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Paweł BADURA*

3D VISUALIZATION OF SEGMENTED CRUCIATE LIGAMENTS

A fuzzy approach to segmentation of the cruciate ligaments of the knee joint and a three dimensional visualisation method are presented in this paper. The cruciate ligaments are the major stabilizers of the knee. The ligaments injuries are common nowadays and a correct diagnostics, preceding the surgical therapy is a very important task. Segmentation of the ligaments is difficult due to a poor visibility of edges in some cases of injuries and their appearance on a small number of slides at Magnetic Resonance Imaging (MRI). The method described here is based on fuzzy connectedness principles. It creates a fuzzy connectivity scene by assigning a strength of connectedness to each possible path between some predefined seed point and any other image element. Then such scene is thresholded to produce final segmentation result. The conventional fuzzy connectedness method with Dijkstra algorithm for creating the fuzzy connectivity scene has been implemented in a 3D space. The object, being the result of segmentation process, is visualised in the Visualisation Toolkit (VTK) environment. The method has been tested on a set of images. An example of its performance is shown along with some plans for future research.

1. INTRODUCTION

The cruciate ligaments are the most important anatomic structures in keeping stability of the knee joint – the most complex joint in the human organism. The anterior (ACL) and posterior (PCL) cruciate ligament connect the femur with the tibia. They form a cross and are their names refer to their tibial attachments [5]. The cruciate ligaments are susceptible to injuries, occurring in both athletes and non-athletes, and a proper diagnostics is a very important matter. The ligaments are visible at the Magnetic Resonance Image (MRI). In the study the sagittal T1-weighted images are considered. Segmentation of the ligaments is a difficult task due to poor visibility of edges in some injuries. There is also a problem of their appearance on a small number of slides – in case of a 4mm distance between slides the PCL appears on 2-4 slices, yet the ACL is located on 1-2 slices. The ligaments can be seen as oval, narrow, dark structures, attached to the femoral and tibial bones [2]. Healthy PCL is almost black and slightly turns in the femoral part. The ACL has a bit higher grey level than the PCL and forms a straight structure. Injured ligament becomes brighter, wider, and less distinct from other tissues of the knee joint [3].

The segmentation process is based on fuzzy connectedness principles [8,9]. In this method the connectivity scene is created based on fuzzy relations between image elements. It has been used in several image segmentation structures in both, MRI and Computed.

* Silesian University of Technology, Institute of Electronics, 44-100 Gliwice, ul. Akademicka 16

Tomography (CT) [8]. Fuzzy connectedness will be described in section 2. Section 3 presents the details of the implemented algorithm, along with some visual 2D and 3D example of its application to the ligaments segmentation. The 3D visualization is performed in the Visualisation Toolkit (VTK) [7] environment. Finally, in section 4 concluding remarks are pointed out.

2. FUZZY CONNECTEDNESS

In the idea of fuzzy connectedness [9] a fuzzy relation ρ between two spels (spatial elements, pixels or voxels) within the image is defined. For any two elements *c* and *d* from a set *C* (image):

$$\rho = \{((c,d), \mu_\rho(c,d)) \mid (c,d) \in C \times C\} \tag{1}$$

μ_ρ is a fuzzy membership function, so $\mu_\rho \in [0,1]$. The relation ρ has to be reflexive

$$\mu_\rho(c,c) = 1, \forall c \in C \tag{2}$$

and symmetric

$$\mu_\rho(c,d) = \mu_\rho(d,c), \forall (c,d) \in C \times C \tag{3}$$

The relation presented in [9] is called fuzzy spel affinity κ. For every two elements a value of $\mu_\kappa(c,d)$ is assigned. It is based on their coordinate adjacency, intensities, gradient, and perhaps even their locations within an image. The general form of $\mu_\kappa(c,d)$ is as follows:

$$\mu_\kappa(c,d) = \mu_\alpha(c,d) \cdot [\mu_\psi(c,d), \mu_\phi(c,d), c, d] \tag{4}$$

where μ_α is an adjacency relation (like a hard 2D 4-neighbourhood or 3D 6-neighbourhood), μ_ψ represents the intensity-based function, and μ_ϕ represents the gradient-based part of the affinity. Several possibilities for (4) have been shown and described [6]. The most often used form of μ_κ is:

$$\mu_\kappa(c,d) = \mu_\alpha(c,d) \cdot [\omega_1 \cdot h_1(f(c), f(d)) + \omega_2 \cdot h_2(f(c), f(d))] \tag{5}$$

with weights $\omega_1+\omega_2=1$, and h_1, h_2 being some membership functions corresponding to μ_ψ and μ_ϕ.

Fuzzy affinity as described above is nonzero only for the adjacent spels. We can call any pair of adjacent spels *c*, *d* a link, and the value of $\mu_\kappa(c,d)$ – its strength. Any sequence of spels $<e_1, e_2, ..., e_m>$ such that for any $i \in [1,m-1]$ a pair $<e_i, e_{i+1}>$ is a link, we call a path. It is noted p_{cd} if $c=e_1$ and $d=e_m$. The strength of a path is the strength of its weakest link – the smallest affinity along the path:

$$\mu_{\mathrm{N}}(p_{cd}) = \min_{i}[\mu_{\kappa}(c_i, c_{i+1})] \tag{6}$$

For any two spels c, d there are many paths p_{cd} between them, forming a set P_{cd}. Now it is appropriate to introduce the definition of fuzzy connectedness. It is a fuzzy relation K between any two spels c, d with membership function $\mu_K(c,d)$ being the strength of the strongest path $p_{cd} \in P_{cd}$:

$$\mu_{\mathrm{K}}(c,d) = \max_{p_{cd} \in P_{cd}}[\mu_{\mathrm{N}}(p_{cd})] \tag{7}$$

It has been shown [9], that a segmentation task can be solved in a following way. The fuzzy $\kappa\theta$ object with affinity κ and some threshold $\theta \in [0,1]$ is defined as a set $O'_{\kappa\theta}$ of spels such that for every $c, d \in O'_{\kappa\theta}$ $\mu_K(c,d) \geq \theta$. It has been proven, that classification of a fuzzy $\kappa\theta$ object does not require the computation of μ_K for all possible pairs of spels in C. First, a seed spel o is chosen, which is supposed to belong to an object $O'_{\kappa\theta(o)}$. Then, the connectivity scene C_o is computed for all $c \in C$:

$$C_o(c) = \mu_{\mathrm{K}}(o,c) \tag{8}$$

with $C_o(o) = \mu_K(o,o) = 1$ according to (2). For each c, $C_o(c)$ describes the degree of its connectedness to o. Thresholding the connectivity scene at some θ gives a fuzzy $\kappa\theta$ object $O'_{\kappa\theta(o)}$. A binary object $O_{\kappa\theta(o)}$ – a result of the segmentation process – is defined as follows:

$$O_{\kappa\theta(o)}(c) = \begin{cases} 1 \Leftrightarrow C_o(c) \geq \theta \\ 0 \quad \text{otherwise} \end{cases} \tag{9}$$

For every two spels $c, d \in O_{\kappa\theta(o)}$ $\mu_K(c,d) \geq \theta$, and for each spel $e \notin O_{\kappa\theta(o)}$ there exist some $c \in O_{\kappa\theta(o)}$, that $\mu_K(c,e) < \theta$. Moreover, if $c \in O_{\kappa\theta(o)}$, then $O_{\kappa\theta(c)} = O_{\kappa\theta(o)}$. It means, that for fixed affinity and threshold it does not matter which point from an object is taken as its seed. If a set O of M seed spels o_i is indicated, then the fuzzy connectivity scene C_O for such a set is defined as the union of the connectivity scenes for all o_i:

$$C_O(c) = \bigcup_{o_i \in O} C_{o_i}(c) = \max_{o_i \in O}[\mu_{\mathrm{K}}(o_i, c)] \tag{10}$$

3. ALGORITHM

3.1. PREPROCESSING

The intensities of the sagittal T1-weighted MR image slices are treated as a three dimensional matrix C. The matrix is normalized into a range [0,1]:

$$C(i,j,k) = \frac{C(i,j,k) - \max_{i,j,k} C(i,j,k)}{\max_{i,j,k} C(i,j,k) - \min_{i,j,k} C(i,j,k)} \tag{11}$$

where i,j,k are the X,Y,Z coordinates, respectively. It has been noted, that healthy cruciate ligaments have dark, close to black intensity. Most of the other knee tissues have higher intensities. This lets an increase of the image brightness without a loss of information about the ligaments. It is made with the linear function, which expands the lower intensity range, and assigns a maximum value of 1 to all levels above a threshold p:

$$C(i,j,k) = \begin{cases} \dfrac{C(i,j,k)}{p} \Leftrightarrow C(i,j,k) < p \\ 1 \quad \text{otherwise} \end{cases} \tag{12}$$

3.2. SEED SLICE, SEED SPELS, FUZZY AFFINITY

From all sagittal slices of C the user chooses the seed slice C_{ss}, where the segmented ligament is visible. On the C_{ss} a seed spel o (or a set O of seed spels o_i), belonging to the ligament is marked. Then, a region of interest (ROI) is defined based on seed spel location and a ligament's size, to avoid unnecessary computation in unimportant parts of an image. Next, a fuzzy connectivity scene is computed.

Fuzzy affinity has to be defined. The general form of it was introduced in (4), and the specific one in (5). The functions h_1, h_2 from (5) are both gaussian [6]:

$$h_1(f(c), f(d)) = e^{\frac{\left(\frac{f(c)+f(d)}{2} - m_1\right)^2}{2s_1^2}} \qquad h_2(f(c), f(d)) = e^{\frac{(|f(c)-f(d)|)^2}{2(m_2+s_2)^2}} \tag{13}$$

Parameters of functions in (13) should have a meaning of degree of "objectness" of a fuzzy affinity relation between c and d inside an object $O_{\kappa\theta}$. That means, they should depend on intensity and homogeneity of an object. They are computed as follows. First, a set N_o consisting of a seed spel o and its 3D 6-neighbours (of a set O of spels o_i and their 6-neighbours) is created. Then, the mean value m_1 and standard deviation s_1 of a set of mean intensities of all pairs of 6-neighbour spels from N_o is computed. Similarly, the computation of the mean m_2 and standard deviation s_2 of a set of absolute differences between intensities of all pairs of 6-neighbours from N_o is performed. The latter of equations in (13) is a gaussian with zero mean, so for two spels with the same intensity, the gradient-based part of a fuzzy affinity will be 1; m_2 just increases the standard deviation of h_2. The weights ω_1, ω_2 from (5) are both equal 0,5.

3.3. FUZZY CONNECTIVITY SCENE

The matrix C consisting of g slices of size $w \times k$ is treated as a connected graph. Its vertices are voxels and its edges are the fuzzy affinities between adjacent spels (adjacency relation in the algorithm is a hard 3D 6-neighbourhood). In [9] authors have proposed dynamic programming method for finding the connectivity scene C_o. In [1] it has been shown, that greedy algorithms for finding paths of lowest cost are more efficient. The Dijkstra algorithm [4], used in this paper, is listed below:

Input data: a 3D image intensities in matrix C, a fuzzy affinity κ, a set O of seed spels o_i.

Output data: a fuzzy connectivity scene C_O.

Auxiliary data structure: a set Q of spels $c \in C$.

1. Insert all $o_i \in O$ to Q.
2. Set C_O to zero except spels $o_i \in O$, for which set $C_O(o_i)=1$.
3. Remove d if $C_O(d)$ reaches maximum in Q.
4. For each spel c adjacent to d:
5. $v=min\{C_O(d),\mu_\kappa(c,d)\}$.
6. If $v>C_O(c)$:
7. Put c into Q.
8. Set $C_O(c)=v$.
9. If Q is empty: stop,
   Else: go to step 3.

Although there can be many seed spels, there is no need to compute many fuzzy connectivity scenes and then apply (10) to achieve final result. The scenes regularly grow from each seed spel during one course of an algorithm.

3.4. THRESHOLDING, POSTPROCESSING, 3D VISUALIZATION

The final step is the interactive thresholding operation. The user chooses the threshold level θ, seeing the actual segmentation result. For each selected θ the slices of binary scene $O_{\kappa\theta(O)}$ are two-dimensionally morphologically closed, resulting in a binary scene $O_{\kappa\theta c(O)}$. The edges of $O_{\kappa\theta c(O)}$ are displayed on corresponding slices of original image, delineating the ligament. Fig. 1 shows the results of such strategy on 2D slices. A sagittal knee joint image, a fuzzy connectivity scene C_O, a closed binary scene $O_{\kappa\theta c(O)}$ and a segmentation result are shown in consecutive rows.

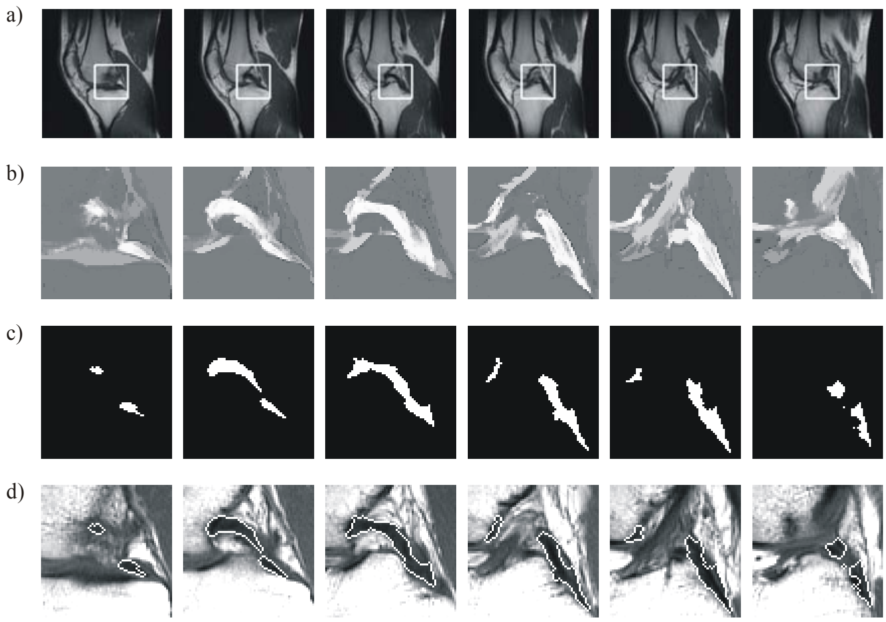

Fig.1. A 3D segmentation of the PCL; (a) an original knee joint image with marked ROI; (b) a fuzzy connectivity scene C_o for ROI; (c) a binary scene $O_{\kappa\theta(o)}$ thresholded at $\theta = 0{,}94$ (d) a ROI from (a) with edges from (c)

After choosing the threshold level θ, a new image is produced:

$$C_{\kappa\theta}(c) = \begin{cases} C(c) \Leftrightarrow c \in O_{\kappa\theta(O)} \\ 0 \quad \text{otherwise} \end{cases} \tag{14}$$

Each spel from $C_{\kappa\theta}$ belonging to a ligament has its original intensity. Each spel from outside of an object has zero intensity. Then, a matrix including image $C_{\kappa\theta}$ is reprocessed, transferred into the Visualisation Toolkit [7] environment and displayed in three dimensions. Fig. 2 shows several views of a ligament segmented and shown in fig. 1. The visualized ligament can be rotated or displayed with different intensity levels and transparencies.

Fig.2. A 3D visualization of the PCL from fig. 1; columns display the front, back and top view, respectively, transparencies have been changed in rows

4. CONCLUDING REMARKS

The paper describes the fuzzy connectedness-based approach to segmentation and visualization of the cruciate ligaments. It has been tested on a set of 20 images with satisfactory results. The method is sensitive to seed points selection – the more points are selected, the better the result is. Furthermore, different voxel size in XYZ directions cause some inaccuracies in a 3D segmentation process, but appropriate preprocessing and 3D image interpolation methods help to improve the performance. The goal is a specified tool for computer aided diagnostics of the cruciate ligaments at MRI, enabling segmentation and visualization of healthy or injured ligaments.

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