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SEGMENTATION OF VERTEBRAE FROM DIGITIZED X-RAY IMAGES

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Abstract— *The Hough transform is a technique which can be used to isolate features of a particular shape within an image. Because it requires that the desired features be specified in some parametric form. A* generalized *Hough transform can be employed in applications where a simple analytic description of a feature(s) is not possible. retains many applications, as most manufactured parts (and many anatomical parts investigated in medical imagery) contain feature boundaries which can be described by regular curves. The main advantage of the Hough transform technique is that it is tolerant of gaps in feature boundary descriptions and is relatively unaffected by image noise*
Keywords: *Generalized Hough Transform, R table, Accumulator bin, Template matching*

I. INTRODUCTION

For examination of X-rays of cervical vertebrae for determining the presence of osteoarthritis and osteoporosis. Segmentation is necessary for proper diagnosis , Manual segmentation is prone to errors due to inter- and intra-subject variability's due to the subjective judgment that is employed .The use of computer vision methods is an attractive alternative to providing an automatic means for segmenting vertebrae For individual vertebra assessment, the bounder increasingly digresses from the General rectangular shape as the vertebra becomes less normal in appearance. For an abnormal vertebra, bony growths ('osteophytes') may appear at the vertebral corners, resulting in a change in the vertebra's shape. General-purpose algorithms present a number of shortcomings that limit their ability to locate and delineate precise vertebral shapes. Therefore, there is a need for a different approach. GHT has the ability to find occurrences of a previously defined template in a target image regardless of orientation and scale variations and in the presence of noise, and occlusions

II Generalized *Hough transform*

GHT is a promising candidate to achieve good segmentation, the original implementation of the GHT uses edge information to define a mapping from orientation of an edge point to a reference point of the shape. In the case of a binary image where pixels can be either black or white, every black pixel of the image can be a black pixel of the desired pattern thus creating a locus of reference points in the Hough Space. Every pixel of the image votes for its corresponding reference points. The maximum points of the Hough Space indicate possible reference points of the pattern in the image. much of the success of this technique depends on three parameters: (1) gradient information, (2) representativeness of the template, and (3) reckoning of the votes in the accumulator structure. GHT uses an edge image to correlate points in a previously defined template to those in the target image using local gradient information. Depending on the good edge image votes will be correlated to the template. Typical implementations of GHT assume that a clear edge image, from which gradient information can be obtained is available.

2.1 Design of Algorithm

A customized process performs Gaussian filtering on a copy of the original image and the result is subtracted from the original. From the resulting edge image, extraction of the gradient information is performed using optimum gradient operators. Success of GHT greatly depends upon the representativeness of the chosen template. Even if good gradient information is available, the template must adequately represent the target object in order to obtain the necessary votes in the accumulator. Across a large set of images, it is common to find great variability in shape of the cervical vertebrae.

The next and very important step in GHT is the reckoning of votes in the Hough domain. Finding the best estimates of orientation and location of the cervical vertebrae is a direct consequence of the above step. Typical implementations of GHT use a simple criterion the best estimates correspond to the bin with the largest number of votes. In the proposed approach, post processing of the accumulator structure is carried out and this leads to valuable information about the shape and orientation of the cervical vertebrae.

binary gradient mask

Fig 1: Unsharp masking to obtain edge image

2.2 Obtaining an edge image

Unsharp masking is the proposed main operation to obtain an edge image. As defined the general procedure of subtracting a blurred image form an original is called unsharp masking. A Gaussian filter will be used to obtain a smoothed version of the original x-ray image. This operation will cancel any subtle variation in the gray scale, preserving only abrupt changes (edges). Some of the most commonly used discrete gradient operators are the Sobel and Prewitt operator

It can be shown that the GHT is effective for finding the approximate location of the target vertebrae or Region of Interests (ROI) The GHT uses a lookup table termed the R-table for an arbitrary shape, so no Analytical description for the shape is necessary. Figure 2 illustrates the geometry

2.3 R table construction

For building the R-table and the format of R-table. $P_r(x_r, y_r)$ is a reference point which is the origin of an axis system fixed in the template shape. An arbitrary pointon the template boundary $P_i(x_i, y_i)$ is specified by equation (2.1) and (2.2).

$r = \mathrm{sqrt}(y_i - y_r)^2 + (x_i - x_r)^2$ …………… (2.1)

$\alpha = \tan^{-1}(y_i - y_r)/(x_i - x_r)$ …………… (2.2)

Where r is the Euclidean distance from the reference point to the boundary point, and α is the angle of the line connecting ($P_i(x_i, y_i)$ and $P_r(x_r, y_r)$. The pairs of (r,α) are then indexed by local edge direction angle θ , which is determined by the20 intersection of the tangent line through $P_i(x_i, y_i)$ and the horizontal axis. The format of the R-table is then defined in terms of discrete value $i\theta$ and the corresponding $(\alpha i, \gamma i)$ pairs, as illustrated in Table 1.

Fig2 Illustration of the geometry for building the R-table.

Table 1 The R-table format.

θ_i	(r, α)
$\Delta\theta$	(r_1, α_1), (r_2, α_2)
$2\Delta\theta$	(r_3, α_3), r_4, α_4,
$3\Delta\theta$	(r_5, α_5), (r_6, α_6)
θ	……………

…
…
.

2.4 Creating a template :

The vertebral shape has been described using landmark points are placed at pathologically significant points on the vertebra boundary. We use the 12-point representation of vertebra shape using the 12 -point model by a board certified radiologist as ground truth. The locations of these template points, shown in Figure 3 are indicative of the pathology found to be consistently and reliably detectable in the image collection. We use the mean of 10 templates randomly selected from the images which were marked using 12 point model. The target shape to be segmented is the cervical vertebrae C3-C6, thus the template is defined by a total of 48 morph metric points for the four vertebrae. As shown in equation each template i *T* contains the *x* and *Y-coordinates* of a single 48-dimensional vector respectively, and *T* denotes the mean of the 50 templates.

$\text{Template})_i = [x_{i1}, \ldots\ldots x_{i80}, y_{i1,\ldots\ldots\ldots} y_{i80}]^T$

$\text{Mean template} = 1/10(\sum_{i=1 \text{ to } 10}(\text{template})_i$

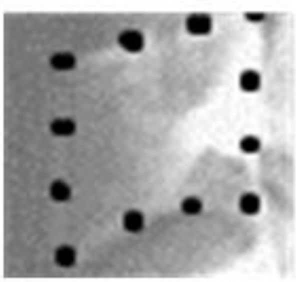


Fig 3: Points marked indicate ROI

2.5Template Matching:

Template matching is conceptually a simple process. We need to match a template to an image, where the template is a sub-image that contains the shape we are trying to find. Accordingly, we centre the template on an image point and count up how many points in the template match those in the image. The procedure is repeated for the entire image and the point which led to the best match, the maximum count, is deemed to be the point where the shape (given by the template) lies within the image Template matching is a fundamental operator in computer vision and is widely used in feature tracking Accumulator updating and reckoning of votes Template matching develops an *accumulator space* that stores the match of the template to the image at different locations, this corresponds to an implementation of Equation below

$\min e = \sum (\mathbf{I}\ x+i,y+j\ \ y\ ,\ \ -T_{x,y})^2$

It is called an accumulator, since the match is *accumulated* during application. Essentially,the accumulator is a two-dimensional array that holds the difference between the template and the image at different positions. The position in the image gives the same position of match in the accumulator. Alternatively, Equation

$\max e = \sum I_{x+i,y+j} \quad T_{x,y}$

suggests that the peaks in the accumulator resulting from template correlation give the location of the template in an image: the
co-ordinates of the point of best match. Accordingly, template correlation and template matching can be viewed as similar
processes. The location of a template can be determined by either process. The binary implementation of template matching,
Equation

$\max e = \sum I_{x+i,y+j} \ \square_{x,y}$

usually is concerned with threshold edge data. This equation will be reconsidered in the definition of the Hough transform, the topic of the following section. Updating the accumulator, as well as picking the best estimate of the reference point, is the remaining part of the algorithm.

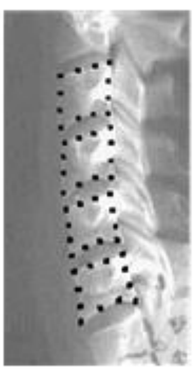


Fig :4 a Target with Land Mark Points.

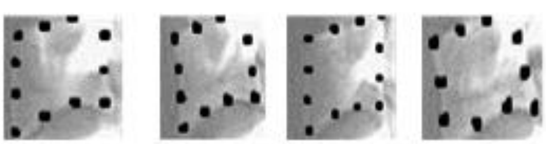


Fig :4 b Four different Templates.

2.6 Hough domain update process

The search process is intended to analyze every edge point *P^* in the target image and, based on the local value of 0, find the corresponding (r,a) pairs in the R-table to update the accumulator. Such procedure will perform a great amount of unnecessary repeated operations.The parameter 0 has a finite number of values. It is reasonable to assume that in the process of analyzing the target image point by point, there will be edge points w it the same values of 0 . Hence, if a search procedure is performed for single point in the target image, then lots of search procedures are to be repeated. Restatement of the search-update process can save a lot of computational time. before any iterative process, which points in the target image and in the R-table are related by finding which points from both images have the same 0 value. Since this is done before any iterative process, no repeated operations will be performed. After findingthe corresponding matches, this information will be plugged into equations

$xr = X_i - s.r_i - cos(ai+\varphi)$ *and*

$y_{i=} \, y_i - s.r_i - sin(ai+\varphi)$.

to know the bins of the accumulator that are to be updated. Search and update processes have to be repeated for every value of rotation,(j), and scale, *s* . However, the process of finding matches of 0 can be performed only once. The output of such process can be temporarily stored and can be used for every variation of scale and orientation. As a consequence, the search-update process is reduced to a one-time search process and as many variations of the parameters, (α) and *s* , as necessary to update the accumulator. Avoiding any repeated calculation and by performing inside of the iterative processes only those operations that are absolutely necessary, the algorithm will be optimized and execution time will be greatly reduced.

2.7Reckoning of the votes in the Hough domain

The accumulator can be treated as a collection of 2-D images of the spatial location of the reference point. Set *m* and *n* to be the number of rows and columns of the target image and ; and j and *k* to be the number of scale and rotation variations respectively.

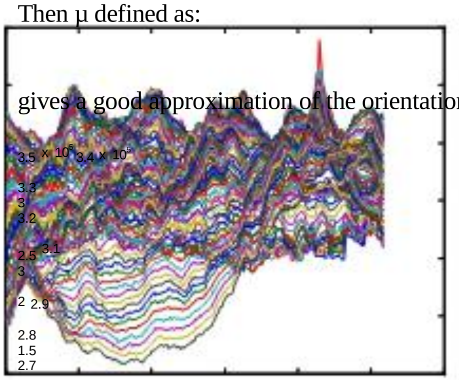
The accumulator is a 4-D structure where 2 of the dimensions (m x n) represent the spatial coordinates and the remaining two (j x k) represent scale and rotation variations of the template. As a consequence, the 4-D accumulator can be seen as a (j x k) collection of 2-D images of the spatial location of the reference and each of those images can be treated individually. If the 2-D accumulator is plotted for a fixed value of scale and rotation [Fig. 2(a)], we would expect as per theory, a well defined peak Excessive noise in the original images makes votes sparse in the accumulator, yielding non-uniform structures.

A small window, having the highest peak as the central point is defined as our region of interest. The next step is to try and find the approximate orientation of the spine and the location of the neighboring peaks with the knowledge of the location of the highest peak. Let γ be the angle that approximates the orientation of the template and Φ, the current rotation angle of the template.

Then μ defined as:

$$\mu = \gamma - \Phi$$

gives a good approximation of the orientation of the cervical spine in the target image



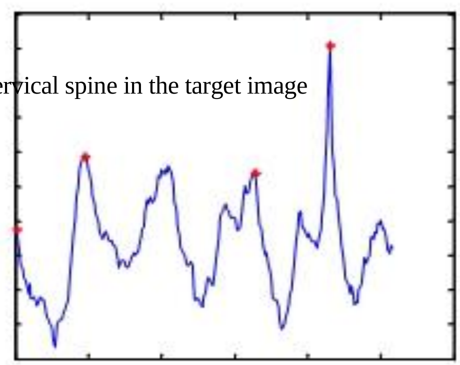


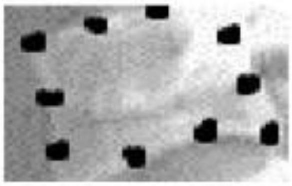
Fig 5 : The highest Peaks defines the max match. Fig 6: Plot of the resulting characteristic profile highest peak showing the match

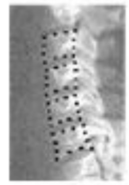
III Experimental Results

A set of 10 images selected database was used as our data set. For each image, a template was defined by placing a series of landmark points (LMP) based on morph metric points, which were placed by expert radiologists and represented our ground truth. These values are experimental and work well with this application.

To assess the performance of the proposed approach, two quantitative measurements were used and three main experiments were carried out.Measurements:
1. Number of original LMP that fall within a bounding box surrounding the template at its final location.
2. Measurement of the difference in orientation between the original shape, described by the LMP, and the final output of the algorithm.

Tem plate Target





M atc hing Result using tm p

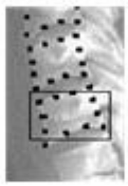


Fig 7: Result showing the match the sixth column .

IV Conclusion:
Thus using image segmentation, the image has been addressed using a customized and robust approach that leads to promising results and it is very helpful in various fields such as medical and defense, etc. It takes into account valuable shape
information present in the voting structure. Current work involves the inclusion of more templates to increase accuracy. As mentioned before, in spite of how much gradient information is available and could be used by the proposed criterion, representativeness of the template

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