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Shape Learning of 3D Surfaces of the Knee using different Image Segmentation Techniques

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ABSTRACT

Field of medical image analysis is evolving at a rapid pace. New advancements have introduced big challenges in analysis and information extraction from the generated images. Usually the scale of input data is so immense that it needs very efficient and smart algorithms to process intended outcomes. Magnetic Resonance Images (MRI) is one of the primary sources for morphometric analysis. Frequently used techniques for this kind of analysis are Principal Component analysis (PCA) and a more robust Incremental Principal Component Analysis (IPCA). Both these techniques apply complex algorithms for producing statistical shape models which ultimately show variance in clinical images. Variance is primarily detected and measured in the articular cartilage. Statistical assessment of cartilage volume and surface area estimation gives an indication of osteoarthritis severity.

This research paper proposes an agile framework for segmentation of images of the knee by using Active contour model. Image texture information is merged in the model with the help of effective mathematical functions. Vector valued geodesic was used during segmentation and also to detect and measure variance in the image at pixel level. By use of efficient algorithms and mathematical tools this technique showed promising results in handling noise and non-uniform intensities within the image. The algorithm effectively provided a quantitative cartilage assessment which could help physicians in classifying osteoarthritis stages.

I. Introduction

In the field of medical image analysis, machine learning techniques have showed promising results in extraction of useful information from big datasets. As the data volume is huge in image analysis so to process this image data very efficient and smart algorithms are needed. Recent work in this field are related to segmentation of the different human organs like heart, liver and structures of the musculoskeletal system. In which very complex and computational intensive algorithms were used [4]–[6]. Magnetic resonance imaging (MRI) is the top imaging modality for noninvasive assessment of the articular cartilage [3], and cartilage decline can be detected using quantitative MRI analysis. Most of quantifiable assessment studies in medical imaging require accurate segmentation of the clinical image data [3]. It is considered to be one of the most crucial steps in this technique. The use of a dedicated low-field MRI has its pros and cons. The negatives are related to image quality with lower resolution and more difficulties in incorporating features such as fat subdual, however fat subdual has been magnificently executed recently for low-field MRI [11]. Typically physicians manually segment cartilage slice-by-slice but this method is time intensive and error prone [2]. If manual labor is linked with the examination and quantification of MRI data in clinical studies, one more cost feature is presented. PCA is the most commonly implemented technique for subspace learning. There is a shortcoming in this technique, after the initial statistical shape model (SSM) has been computed if new data arrives the whole shape model has to be recomputed which requires access to the whole dataset. As the dataset increases the matrices become very large on which PCA operates. The larger the matrices the more compute power it needs to process them. Another version of PCA was introduced by Skočaj et al [8] which is more robust in comparison to the traditional one. This technique extracts useful information from a large dataset and discards the rest of the data which is not useful. It has partially improved the computational complexity but it still requires access to all data. To overcome the shortcomings in PCA a new modified version of PCA was introduced named as IPCA [12]. Incremental Principal Component analysis (IPCA) is more advance and efficient as associated to PCA. It requires access to the initial input data (MR Images) only once when it is added to model. After processing, only significant data is stored and all other less important data and noise is discarded in this way it needs less storage and compute capacity. As IPCA maintains only relevant information from the training data it has faster computational time than batch PCA. It allows the efficient addition of new data to the model without repeatedly processing the original dataset. This method proved to be very effective and accurate in comparison to the traditional PCA. On the given dataset of images an automated segmentation algorithm was applied which extracted Bone-Cartilage interface, bone segmentation and cartilage segmentation. After the segmented images were available eigenvectors and eigenvalues were identified. Eigenvalue represents the variance in the dataset. After this all vector were concatenated into a matrix. Covariance of this matrix was computed and in the next step singular value decomposition algorithm was applied. The output of this algorithm was a principal component, eigenvalue and a shape coefficient. In the last step a statistical shape model was generated. A few studies have previously explored the use of IPCA in medical image analysis and/or statistical shape modeling. Salehian et al. [10] showed benefits of the IPCA in computationally expensive principle geodesic analysis of diffusion tensor data. Wang et al. [11] applied IPCA for learning subject specific shape variations in combination with a SSM of normal shapes. This adaptive mixture model was used for segmentation of abnormal structures, rather than for generation of large learning databases. A few advantages of the IPCA subspace learning are, it has faster computational time than batch PCA, it maintains only relevant information from the training dataset and it allows the efficient addition of new data to the computed model [12].

This research is structured in a way that at first a brief introduction was given of the current tools and techniques used in clinical image analysis. Related work and domain specific techniques were explored. Next a detailed implementation of relevant technique was explained. All the algorithms used in Active contour models were discussed and explained in detail. Later experimental verification steps were revealed. At the end based on the experimental results a conclusion was made

II. IMPLEMENTATION

A. Geodesic snakes

The segmentation techniques described in [4] require some amount of manual collaboration except for the method of Pakin et al. [12], the 3-D procedures are evaluated only on relatively minor data sets which evaluate their methods on scans from osteoarthritis test cases. In this research a model was proposed that can fully repeatedly segment cartilage in both healthy and osteoarthritic knee scans. Selected segmentation method was the first step in a quantitative fully automatic cartilage valuation and is principally envisioned for clinical studies by low-field MR scanners. The segmentation algorithm was built on a one versus all approach of combining binary approximate NN classifiers which is described in [14]. Algorithm also had an iterative place alteration process that was intended to correct for the variations of the placement of the test subject [15]. Segmentation end product was assessed not only to manual tracings of a radiologist but also in terms of accuracy. This technique is used for detection of object boundaries. It measures the internal geometry of the object using active contours. Both interior and exterior boundaries were detected by splitting and merging contours. A polygon was generated on the targeted image by setting a number of contours on the image. In result of this a set of contours were populated. Curve evolution was used to lessen the set of vertices of the polygon to a subset of vertices only having relevant and genuine information about the original image as shown in figure 1. A geodesic curve is the minimal distance between given points. The mathematical modeling was based on the theory of curve evolution [10]. An efficient algorithm was used for implementation of this curve evolution. The algorithm ensured sub-pixel accuracy [14]. Active contour approach used was both geometric and topological independent. Algorithm produced anticipated results after a number of iterations. This iterative process improved the segmentation process at every repetition. All features were examined in every iteration and important features were delineated. The dataset was segmented and dimensionality was reduced at each step. After number of iteration met the defined threshold algorithm stopped. At this stage there was no room for any significant improvement in the segmentation process. The boundaries delineated were pretty much accurate in comparison to the original features in the data. The feature selection system provided optimum results. Intensity and position of the concerned features both are highly relevant in view of physicians. The algorithm also adopted mathematical tools to precisely measure the geometry of the object. A third order derivative mathematical tool was used in the algorithm. A mathematical minimization function was used to achieve desired results on multi-valued images [15]. Images were represented in form of vectors. These vectors were eigenvectors and the corresponding values were known as eigenvalues which were used in the mathematical calculations [16]. The eigenvalues helped in spatial averaging of the objects. Tibial and Femoral compartments are primary classifiers during the segmentation process.

B. Variance Detection

A robust algorithm was implemented to classify the variance in the image. Although MR images vary in intensity but they have almost uniform texture throughout the region that's why it is difficult to identify variance in two images. The algorithm used initial contours and had a robust capability to converge the contours automatically over the curve. Image texture was also incorporated in the analysis [7]. It facilitated the identification process of image variance. The algorithm computed variance at pixel level. Most of the mathematical modeling implemented in the algorithm was done with the help of conventional snakes formulation. After a number of iterations the contours converged with respect to the curve. For good results the number of iterations were set to a minimum of 10 iterations. The algorithm also showed spatial relationship among the features of the targeted object. The final model was best fit in terms of scaling, orientation and shape.

C. Pseudo code

Input: Grey scale images of resolution [256x256]

Output: Segmentation of grey scale images, Variance Value

Foreach Grey Scale Image k, k=1: To do

Compute (Mathematical Function for geodesic snakes);

Calculate InitialModel for Segmentation;

Calculate Contours on previous output;

Incorporate ImageContrast on contoured image;

Calculate Variance (Make Comparison);

End

III. EXPERIMENTAL RESULTS

This research has introduced automation in segmentation as well as image analysis for variance detection. It took around two hours for a trained radiologist to manually segment MR images and then detect the difference in the images to predict osteoarthritis stage. Whereas the algorithm proposed in this paper has automated this process and it took approximately ten minutes to process all this. The hardware platform used was a standard desktop 2.8 Ghz PC. Experimental verification was done in phases.

A. Manual Vs Automatic Segmentation

The 45 grey scale images of the knee were segmented both manually by a radiologist and by the algorithm [1]. Each image was of resolution 256 x 256. The Femer and Tibia were segmented independently and boundaries were identified. Boundaries were well approximated by the algorithm. The initial contours defined the curves in the structure. The segmented structure is then overlaid on the original image for better understanding [8]. Automatic estimates for tibial volume were 10 % better than manual. There were also significant improvements in the groups mean of overall objects. With this algorithm the problem of overestimating the object boundaries was also solved. As the algorithm implemented robust probalistic models the tibial and femerial border were clearly delineated. The medial cartilage volume was also segmented during this phase which later helped in variance detection. Segmentation phase also involved the absolute volume and area differences which moved between 10% to 12% as compared to manual segmentation. The algorithm adopted the technique from Bland–Altman plots for area and volume estimation [13]. The automatic segmentation process generated average sensitivity of 81.1 % in comparison to manual segmentation.

Automatic position normalization was also done by this algorithm and it yielded an average sensitivity of 81. 9 % in comparison with the manual technique. Low contrast between tissues near to the boundary were also measured and it helped in boundary delineation.

B. Classification of tibial and femoral cartilage

Three object classes were defined in context of cartilage; tibial cartilage, femoral cartilage and background. Geometrical relationship among these objects were established. A complex probalistic model was defined to measure these objects in the original image. As the background was dominant in all images it was very difficult to extract tibial and femoral cartilage. A sequential background selection algorithm was used for this task [9]. It helped in extraction of region of interest and discarded the rest of the background. The algorithm added one feature at a time in the model and the background was sequentially removed from the images for better visibility and understanding. Features were examined in every iteration of the algorithm which helped in weighting important feature separately. A threshold was defined for feature extraction. In established test bed after 25 iteration intended results in context of feature classification were seen. It was observed that the signal to noise ratio was not high enough at the contour of attention, but still the algorithm was able to detect it accurately. Furthermore, the algorithm efficiently spotted the contours with advanced value between markers, which are not constantly the contours of attention. The usual way of determining the number and approximate location of the regions provided by the dataset consists in the adjustment of the homotopy of the function to which the algorithm is applied. This amendment was carried out Via a mathematical morphology operation, geodesic reconstruction [14], by which the function is altered so that the minima can be executed by an exterior function.

C. Variance calculation

A complex mathematical model was adopted to detect variance in the clinical images. The algorithm was able to detect large intensity variation in the bone region. It also incorporated mathematical energy function. A quantitative analysis was done in which main focus for evaluation was on the volume and surface area of articular cartilage. The assessment was done on the segmented image acquired from the prior step. The algorithm estimated surface area as well as volume. Kellgren– Lawrence index radiographic score was used to measure variance in the cartilage. The readings with KL i = 1 were considered borderline or mild cases of osteoarthritis while any readings above KL i >= 2 were considered severe osteoarthritis. Classical quantitative disease identification for OA was the articular cartilage capacity, thickness and surface area.

IV. CONCLUSION

Implementation of Active contour framework was proposed in this research effort. During the test bed development a dataset of 45 grey scale images of knee were taken each having resolution of 256 x 256. Femer and Tibia were primarily focused during the segmentation process. Both manual and automatic segmentation techniques were used and results were compared. Automatic segmentation technique as anticipated proved to be more effective in comparison with the manual technique. Automatic segmentation not only outperformed manual technique in efficiency but it also showed better results in accuracy. The algorithm delineated the structure boundary based on mathematical approximation. Initial contours helped in defining the curves in the structure. The segmented images were overlapped on the original images for better understanding. Segmentation algorithm also incorporated image contrast information for better boundary delineation. Variance was computed on the segmented images. Quantitative analysis was done to measure articular cartilage deterioration. Kellgren– Lawrence index radiographic score was benchmark for cartilage assessment. The quantitative analysis results were mapped to KL index and osteoarthritis grades were identified.

The use of active contour framework showed promising results in segmentation and variance detection in clinical images of the knee. Although it used complex mathematical and statistical tool but during the test bed performance analysis algorithms performed very efficiently and accurately. The research results will help radiologists and physicians in determining osteoarthritis more effectively.

One direction for future work may be to incorporate other texture measures of the MR Images. These measures may improve the results for this application. Such measures include orientational filters and gray-level co-occurrence [10]. Also textures across multiple scales can also be very useful in enhancing image.

Figure.1: Sagittal MRI of Knee before Segmentation

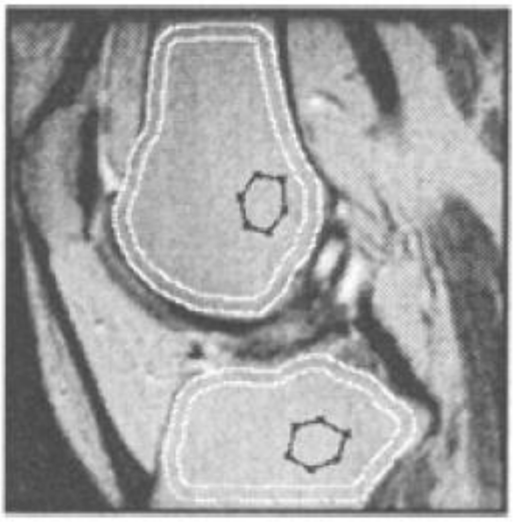

Figure.2. Sagittal MRI of Knee after Segmentation

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