Detection of Elongated Structures with Hierarchical Active Partitions and CEC-Based Image Representation

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Abstract. In the paper a method of elongated structure detection is presented. In general this is not a trivial task since standard image segmentation techniques require usually quite complex procedures to incorporate the information about expected shape of the segments. The presented approach may be an interesting alternative for them. In its first phase it changes the representation of the image. Instead of a set of pixels image is described by a set of ellipses representing fragments of the regions of similar color. This representation is obtained using Cross-Entropy Clustering (CEC) method. The second phase analyses geometrical and spatial relationships between ellipses to select those of them that form an elongated structure within an acceptable range of its width. Both phases are elements of hierarchical active partition framework which iteratively collects semantic information about image content.

Keywords: CEC, hierarchical active partition, structural description

1 Introduction

Detection of different structures in the images is a crucial part of almost any system analyzing image content. A typical example of such systems are tools supporting medical diagnosis. Elongated objects are frequent structures that need to be detected in those systems. A good examples are not only arteries and veins, because of their natural shape, but also different types of tissues are visible in such a way if different sections of 3D structures are analyzed separately. In

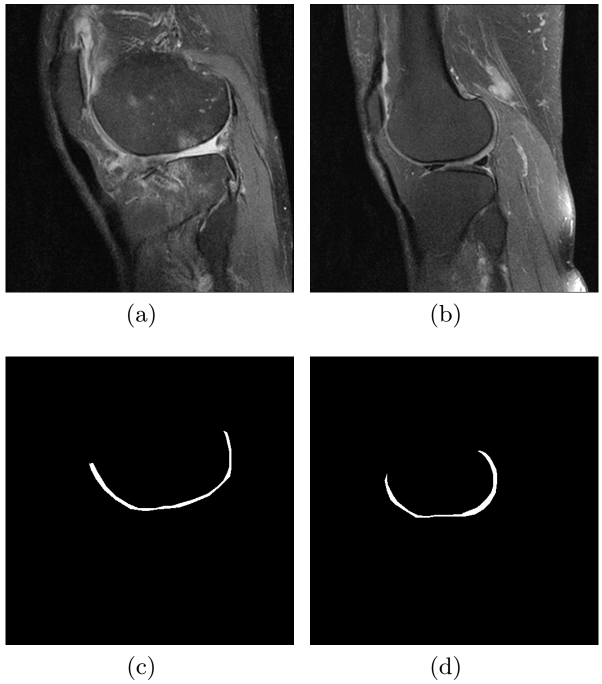


Fig. 1. Sample sections of knee MRI examinations: (a), (b) - images, (c), (d) - fragments of articular cartilage.

medical images detection of such structures is usually not a trivial task. First problem is the noise being a result of image acquisition process. Second, and maybe even more important, is the fact that different, adjacent structures have similar color of the pixels representing them which in consequence results in blurred borders between those structures.

There are different methods that can be used to detect such structures. Typical segmentations techniques have, however, problems with this task [2, 4, 12]. Application of region based techniques with standard pixel similarity criteria would lead to region leaks. Edge based methods would require precise contour tracing which usually fails in areas with blurred borders between structures. To overcome those problems an additional knowledge about expected shape must be used. In the aforementioned approaches it is not impossible but very troublesome. A natural solution of this problem are active contour techniques where additional knowledge may be incorporated either in energy function or in contour evolution constraints [1, 7]. This, however, also requires additional, sometimes complex procedures like, for example, training of a shape model [1]. In this work an alternative method is proposed which, instead of focusing on complex methods, uses a hierarchical approach with a sequence of simpler techniques and specific representation of image content.

The results of the described method are illustrated with a problem of articular cartilage detection that can be of use in a process of osteoarthritis (OA) diagnosis. OA is a chronic, degenerative disease that leads to loss of articular cartilage and joint deterioration [13]. It is a leading cause of disability worldwide [10]. Knee is most commonly affected, especially in elderly and obese individuals [8, 13]. Although, plain radiography is traditionally used to diagnose OA, the joint space narrowing is observed typically at the late-stage disease [17]. Due to the fact that evaluation of structural changes in articular cartilage is important for assessment of the progression and the effect of OA treatment, more sensitive methods are required [5]. MRI enable high-resolution visualization of the cartilage, it is non-invasive and does not use ionizing radiation, thus it was applied for quantitative evaluation of knee join articular cartilage [5], see Fig. 1(a) and Fig. 1(b). By application of automated or semi-automated segmentation methods analysis can be performed comprehensively and easily [5].

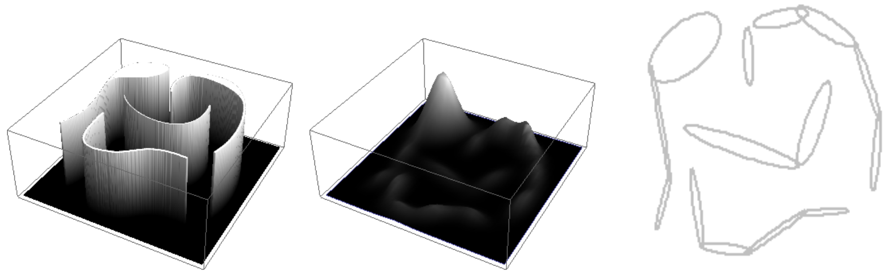
The paper is organized as follows: in the second section the hierarchical active partition approach is described as a framework of image analysis, next the CEC method and resulting image representation is presented, the fourth section focuses on detection of elongated structures, finally the last two sections are devoted to presentation and discussion of the results.

2 Hierarchical Active Partitions

The concept of active partitions originates in active contour techniques [16]. Those methods look for an optimal contour describing object in the image. The search objective is defined by an energy function and as a search procedure any appropriate optimization technique can be used. As it was mentioned in previous section, one of the biggest advantages of this approach is that it is prepared to incorporate any kind of additional, expert knowledge expressing expectations about sought structures.

In [16] and earlier works of the same authors it was shown that contours can be considered as classifiers of pixels as they allow to discriminate pixels representing object and background. In other words they partition the whole set of pixels into two subsets. As, in general, classification techniques can be used to recognize almost any kind of objects, the idea of active partitions was proposed where insted of pixels other objects representing image content are considered. Also in this case to find an optimal partition any reasonable optimization process can be used. If this process is an iterative algorithm then partitions changes in every iteration and consequently they can be called active. In practice different types of objects can be considered. This can be line segments, circular regions of the same color, etc. In this work CEC-based image representation is proposed where image content is describe by a s set of ellipses.

The process of object detection can be considered as a hierarchical problem where consecutive phases deliver additional information about image content. Such an interpretation has strong biological foundations in human vision system [3, 9] as well as in conscious process of image analysis. All the mentioned



(a) (b) (c)

Fig. 2. CEC method applied to white regions of Fig. 3(a): (a) - uniform distribution, (b) - several Gaussian functions approximating given distribution, (c) - ellipses corresponding with those functions.

so far segmentation techniques, including active partitions, can be elements of such a hierarchy. As an example of the problem where such an approach can be considered is the discussed in this work cartilage detection task. Instead of complex algorithm it focuses first on localization of regions with similar color and representation of those regions by a set of ellipses, then elongated structures are extracted which later can be used to detect specific tissues basing on medical knowledge about knee structure.

3 CEC-Based Image Representation

In this section we present a method which uses CEC[1] algorithm to construct a new type of image representation. It can be interpreted as approximation of uniform distribution by several Gaussian densities. Since level-sets of Gaussian densities are ellipses it can be understood as covering a data set by ellipses. The simple example is presented in Fig. 2 and Fig. 3. Image of given set depicted in Fig. 3(a) can be interpreted as a uniform distribution on white parts of this set, see Fig. 2(a). We can approximate the distribution by several Gaussian functions, see Fig. 2(b). Finally, each of Gaussian component we can interpret as a ellipses which is presented in Fig. 2(c). More precisely we represent a Gaussian densities by one level-set.

Before we present how to choose the optimal one, let us recall that the normal random variable with the mean equal to zero and the covariance matrix Σ has a density:

$$g_{\Sigma}(x) := \frac{1}{2\pi\sqrt{\det(\Sigma)}} \exp(-\frac{1}{2}\|x\|^2_{\Sigma}) \tag{1}$$

where by $\|x\|^2_{\Sigma} := x^T \Sigma^{-1} x$ we denote the square of the Mahalanobis norm. The 2D ellipse generated by positive definite matrix Σ (of size 2×2) with its center

[1] Implementation of the CEC algorithm for the Project R – a free software environment for statistical computing and graphics – is available at [6].

in zero is defined as follows:

$$\mathbb{B}_{\Sigma} := \left\{(x_1, x_2) \in \mathbb{R}^2 \colon \|(x_1, x_2)\|^2_{\Sigma} < 1\right\}. \tag{2}$$

The eigenvectors of Σ define the principal directions of the ellipse and the eigenvalues of Σ are the squares of the semi–axes: a^2, b^2. On the other hand, the covariance matrix of uniform density of an ellipse $\left\{(x_1, x_2) \in \mathbb{R}^2 \colon \frac{x_1^2}{a^2} + \frac{x_2^2}{b^2} < 1\right\}$ is given by $\begin{bmatrix} \frac{a^2}{4} & 0 \\ 0 & \frac{b^2}{4} \end{bmatrix}$. Therefore, we represent a Gaussian distribution by ellipse with radiuses $2\sqrt{\lambda_1}$, $2\sqrt{\lambda_2}$ and the principal directions v_1, v_2, where λ_1, λ_2 are eigenvalues and v_1, v_2 are eigenvectors of the covariance matrix.

There are few possible methods for extracting Gaussian-like clusters in the data. In this paper we use Cross–Entropy clustering (CEC) [15] algorithm, which is a modification of the classical EM approach. In general CEC aims to find parameters:

$$p_1, \ldots, p_k \geq 0 : \sum_{i=1}^{k} p_i = 1, \tag{3}$$

and $f_1, \ldots, f_k$ Gaussian densities such that the convex combination:

$$f := \max(p_1 f_1, \ldots, p_k f_k) \tag{4}$$

optimally approximates the scattering of the data under consideration $X = \{x_1, \ldots, x_n\}$. The optimization is taken with respect to cost function:

$$\mathrm{CEC}(f, X) := -\frac{1}{|X|} \sum_{j=1}^{n} \ln\big(\max(p_1 f_1(x_j), \ldots, p_k f_k(x_j))\big), \tag{5}$$

where all p_i for $i = 1, \ldots, k$ satisfy the condition (3). It occurs, see [15], that the above formula implies that it is profitable to reduce some clusters (as each cluster has its cost). Consequently, after the stop of the procedure some parameters p_i for $i \in \{1, \ldots, k\}$ can equal zero, which implies that the clusters they represented have disappeared. Consequently, CEC determines optimal number of clusters, and therefore reduces the complication of the model. Moreover, it is easy to adapt method to the various type of Gaussian model. In particular, we can use diagonal (Gaussians with diagonal covariances) or spherical models (Gaussians with covariances proportional to identity matrix) – compare with [11, 14].

4 Detection of Elongated Structures

CEC algorithm can be used to approximate a given segment of the image with ellipses. However, since usually we are interested in regions of similar characteristic, in this work the first step of changing image representation is to find connected components of the image that have similar color, see Fig. 3(b). For

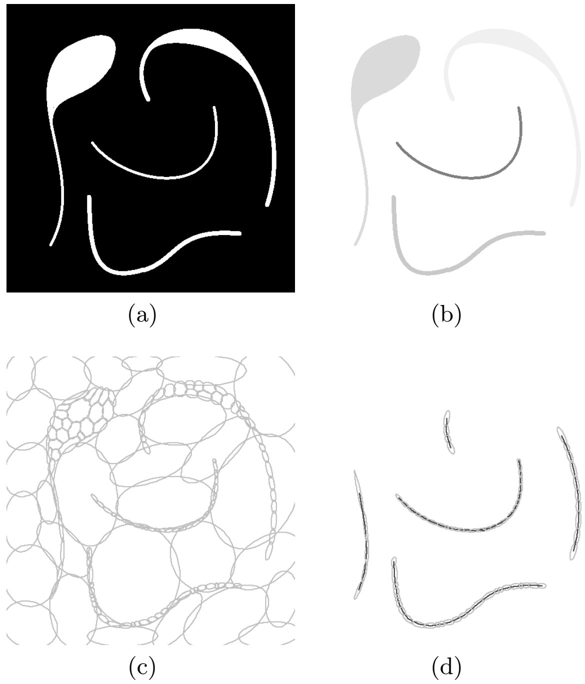
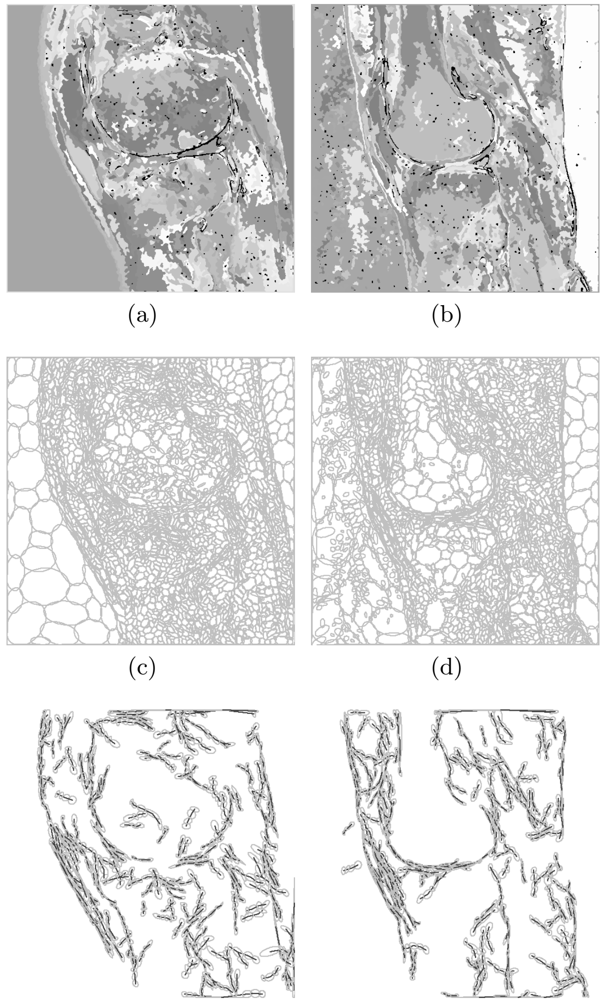


Fig. 3. Detection of elongated structures: (a) - sample image, (b) - regions of similar characteristic, (c) - CEC-based represtation, (d) - detected structures.

that purpose region growing algorithm is used preceded by median filter to remove noise. Region growing is applied many times as long as there are pixels that are not assigned to any segment. Each execution starts from the brightest unassigned pixel. The similarity criterion accepts points with tolerance 20 of intensity difference between current and seed pixels. Too small regions are removed if necessary. In the next step CEC algorithm is executed separately for each segment. The algorithm is executed 10 times to find possibly the best value of the cost function (5). It starts with at most $k = 30$ Gaussian functions and the precise number depends on the size of the considered segment (the smaller region the less number of functions is considered). The sample results of this phase are presented in Fig. 3(c).

The obtained set of ellipses describing whole image is a input for the second phase – elongated structures detection. It constructs first a graph where the ellipses are vertexes and edges indicates which ellipses are close to each other. Thus neighboring ellipses for a given vertex can be easily found. Next, starting from every ellipse its neighbors are examined to check if, in the direction determined by a line connecting centers of those ellipses, their width do not differ too much (in this work the tolerance of 2 pixels was considered). If this condition is satisfied the procedure is continued recursively comparing the width of successive



(a) (b)

(c) (d)

(e) (f)

Fig. 4. Sample results for MRI images presented in Fig. 1, (a), (b) - regions of similar characteristics, (c), (d) - CEC-based represtations, (e), (f) - detected structures.

ellipses with the width of the starting ellipse. The width is always considered in a direction defined by current and previous ellipse. Additionally, starting from the third ellipse, it is also checked if the angle between lines connecting last two pairs of ellipses is not too small (it should be larger than 150 degrees). The recursion is stopped if one of the described criteria is not satisfied.

As there can be more than one ellipse satisfying those conditions at each level of the recursion as a result for a single ellipse we can obtain a tree where branches represent a chain of ellipses reflecitng elongated structures. When the number of ellipses is huge it is computationally inefficient to consider all the paths in the graph as some paths will be analyzed many times. An acceptable solution requires remembering which vertex has been already visited. This implies, however, that to obtain the final result the additional post-processing must be performed. It connects some of the paths that starts with the same or neighboring ellipses. The sample results with paths connecting more than 4 ellipses are presented in Fig. 3(d).

5 Results

The method proposed in this work was applied to a set of 103 selected images coming from MRI examinations. For all of them the fragment of articular cartilage was manually pointed out by radiologist, see Fig. 1(c) and Fig. 1(d). Fig. 4(a) and Fig. 4(b) present the detected connected components of the image. The complexity of the considered images causes that the number of regions is quite large. The CEC-based representation of the images basing on those segments is depicted in Fig. 4(c) and Fig. 4(d). Finally, the structures detected with a discussed method are presented in Fig. 4(e) and Fig. 4(f).

Those results reveal that a large number of elongated structures is detected. It is, however, an expected outcome. There are two main reasons explaining this effect. Firstly, the analyzed images contain many structures with the sought characteristic as there are many layers of different tissues of human body visible in selected sections of MRI examinations. Secondly, in this work only geometrical and spatial aspects of structures were considered and no information about color of the region represented by ellipses was taken into account. It can lead to detection of structures lying in regions of different colors. Moreover, it can also be observed that not all the fragments of articular cartilage are always detected. The reason maybe its actual loss or blurred borders between different tissues of the knee. This problem can be overcome only by additional medical knowledge about its precise localization or shape. This would also significantly reduce the number of detections. Such information can be used in the next phase of analysis where from among the elongated structures their subset will be selected. This phase, although it is an element of hierarchical active partition approach, is out of the scope of this work.

To measure objectively the effectiveness of the proposed method the regions manually indicated by physician were used. As they only represent a fragment of articular cartilage and there are other elongated structures in the images we could only check what percentage of those regions was covered be ellipses. Precisely, in the conducted experiments, we checked how many pixels from those regions was covered by a smallest rectangles containing those ellipses. For a considered set of images it was on average 60.6% which, taking into account that there are usually blurred borders in the center of the fragments in question and no additional, medical knowledge was considered, is a satisfactory result.

6 Summary

In this paper a method for elongated structures in the images was presented. It utilizes a CEC-based image representation with a set of ellipses covering regions of similar color. The presented approach can be used in hierarchical articular cartilage detection with three phases: detection of ellipses, detection of elongated structures and detection of sought tissue. The last phase was out of the scope of this work but will be investigated in future. What should be emphasized is fact that each phase increases the semantic knowledge about image content reducing the number of details that had to be considered if bare pixel representation was used. Moreover this approach resembles the human process of such detection as first the regions of different colors are identified, they are connected to compose elongated structures and finally those regions are combined using anatomical knowledge to find the whole articular cartilage even in those areas where information in the image is not sufficient (blurred borders).

The conducted experiments revealed that crucial element of the proposed method is proper extraction of regions with similar colors which will be suitable for images obtained by different MRI devices. The method itself has also a great potential which can used for other tasks. First of all CEC allows to obtain image elements of different characteristic: only circles, only flattened ellipses, etc. Secondly the method of looking for an optimal subsets of the ellipses can be chosen freely depending on specific tasks. It can not only consider geometrical properties of those ellipses but it can also take under consideration color of the circumscribed region, the neighboring ellipses and almost any external knowledge. The results presented in this work were not compared to other, mentioned techniques that can be applied to articular cartilage detection as the main goal of the authors was to present an alternative approach to image analysis. Such comparison is also, however, under further investigation.

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