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Evaluation of Segmentation in Magnetic Resonance Images Using *k*-Means and Fuzzy *c*-Means Clustering Algorithms

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Abstract. The purpose of cluster analysis is to partition a data set into a number of disjoint groups or clusters. Members within a cluster are more similar to each other than to members from different clusters. Applicability of the centroid-based *k*-means and representative object-based fuzzy *c*-means algorithms for study of the Magnetic Resonance Images is analysed in the work. The two algorithms are implemented and their applicability for the analysis of the MRI is evaluated. The criterion is the quality of the clustering compared to the clusters in the reference images. The quality of clustering in both algorithms depends on the number of data points in the image and on the number of the to-be-formed clusters. The algorithms are implemented, they are applied to the reference two-dimensional multispectral MR images and the resulting image segmentation is analysed by the objective criteria. The object-based fuzzy *c*-means algorithm outperforms the centroid-based *k*-means algorithm by all means. The advantage of the former stems from utilization of the cluster membership fuzziness.

Keywords: image segmentation, fuzzy *c*-means clustering, *k*-means clustering, magnetic resonance imaging

1 INTRODUCTION

Importance of medical imaging is undisputable in modern medicine. Imaging is the only source of information when adjusting skeleton fractures; it is combined with other diagnostic means for early detection of tissue changes that can develop to a fatal disease when not successfully cured. Progress in micromachining, mechatronics, development of micro motors and real-time graphics processing has given means to build surgeon-controlled robotic hands with great geometric precision. Incisions are smaller, less harm is made to the tissue and surgeons can perform operations based on enlarged images of the body internals.

Different principles of physics are applied in medical imaging. Most techniques produce images that consist of different levels of grey. Image background represents the space around the body and it is usually black.

Medical imaging started with the invention of X rays. Invention of the ultrasound diagnostics followed. Progress in computer technology has given means for intense graphic processing that has evolved [1] X ray examinations to the Computer Tomography. The most recent is Magnetic Resonance Imaging (MRI).

Medical images are adequately analysed by a specialist – a medical doctor that has been learning reading the images for years. Machines can help with the reading. They can be programmed to read the diagnose for many of the medical cases.

The process, where tissues and structures are classified into areas representing different objects, is image segmentation. Different approaches are utilised in the segmentation process: segmentation rules can define characteristics of the surfaces, homogeneity of the surface can be a segmentation criterion, and edge detection algorithms can be applied to define the image segments [2].

MRI is a medical imaging technique for visualization of detailed internal structures [3, 4, 5]. MRI makes use of the property of nuclear magnetic resonance to image nuclei of atoms inside the body. MRI provides good contrast between the different soft tissues of the body, which makes it especially useful in imaging the brain, muscles, the heart, and cancers compared with other medical imaging techniques such as computed tomography (CT) or X-rays. Unlike CT scans or traditional X-rays, MRI does not use ionizing radiation.

MRI images are constructed by many methods that are optimized for visualization of different tissues and, more important, for different conditions of the same tissue. Search criteria are grouped into different modalities of image construction. The most used modalities are T1, T2 in PD.

MR images are designed to have high contrast between different types of the tissue. The images can be most detailed – as such they are utilized even for the teaching purposes in the undergraduate anatomy courses. MR is the de-facto most productive imaging method for the brain diagnostics. Tumours and other irregularities can be detected in an early phase of

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disease where treatment can result in improvements or cure of the condition.

To grade effectiveness of the MR image clustering by different computerized methods one needs doctors' hand-drawn clusterification of the image first. This makes reference results. Machine-generated results are then compared to the reference. A comparison of the results defines ranking among different machine clustering methods.

Segmentation of the image into clusters that represent areas of different types and conditions of a tissue, and classification of the conditions can be performed by an algorithm to a significant extent [6]. Characteristics of each cluster (representing the type and condition of the tissue) in the designed set of clusters, and the images themselves are input to the clustering process. Pixels with properties that adhere to classification conditions for particular cluster, become members of that cluster. Results of automatic image segmentation are images where different tissues and different conditions of the tissue are well differentiated among themselves. A medical doctor, specialized in reading the images, examines original and segmented images for inadequate segmentation and approves flawless segmentation results. A data base of reference pairs of the original and segmented image is created. The data base serves for teaching new specialists reading the images, and for construction of automatic diagnostic procedures.

In this work we are examining efficiency of two clustering methods, namely *k*-Means (kM) and Fuzzy *c*-Means (FcM) clustering algorithms, for the MR brain image segmentation into the grey matter (GM), white matter (WM) and the cerebrospinal fluid (CSF).

Individual members (pixels, groups of pixels) of each cluster are to be similar to each other by a set of predefined criteria. Similarity defines them as members of a particular cluster. They are more similar to each other than to the members of other clusters. Similarity is measured by an objective criterion that produces a similarity index, a real number, as a measure of similarity between the two different surfaces. Indices are calculated for different matching criteria – a similarity vector is a result of the similarity evaluation. To condense the amount of data, the Euclidian distance among similarity vectors is calculated from their components. The size of the Euclidian distance is a measure of matching – a smaller number adheres to better matching.

In both, the k-means and fuzzy c-means clustering algorithms one first sets initial properties for the cluster, the centre vector [7]. Properties of individual candidates for membership of the cluster are tested for matching to the centre vector. The resulting Euclidian distance between the centre and the candidate vector is a measure of matching. A threshold matching value defines inclusion or exclusion of the candidate to/from the cluster. The centre vector is adjusted by weighted averaging with the vectors of the included surface in the process of matching. The clustering process gets stable when addition of new vectors does not affect the value of the central vector.

Fuzzy c-means unsupervised clustering is reported as effective clustering technique for segmentation of different medical images [7, 8, 9, 10]. It has even wider applicability. Reports on fuzzy c-means segmentation in astronomy, geology and war industry for target recognition are given in [11, 12, 13]. Among different approaches to segmentation, the fuzzy c-means method has an advantage of retaining more information from the original image than the classical segmentation methods [11].

Initial values of the centre vectors of the clusters can be chosen by many different approaches: the values can be set randomly; they can be calculated from the first k samples of the data points, or from some other image-characteristic data points.

Starting the segmentation by evaluation of influence of different initial values for centre vectors on the outcome of clustering is not practical, especially for a large number of clusters [9]. Therefore, different methods have been proposed in the literature for the clustering setup [7, 14, 15, 16].

Since image clustering is an effective tool for segmentation of the medical images, the medical condition treatment depends on reading the image, whether by a specialist only or by a doctor – machine tandem. The brain tissue is a complex structure and hence proper diagnosis of many brain disorders significantly depends upon accurate segmentation of the three brain tissues – GM, WM and CSF.

2 IMAGE SEGMENTATION

Image segmentation is the most essential process of any machine or man-made image analysis. Machine made image segmentation can be performed “off line”, or it can be designed for real-time applications, e.g., for machine vision of autonomous robots, quality control of industrial processes, management and control of production and similar.

In medicine, segmentation of the image can take some time since diagnostics is not considered to be in the domain of real-time applications. That takes burden from the constraints on hardware and from constraints on speed optimization in the first pass of the algorithm design.

Machine-made diagnostics has potential in early detection of tissue changes in preventive check-ups, which need to be cost and time effective since prevention involves periodical check-ups of a significant number of people.

The final knowledge, obtained by analysis of the image, is crucially dependant on the quality of segmentation where the image is partitioned into nonoverlapping surfaces that adhere to the homogeneity criterion [17].

The criterion is defined as follows: Let $f(x,y)$ be a set of characteristic values for the different spots in the image. Let $P()$ be a homogeneity predicate which is defined for the surface of the image. Clustering is segmentation of the image $f(x,y)$ into n connected subsets of the image $(S_1, S_2, \ldots, S_n)$, where

$$\bigcup_{i=1}^{n} S_i = f(x,y) \quad ; \quad S_i \cap S_j = 0, \quad i \neq j. \qquad (1)$$

The value of the homogeneity predicate is 1 for any subset of the image - $P(S_i) = 1$, and it is 0 for two neighbouring subsets - $P(S_i \cup S_j) = 0$. Such is the definition of the homogeneity predicate for all image types. In grey images, the $P(S_i)$ is about levels of grey; in colour images, the $P(S_i)$ is about colour intensity; in vector images, the $P(S_i)$ is about homogeneity of colour or texture.

One finds in the literature many different image segmentation procedures. None of them gives optimal results for all different types of images, and one image cannot be segmented in identic surfaces by different segmentation procedures. [17] gives a survey of procedures for image segmentation.

Algorithms that are developed for segmentation of one type of an image (e.g. image consisting of surfaces having many grey levels) are not productive in segmentation of other type of an image (e.g. MRI). Not surprisingly, one should look into mechanisms that were applied in the process of image formation to decide on a most appropriate segmentation algorithm.

The first task in segmentation is to choose or develop a most successful segmentation approach. This is a multidomain problem. For example, Pavlidis [18] understands image segmentation as a problem in the domain of psychophysical perception.

Being so, mathematical algorithms are in many occasions supported by heuristics to improve the overall segmentation efficiency.

A logical development in image recognition is inclusion of fuzzy techniques into the making of the algorithms. At present, two approaches compete in image recognition: deterministic and fuzzy [17].

There are not many methods to accurately assess the quality of segmentation. For the case of range images, an accurate assessment method is reported in [19], where there is a specially prepared reference image.

We perform the brain MRI segmentation by clustering [6], not by edge detection. Two methods were implemented and evaluated: *k*-means (kM) and fuzzy *c*-means (FcM) clustering.

Other candidate clustering methods include knowledge about specifics of particular images or/and some heuristics. Being so, we excluded them from our study of the segmentation algorithms.

The clustering algorithms [6] are classified by different criteria: approach - objective, theory of graphics, hierarchical: type - deterministic, statistic, fuzzy.

kM and FcM are objective clustering algorithms. Usability of the two algorithms is extensive, which is due to the theoretical and implemental progress in the last couple of years [12].

2.1 k-means segmentation

k-means segmentation is a parametric type of segmentation. Criterion function *J* is introduced, (2). Segmentation is performed in iterative steps. The mean intensity is calculated in each iteration for each cluster, and each part of the image is categorised into the cluster with a most similar mean intensity. Function *J* (2) represents the sum of squares of the distances among cluster members. The mean cluster intensity is calculated by (3).

$$J = \sum_{j=1}^{N_c} \sum_{i=1}^{N} \left\| \mathbf{x}_i - \mathbf{c}_j \right\|^2 \qquad (2)$$

$$\mathbf{c}_j = \frac{1}{N_j} \sum_{i=1}^{N} \mathbf{x} \qquad (3)$$

x is an *n* dimensional sample, N_c is the number of clusters, index *j* in S_j stands for the *j*-th cluster, $\mathbf{c}_j$ is the mean intensity value of the *j*-th cluster, N_j is the number of samples in the cluster S_j.

The following procedure applies in calculation of the k-means:

(1) One first chooses $N_c \leq N$, where *N* stands for the number of clusters having mean intensity values $\mathbf{c}_1(1), \mathbf{c}_2(1), \ldots, \mathbf{c}_{N_c}(1)$.

(2) In the k-th iteration, the samples are grouped into the N_c clusters. Sample x becomes a j-th cluster member if

$$\left\| x - m_j(k) \right\| < \left\| x - m_i(k) \right\|$$
$$\forall i = 1, 2, \ldots, N_c \wedge i \neq j.$$

(3) Next, new mean intensity values $\mathbf{c}_j(k+1),\ j = 1, 2, \ldots, N_c$. are calculated.

(4) When $\mathbf{c}_j(k+1) = \mathbf{c}_j(k)$ for all the $j = 1, 2, \ldots, N_c$, *k*-means iterations stop.

To apply the k-means algorithm to a particular segmentation problem, one first needs to define the number of clusters and the initial cluster intensity values. We defined the latter ones by taking into account the hierarchical nature of clustering. The lowest level of hierarchy is represented by individual samples, and the highest hierarchical level is represented by a cluster that includes all samples [9].

On each hierarchical level of clustering, one makes a cluster from two most similar clusters in a lower hierarchical level. Such a cluster stays put; it is not divided into sub clusters as the procedure continues.

The iterative clustering procedure is ended when three clusters, representing the GM, WM and CSF, are obtained. The mean intensity values of these clusters are the initial mean values when searching for the k-th mean values.

2.2 Fuzzy c-means procedure

In fuzzy clustering, each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the centre of the cluster. Besides, the points can belong to more than one cluster, with different levels of belonging.

The method is based on minimization of the following objective function (4):

$$J_{MR} = \sum_{j=1}^{N_c} \sum_{i=1}^{N} (\mu_{ij})^m \left\| \mathbf{x}_i - \mathbf{c}_j \right\|^2 \tag{4}$$

where $1 \le m \le \infty$ and m is a real number. N is the number of samples, N_c is the number of clusters, μ_{ij} is the degree of the sample $\mathbf{x}_i$ membership to the cluster j, $\mathbf{x}_i$ is the ith of the d-dimensional measured data, $\mathbf{c}_j$ is the d-dimension centre of the cluster, and $\left\| \mathbf{x}_i - \mathbf{c}_j \right\|$ is any norm expressing the similarity between any measured data and the centre.

The Euclidian distance (5) is a most used measure on similarity:

$$\|x\| = \sqrt{x^T \cdot x} \tag{5}$$

Fuzzy partitioning is carried out through an iterative optimization of the objective function (4), with the update of membership μ_{ij} and the cluster centres $\mathbf{c}_j$ by (6) and (7):

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N_c} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{(m-1)}}}, \tag{6}$$

$\sum_{j=1}^{C} \mu_{ij} = 1$ for each $i \in \{1, \ldots, N\}$.

$$\mathbf{c}_j = \frac{\sum_{i=1}^{N} \left(\mu_{ij} \right)^m x_i}{\sum_{i=1}^{N} \left(\mu_{ik} \right)^m} \quad for\ \forall\ i. \tag{7}$$

In equations (6) and (7), i is the index of the individual sample, j and k are indices of the individual soft cluster – specifically of its centre. The m value is a measure of softness / sharpness in the distribution of membership functions in the space.

In the extreme case of $m = 1$ are the membership functions, which are defined above the space, degenerated into a sharp level of membership. The membership functions can therefore have only one of the values in the $\mu_{ij} \in \{0,1\}$

Equation (6) shows that the $\mu_{ij} = 1$ if the norm of the $\left\| x_i - c_j \right\|$, for the i-th sample and the centre of the j-th cluster, is the smallest – regarding the centres of all clusters. $\mu_{ij} = 0$ for the other clusters where $k \in \{1, \ldots, C\}$.

In the other extreme case of $m = \infty$ are the membership functions degenerated into a completely soft level of membership. The membership functions therefore have the same values of $\mu_{ij} = 1/C$ in the whole space, for each $j \in \{1, \ldots, C\}$.

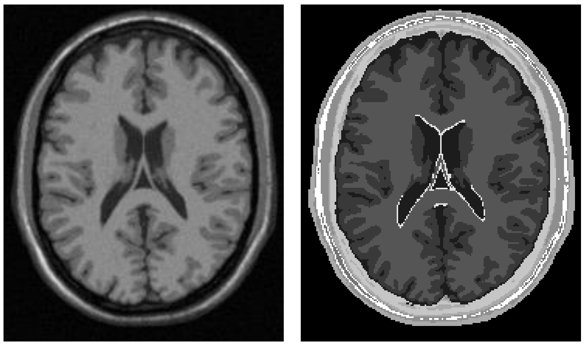

Figure 1: Reference MR image and the reference segmentation of the reference image.

In practical calculations, authors usually report choice of the m values being 1.25 or 2.00 [20].

The procedure for soft clustering the c-means is:

(1) One chooses the number of clusters C and the parameter m. Then the membership matrix $\Upsilon(0) = [\mu_{ij}]$ is defined.

(2) In the k-th iteration, one defines the centres of clusters c_j, for $j = 1, \ldots, C$, according to $\Upsilon(k)$.

(3) One then defines a new membership matrix $\Upsilon(k+1)$.

(4) If $\left\| \Upsilon(k+1) - \Upsilon(k) \right\| < \varepsilon$, the procedure is finished, else one returns to (2).

3 RESULTS

The clustering process depends on the initial randomly set conditions thus making the clustering results to be slightly different in each reiteration of the method.

The brain images analysed in our case, were made in different modalities. Image segmentation was aimed at structuring the image into the three types of tissue: GM, WM and CSF. Figure 1 shows the reference MR image and the reference segmented image. In our study we analysed 30 MRIs of the brain in the T1 modality and in the axial projection [21].

3.1 Grading the efficiency of the brain MR image segmentation by the two algorithms

The objective grading criteria are needed first. Since the clustering is an iterative process, the grading metrics needs to be built into iterative loops of the process. Not only to monitor convergence of the clustering process but primarily to intervene at the onset of ambiguity about how to proceed.

Grading metrics needs to be simple [21]. Ideally, it should be as simple as evaluation of the students' knowledge. An integer number (in continental Europe) or a letter (in the UK and in the US) represents the quantity and quality of the students' knowledge.

To evaluate image segmentation performance, one needs input reference images and output reference segmented images. The latter are usually made by specialists – a certain amount of freedom in interpretation of the original image is possible. To minimize the subjective factor, the following two approaches are recommended [22]:

a) Many specialists should segment the same image. Then, a reference segmented image needs to be produced by a statistical method that takes information from work of all the individual specialists.
b) Generation of pairs of images consisting of a mock-up reference image and a corresponding mock-up reference segmented image [22].

As a measure of grading we took the expression for p in equation (8), where $f(x,y)$ is the number of image segments in the image which is segmented by the procedure, and $f_n(x,y)$ is the number of image segments in the clustering norm.

$$p = \frac{f(x,y) \cap f_n(x,y)}{f(x,y) \cup f_n(x,y)} \tag{8}$$

3.2 Quantitive results

The MR images were produced by three different modalities. The 20 images used in our experimentation were segmented by both algorithms. The algorithms were operating in the auto mode, with no human intervention. The initial values for the process variables were produced by a random value generator. For the *c*-means method, m = 2 resulted in best results.

Table 1 shows the quantitative results.

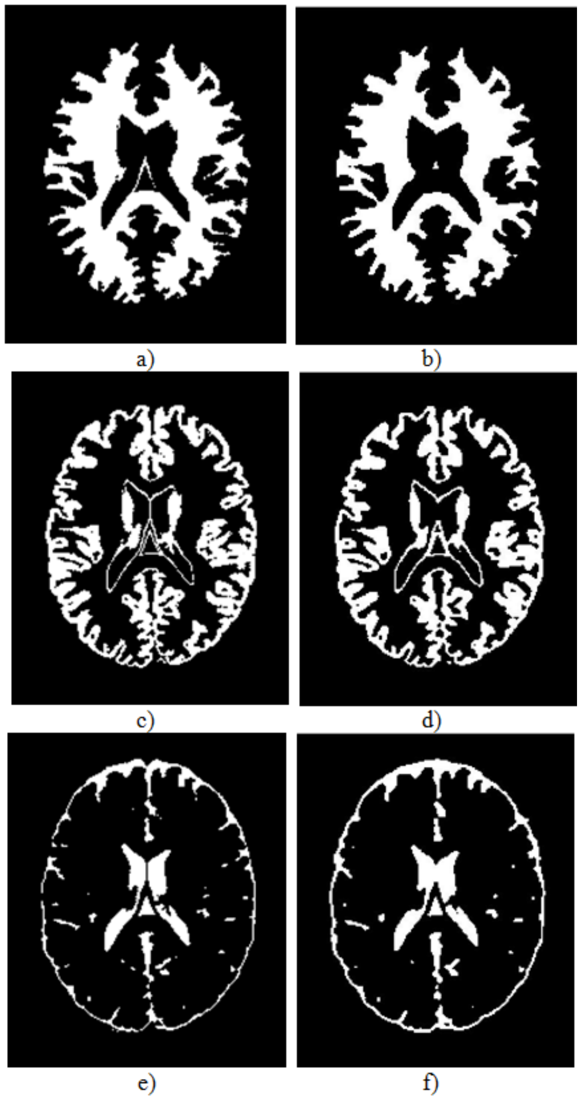

Figure 2: Results of clustering for the MR image in T1 modality: k-means – a) white tissue, c) grey matter, e) brain liquor; fuzzy c-means – b) white tissue, d) grey matter, e) brain liquor

Application of the fuzzy c-means algorithm results in better matching to the reference segmented images than the application of the k-means algorithm,

Matching for the WM is better than matching for the GM. CSF matching has the lowest value – CSF is manifested in many levels of grey in the original MR images.

Table 1: Efficiency of the k-means and fuzzy c-means algorithms in segmentation of the MR images into GM, WM and CSF

Tissue/ algorithm	**WM**	**GM**	**CSF**
k-means	0.8446	0.6644	0.7045
Fuzzy c-means	0.9402	0.8295	0.7815

4 DISCUSSION

Segmentation methods are essential components in machine-derived medical diagnostics. Segmentation of medical images differs from image segmentation in most of other technical fields by the following:

a) The majority of medical images are made of different levels of grey only. The implication is there is less information in such an image than in the colour images.
b) The MR images are produced by algorithms; many other images are produced by a camera only. The implication is there is more research space in imaging recognition for the MR images than for the camera-taken images.
c) Medical diagnostics and therapy are an irreversible process. Wrong or incomplete diagnostics is a legal wrongdoing.

In line with the c), the results not completely adhering to requirements cannot be accepted. Consequentially is the progress of machine-made medical diagnostics relatively slow, compared to a similar development in other technical fields.

In this work, applicability of the k-means and fuzzy c-means algorithms for segmentation of the MR brain images is explored. The study shows that the fuzzy c-means algorithm is better suited to the requirements of the MRI segmentation than the k-means algorithm. Such a result could be intuitively expected since Nature behaves in many occurrences more fuzzily than deterministically. Fuzzy technical field was invented to fill the vacancy where deterministic approaches showed less than optimal results.

It is the author's understanding that machine-made image clustering and derived diagnostics has considerable potential in machine-supported diagnostics, and less potential in building-up an autonomous diagnostic system.

5 CONCLUSION

The clustering methods have potential to support diagnostics and to contribute to classification of many images for different diagnostic purposes. Since lots of parameters are to be set for most successful clustering in each type of images, medical and engineering competences are needed for set-ups of batch jobs.

The clustering methods for medical imaging are similar to those developed in other fields, where image analysis is important. But there is one important difference: since human lives and life quality are involved, the error rate in detection of different objects has to limit toward zero. This is achievable by team working of medical specialists and image-processing engineers.

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