An Active Contour Method for MR Image Segmentation of Anterior Cruciate Ligament (ACL)

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Abstract:

Image segmentation is a fundamental task in image analysis which is responsible for partitioning an image into multiple sub-regions based on a desired feature. Active contours have been widely used as attractive image segmentation methods because they always produce sub-regions with continuous boundaries, while the kernel-based edge detection methods, e.g. Sobel edge detectors, often produce discontinuous boundaries. The use of level set theory has provided more flexibility and convenience in the implementation of active contours. However, traditional edge-based active contour models have been applicable to only relatively simple images whose sub-regions are uniform without internal edges. Here in this paper we attempt to brief the taxonomy and current state of the art in Image segmentation and usage of Active Contours. The goal of medical image segmentation is to partition a medical image in to separate regions, usually anatomic structures that are meaningful for a specific task. In many medical applications, such as diagnosis, surgery planning, and radiation treatment planning determining of the volume and position of an anatomic structure is required and plays a critical role in the treatment outcome.

Keywords: Active Contours, Snakes, Level Sets.

I.INTRODUCTION

In the human body knees are most complex and delicate joints. Knee joints are frequently injured and damaged due to articulations. The knees are among the joints most commonly affected by osteoarthritis (OA) [1].The ligaments like: *medial collateral ligament*, *lateral collateral ligament*, *anterior cruciate ligament*, *posterior cruciate ligament* are responsible in maintaining the structural integrity of knee joint. Anterior cruciate ligament (ACL) injury is most commonly diagnosed. Recent advancement in clinical imaging technology has led to wide employment of magnetic resonance imaging (MRI) in such injury assessment. However, the visual assessment conducted with these images often requires the boundaries of selected structures to be manually traced using computer software. Such interpretation is often time consuming and subjective as it is based on the radiologist's opinion and past experiences. In this project, a semiautomatic ACL Segmentation program that utilizes morphological operation proposed.

It takes advantage of the ACL's unique shape and orientation within MR images to carry out the segmentation. The main motivation is to reduce the amount of time spend in image analysis while providing a more reproducible and objective assessment with regard to ACL injury severity.

II.LITERATURE SURVEY

Over the last five years, new generations of medical data mining tools have dramatically impacted the health care industry by improving the diagnosis of medical diseases and by reducing the time pressure on physicians. Image segmentation plays a crucial role in many medical imaging applications by automating or facilitating the delineation of anatomical structures and other regions of interest.

Methods for performing segmentations vary widely depending on the specific application, imaging modality, and other factors. Diagnostic imaging is an invaluable tool in medicine today. Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and other imaging modalities provide an effective means for noninvasive mapping the anatomy of a subject. The algorithms for the delineation of anatomical structures and other regions of interest are a key component in assisting and automating specific radiological tasks & these algorithms are called image segmentation algorithms, which play a vital role in numerous biomedical imaging applications such as the quantification of tissue volumes, diagnosis, localization of pathology, study of anatomical structure, treatment planning, partial volume correction of functional imaging data , and computer integrated surgery[1][2] .

Segmentation of images holds an important position in the area of image processing. It becomes more important while typically dealing with medical images where pre-surgery and post surgery decisions are required for the purpose of initiating and speeding up the recovery process[1].Methods for performing segmentations vary widely depending on the specific application, imaging modality, ect,. For example, the segmentation of brain tissue has different requirements from the segmentation of the liver. General imaging artifacts such as noise, partial

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volume effects, and motion can also have significant consequences on the performance of segmentation algorithms. Furthermore, each imaging modality has its own idiosyncrasies with which to content [3]. There is currently no single segmentation method that yields acceptable results for every medical image. Some of the practical applications of image segmentation are: medical imaging, visualization Volumetric Measurement, Shape Representation and Analysis Image-Guided Surgery. The segmentation method is divided into different categories as thresholding, region growing, etc,.

Thresholding approaches a segment of scalar images by creating a binary partitioning of the image intensities as shown in fig.1. A thresholding procedure attempts to determine an intensity value, called the threshold, which separates the desired classes. The segmentation is then achieved by grouping all pixels with intensity greater than the threshold into one class, and all other pixels into another class. Determination of more than one threshold value is a process called multi thresholding. From a grayscale image, thresholding can be used to create binary images. . Its main limitations are that in its simplest form only two classes are generated and it cannot be applied to multi-channel images. In addition, thresholding typically does not take into account the spatial characteristics of an image [3].

(a)

(b)

Fig. 1(a) Original imaging (b) Effect of thresholding.

Region growing is a technique for extracting a region of the image that is connected based on some predefined criteria. These criteria can be based on intensity information and/or edges in the image. In its simplest form, region growing requires a seed point that is manually selected by an operator, and extracts all pixels connected to the initial seed with the same intensity value. Like thresholding, region growing is not often used alone but within a set of image processing operations, particularly for the delineation of small, simple structures such as tumors and lesions. Its primary disadvantage is that it requires manual interaction to obtain the seed point.

Split-and-merge segmentation is based on a quad tree partition of an image. It is sometimes called quad tree segmentation. This method starts at the root of the tree that represents the whole image. If it is found non-uniform (not homogeneous), then it is split into four son-squares (the splitting process), and so on so forth. Conversely, if four son-squares are homogeneous, they can be merged as several connected components (the merging process). The node in the tree is a segmented node. This process continues recursively until no further splits or merges are possible [3].

An active contour [3] is a method to find the contours of objects. It can be performed in 2D, also called snakes, or in 3D which is called active surfaces. The idea is to place a contour, or snake, in the image. This snake is then supposed to find the contours of the searched object in an automatic manner. The snake is affected by different forces so that it changes its shape to fit the contour of the object that one wants to find. The problem in active contours is to find the optimal parametric contour $C(s)$.

$$C\,(s) = (x(s),\, y(s)) \tag{1}$$

$$S \in [0,\, 1] \tag{2}$$

There are internal and external forces affecting every point on the contour. This called energy of a point on the contour can be written as:

$$Ec(s) = E_i\,(c(s)) + E_e\,(c(s)) \tag{3}$$

E_i is the energy due to the internal forces and E_e is the energy due to the external forces. The total energy of the contour is:

$$E = \int_0^1 Ec(s)d(s) = \int_0^1 (Ei\,(c(s)) + Ee\,(c(s)))d(s) \tag{4}$$

when using active contours, the contour changes its shape until a local minimum of the energy function E is reached. The difficulty with active contours is that the choice of the parameters, which decide how much the different forces should affect the contours, is not always straightforward. Fine tuning by the user is often needed to get the best results on different sets of images.

Classifier methods are pattern recognition techniques that seek to partition a feature space derived from the image using data with known labels [4]. A feature space is the range space of any function of the image, with the most common feature space being the image intensities themselves. All pixels with their associated features on the left side of the partition would be grouped into one class.

Clustering algorithms essentially perform the same function as classifier methods without the use of training data. Thus, they are termed unsupervised methods. In order to compensate for the lack of training data, clustering methods iterate between segmenting the image and characterizing the properties of the each class. In a sense, clustering methods train themselves using the available data.

Markov random field (MRF) modeling itself is not a segmentation method but a statistical model which can be used within segmentation methods. MRFs model spatial interactions between neighboring or nearby pixels. Artificial neural networks (ANNs) [5] are massively parallel networks of processing elements or nodes that simulate biological learning. Each node in an ANN is capable of performing elementary computations. Learning is achieved through the adaptation of weights assigned to the connections between nodes.

Deformable models are physically motivated, model-based techniques for delineating region boundaries using closed parametric curves or surfaces that deform under the influence of internal and external forces. Mathematically, a deformable model moves according to its dynamic equations and seeks the minimum of a given energy functional.

Atlas-guided approaches are a powerful tool for medical image segmentation when a standard atlas or template is available. The atlas is generated by compiling information on the anatomy that requires segmenting. This atlas is then used as a reference frame for segmenting new images. These approaches are generally better-suited for segmentation of structures that are stable over the population of study. [4][5]

The knee joint, medically known as the tibia femoral joint, is the largest joint in the body. Two bones make up this joint; the femur and tibia[6]. This joint is dependent on the muscles and ligaments which surround it for strength. It joins the thigh with the leg and consists of two articulations: one between the femur and tibia, and one between the femur and patella. The knee is a mobile trocho-ginglymus (a pivotal hinge joint), which permits flexion and extension as well as a slight medial and lateral rotation. Since in humans the knee supports nearly the whole weight of the body, it is vulnerable to both acute injury and the development of osteoarthritis [7].

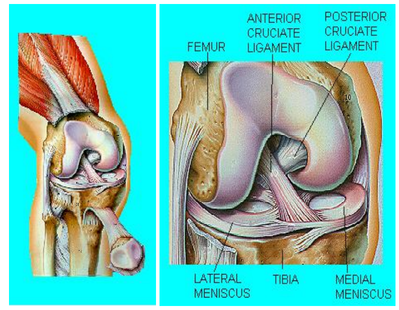


Fig. 2 Knee joint

Four ligaments are present in the knee joint, and are as follows:

The *medial collateral ligament* is located at the inside of the knee joint. It extends from the medial femoral epicondyle to the tibia. This ligament prevents excessive abduction of the knee.

The *lateral collateral ligament* is located at the outside of the knee joint. It extends from the lateral femoral epicondyle to the head of the fibula. This ligament prevents excessive adduction of the knee.

The *anterior cruciate ligament* extends poster laterally from the tibia and inserts on the lateral femoral condyle. This ligament prevents excessive posterior movement of the femur on the tibia.

The *posterior cruciate ligament* extends anteromedially from the tibia posterior to the medial femoral condyle. This ligament prevents excessive anterior movement of the femur on the tibia.

The ACL or anterior cruciate ligament is a strong ligament located in the anterior, or front, portion of the knee. It runs from the femur (thigh bone) to the tibia (leg bone) connecting these two bones together. The purpose of the ACL is to control the movement of the knee joint. It acts to limit side-to-side motion as well as prevents the knee from straightening beyond its normal range of motion. The anterior cruciate ligament (ACL) links the upper leg bone (femur) with one of the lower leg bones (tibia) by running crosswise inside the center of the knee joint. The ACL helps stabilize the knee.

An ACL [7], injury is a tear in one of the knee ligaments that joins the upper leg bone with the lower leg bone. The ACL keeps the knee stable. Injuries range from mild, such as a small tear, to severe, such as when the ligament tears completely or when the ligament and part of the bone separate from the rest of the bone. ACL can be injured if knee joint is bent backward, twisted, or bent side to side. The chance of injury is higher if more than one of these movements occurs at the same time. Contact (being hit by another person or object) also can cause an ACL injury. An ACL injury often occurs during sports [7]. The injury can happen when foot is firmly planted on the ground and a sudden force hits the knee while leg is straight or slightly bent. Symptoms of an ACL injury include: Feeling or hearing a pop in the knee at the time of injury, Pain on the outside and back of the knee, swelling of knee within the first few hours of the injury[8]. This may be a sign of bleeding inside the knee joint. Swelling that occurs suddenly is usually a sign of a serious knee injury and the knee feeling unstable, buckling, or giving out.

III.METHODOLOGY

The proposed semi-automatic ACL segmentation program is implemented using MATLAB and according to the methodology illustrated in fig 3

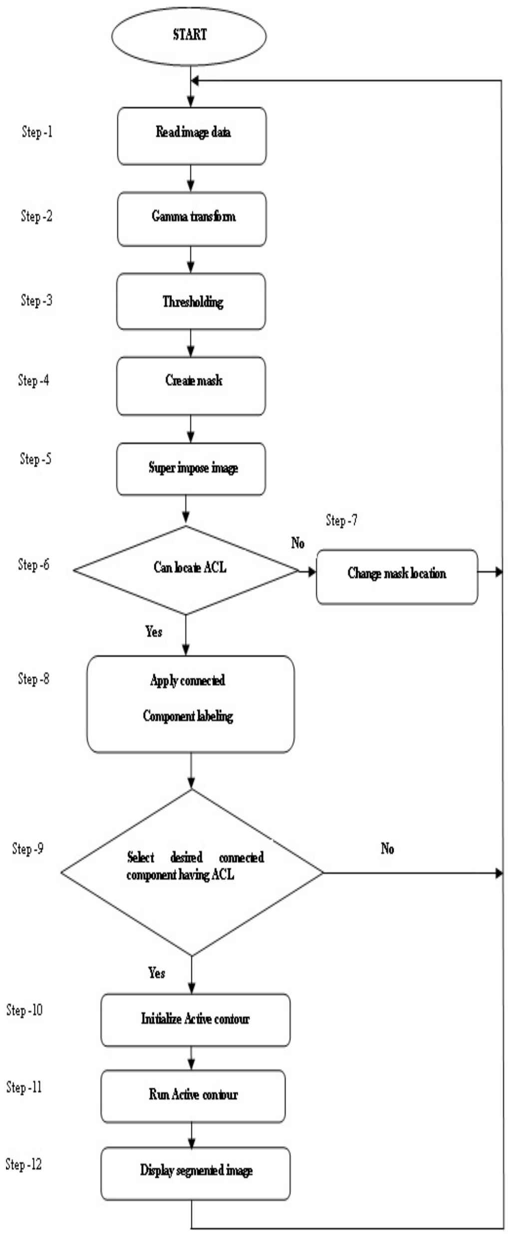


Fig. 3Methodology

At the start of the program, the user is prompted to specify the number of images present within the image set that is to be segmented. Data of the first image within the set is read and duplicated. The duplicated image undergoes a pre-processing procedure that comprises steps 3 to 4 .During this process, gamma transformation is first applied to the image to suppress the low intensity features while amplifying the differences of features with high intensity values. This is to improve the contrast of ACL relative to its surrounding features since it tends to appear as a homogenous low intensity feature in MR images[9]. Thresholding is then performed using Otsu's method to convert the resultant into a binary image. By utilizing the femur and tibia as references, a predefined cropping mask as displayed in Fig.5 is used with morphological operations to crop the binary image. Thus, only features surrounding the ACL remained as in steps 5 to 7. In order to improve the segmentation accuracy, connected components labeling and selection of component by user carried out in steps 8 to 9 as illustrated in Fig.ure.3.1. This involves the use of additional morphological operations to further remove undesirable features.

Finally in steps 10 to 11, the achieved image is used as an initialization mask for the application of an active contour onto its corresponding original image. The principle of this hybrid active contour is based on a paper by Kaihua Zhang, which is a hybrid level set active contour which is implemented special processing named Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) method. This active contour is ideal for the present study since it does not rely on edge information and can detect objects whose boundaries are not necessarily defined by gradient. Hence, these characteristics ensure that a good ACL segmentation is obtainable.

In Canny edge detection method**,** EDGES carry important information of an image. Numerous edge detection techniques have been proposed. The common approach is to apply the first (or second) derivative to the smoothed image and then find the local maxima (or zero-crossings). Canny first presented the well-known three criteria of edge detectors: good detection, good localization, and low spurious response and showed that the optimal detector for an isolated step edge should be the first derivative of Gaussian (FDOG).

IV.RESULTS

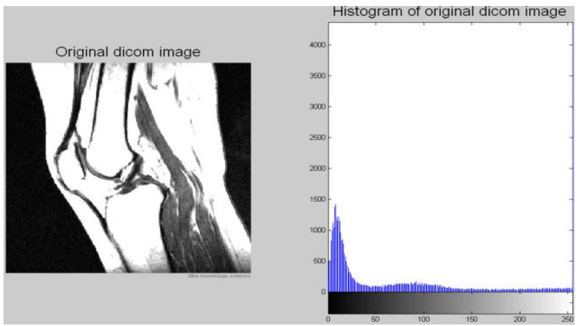


Fig. 4: Resultant image original dicom image & its histogram.

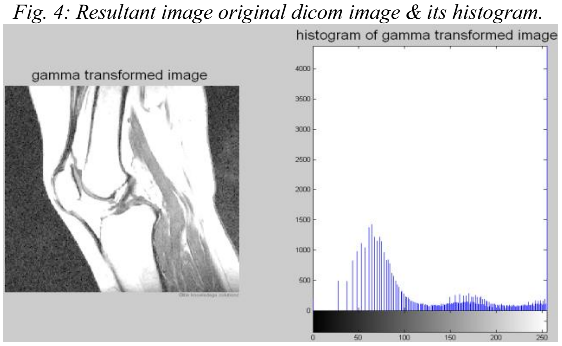


Fig. 5: Resultant image of Gamma transformed image & its histogram.

Fig. 6: Resultant image of Thresholded image using otsu's method.

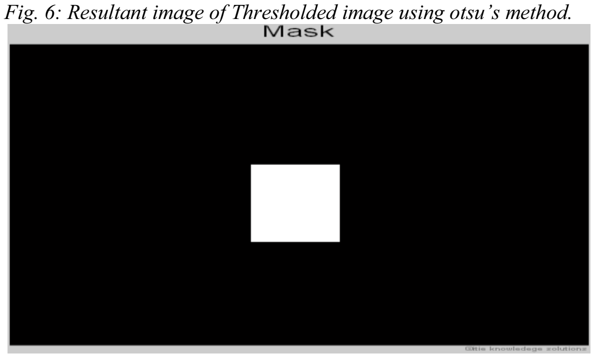


Fig. 7: Resultant image of Mask creation for the region of interest.

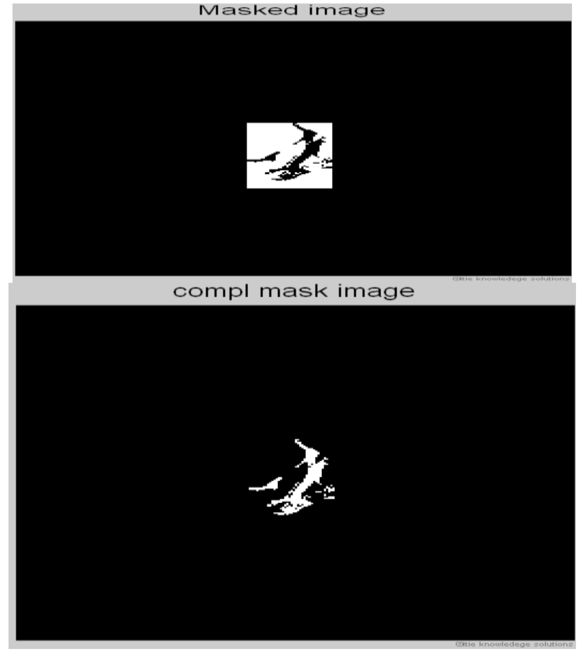


Fig. 8: Resultant images of Masked image & its compliment.

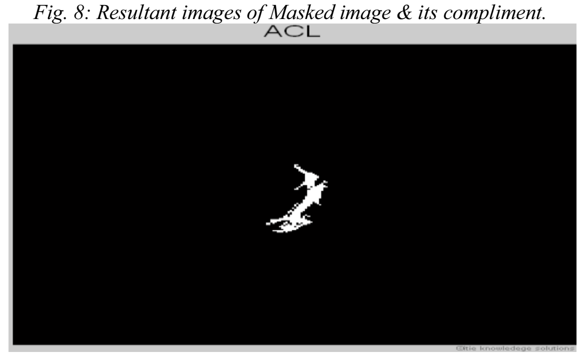


Fig. 9: Resultant images of chosen ACL by user through connected component labeling.

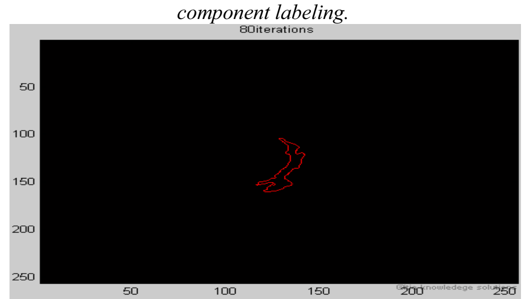


Fig. 10: Resultant image of step 10 includes .Initialization of Active contour.

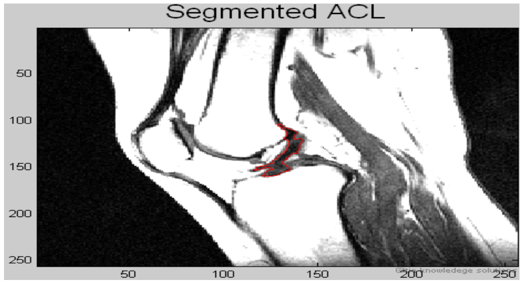
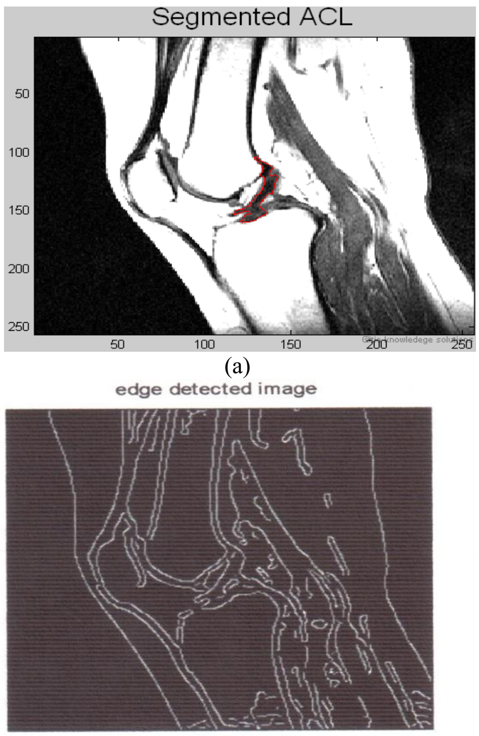


Fig. 11: Resultant images of step 11 & 12 includes Segmented image showing ACL.



(a)

(b)

Fig. 12: (a) Input image (b)Output of Canny edge detector

V.CONCLUSION AND FUTURE WORK

A program that allowed semi-automatic ACL segmentation in MR images had been developed. Which utilizes morphological operations, connected component labeling and hybrid level set active contour, while taking advantage of the ACL's unique shape and orientation within MR image. Although much improvement is still necessary before this program can be deployed for clinical image diagnosis, this study had proven its feasibility and potential in providing an objective ACL segmentation with high reproducibility. One of the advantages with our own algorithm is that even it can work on the MR images.

The future work of this paper involves the Development of fully automatic ACL segmentation algorithm, Case study of different MRI knee images of different subjects. And also this Program has to be deployed for clinical image diagnosis of MR images of other human body parts.

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