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Fuzzy Automatic Classification and without a prior knowledge - Mean Shift Application to MRI brain images segmentation

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Abstract-The objective of this paper is to propose a blind segmentation method able to localize all relevant objects in medical images by using a fuzzy classification based mean shift algorithm. To achieve this, we have to build a cartography of attributes consequent upon images characterization. The objects localization is realized by searching modes from a point sample distribution through mean shift procedure. In order to obtain an image automatic segmentation, the approach is joined at a fuzzy classification based fuzzy c-means (FCM) approach. The fuzzy insertion here allows to take into account imprecision related to information extraction which is necessary for a region classification. Actually, the obtained results by our approach are very encouraging and show an accurate segmentation compared to others supervised techniques.

Keywords: fuzzy c-means, mean-shift, image segmentation.

I. INTRODUCTION

In this paper, we are interesting about an original method of unsupervised medical images segmentation which operates according to a fuzzy classification based mean shift algorithm. Due to the very particular kind of these images which are likely to show both multiple mode and multiple texture, it is not conceivable to segmentate these images with in advance a fixed clustering number. Many current algorithms of classification are most certainly needed the previous knowledge about the cluster number to minimize the point partitioning criteria. The application of these algorithms generally produces a reduction of clusters number and unfortunatly introduces some false results. Our objective here is to deal with an automatic segmentation applied to medical images particularly the both background detection and extraction in order to obtain a good visual of brain structures which can find neuronavigation application and scanning ways investigation. In order to overcome the sensitive problem of the misclassification in brain tissues between the gray matter and the cerebrospinal fluid, we lead our framework by using a nonparametric statistical method able to detect all objects from an image and without a prior knowledge about classes number. For obtaining this, an attribute map consisted of gradient and level gray components is built from images characterization. The cartography analysis is made through the mean shift algorithm which operates on modes detection whose the end counting corresponds to the found classes number. Over this last decade, mean shift algorithm knows an undeniable attraction. The mean shift efficiency has been demonstrated in many vision problems such as low level image segmentation [1] or faces traking [2] or blobs detection [3]. From this unsupervised learning, we proceed to image segmentation by using the modified FCM classification through the insertion of a boostrap tuned by mean shift procedure. This paper is organized as follows. Section 2 deals with the used statistical tools to estimate the density of point distribution and the using of mean shift for modes seeking which correspond to the classes center. In section 3, we describe the nonparametric image segmentation whose we explain our motivation about the pratical development of fuzzy c-means. In the last section, we present segmentation results on MRI brain images.

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II. Statistical tools

A. *Estimation of the density function*

One of the used ways for image analysing consists in transforming it according to a point distribution in a space of R^2. Various techniques can be used to solve this point tesselation set. With the statistical parametric method, the density function of the tesselation point will be modelled by a prior knowledge and it will follow a normal law if the distribution is characterized by an alone mode or by a decomposition of the same law for data underlying manifold modes. The other solution which consists in doing without hypothesis on data points is to use a kernel based nonparametric statistic method. The most known of them is certainly Parzen window which is able to yield an estimation of the density function of point distribution : let $\{x_i\}_{i=1..n}$ be the set of n data points in a d-dimensional Euclidean space R^d, the function of Parzen density is estimated by the following formula :

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \quad (1)$$

where K(.) is a kernel function and h is the window radius centered on x. The deviation measure between the estimated density function and the target density function is computed by the mean integrated squared error (MISE) :

$$EQMI = E\left(\int_{R^d} \left(\hat{f}(x) - f(x)\right)^2 dx\right) \quad (2)$$

The optimum kernel yielding minimum mean integrated square error is the Epanechnikov kernel [4]:

$$K_E(x) = \begin{cases} \frac{1}{2} C_d^{-1}(d+2)(1 - \|x\|^2) & \text{si } \|x\| < 1 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

in which C_d is the volume of a unit d-dimensional sphere.

B. *Mean shift procedure*

The mean shift algorithm is a nonparametric statistical method to estimate the modes of a point distribution [5][6]. The procedure has been proposed in 1975 by Fukunaga for pattern recognition problems in order to estimate the gradient of a density function. The mean shift uses a simple mecanism which consists in moving each point iteratively towards the mean of its neighbour points. Each data points thus become associated to a point of convergence which presents a local mode of the density on the d-dimensional space. The kernel of the mean shift algorithm is formulated as follows :

$$m(x) = \frac{\sum_{s \in S} K(s - x) W(s) s}{\sum_{s \in S} K(s - x) W(s)} \quad (4)$$

with $S \subset X$ wich represents a fixed number of sample points such as $X \in R^n$; K(.) is the mean shift kernel and W(.) is the weighting function. In the literature, three kind kernels are frequently used. We have the unit flat kernel F(x), the unit Gaussian kernel G(x) or the truncated Gaussian kernel $G_\lambda(x)$ which are defined in [5] by :

$$F(x) = \begin{cases} 1 & \text{if } \|x\| \le 1 \\ 0 & \text{if } \|x\| > 1 \end{cases} \quad (5)$$

$$G(x) = \exp\left\{-\|x\|^2\right\} \quad (6)$$

$$G_\lambda(x) = \begin{cases} \exp\left\{-\beta\|x\|^2\right\} & \text{if } \|x\| \le \lambda \\ 0 & \text{if } \|x\| > \lambda \end{cases} \quad (7)$$

The removal process of the mean shift is related to the centroid parameters T ($T \subset X$) of clustering group and the weighting function W which can be fixed during the learning step or modified for each iteration step. Moreover, we observe the using of Gaussian kernel presents the advantage to normalise the weighting function in order to guarante its convergence.

III. Fuzzy image segmentation

A. *Unsupervised classification*

The segmentation application based the supervised classification on the complex patterns and textured of medical images generally produces poor results. These bad results can be explained by an a prior selection of clusters number which bounds the expansion of little classes or a yielding of irrelevant classifiers whose the analysis window is not appropriated for the seeking modes. In order to take into account the dynamic of classifiers, the followed segmentation strategy will be based on a adaptive behavior and unsupervised method. The highlight of this method consists in its design of classification which does not need to know previously neither the shape nor the data distribution on the one hand and the approach does not make hypothesis about the clusters number on the other hand.

B. *Fuzzy approach contribution*

Within the field of the image segmentation, the using of the supervised or unsupervised classification is based on the determination of the partition called *hard* partition on a data set. All these approaches assume an element belongs to an alone and unique class. In practice, we often are fitted the classes overlapping whose the unprecise boundaries are not taken into account in this kind of segmentation. In order to overcome this problem and improve the accurate segmentation results, we integrate in this framework a fuzzy concept which allows an element to belong at one or several classes with some shade. The assignment of an object or an element to a class is determined by a supervisor containing a bank of membership functions which would shade the decision makings avoiding thus the risk of added errors during the learning steps.

C. *Fuzzy c-means classification*

As mentioned above, fuzzy classification consists in distributing at best the image pixels into C classes according to a shade degree of membership by using the FCM approach widely used in pattern recognition [7]. We proceed this classification algorithm for its flexible utilization and its performance in the data partitioning domain [8][9]. From a set of learning steps which initializes the centroids of class and by fixing a terminate criteria, the algorithm proceeds iteratively the image partitioning by minimizing an objective function J_m defined by :

$$J_m(U,V:X)=\sum_{i=1}^{c}\sum_{j=1}^{n}(u_{ij})^m d^2(x_j-v_i) \tag{8}$$

with the constraints :

$$u_{ij}\in[0,1],\ \sum_{i=1}^{c}u_{ij}=1\,\forall j,\ 0<\sum_{j=1}^{n}u_{ij}<N\,\forall i. \tag{9}$$

The parameter m (m>1) is a weighting exponent which determines the degree of fuzziness of FCM. The u_{ij} notation is the degree of membership of the labelled pattern j to the cluster i represented by the clustering centers V_i and the d(.) is the distance of similarity between the measured sample and the cluster center. The minimization of the objective function requires the membership values to be defined as :

$$u_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \tag{10}$$

and the centroids of class :

$$v_i=\frac{\sum_{j=1}^{n}(u_{ij})^m x_j}{\sum_{j=1}^{n}(u_{ij})^m} \tag{11}$$

The iterative process will terminate when the criteria based on the maximization criteria of within-cluster scatter is verified :

$$\max_{i\in[1,c]}\left\|v_{new}-v_{old}\right\|<\varepsilon \text{ with } 0<\varepsilon<1. \tag{12}$$

The last step called defuzzification is applied to produce the crisp output corresponding to the pixels assignment at various classes by means a decision making. In this study, we have used the α-cut membership rather than the maximum of membership for pratical reasons, because this model takes into account both spatial and contextual informations. Thus, this decision function is aimed to assign an object to a class if its degree of membership is superior or equal at a threshold defined by the α-cut game. On the other hand, the decision function resulting of the maximum membership depends strongly on the maximum value and above all without taking into account neither spatial information nor contextual data, yielding ambiguity situations when the maximum value is about 0.5.

D. *Proposed classification approach*

In this section, we present the proposed approach to segmentate medical imaging. We use the modification of an unsupervised fuzzy clustering technique to guide the clustering process by including a boostrap algorithm which is going to rectify a prior obtained classes in order to improve the final segmentation result. This method is based on the mean shift procedure which, because of its ability of expansion and modes detection, is controlled according to an itirative processing. To stop the process, we apply the well hnown criteria based on the minimization errors quadratic of between-cluster scatter. With this approach, we avoid the encountered problems in the others techniques described previously such as the geometrical shape of clusters, the fixed class number in advance, the using of parametric model. For our application, the combination of mean shift procedure and FCM approach seems appropriated and efficient to describe a brain anatomic in terms of segments. By applying our approach which uses the attractive behavior and the unsupervised clustering properties, we can obtain a segmentation result nearby the reality since the healthy or pathological anatomic structure is not neither geometrical nor regular but any shape.

E. The MSFCM algorithm

We now describ the steps of our novel approach called MSFCM (mean shifted fuzzy c-means) which is divided in two parts. In the first step, the mean shift procedure is run to find the initial classes centers. When the mean shift kernels are found on the attribute cartography, we initialize the FCM approach by this data determined previously. The second step focuses the mechanism of segmentation. we perform the classification process in order to segmentate a given image. In figure 1, we illustrate the steps to implement the algorithm based FCM controlled by mean shift procedure for medical image segmentation.

Algorithm:

- *MEAN-SHIFT (Bootstrap)*

  - Determine modes distribution.
  - Fixe K kernel and W weight function.
  - Initialize $T \subset S$ around of these modes.

  Repeat
  - $\forall t \in T$ compute m(t) (eq. 4)

    For all t do

    $$t \leftarrow m(t)\ ;$$

    End For

  Until

  $m(t) = t \ \forall t \in T$

  End repeat

  Let C = T' such as $T' = \{t \in T \text{ and } m(t) = t \ \forall t \in T\}$ (discard redondant clusters)

- *FCM initialized with C*

  - Initialize C (from mean-shift procedure)
  - Minimize objective fonction J_m (eq.8).

Figure 1 : Modified FCM approach by mean shift procedure.

IV. EXPERIMENTAL RESULTS

A number of experiments is performed in MRI brain tissues. We present the segmentation results obtained by using the combination of mean shift procedure and FCM approach. We observe the mode seeking requires many computation times, so in order our approach is able to be used in practice, the seed implantation is made according to a previous work based on image histogram. The used heuristic consists in taking a set of points (4 to 6 points) nearby detected modes. This approach can us obtain a speed of convergence towards an available number of classes regarding of this initialization scheme. We show in table 1a and 1b synthesis results from a traditional HCM (hard c-means) and a FCM tuned by mean shift procedure.

	Hard c-mean	Mean-shift (noyau applati)	Mean-shift (noyau gaussien)
Iteration number	20	5	30
Cluster Number	3	4	5
Execution time	120	20	16

Table 1: Comparison of segmentation results performed by classical hard c-means and modified fuzzy c-means controlled by mean-shift procedure on brain MRI images of horizontal section.

	Hard c-mean	Mean-shift (flat kernel)	Mean-shift (gaussian kernel)
Iteration Number	60	5	100
Cluster number	3	6	5
Execution Time	156	20	12

Table 2 : Comparison of segmentation results performed by classical hard c-means and modified Fuzzy c-means controlled by mean-shift procedure on brain MRI images of vertical section.

These two tables indicate a long computation time for a hard c-means (HCM) in comparison to our approach. This time adding can be explained that our classification approach is dealed previously with the mode seeking. This solution can lead a rapid convergence towards the optimun of centroids. When the HCM approach is applied, the computation time is very long due probably to the initialization step and the iterative calculation to select good starting points. Moreover, the computation strongly depends on the initial centroids which would not be shifted fairly. We present in figure 2 and 3 segmentation results obtained on level gray MRI images, size of 171x220 pixels and weighted in T1. From the experimental results, we can see that our proposed approach provides a better segmentation than the conventional HCM approach which does not deal the overlapping between classes. The fact of fixing a priori the classes number makes to loose many details in the classical FCM approach which may be worried in the pathologic tissues detection or the brain hurts investigation.

V. CONCLUSION

The objective of this framwork is to use the optimum algorithms among the existing techniques for a blind segmentation applied to medical images. The followed approach performs a nonparametric statistical analysis which emphazises mean shift algorithm in order to obtain an optimum value of centroids. During the segmentation stage, we apply the MSFCM to carry out an improved classification mapping compared to a conventional classification technique. In this context, it seems the point initialization around modes is reliable. We indeed observe, even in view of noise or lake information or missing data such as MRI images, the obtained classification is quite consistent and the number of classes is nearby the reality, since we can significantly recognize the three major brain tissues of interest such as : the white matter, the gray matter and the cerebrospinal fluid. We also note for a gaussian kernel applying the iteration number is sometimes very important, but the execution time is in mean generally more short comparing to a classical FCM clustering. This achievement might be only owing to an aggregation process of centroids which speeds up the clustering. Finally, by mean shift adding into the objective function, we obtain a segmentation result which is regarded as available representation for biological tissues. The presented results in this paper are preliminary and further clinical evaluation is required for validating segmentation method.

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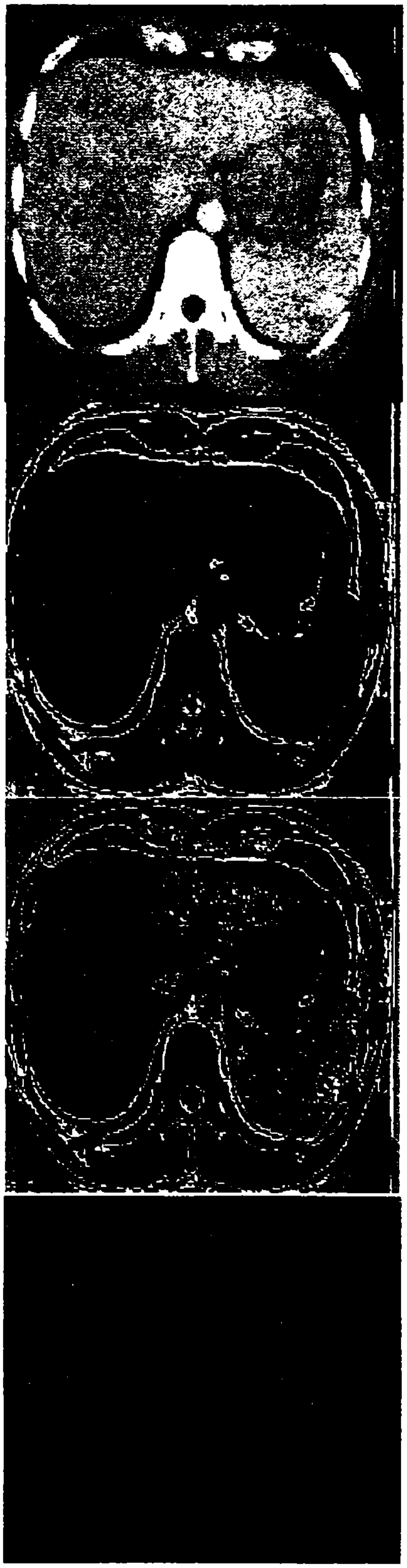


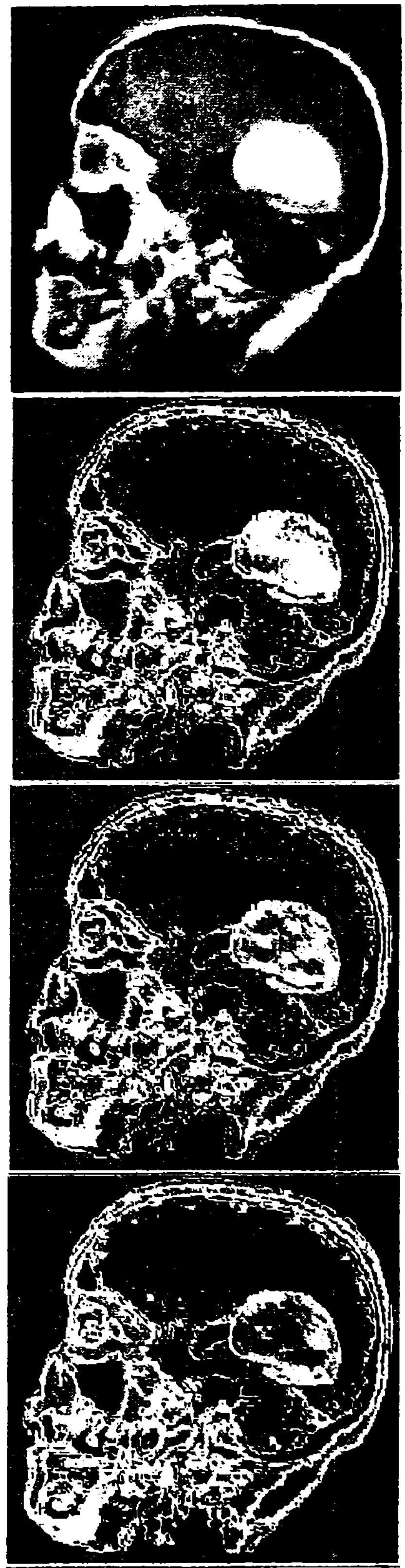
a

b

c

d

Fig . 2 : Comparison of image segmentation results obtained on horizontal IRM section: (a) original image; (b) classification by using a classical hard c-means (HCM); (c and d) fuzzy classification by including mean shift procedure (MSFCM) with a flat kernel and with a gaussian kernel through a fixed α-cut around 0.5 value.



a

b

c

d

Fig. 3 : Comparison of image segmentation results obtained on vertical IRM section: (a) original image; (b) classification by using a classical hard c-means (HCM); (c and d) fuzzy classification by including mean shift procedure (MSFCM) with a flat kernel and with a gaussian kernel through a fixed α-cut around 0.5 value.