TOPOLOGY CODING IN SPECTRAL DOMAIN FOR EFFECTIVE MEDICAL IMAGE RETRIEVAL

[1]S.Vyshali [2]M.V.Subramanyam [3]Dr.K.Soundara Rajan
[1] Asst. Professor, G.Pulla Reddy Engineering College, Kurnool, A.P, India, surashali@gmail.com
[2]Principal, Santhi Ram Engineering College, Nandyal.
[3]Professor, Jawaharlal Nehru Technological University, Anantapur.

Abstract: *This paper present an approach for image retrieval based on shape based approach. The approach is developed with a curvature representation approach and the information for the contour variation is explored with the usage of spectral based approach. The integration of spectral transform approach with shape based representation by the usage of curvature scale space representation for contour evolution is proposed. The suggested approach is used as in representative co-efficient for a given image and the resolution information exploit the curvature nature of the curvature scale information. This approach is observed to be faster and higher accurate approach than the existing shape based segmentation approach.*
Keyword: Discrete Spectral transform, curvature representation, shape based coding, image retrieval.

I. INTRODUCTION

Image retrieval is observed to be a research area from many a decades. There are various methods been developed in past for the realization of faster and highly accurate retrieval algorithm to achieve improved retrieval ratio over existing methods. Image retrieval basically performed to achieve faster data transfer or proper resource utilization for image processing. Current scenarios the image capturing devices are modeled capture very high-resolution image or video sequences to attain high visual quality in imaging applications. Though high-resolution representations are better to have higher visual quality they have the problem of very large data to process or transfer. Imaging application has emerged from a basic image capturing process to high end imaging applications. The area of image processing has diversified from basic computer visionary application to real-time imaging application such as industrial automation, medical processing, aeronautical processing etc. though the approach of imaging application is diversifying in various ways with the increase in the need for imaging applications in run time environment the approach is getting complex. This complexity results in higher resource utilization and intern demands for high power and larger computational devices. This limitation results in making out research work in providing the approach for image processing application more reliable and faster in real time processing using simpler and high end tools. There are many applications where the shape of objects needs to be encoded, such as CAD, 3D modeling, signature encoding [9], as well as region oriented video coding techniques [1], where the shape information is described by a binary mask having the same values for all the pixels inside the shape. The binary mask indicates the region(s) in which the texture of the object needs to be coded [7]. Contours around the shape in binary masks are generally simple closed ones, without intersection and ambiguous contour continuations .They are defined usually in pixel resolution, consisting of a number of adjacent pixels that are called contour points. They can be represented, eg, by a chain code [8] or approximated with a polynomial function and subsequently entropy coded [9].
Shape representation is a pivotal step in shape analysis and matching systems. After the shape is located and segmented from an image, a representation technique is used to efficiently characterize the shape. The complexity and the performance of the subsequent steps in shape analysis systems are largely dependent on the invariance, robustness, stability, and uniqueness of the applied shape representation technique. In the past decade, several techniques have been proposed for 2D shape representation and matching. They include curvature scale space (CSS) [1], [2], [3], fuzzy-based matching [4], dynamic programming [5], shape contexts [6], shock graphs [7], geodesic paths [8], Fourier descriptors [9], and spectral descriptors [10]. Objects can be recognized by their color, texture, and shape. Shape descriptors have become more popular, since they were adopted in the MPEG-7 system [11]. Region, contour, and skeleton shape descriptors were evaluated under the MPEG-7 system using a single shape data set [12]. Generally, contour based descriptors performed significantly better than other category descriptors [13]. Recent work in the area of extracting spectral features, which are invariant to geometric transformations, has been very promising [14]. Spectral analysis has become a powerful tool in several disciplines, including shape analysis and recognition [15]. Many researchers have adopted the Spectral Transform (WT) in shape representation and matching. For example, WT was applied in 2D domains in

[8], [9], and [10], whereas WT was applied to 1D shape boundary in [12], [13], [14], and [10]. Due to the spatial and frequency localization property of the spectral basis functions, spectral descriptors are more efficient in representing and describing shapes than Fourier descriptors and moments [8]. In many image-processing applications, exact reproduction of the image bits is not necessary. In this case, one can perturb the image slightly to obtain a shorter representation. If this perturbation is much smaller than the blurring and noise introduced in the formation of the image in the first place, there is no point in using the more accurate representation. Such a code procedure, where perturbations reduce storage requirements is known as Image loss coding. However to improve the time of transmission and the overall efficiency of system the Image is always compressed before transmission. There were various retreival approaches and standards been suggested in past the most commonly used approach is the JPEG or JPG2K standards. Though these techniques are used for retreival they are observed to be highly erroneous under noisy environment and are less accurate in retreivation due to noise effects and quantization effect. A modified approach of the existing coding standards is hence required for the retreival. To achieve higher retreival rather to process the image directly the content of image is processed, as the surrounding image information may not be of higher importance. These type of retreival are achieved by shape based segmentation approach. Though most of the shape based retreival approaches were made with the approach of edge information, they may be low in retreival due to additional information. To over come this issue a segmentation approach based on the curvature scaling is proposal and further presentation with spectral transformation for the exploration of resolution information to represents image coefficients is presented.

II. SHAPE IMAGE REPRESENTATION

A useful general – purpose shape representation method in computational vision should make accurate and reliable recognition of an object possible. Therefore, such a representation should necessarily satisfy a number of criteria. The following is a list of such criteria. Note that when two planar curves are described as having the same shape, there exists a transformation consisting of uniform scaling, rotation, and translation, which will cause one of those curves to overlap the other.

a) Invariance: If two curves have the same shape, they should also have the same representation.

b) Uniqueness: If two curves have the same shape, they should also have the different representation.

c) Stability: If two curves have a small difference, their representations should also have a small difference, and if two representations have small difference, the curves they represent should also have small shape difference.

The importance of the invariance criterion is that it guarantees that all curves with the same shape will have the same representation. It will therefore be possible to conclude that two curves have different shapes by observing that they have different representations. Without the invariance criterion, two curves with the same shape may have different representations. It will therefore be possible to conclude that two curves have the same shape by observing that they have the same representation. Without the uniqueness criterion two curves with different shapes may have the same representation. As a result, when two representations are close, the curves they represent are close in shape, and when two representations are not close, the curves they represent are not close in shape. When this criterion is satisfied, the representation can be considered to be stable with respect to noise. One way to measure the shape difference between two planar curves is the Hausdorf distance. It is useful for a shape representation to satisfy a number of additional properties in order to become suitable for practical shape recognition tasks in computer vision. The following is a list of such criterion.

d) Efficiency: The representation should be efficient to compute and store. This is important since it may necessary for an object recognition system to perform real-time recognition. By efficient, we mean that the computational complexity should be a low-order polynomial in time and space (and in the number of processors if a parallel computing architecture is used) as a function of the size of the input curve.

e) Ease of implementation: If two or more competing representations exist, it is advantageous to choose one of those representations such that the implementation of the computer program that computes that representation requires the least time spent on programming and debugging.

f) Computation of shape properties: It may be useful to be able to determine properties of the shape of a curve using its representation. For example if a curve has a symmetric shape, it may be desirable to be able to determine that fact from its representation (the symmetry criterion). Furthermore, if the shape of a whole curve or part of a curve is the same as the shape of part of another curve, it may be useful to be able to determine that relationship using their representations (the part/whole criterion).

Shape representation methods for planar curves previously proposed in computational vision fail to satisfy one or more of the criteria outlined above. Note, however, that each may be quite suitable for special-purpose shape representation and recognition tasks.

A) Contour representation

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 5.3.
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.

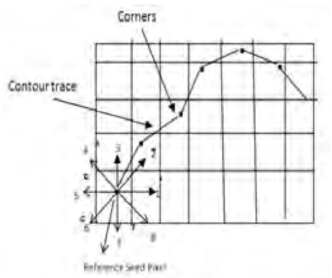


Figure 1 probable scanning order for -region neighborhood-growing algorithm

Once the contour is detected the curvature for the obtained contour is calculated.

III. SPECTRAL REPRESENTATION

The spectral transform (WT) of a real function s(t) is defined as [1]:

$$S(\lambda,\tau) = {}^{1}\!/\!_{\sqrt{\tau}} \int_{-\infty}^{\infty} s(t)\varphi\left(t-\frac{\tau}{\lambda}\right)dt \qquad \text{eq.(1)}$$

Where $\psi(t)$ is a zero mean mother spectral. The final function $S(\lambda,\tau)$ as well as the particular spectrals are described with two parameters: time shift τ also called translation factor and dilation parameter λ, known as the scale factor. The normalization constant $\lambda^{-1/2}$ compensates the different energies of spectrals. The special case of spectral transform described above is a dyadic discrete spectral transform (DWT), where the dilation parameter $\lambda = 2^m$, and the translation factor $\tau = 2mk$, $m > 0$, k and m are integer numbers. The dyadic DWT can be realized with the bank of filters having impulse responses hm [1]. For discrete signal s(n) , the dyadic spectral transform (DTWT) is defined:

$$S_m(k) = \sum_{n=-\infty}^{\infty} s(n)h_m\left(2^m k - n\right) \qquad \text{eq(2)}$$

The spectral decomposition realized with the bank of filters, which breaks down a signal into many lower-resolution components (frequency bands) by low-pass end high-pass filters. Generally the output from any low-pass filter can be split iteratively until the last branch consists of a single sample. In practice, the suitable number of levels is based on the nature of the signal, or on the application [9]. The spectral retreival filter-banks structure is similar to the decomposition structure: The conditions for perfect retreival $s(n) = s'(n)$, are given by the following formulae [1]:

$$\begin{aligned} F_{LP}(z)H_{LP}(z) + F_{HP}(z)H_{HP}(z) &= 2, \\ F_{LP}(z)H_{LP}(-z) + F_{HP}(z)H_{HP}(-z) &= 0. \end{aligned} \qquad \text{eq(3)}$$

Note: The conditions above and block diagram in Fig. 3 are valid, when non-causal filter-banks are considered with zero time delay. Otherwise time delay blocks should be entered into particular branches. Several different approaches exist for filter-banks de- sign that create orthogonal or biorthogonal structures [8]. The structure of the orthogonal filter-banks is very special. For example, if the length of their impulse response is four: all filters (decomposition HP, LP and retreival HP, LP filters) use four coefficients a, b, c, d, where the convolution along the bottom channel (multiplication of polynomials

$$H_{LP}(z) = a + bz^{-1} + cz^{-2} + dz^{-3}$$

and

$$F_{LP}(z) = d + cz^{-1} + bz^{-2} + az^{-3} \quad \text{eq.(4)}$$

Fig. 4 illustrates a particular “half band filter” [8]. For this example the half band filter coefficients are (−1/16, 0, 9/16, 1, 9/16,0, −1/16). Note: The odd powers of z−1 are missing for this type of filter.

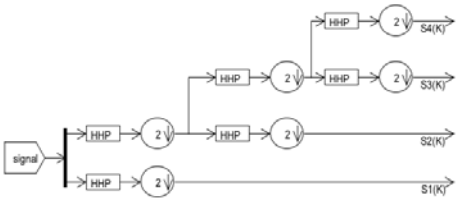


Figure. 3. Dyadic spectral transform realized with the tree structure of high-pass (H_{HP}) and low-pass (H_{LP}) decomposition filters.

The circles represent down sampling with a factor of two (the odd numbered components are removed after filtering).

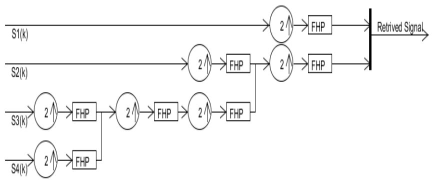


Figure. 4. Inverse dyadic spectral transform realized with the tree structure of high-pass (FHP) and low-pass (FLP) retreival filters. Note: The up-sampling operation ↑ 2 inserts zeros between the samples.

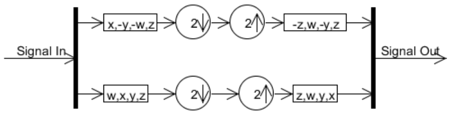


Figure. 5. The form of the orthogonal filter bank with four coefficients. The left part corresponds with the decomposition (analysis) and the right part corresponds with the retreival (synthesis) part of the spectral transform.

The biorthogonal filter-bank design is less restricted than the design of an orthogonal one. The multiplication of two polynomials along the bottom channel gives also the half band filter, but the retreival low-pass filter coefficients do not have to be the transpose (the flip) of the decomposition low-pass filter coefficients. Figure 5 shows how the filters on the retreival side are related to the decomposition filters. The relation between their transfer functions is derived from the equation 3 giving the following formulas:

$$F_{LP}(z) = H_{HP}(-z), \qquad F_{HP}(z) = -H_{LP}(-z) \quad \text{eq(5)}$$

where the simple substitution provides a high-pass filter based on the low-pass one, or vice versa [10].

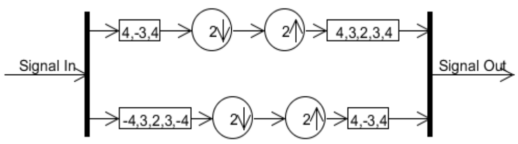


Figure. 6. The biorthogonal filter bank

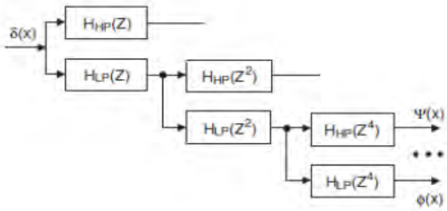


Figure. 7. Scaling function $\phi(x)$ and spectrals (x) from iteration of the low-pass filters.

Where: $\Psi(x)$ is the Dirac delta function, $H_{HP}(z)$ is a transfer function of the highpass filter, $H_{HP}(z^2)$ is a modified transfer function of the highpass filter (the filter coefficients are zero padded).

The above-mentioned discrete-time filters have the following relation with the continuous-time spectrals (t). The approximation of spectrals (their shape) comes from the iterative convolution of impulse responses of the rescaled filters as it is shown in Fig. 6. Continuing the decomposition we approximate more and more the continuous-time spectrals' shape [8]. The output from the last LP filter approximates the so-called scaling function $\phi(t)$ and the output from the last HP filter approximates the continuous-time spectral $\psi(t)$.

IV. RETREIVAL SYSTEM

Spectral transform offers good properties for data retreival. The signal-decomposition to several frequency bands leads even to the signals with low entropy and thereby to more efficient entropy coding. The process of contour image retreival/deretreival with spectral transform is shown in Fig. 9.

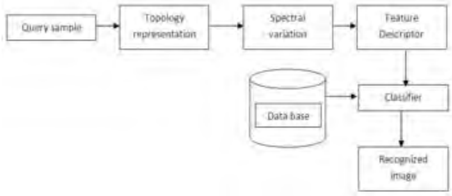
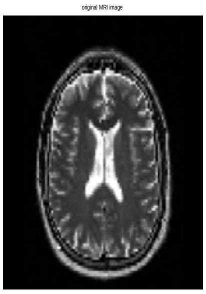


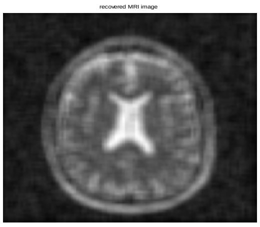
Figure. 8. Spectral-based contour image coding and retreival.

The two-dimensional discrete contour is represented as a set of two discrete parametric functions x(k) and y(k) , where parameter k indicates the pixel position at the contour. These functions are decomposed by spectral transform (low-pass and high-pass filters) to frequency bands $S_m(k)$ and entropy coded with Huffman coding. The deretreival is an inverse process, where the de- coded binary data are transformed to parametric functions with spectral retreival and displayed as the contour image. The biorthogonal spectral transform based on the filters listed are reversible. It means, that perfect retreival is possible if the output from spectral-decomposition-block $S_m(k)$ are with no change transformed back by retreival block. Higher data reduction can be achieved when $S_m(k)$ are threshold (values not exceeding the threshold are set to zero) .

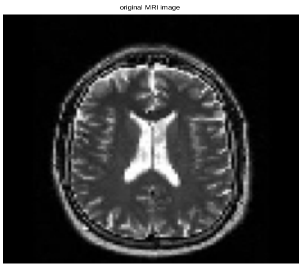
V. RESULT OBSERVATION

(a) Query MRI image sample
(b) Retreived image at 0.1 bpp

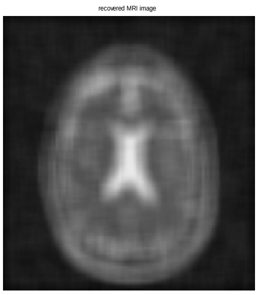




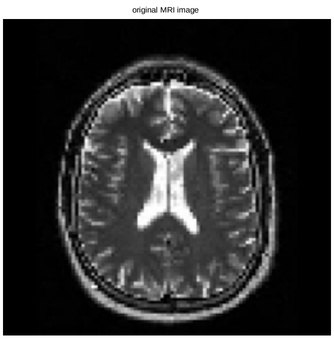
(c) Query image at 0.5 bpp
(d) Retreived image at 0.9 bpp



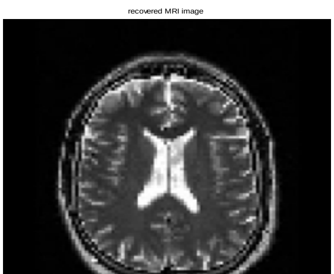
(c) Query MRI image at 0.5 bpp



(b) Retreived MRI image sample at 0.1 bpp



(c) Query MRI image sample at 0.5 bpp



(d) Retreived MRI image sample at 0.9 bpp

VI. CONCLUSION

An efficient image retreival approach based on curvature scale spacing is developed. The evolution of contour region is developed based on 8-neignhbour region growing method and a zero crossing method is applied for the contour evolution. The approach of contour based retreival is processed with spectral transformation and entropy coding for performing image retreival. The obtained performance is observed to be better compared to the conventional DWT based coding technique.

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