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Fuzzy Image Segmentation Using Human Interaction

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Abstract: The aim of this study is presentation of a new fuzzy image segmentation algorithm. In the proposed algorithm, human knowledge is used in clustering features for fuzzy image segmentation. In fuzzy clustering, the membership values of extracted features for each pixel at each cluster change proportional to zonal mean of membership values and gradient mean of adjacent pixels. The direction of membership variations are specified using human interaction. The proposed segmentation approach is applied for segmentation of texture and documentation images. Results show that the human interaction eventuates to clarification of texture and reduction of noise in segmented images.

Key words: Fuzzy image segmentation . Human computer interaction . Image noise reduction

INTRODUCTION

Image segmentation is not done as well without consideration of semantic respects [1, 2]. The human brain uses methods which has semantic respects in image segmentation to receive specific aims. Albeit researchers have presented numerous segmentation approaches [3] but image segmentation by a human being is completed intelligently so that different mathematical approaches and or learning based methods can not present suitable effective method [2, 4].

Image segmentation based on recognition [4, 5] tries to use recognition of objects in the scene. As a result, segmentation is performed perfectly, but applied recognition systems in these methods utilize low level features such as color, texture and edges therefore, can not be accept as semantic segmentation approachs.

Although, one aim in image segmentation in various applications is automation, but because of need of wide initial knowledge or an expert system like human, segmentation can not be completed unless with human interaction. Figure 1 shows this interaction.

A few researches have been accomplished to image segmentation by Human Computer Interaction (HCI) which can be categorized in three groups,

- Using suitable interaction equipments for interactive image segmentation in which segmentation is performed by high-performance hardware for better usage of human mind, like three dimensional mice [6].

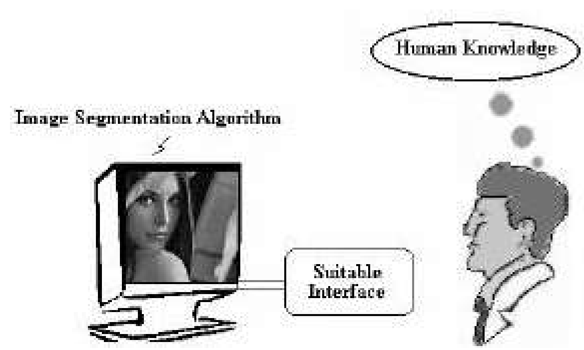

Fig. 1: Interactive image segmentation system

- Manual segmentation using professional operator in medical image segmentation [7-9] and map recognition [10].
- Manual initialization in image segmentation algorithms, for example applying initial value in 3D image segmentation to deformable surfaces [11].

In this study a novel human interaction image segmentation algorithm is presented which have manifest features as follows,

- Increasing the performance of image segmentation algorithms by increasing suitable controllable parameters.
- Prediction of parameters using human interaction.

Figure 2 shows configuration of the proposed interactive fuzzy image segmentation.

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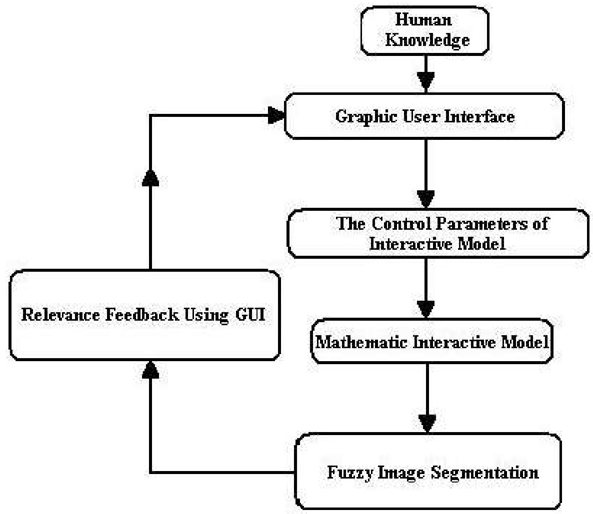


Fig. 2: Structure of the proposed interactive fuzzy image segmentation system

The control parameters of the interactive model are extracted and completed using graphic user interface (GUI), human knowledge and image segmentation algorithm. Then, these parameters are applied to the mathematical model which is utilized in image segmentation algorithm. The results of executing algorithm is shown to the operator using suitable GUI and knowledge of operator enters the search loop and therefore best parameters are selected gradually for obtaining suitable segmented image. Details of the proposed system are discussed in section 3.

In section 2 fuzzy image segmentation algorithms are reviewed. Section 3 is devoted to presentation of the proposed approach and results of applying the proposed method are brought in section 4 and final section includes conclusions.

FUZZY IMAGE SEGMENTATION

The numerous algorithms based on fuzzy techniques are used for image segmentation. Some of those are based on finding optimum threshold for minimizing of fuzzy entropy or degree of fuzziness [12, 13]. In references [14, 15], K-means and Fuzzy K-means are used in image segmentation.

Pal *et al.* [12] proposed a thresholding algorithm for image binarization. In their algorithm, fuzzy entropy is used instead of image histogram. Pal [13] defined new entropy that obtained good segmentation results.

Cannon *et al.* [14] applied a two stage algorithm for image segmentation. In the first stage, images are segmented to homogenous zones with Fuzzy K-means and the second stage combines zones based on an specific criteria. Wang in [15] proposed the supervised classification algorithm which is a type of maximum likelihood fuzzy estimation.

Aforementioned fuzzy image segmentation methods utilize one of specific analytical models which may cover part of human desires. In this work, for the first time this, analytical model is changed according to expert operator and desired image segmentation. In the next section the proposed method is explained.

FUZZY IMAGE SEGMENTATION WITH HUMAN INTERACTION

In this section, the proposed system shown in Fig. 2 is presented which includes relevance feedback with operator, type of interaction, control of parameters and interactive models.

Methods of interfacing with operator in image segmentation system: Approaches of interfacing with operator are as follows, presenting of example, random query, presenting of simple image and text query [16-19].

In the proposed interactive interfacing, the semantic gap between the segmentation algorithm and knowledge of expert is reduced with showing image options to operators. This interaction between system and human continues until desired images are achieved. In this interaction, the system tries to use selected operator query, i.e. and operator's knowledge is used in image segmentation with adjusting control parameters. Generally, when the operator starts segmentation of an image, he or she doesn't obviously know what image follows and even it is possible him or her to change the segmentation process. Therefore interaction between human and computer is necessary to receive suitable final image. This action is done in the form of relevance feedback with operator using graphic user interface (Fig. 2).

Types of interaction: Interactive fuzzy image segmentation is performed based on semantic and existing segmentation methods. Usually, in image segmentation, low level features, such as gray level, edges, color and classification tools like bays classifier and neural networks are used. But specialist operator requests semantic features latent in the image which may be extracted by complicated unknown classifiers. In other words, distance between low level features and semantic features and also between used classifier and real classifier, which is named semantic gap is prevented to receive complete performance in image segmentation.

In this part, semantic segmentation is studied from point of view of clustering. We define two interactions in segmentation: linear and nonlinear. Linear or nonlinear mathematical model may be use to impose operator's opinions in clustering. If a linear mathematical model is use to change the membership value of samples of clusters, we encounter the linear interaction. We will utilize this model in this paper.

Interactive model and control parameters in the image segmentation system: In linear interactive model, a linear formula is used to change the membership value of each sample in each cluster according to regional average of membership values and mean gradient of adjacent pixels. These variations are determined among human interaction. Since the fuzzy K-means clustering technique is used, at first we explain this algorithm briefly and then proceed to interactive model and its parameters.

Fuzzy k-means clustering approach: The fuzzy clustering algorithm is one of the most important methods used in unsupervised pattern recognition. After defining the fuzzy sets by Zadeh, the first step in this way was taken by Ressini in 1969 [22].

In recent years, this method is employed in a wide range of applications, including fuzzy control and machine vision. Among numerous method of fuzzy clustering, the k-means is the most known method [20, 23-25].

The purpose of fuzzy clustering is to classify the data $\{Y_1,\dots Y_n\}\subset R^S$ into some c clusters on the basis of minimization of minimum distance function criterion as:

$$J_m(U,V)=\sum_{k=1}^{n}\sum_{i=1}^{c}\mu_{ik}^{m}\left\|Y_k-v_i\right\|^{p} \tag{1}$$

Where, m is a value greater than one and is the fuzzification parameter. v_I is the center of the ith cluster. $\mu_{ik}\in[0,1]$ is the degree of membership of data to each cluster and p is the power of the Euclidian distance. Using the optimization algorithm, the optimum values $V=\{V_i, i=1,2,\dots,c\}, U=\{\mu_{ik}^{m}\}$ are obtained. In this equation, data set is clustered to C clusters such that the following requirement is satisfied.

$$M_{fcm}=\left\{U\in R^{c*n}\left|\begin{array}{l}\forall i,k:0\le\mu_{i,k}\le 1\ ;\\ \sum_{i=1}^{c}\mu_{ik}=1\ ,\sum_{k=1}^{n}\mu_{ik}>0\end{array}\right.\right\} \tag{2}$$

In order to optimize the function J_m (U,V) on parameters U,V, the optimizing algorithm is performed in two steps [10]. The procedure is that the cluster centers (v) in step ith, is calculated with respect to the value of U in step (r-1) as follows:

$$v_i=\frac{\sum_{k=1}^{n}(\mu_{i,k})^m x_k}{\sum_{k=1}^{n}(\mu_{i,k})^m} \tag{3}$$

Then the new value of U (using the computed value for V in the previous step) is obtained by the following relation:

$$\mu_{ik}=\sum_{l=1}^{c}\left(\frac{\left\|Y_k-v_i\right\|}{\left\|Y_k-v_l\right\|}\right)^{-2/(m-1)} \tag{4}$$

Now, in the proposed algorithm, the type of model and selections of operator membership values are changed to receive suitable clusters which we explain in following sub-section.

Linear interactive model and control parameters: In fuzzy image segmentation, segmentation is performed with assigning bigger membership values to each cluster until finding homogenous clusters with far away centers from each other. Also, image segmentation frequently has been done based on edge and region features. Applied model for changing membership values is based on aforementioned features (edge and region) which bring in (5).

$$\bar{\mu}_{j+1}=\bar{\mu}_j-\gamma M_{jc} \tag{5}$$

Where M_{jc} is innovation value for membership degree of each pixel which is one matrix with the same dimension as image in jth iteration for cluster center C. $\bar{\mu}_j$ is 2-dimensional matrix containing membership value of each pixel to each cluster and γ is the gain of membership variations of each pixel which is determined with human interaction. M_{jc} is obtained according to following relation:

$$M_{jc}(m,n)=\alpha\bar{\nabla}I(m,n)+\beta\hat{\bar{\mu}}_j(m,n) \tag{6}$$

Where $\bar{\nabla}$ is gradient mean of image over each zone and $\hat{\bar{\mu}}_j$ is regional average of $\bar{\mu}_j$ with 3*3 window size for pixel with m,n coordinates. α is the coefficient of regional gradient of image and ß is the coefficient of homogenous criterion of image.

α β γ are interactive control parameters. Following notes are important about these parameters,

- Optimum values of these parameters are specified via human interaction.
- Human interaction plays the role of directing the variation of parameters.

- Rate of variation is determined using random search with normal distribution.

With regard to above notes the optimum value of control parameters are obtained from:

$$\rho_{new} = \begin{bmatrix}\alpha\\ \beta\\ \gamma\end{bmatrix}_{new} = \begin{bmatrix}\alpha\\ \beta\\ \gamma\end{bmatrix}_{old} + \begin{bmatrix}N_{\alpha}(0,1)\\ N_{\beta}(0,1)\\ N_{\gamma}(0,1)\end{bmatrix} \qquad (7)$$

Where α_{new} is the new value of α_{old} which is found based on normal distribution $N_{\alpha}(0,1)$. Other parameters are found likewise.

Fig. 3 shows operation of the proposed algorithm. In this algorithm, two ρ_{new} are selected in each phase and operator selects one of images generated from ρ^{1}_{new}, $\rho2_{new}$, ρ_{old}. In the next section the proposed algorithm is applied to image segmentation.

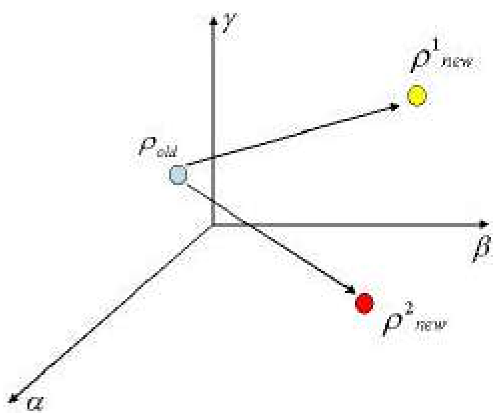
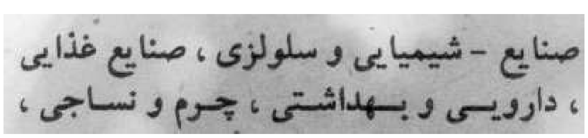
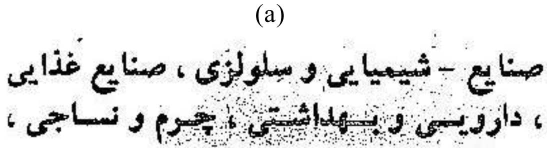


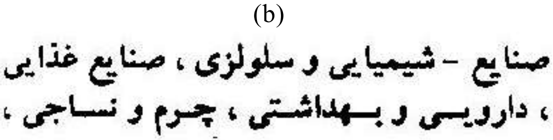
Fig. 3: Human interaction based parameters search



(a)

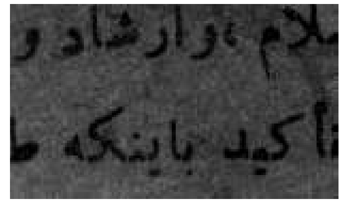


(b)

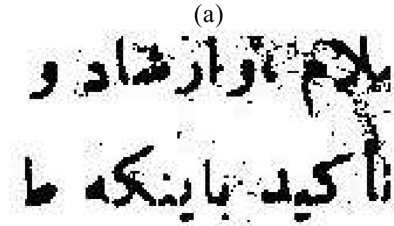


(c)

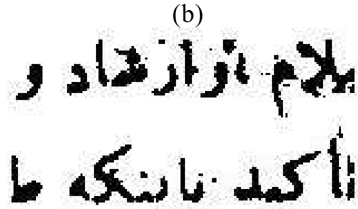
Fig. 4: Segmentation of main image (a) using fuzzy K-means result (b) and proposed algorithm eventuate (c)



(a)



(b)



(c)

Fig. 5: Image segmentation with reducing noise aspect using fuzzy K-means and the proposed approach a) main image b) segmented image by fuzzy K-means c) and with the proposed method

EXPERIMENTAL RESULTS OF THE PROPOSED ALGORITHM IN IMAGE SEGMENTATION

Three experiments are performed to check the proposed algorithm in image segmentation which are noise reduction, texture clarification and enhancement of desired part of image.

Noise reduction in image segmentation: In this experiment, document images with disturbed quality are segmented. Figure 4 is the first example in noise reduction of segmented image. Fig. 4b shows the obtained segmented image using fuzzy K-means algorithm which contains a great amount of noise whereas Fig. 4c shows a suitable result by the proposed algorithm. This image has obtained after three query and changing membership value of pixels (without second clustering). This result is obtained according to (5), (6) and (7). Final obtained parameters with human interaction are $\alpha = 0.0766$, $\gamma = -0.57$ and select $\beta = 1-\alpha$.

Another example in noise reduction in segmented image is shown in Fig. 5. The control parameters in final iteration (4 iterations) are $\alpha = -0.1202$ and $\gamma = -0.2253$.

(a)

(b)

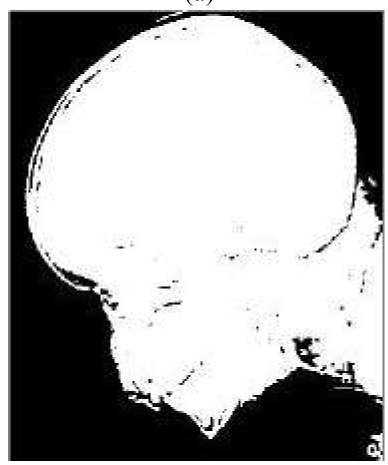
(c)

Fig. 6: Texture clarification in image segmentation using fuzzy K-means and the proposed algorithms a) main image b) segmented image by K-means algorithm c) the proposed method

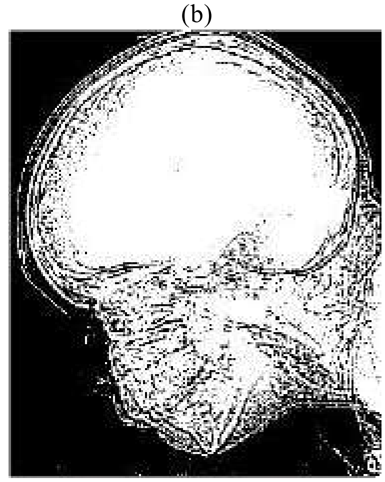
Texture clarification: In this example the main purpose of segmentation is emphasis to texture. In Fig. 6 after 6 try with operator, resulted image has obtained with suitable texture clarity. The final control parameters are α = 0.1114 and γ = 1.03. In Fig. 6c obtained image with the proposed approach have light texture relative to fuzzy K-means algorithm. In right corner of image in Fig. 6c because of sequential selections with respect of texture clarification, texture lucidity have obtained. The selected control parameters after operator interaction have bigger gradient coefficient in this example.

In the next experiment which is shown in Fig. 7, the aim is to see soft texture in x-ray image whereas bony texture is observed too. Control parameters in final try are α =-0.0168 and γ = 1.0852.

(a)



(b)



(c)

Fig. 7: Texture clarification in image segmentation using fuzzy K-means and the proposed method a) main image b) segmented image by fuzzy K-means algorithm c) the proposed approach

Increasing clarification of image details: In this experiment, parts of the segmented image are not

(a)

(b)

(c)

Fig. 8: Clarification of image details a) main image b) using fuzzy K-means algorithm b) the proposed algorithm

observed after segmentation (Fig. 8). The control parameters in final try of operator are α =-0.0704 and $\gamma = 0.74704$.

CONCLUSIONS

In this paper, a new method for fuzzy image segmentation is presented which is based on human interaction. Manifest features of this method are increasing the performance of fuzzy segmentation algorithm by changing suitable parameters, estimation of parameter using direction of variation of parameters via interaction by human.

Semantic segmentation was studied from clustering view and two nonlinear and linear interactions were defined and linear interaction was implemented. Performance of this algorithm was evaluated with three examples. The obtained results show better performance compared to fuzzy segmentation algorithm.

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