Increasing of low contrast medical multispectral image segmentation sensitivity on base regularized method of the Gram-Schmidt orthogonalization

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Annotation

In given work methods, which allow to increase of low contrast medical multispectral image segmentation sensitivity are considered. Algorithm of fuzzy c-means, which allows to rather precisely select areas of image, having uniform structure is described. For increasing of segmentation algorithm sensitivity principal component method and method of pereorthogonalization are used to source images. The practical results were received on base of a multispectral medical image of head brain of the man obtained through system of a nuclear magnetic resonance (NMR).

1. Introduction

The segmentation of tissues of medical images obtained with the help of NMR-systems, is a first step in the analysis and manipulation by interior tissues of a human body. As against other systems of deriving medical images, NMR-systems can generate some images, each of which emphasizes its own parameter of anatomic structure.

As algorithms of segmentation which allow to allocate areas of an image with a homogeneous structure it is possible to choose as precise logic algorithms, and fuzzy logic algorithms.

In methods of precise logic (for instance, precise k-mean) is supposed that each pixel can belong to only one class; this significantly reduces sensitivity of the whole process of segmentation and does not allow to select the finest details of the image. In algorithms of fuzzy logic (for instance, fuzzy c-means) is supposed that pixel can belong to several classes simultaneously that allow to carry out more exact analysis of the initial image.

The complexity of the practical decision of the problem of low contrast areas segmentation can be caused by influence of three factors:

1. The areas representing the greatest interest, frequently are poorly distinctive, or at all not distinctive under direct visual analysis of source images;
2. In accordance with physical nature of a multispectral registration, the most important particularities of areas of medical images can reveal itself only on small part of the set of source images;
3. All snapshots, as the images of the same site of a human body, are force correlated, that can hinder at attempts of visual selection of the most informative sites.

For overcoming these shortages and for increasing of segmentation sensitivity most attractive is the application of various orthogonal transformations, which convert the initial images to new information basis, in which the synthesized images are uncorrelated.

2. Fuzzy c-means method

In the fuzzy c-means method is supposed that each pixel belongs to all classes with the different degree of accessory. Such approach allows to receive more exact results in that cases, when values of samples of several classes are closely located to each other, as well as reduces influence of noise by the result of segmentation.

Let is given a set of a vector-pixels $Y=\{y_k: 1 \le k \le n\}$, where n – a whole number of pixels.

Algorithm of fuzzy segmentation can be described as follows [1]:

Step 1. Arbitrarily choose initial values of centres of clusters z_{qk}, $1 \le q \le c$, $1 \le k \le p$,, where c – number of classes, p – number of images in multispectral image.

Step 2. Calculate square of Euclidean distance between a vector-pixels y_q and class centres z_k for all classes under formula

$$d_{qk}^2 = \left\| y_q - z_k \right\|^2, \; 1 \le q \le n, \; 1 \le k \le c \qquad (1)$$

Step 3. Calculate matrix of accessory U^t, using formula

$$u_{qk} = \frac{\left[\dfrac{1}{d_{qk}^2}\right]^{\frac{1}{m-1}}}{\sum_{j=1}^{c}\left[\dfrac{1}{d_{qj}^2}\right]^{\frac{1}{m-1}}} \qquad (2)$$

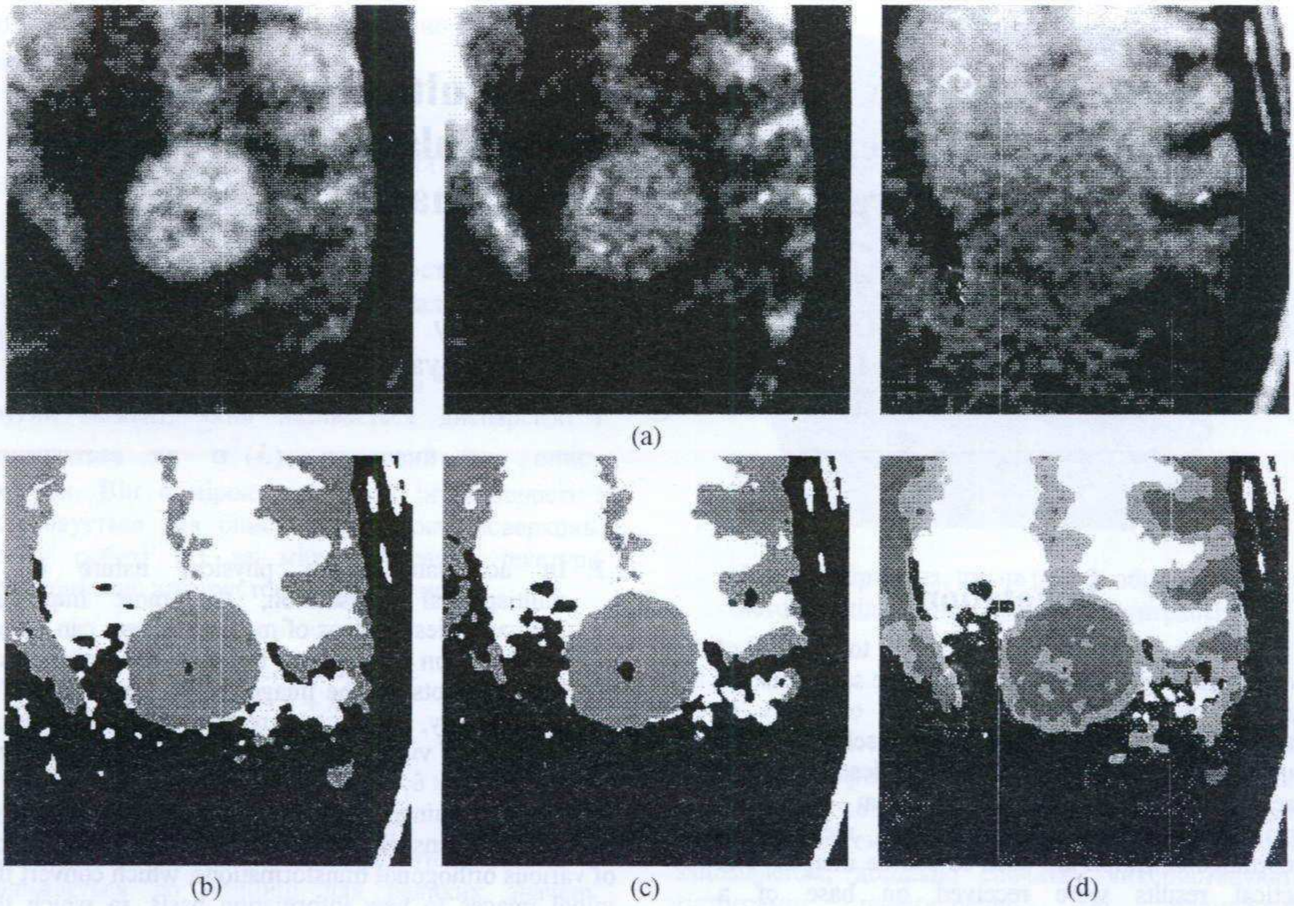

Fig. 1. a). Source images of part of head brain; b), c), d). Results of using the fuzzy c-means algorithm for segmentation of images in the fig. 1a on 3, 4 and 5 classes accordingly

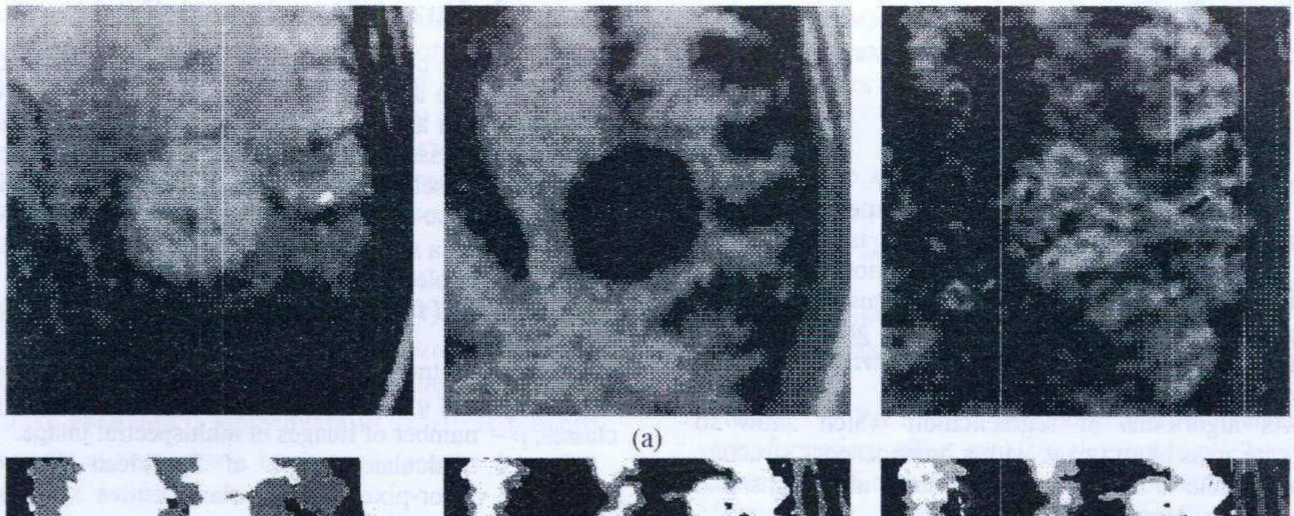

Fig. 2. a). Using the principal component method to source images (fig. 1a); b), c), d). Results of using the fuzzy c-means algorithm for segmentation of images in fig. 2a on 3, 4 and 5 classes accordingly

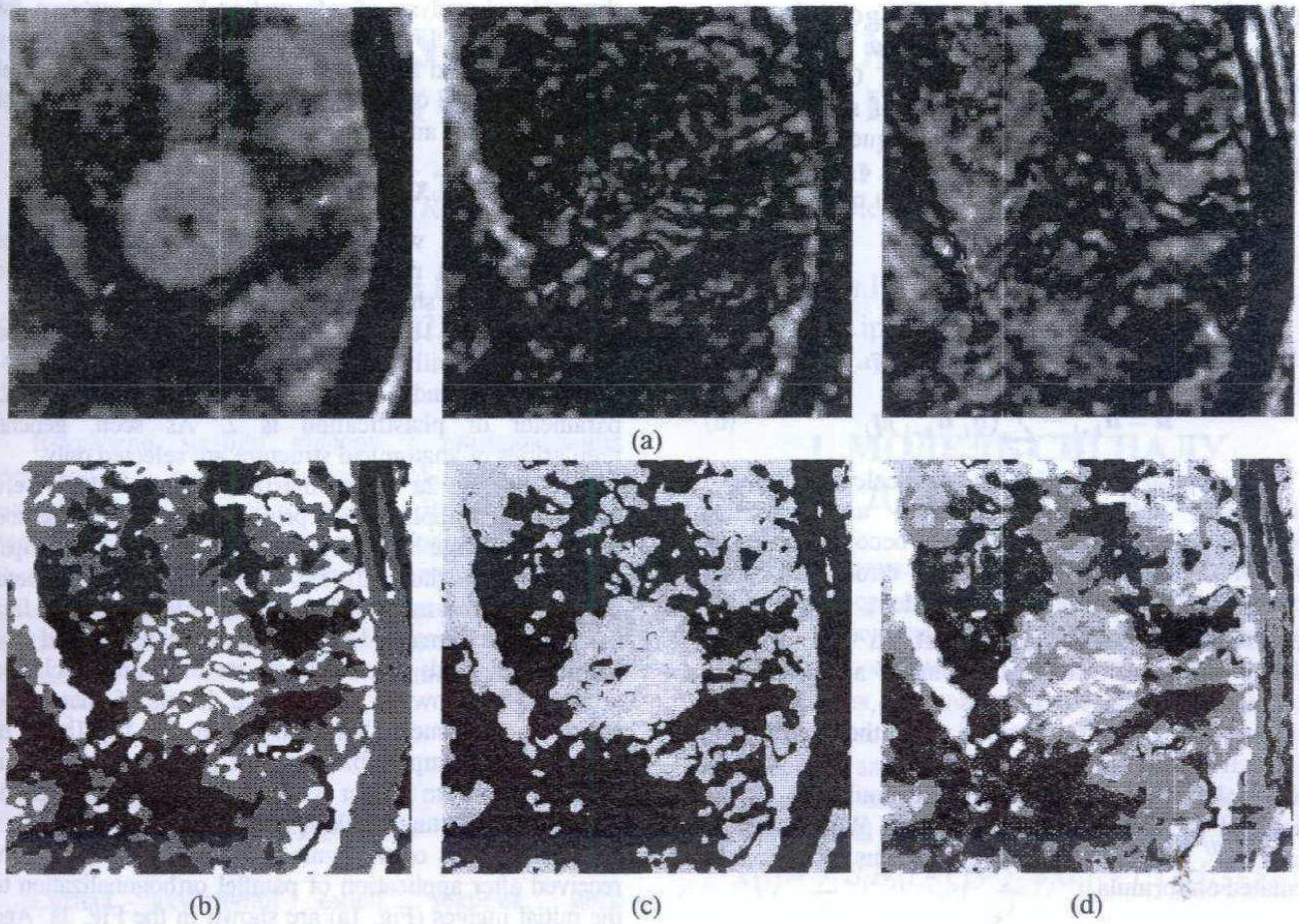

Fig. 3. a). Module of synthesized images, which were derived after using parallel orthogonalization to source images (fig. 1a); b), c), d). Results of using the fuzzy c-means algorithm for segmentation of images in fig. 3a on 3, 4 and 5 classes accordingly

Step 4. Recount values of cluster centres:

$$z_{qk} = \frac{1}{\sum_{j=1}^{n}(u_{jk})^m}\sum_{j=1}^{n}(u_{jk})^m y_{jk} \qquad (3)$$

Step 5. Check up the convergence of segmentation process $\Delta = max\|U^{t+1} - U^t\|$. If $\Delta > \varepsilon$, then pass to a step 2, otherwise terminate algorithm

Value of parameter of phasification m lies in a range from 1 to ∞ and reduces effect of noise at the calculation of cluster centres.

The direct application of a fuzzy c-means method to force correlated multispectral image allows to select only most common areas of image. Therefore for selection of finer details, i.e. for increasing of segmentation sensitivity, it is necessary beforehand to process image for suppression correlations.

3. Principal components method

One of the methods, which the most often is applied to the suppression of correlations between images, is a principal component method. But, being based on personal experience of using this method in various areas, it is possible to conclude, that at projection of many-dimensional images in this basis, one-two synthesized images $Z_l(x,y)$, which appropriate to the greatest eigenvalues λ_l of correlation matrix $\boldsymbol{R}$ of a cumulative many-dimensional image can be informative only, i.e. the synthesized images are formed on base of expression

$$Z_l(x,y) = \sum_{m=1}^{M}\Phi_l(m)I_m(x,y), \quad l=1,\dots,L \qquad (4)$$

where L – rank of a correlation matrix $\boldsymbol{R}$; M – a number of multispectral image; $\boldsymbol{I_m}$ - initial images; $\boldsymbol{Z_l}$ – synthesized images; $\boldsymbol{\Phi_l}$ – eigenvector (principal component) of correlation matrix $\boldsymbol{R}$.

As the expression (4), as a matter of fact, represents Karunen-Loeve decomposition [2], then, being based on common reasons, it is possible to conclude, that this transformation selects only common regularities peculiar to all multispectral image, that does not correspond in any way to task of segmentation of low contrast sites.

4. Orthogonalization of multispectral image

In the context of problem of segmentation of low contrast areas more perspective is an orthogonalization of the initial images on basis of Gram-Schmidt method, which allows not only to dispose of force correlation between initial multispectral image, as well as considerably increase segmentation sensitivity.

Method of Gram-Schmidt orthogonalization

Let it is necessary to orthogonalize n vectors of height m : $a_1, a_2, \dots, a_n$. Method of Gram-Schmidt orthogonalization consists in forming of some basis of vectors $q_1, q_2, \dots, q_n$, so that each subsequent vector q_{k+1} will be orthogonal to previous vectors $q_1, q_2, \dots, q_k$ [3].

The first step of a method consists in replacement of the first column a_1 on:

$$q_1 = \frac{a_1}{\| a_1 \|} \tag{5}$$

Further, if already derived $q_1, q_2, \dots, q_k$, , find

$$u = a_{k+1} - \sum_{i=1}^{k} (q_i^T a_{k+1}) q_i \tag{6}$$

Then suppose $q_{k+1}=u/\|u\|$ and pass calculation q_{k+2}

However if the calculations are executed approximately, the described process becomes unstable, moreover the influence of rounding errors that more, than closer columns a_i to linear dependent.

Method of pereorthogonalization

Let's describe a way of deriving of a column q_{k+1} which is orthogonal to columns $q_1, q_2, \dots, q_k$. This method is named by a method of pereorthogonalization, which is firm to rounding errors [4].

Let column u, received on the formula (6), is not orthogonal to columns $q_1, q_2, \dots, q_k$. We express it through $u^{(1)}$ and then following columns $u^{(s+1)}$ can be calculated on formula

$$u^{(s+1)} = u^{(s)} - \sum_{i=1}^{k} (q_i^T u^{(s)}) q_i \tag{7}$$

After nonzero column $u^{(s)}$, with due accuracy orthogonal to columns $q_1, q_2, \dots, q_k$, is derived, suppose $q_{k+1}=u^{(s)}/\|u^{(s)}\|$ and pass calculation q_{k+2} .

Using a method of pereorthogonalization

At choice of technique of orthogonalization procedure there are possible two different approaches:

1. Orthogonalization on columns with following orthogonalization of the received result on rows (in this sense a technique is similar to algorithm of two-dimensional Fourier transformation) – two-dimensional orthogonalization. Thus the received images are real and their number is number of the initial multispectral image, i.e. synthesized image $Z(m,n)$ will be characterized by expression

$$Z(m,n) = O_V \{O_H \{I(m,n)\}\} \quad m=1,\dots,M; n=1,\dots,N \tag{8}$$

where O_V and O_H – orthogonal projection operators on columns and on rows accordingly;

2. Independent orthogonalization on rows and on columns – parallel orthogonalization. In this case synthesized images can be considered as complex and characterized both amplitude-spatial, and phase-spatial characteristics, i.e.

$$\begin{aligned} Z(m,n) &= O_V \{I(m,n)\} + jO_H \{I(m,n)\} = \\ &= |Z(m,n)| \exp(j\varphi(m,n)) \end{aligned} \tag{9}$$

where $|Z(m,n)|$ and $\varphi(m,n)$ – amplitude-spatial, and phase-spatial characteristics of synthesized image accordingly.

This allows to pass from multi-dimensional to hyper-dimensional analysis of information So, for instance, for 3 initial images 17 variants of display of the information are possible, and for 4 initial images – 31 variants, that opens additional opportunities for deciding a problem of segmentation of anatomical structure of tissues.

5. Experimental results

Experiments were carried out on an example of processing of a multispectral medical image of head brain, which are shown in the Fig. 1a.

On the Fig. 1b, c, d results of segmentation of the initial images with the help of the fuzzy c-means algorithm on 3, 4 and 5 classes accordingly are presented; parameter of phasification is 2. As seen, general regularities of anatomical structure are selected only.

On the Fig. 2a the synthesized images, which were received after application a principal component method to source image (see the fig. 1a). Using a principal component method allows to eliminate correlations between source images, hereunder, selecting more fine details in each image. Using fuzzy c-means method (see the fig. 2b, c, d; segmentation on 3, 4 and 5 classes accordingly) allows to select more details of anatomical structure of tissues, than images on the fig. 1b, c, d. However it is impossible say that principal component method allow to select very small particularities of anatomical structure of tissues.

The modules of the synthesized images, which were received after application of parallel orthogonalization to the initial images (Fig. 1a) are shown in the Fig. 3a. And already these images allow to select a number of additional particularities, not visible in the Fig. 1a and 2a. Segmentation of the received images on 3, 4 and 5 classes by the fuzzy c-means method is presented in Fig. 3b, c, d accordingly. At segmentation the finer areas of a tissue having homogeneous structure are precisely selected. Sufficiently exactly stand out areas, in which values of centres of clusters are located close to one another.

6. Conclusion

In given work methods of processing medical multispectral image, which allow to increase segmentation sensitivity of low contrast sites of the initial images, are considered.

The results of experimental researches allow to conclude, that the transition to Grama-Shmidt orthogonal basis allows to considerably increase low contrast multispectral medical image segmentation sensitivity.

Literature

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