on the evolved contour r_σ. To overcome this problem, a 1-D contour plane scale space image is proposed defined by, Let

$\mathrm{R}(\mathrm{u},\sigma) = (\mathrm{x}(\mathrm{u},\sigma), \mathrm{y}(\mathrm{u},\sigma)),$ and

$$w = \Phi_\sigma(u) = \frac{\int_0^u |R_v(v,\sigma)|\,dv}{\int_0^1 |R_v(v,\sigma)|\,dv}$$

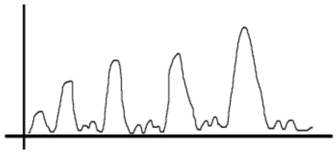

Fig.5: Renormalized 1-D scaled contour pattern

Now, define

$\hat{X}(w,\sigma) = X\left(\Phi_{\sigma}^{-1}(w),\sigma\right) \qquad \hat{Y}(w,\sigma) = Y\left(\Phi_{\sigma}^{-1}(w),\sigma\right)$

That is each evolved contour Γ_δ is re-parameterized by its normalized arc length parameter w, notice that

$\Phi_\sigma(0) = 0 \qquad \Phi_\sigma(1) = 1$

and

$\frac{d\Phi_\sigma(u)}{du} = \frac{|R_u(u,\sigma)|}{\int_0^1 |R_v(v,\sigma)|\, dv} > 0$ at nonsingular points.

In addition $\Phi_0(u) = u$. $\Phi_\sigma(u)$ deviates from identity function $\Phi_\sigma(u) = u$. only to the extent to which the scale related statistics deviate from stationary along the original contour.Once parameters are varied, the contour plane of the contour with the normalized path length parameter is given by

$k(w,\sigma) = \hat{X}_w(w,\sigma)\hat{Y}_{ww}(w,\sigma) - \hat{X}_{ww}(w,\sigma)\hat{Y}_w(w,\sigma)$

The function defined implicitly by

$$K(w,\sigma) = 0$$

is the renormalized contour plane scale space image of г. This 1-D reorganized sample is then processed for feature description using 1-D spectral decomposition and the power spectral density for each band is evaluated as the feature descriptor.

The 1-D contour signal x(n) is separated or decomposed into components belonging to different frequency channels using a collection of filters, this is referred to as sub band filtering or sub band decomposition. For example, in a two-channel sub band filtering scheme, a pair of half-band filters $\{c_n\}$ and $\{d_n\}$ (called an analysis filter bank), one low pass and one high pass, is used to separate the incoming signal into two sets of data.

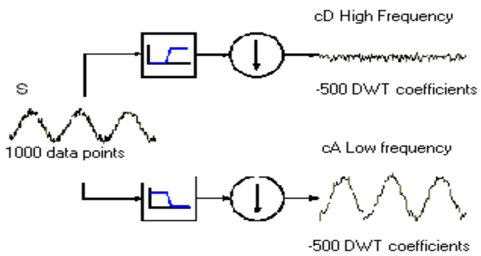

Fig 6: spectral decomposition of the 1-D contour signal

The features are described as the finer spectral information developed by a hierarchal band decomposition obtained from a set of signal decomposition process.

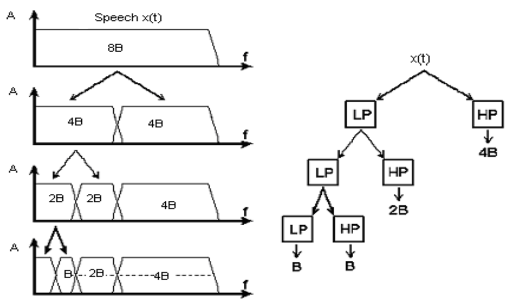

Fig 7: Hierarchical decomposition of signal into bands

The filter banks are built by many band pass filters to split the spectrum into frequency bands. The advantage is that the width of every band can be chosen freely, in such a way that the spectrum of the signal to analyze is covered in the places of interest. The disadvantage is that it is necessary to design every filter separately and this can be a time consuming process. Another way is to split the signal spectrum in two equal parts, a low pass and a high-pass part. The high-pass part contains the smallest details importance that is to be considered here. The low-pass part still contains some details and therefore it can be split again. And again, until desired number of bands are created. In this way an iterated filter bank is created.

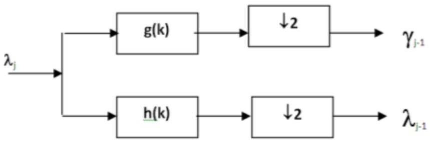

Fig 8: Implementation of one stage iterated filter bank**.**

Usually the number of bands is limited by an instance of the amount of data or computation power available. The process of splitting the spectrum is graphically displayed in figure 8. The advantage of this scheme is that it is necessary to design only two filters; the disadvantage is that the signal spectrum coverage is fixed. For the obtained spectral bands a power spectrum density is computed to reveal the strength of the curvature variation existing in each band. For each obtained band (C_1,C_2,C_3,C_4) PSD is computed. The feature is then described as,

f_1 = PSD ($\|C_1\|^2$)
f_2 = PSD ($\|C_2\|^2$)
f3 = PSD ($\|C_3\|^2$)
f_4 = PSD ($\|C_4\|^2$)

For the obtained features (f_1,f_2,f_3,f_4) a recognition approach is used. To achieve a retrieval accuracy for the extracted feature a relevant feedback system is used. According to relevance feedback technique in CBIR [12], animage object model O(D, F, R) together with a set ofsimilarity measures M = {m_{ij}},specifies a CBIR model O(D,F, R, M).

- D is the raw medical sample to be processed for retrieval.
- F = {f_i} is a set of low level shape features associated
- R = {r_{ij}} is a set of representations for a given feature

Eachrepresentation r_{ij} itself may be a vector consisting ofmultiple components i.e., r_{ij} = {r_{ij1}, ……., r_{ijk}, …..,r_{ijK}}
Based on the image object model and the set of similaritymeasures the retrieval process is described below:
1) Initialize the weights W = [W_i, W_{ij}, W_{ijk}] to W0 which is aset of no bias weights. That is every entity is initially of thesame importance.
2) The user's information need, represented by the queryobject Q, is distributed among different features f_i according totheir corresponding weights W_i.
3) Within each feature fi the information need is furtherdistributed among different feature representations r_{ij} according to the weights W_{ij} .
4) The objects similarity to the query in terms of r_{ij}, fi iscalculated according to the similarity measure m_{ij} and the weights W_i, W_{ij}, and W_{ijk}. .
5) The objects in the database are ordered by their overallsimilarity to Q . The NRT most similar ones are returned to theuser where NRT is the number of objects the user wants toretrieve.
6) For each of the retrieved objects the user marks it as highlyrelevant, relevant, no opinion, non-relevant or highly nonrelevant according to his information need and perceptionsubjectivity.
7) The system updates the weights according to the user'sfeedback such that the adjusted Q is a better approximation tothe user's information need.
8) Go to Step 2 with the adjusted Q and start a new iteration ofretrieval.

V. Experimental results

To evaluate the proposed approach in this work a database images of medical images are recorded and is passed for the evaluation of the proposed approaches.

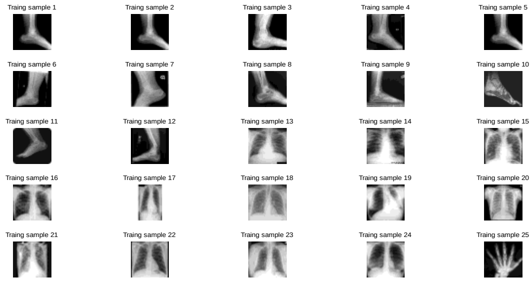

Fig 9: Few Samples taken for training

Fig10. Test sample

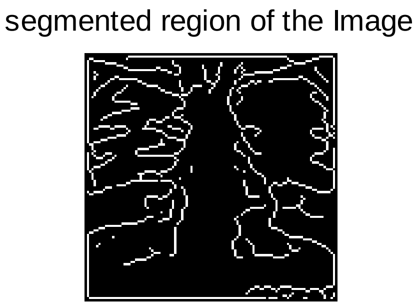

Fig 11: Segmented region for given sample

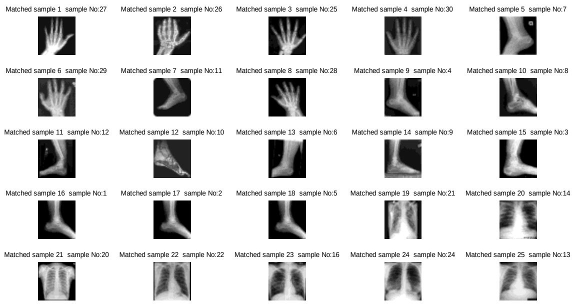

Fig 12: Recognized samples for give query

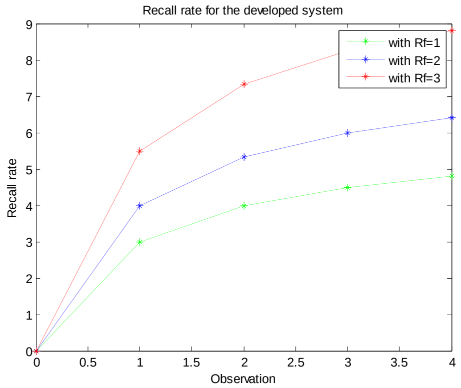

Fig 13: Recall rate for the developed approach

Figure illustrates the recall rare for the developed system for various medical samples been processed. The observation illustrate an improvement in the recall rate due to incorporation of finer feature information and feedback information's.

VI. Conclusion

This paper defines a new approach to medical image retrieval based on contour coding. The approach defines a new approach for shape feature extraction using 1-D representation of the computed contour. This approach reduces the repetitive coding overhead of the Curvature based coding. The system also improves the retrieval accuracy due to the simpler and finer shape feature vectors resulting in more feature information to retrieval system. The system incorporates a feedback retrieval mechanism to achieve the improvement in retrieval accuracy.

References

[1]. Yiping Liu, Hui Liu, Zuowei Zhao, Lina Zhang, Xiang Liu, "A new active contour model-based segmentation approach for Accurate extraction of the lesion from breast DCE-MRI", ICIP, IEEE, 2013.

[2]. H. Imran, S. Vikash, and K. S. Vivek, "Review on offline signature verification methods based on artificial intelligence technique," International Journal of Advancements in Research & Technology, vol. 2, no. 5, pp. 383–388, 2013.

[3]. G. Zhang, Z. Ma, L. Niu, and C. Zhang, "Modified Fourier descriptor for shape feature extraction," Journal of Central South University, vol. 19, no. 2, pp. 488–495, 2012.

[4]. B. Zhong andW. Liao, "Direct curvature scale space: theory and corner detection," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 3, pp. 508–512, 2007.

[5]. Y. Cui and B. Zhong, "Shape retrieval based on parabolically fitted curvature scale-space maps," in Intelligent Science and Intelligent Data Engineering, vol. 7751 of Lecture Notes inComputer Science, pp. 743–750, 2013.

[6]. Y. Gao, G. Han, G. Li, Y.Wo, and D.Wang, "Development of currentmoment techniques in image analysis," Journal of Image and Graphics, vol. 14, no. 8, pp. 1495–1501, 2009.

[7]. Y. Ge and D. Zhang, "A fast matching way using the legengre orthogonal moment and application in image guided radiotherapy," Acta Electronica Sinica, vol. 37, no. 7, pp. 1529–1531, 2009.

[8]. S. A. Grace and S. Annadurai, "Content based image retrieval for medical images using generic fourier descriptor," Journal of Computational Intelligence in Bioinformatics, vol. 1, no. 1,pp. 65–72, 2008.

[9]. A. Sajjanhar, G. Lu, and D. Zhang, "Coherence based histograms for shape retrieval," in Proceedings of the 3rd International Conference on Computer Sciences, Software Engineering, Information Technology, E-Business and Applications, pp. 1–5, Cairo, Egypt, 2004.

[10]. J.X. Zeng, Y.G. Zhao, and X. Fu, "An improved distance coherence vector algorithm for CBIR," Pattern Recognition and Artificial Intelligence, vol. 23, no. 5, pp. 715–719, 2010.

[11]. B.Xie and J.Wang, "Acontour-based image retrieval algorithm," Journal of Image andGraphics, vol. 13,no. 7, pp. 1367–1373, 2008.

[12]. Yong Rui, Huang, T.S Ortega, M. Mehrotra, "Relevance Feedback: A Power Tool for Interactive Content Based Image Retrieval." IEEE Transactions On Circuits And Video Technology. Vol-8, issue 5. pp 644-655. 1998.