Cluster-Based Image Segmentation Using Fuzzy Markov Random Field

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Abstract

Image segmentation is an important task in image processing and computer vision which attract many researchers attention. There are a couple of information sets pixels in an image: statistical and structural information which refer to the feature value of pixel data and local correlation of pixel data, respectively. Markov random field (MRF) is a tool for modeling statistical and structural information at the same time. Fuzzy Markov random field (FMRF) is a MRF in fuzzy space which handles fuzziness and randomness of data simultaneously. This paper propose a new method called FMRF-C which is model clustering using FMRF and applying it in application of image segmentation. Due to the similarity of FMRF model structure and image neighbourhood structure, exploiting FMRF in image segmentation makes results in acceptable levels. One of the important tools is Cellular learning automata (CLA) for suitable initial labelling of FMRF. The reason for choosing this tool is the similarity of CLA to FMRF and image structure. We compared the proposed method with several approaches such as Kmeans, FCM, and MRF and results demonstratably show the good performance of our method in terms of tanimoto, mean square error and energy minimization metrics.

Keywords: Clustering, Image segmentation, Markov random field, Fuzzy markov random field, Cellular learning automata.

1. Introduction

Image segmentation is a major step in most image processing and computer vision tasks. Image segmentation is the process of dividing an image into two or more segments in a way that each segment should be heterogeneous. Pixels in a segment should have maximum similarity and minimum similarity with pixels in other segments. This process can be used as a feature extraction for pattern recognition, object detection, image retrieval, stereo matching, and many other tasks. Among the works which are applied well and obtained good results, we can refer to mammography image segmentation using cluster-based Markova random field [1], fast and robust image segmentation using FCM with spatial information [2], color image segmentation using k-means clustering and Otsu's adaptive thresholding [3], normalized cuts and image segmentation [4], and random walks for image segmentation [5], to name a few.

Cluster analysis or clustering is the task of grouping a set of objects together in such a way that objects in the same group (called a cluster) are more

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similar (in some sense or another) to each other than to those in other groups (clusters). There are several methods to define quantity similarity between data points, among them Euclidian distance and Cosines distance are more common. The most popular methods are k-means [6], FCM [7], spectral [8], hierarchical [9], ant colony [10], SOM [11], and Evolutionary [12] clustering.

Image segmentation is one of the most applications of clustering in computer vision field (colour, medical, grayscale, and etc.). In this case, pixel values form the clustering space data. Number of clusters indicates number of desired segments; hence, each obtained cluster refers to a segment of original image. Accuracy of segmentation results depends on clustering performance, so higher accuracy clustering leads to better segmentation results.

Fuzzy Markov random field (FMRF) [13] is a Markov random field (MRF) in fuzzy space, which applies fuzzy random variables in target process. In FMRF, a data point only can take one value from label set L, which means that each data only should belong to one label of L. While, in FMRF, each data point belong to all of the labels in L with different membership value for each one simultaneously. Estimating the optimal labelling of FMRF is similar to MRF, and both of them are based on MAP framework. Therefore to derive labelling with minimum energy, we can utilize energy minimization methods such as α-expansion [14], loopy belief propagation [15], and min-cut/max-flow [16].

Cellular Automata (CA) [17], is a mathematical model for systems consisting of large number of simple identical components with local interactions. CA is a non-linear dynamical system in which space and time are discrete. The simple components act together to produce complicated patterns of behaviour. The cells update their states synchronously on discrete steps according to a local rule. The new state of each cell depends on the previous states of a set of cells, including the cell itself, and constitutes its neighbourhood.

Learning Automata (LA) [18], are adaptive decision-making devices that operate on unknown random environments. A learning automaton has a finite set of actions to choose from and at each stage, its choice (action) depends upon its action probability vector. For each action chosen by the automaton, the environment gives a reinforcement signal with fixed unknown probability distribution. The automaton then updates its action probability vector depending upon the reinforcement signal at that stage, and evolves to some final desired behaviour.

Cellular Learning Automata (CLA) [19], which is a combination of CA and LA, is a powerful mathematical model for many decentralized problems and phenomena. The basic idea of CLA, which is a subclass of stochastic CA, is to utilize LA to adjust the state transition probability of stochastic CA. A CLA is a CA in which a learning automaton is assigned to every cell. The learning automaton residing in a particular cell determines its action (state) on the basis of its action probability vector. Like CA, there is a rule that the CLA operates under. The local rule of CLA and the Actions selected by the neighbouring LAs of any particular LA determine the reinforcement signal to the LA residing in a cell. The neighbouring LAs of any particular LA constitute the local environment of that cell. CLA has found many applications such as image processing [20], rumour diffusion [21], modelling of commerce networks [26], channel assignment in cellular networks [22, 23], and VLSI placement [24].

This paper aims to provide a cluster-based image segmentation framework based on FMRF model. Fuzzy attribute of FMRF lead to boundary, noisy, and outlier data take correct label, and somehow deal to uncertainty. Similar to the MRF, FMRF also need to initial labelling. This is a critical stage in problem modelling and has an important role in final performance. For initial labelling of FMRF we use cellular learning automata clustering proposed in [25]. The reason for choosing this tool is the similarity of CLA to FMRF and image structure. In order to evaluate the proposed method, we compare the obtained result with cluster-based image segmentation methods like k-means [3], FCM [2], and MRF [1], which demonstrate acceptable performance than other algorithms. The rest of the paper is organized as follows. The proposed model is discussed in section 2, which includes initial labelling step, define energy function, and describe energy minimization method for reach to optimal labelling of FMRF, section 3 presents experimental results and analysis of them, and finally section 4 concludes the paper.

2. Proposed Method

This section presents the proposed FMRF clustering model. In the MRF model, a pixel can only take one value from a state space, which means each pixel must belong to one and only one region. Nevertheless a fuzzy MRF model allows each pixel belonging to all regions simultaneously with different variables. Then each pixel has a vector $(u_1, u_2, \ldots, u_K)$, with $u_1 + u_2 + \ldots + u_K = 1$, and the value u_i, $i = 1, 2, \ldots, K$ represents the likelihood that the pixel belongs to region i. If $u_i = 1$, the fuzzy MRF becomes the pure MRF. The FMRF model-based image segmentation is still performed under the MAP-MRF framework (also called MAP-FMRF framework). The main difference between MRF and FMRF model is in energy function modelling. The function in FMRF should be defined based on membership value of each data for any label l from L, compute energy for the correspond node in FMRF.

2.1. Initial Labelling

Similar to MRF, performance of FMRF model closely related to initial labelling step. Hence, the role of initial labelling in efficiency of results is obvious. In this paper we use irregular cellular learning automata clustering provided by [25] for this task. The clustering approach is applied for data clustering which obtained results demonstrate which is more powerful than existing clustering methods such as K-means [6], FCM [7], and SOM [11]. Notable characteristics of the mentioned method are using of structural and neighbourhood information of data, ability for careful separation data points belong to each cluster, and avoid of local minimal solution.

In this paper we use CLA clustering method for initial image segmentation. CLA is a suitable tool for modelling neighbourhood information which has some similarity with FMRF. In image segmentation problem with CLA, each pixel corresponds to a cell of CLA grid. The number of automata actions set to desired segments. After that initial segmentation is performed, membership value of each data (pixel) to all centers in range [0, 1] is calculated via equation 1. Then, we assign them as data membership vector to each correspond node in FMRF. Finally, energy minimization method uses the obtained vector for following optimization process.

$$w_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \tag{1}$$

$X=\{x_1,x_2,\ldots,x_n\}$ refer to data set X, $C=\{c_1,c_2,\ldots,c_n\}$ is the set of cluster centers, w_{ij} defines membership value of data i for center j, and m determines the fuzziness of membership value (*m should be set equal or greater than one*). Higher value of m leading to smaller membership values, and in contrary $m = 1$ results in membership values with $\{0, 1\}$ which implies to crisp membership. Usually in most problems $m = 2$ is assumed.

2.2. Energy Function Modelling

One of the most important issues in FMRF-based problems is to define energy function, so defining correct form for that leads to final optimized labeling. Although this is possible if an efficient energy minimization method applied. Another issue is the type of neighborhood system which we chosen that is 4-neighborhood, meaning that four node (top, bottom, left, and right) surrounding node i, are neighbors of that.

Likelihood energy defined as sum of likelihood potentials. In FMRF-C, likelihood energy determined based on membership value of each data to labels in labels set *L*, which via equation 2 calculated.

$$V_F(y_i \mid x_i) = e^{-w_{y_i x_i}} \quad (2)$$

Which y_i refer to observed value of data i, x_i is the label of node i, and $w_{y_i x_i}$ presents degree of membership of data y_i to label x_i, by using negative exponential, higher membership value results in lower energy and vice versa. By defined likelihood potential, appropriate label will be selected for the observed data.

In order to eliminate the spatial discriminant of labelling, second order clique potential is defined. This function checks that whether the two neighbour data (pixels) are in a same cluster or not. Typically, second order clique potential complies with using model which can be defined as equation 3.

$$V_F(x_i, x_{i'}) = \begin{cases} -\beta, (x_i = x_{i'}) \\ \beta, (x_i \neq x_{i'}) \end{cases} \quad (3)$$

Which β is a constant penalty value in range [0, 1], and x_i, x_i' are labels of two neighbouring nodes in FMRF. So as two nodes have same label, penalty would be $-\beta$, otherwise β be considered as penalty that two neighbouring nodes which have different label. Clique potential forcing two similar neighbours have different label.

Finally, energy function is defined as sum of the likelihood and second order energies, while presented in equation 4.

$$U_F(x \mid y) = \sum_{i \in S} V_F(y_i \mid x_i) + \sum_{i' \in S} \sum_{N_i} V_F(x_i, x_{i'}) \quad (4)$$

Due to the favorable performance of belief propagation energy minimization method [15] in Markov random field-based applications, also inference optimal labeling of FMRF is performed by.

2.3. Energy Minimization Using Loopy Belief Propagation

Loopy belief propagation (LBP) [15] is a widely used method for MRF-based application, which achieves labelling with minimum energy. In this paper, we applied LBP method to inference optimize clusters. Actually, LBP is an iterated algorithm, which using propagates messages along nodes in MRF, trying to find optimal labelling. In each iteration, every node send message to its neighbours, also receive incoming message from them. This process repeated until all messages will be stable, that’s mean not change. Summation of the algorithm described at below:

1. Before a node p sends a message to another node q, it must first receive messages from rest of its neighbours, and consult with them. During the belief propagation, all nodes of FMRF collaborate with each other, and about which label which ultimately must choose, decide. The partnership between nodes reflected by exchange of views (i.e. messages), which is done during the algorithm.

2. Updating messages continued until all of them converges. Then, after convergence, a set of beliefs for each node p in FMRF will be calculated. Belief, represent that how much is possible to node p think which label xp should assign to it.

3. In each iteration once total belief will be calculated, then every node assigned with a label whose belief is greater.

Mentioned process will be repeated until minimized energy value be stable and in some sequential iteration be unchanged.

3. Experimental Results

This section investigates the performance of the proposed model in image segmentation. For this purpose a large number of images are selected from Berkeley dataset [26]. The number of clusters represents the number of desired areas (segments) and it is considered as 2 for all images which divides the image into background and foreground parts. In order to evaluate the proposed method, segmentation results are compared with Kmeans [3], FCM [2], and MRF model [1]. The main reason to compare our proposed model with the aforementioned models is that all of them use clustering in image segmentation.

The obtained results from applying the mentioned algorithms are studied in terms of minimized energy, tanimoto metric, and mean of squares. This metrics are used to compare the functionality of the algorithms.

Labeling with minimum energy means that constraints for fuzzy markov random field are satisfied. Therefore, on one hand the assigned label should match the observed data and in another hand it should be consistent with its neighbors. Definitely, an algorithm which minimizes the energy is more acceptable. Tanimo metric is used to represent the similarity of two images which return a value in [0, 1] range. The greater value of this metric means that the segmented image and reference image are more similar. Hence, the greater value of this metric results in more desirable segmentation. Mean square of error is used to estimate the error between the obtained segmented image and the correct segmentation. The value of this metric lies in [0, 1] range. The smaller values of this metric means that the results have a small difference with the correct solution and the image segmentation results are more similar to the correct segmentation. Fig. 1 to 3 present the evaluated values for energy minimization, tanimoto metric, and mean square error, respectively, and Fig. 4 shows multiple instance of the segmented images.

Fig. 1 illustrates the minimized energy values of segmentation results using the aforementioned algorithms. The smaller value for energy means the smaller cost and penalty for labeling has been achieved. A labeling is more desirable if its energy is minimized. From a lesser energy we can interfere that the obtained labeling has satisfied both similarity with the observed data and smoothness within the region principle which is the basic for segmentation algorithm.

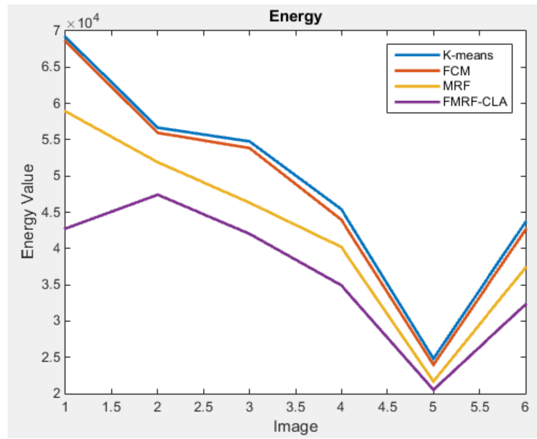

Fig. 1. Energy value of methods for segmented images.

Among the applied methods Kmeans has the worst functionality and our proposed method FMRF-C is best. The MRF cluster based segmentation model which utilizes ICM minimization method to achieve optimal labeling, even though, cannot achieve global optimum and work locally; it shows better performance in comparison to Kmeans and FCM. By looking at t 1 the fuzzy property of FMRF can be realized. The fuzzy membership values caused to assign correct labels to data (pixels) and a labeling with lower energy can be achieved. The proposed FMRF-C model leads to labeling with lower energy for all examined images.

Tanimoto metric is utilized for describing the similarity of tow images, which has a value in [0, 1] range. The greater value of this coefficient indicates more similarity between the segmented images with the reference image. As a result the greater value of this coefficient results in better segmentation. This metric can be computed using equation 5.

$$coeff = \frac{I^t S}{\|I\|^2 + \|S\|^2 - I^t S} \tag{5}$$

In equation (5), I is the reference image, S is the segmented image and t is the transpose. Fig. 2 shows the tanimoto metric values which are obtained from executing different algorithms on dataset images. As we expected, the proposed FMRF-C model has greater tanimoto value for all exanimated images. The greater value for tanimoto means that better segmentation and acceptable results are achieved.

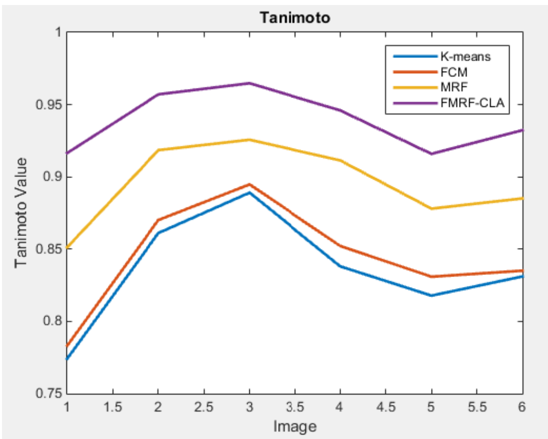

Fig. 2. Tanimoto value of methods for segmented images.

Mean square error can be calculated pixel by pixel with adding the subtraction of all pixels diving by number of all pixels. The MSE value is in [0, 1] range. The smaller value of MSE means that the segmentation is better and it is calculated by equation 6.

$$MSE(I,S) = \frac{\sum_{i=0}\sum_{j=0}(I(i,j),S(i,j))^2}{MN} \qquad (6)$$

Where M and N are the number of rows and columns for an image, respectively. I and S are reference and segmented image, respectively. Fig. 3 demonstrates the means square error values achieved from executing different algorithms on data set images. Based on this metric, the performance of the proposed method against other method is proven. The proposed FMRF-C model has gained optimal labeling for all dataset images. The achieved segmentation by this model has minimum difference with correct segmentation and because of this the smaller MSE is achieved.

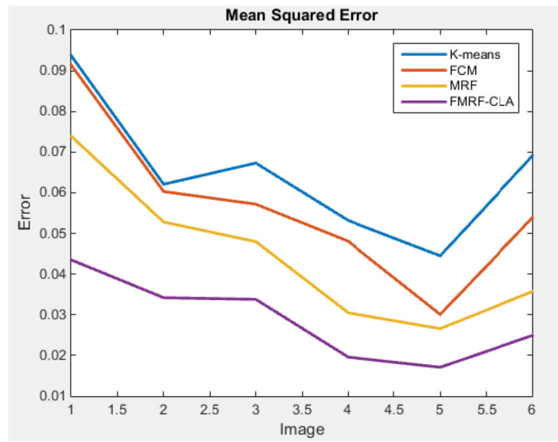

Fig. 3. Mean square error value of the methods for segmented images.

As image segmentation results in Fig. 4, the MRF model considered details of the image in segmentation, which leads to energy increasing. Whereas, the proposed FMRF-C algorithm archives homogeneous and uniform regions which results in quick and simple separation of background from foreground. More desirable and better features can be extorted from this segmentation, which can respond to application requirements, computer vision tasks and image processing.

4. Conclusion

This paper proposed a clustering method called FMRF-C, which is based on fuzzy Markov random field and cellular learning automata. This algorithm has its application in image segmentation.

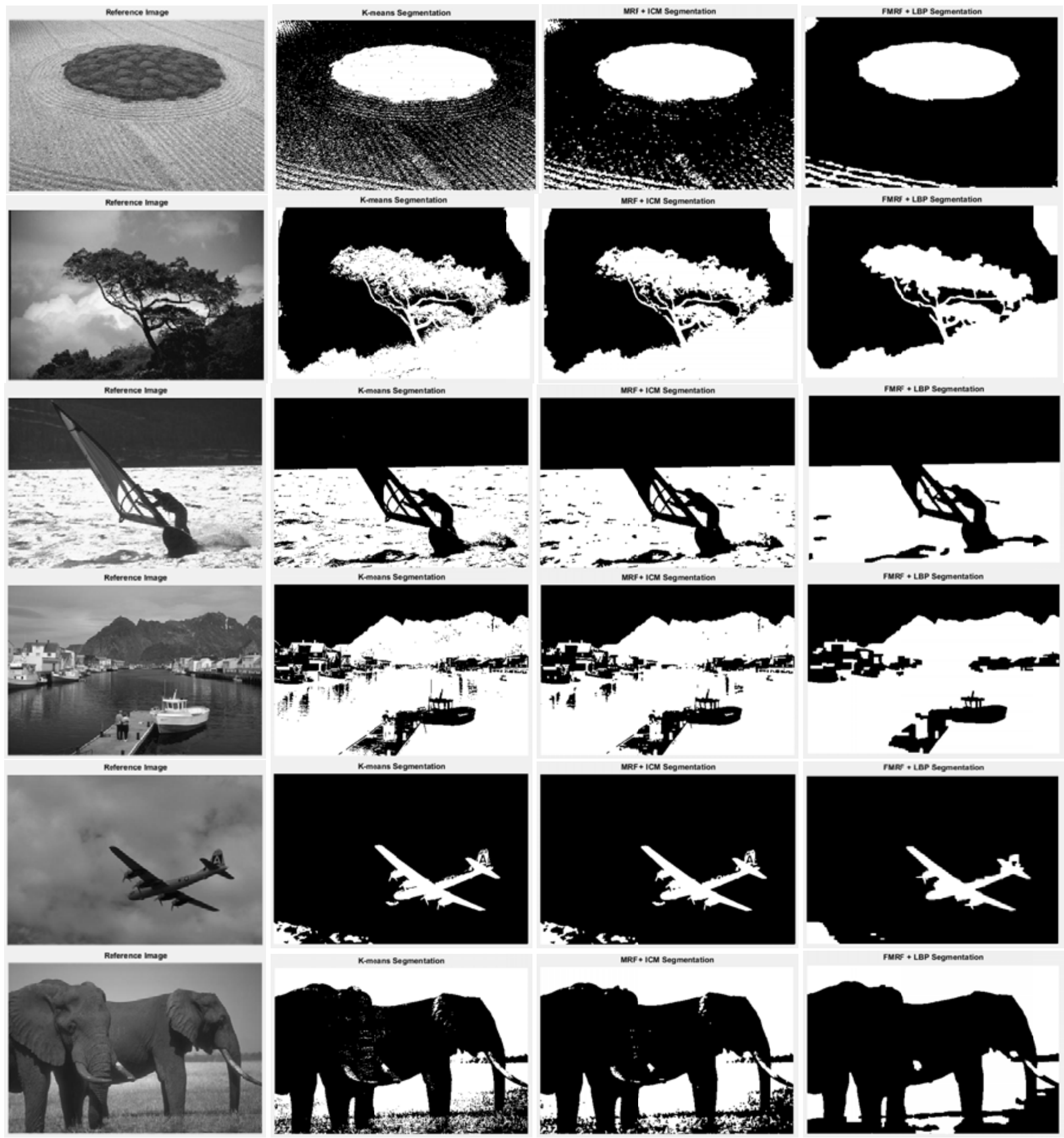

Fig. 4. Berkeley image segmentation dataset and segmentation results [26], from left to right column: reference images and K-mean [3], MRF [1], and FMRF-C segmentation results, respectively.

The first step in FMRF model is the initial labeling. Initial labeling has a major role in the performance of the algorithm. For this purpose, the initial labeling is done by cellular learning automata clustering. This method is robust and resilient against noise and outlier data, and involves the dataset neighborhood structure in result generating. Using this method data (pixels) is clustered. The results from clustering are used to compute the initial labeling for fuzzy Markov random field to optimize it using energy minimization method. With regards to minimization method in MRF and FMRF, the Loopy belief propagation energy minimization algorithm is used to achieve labeling with minimum energy on FMRF-C.

The proposed method is applied on Berkeley image dataset. The obtained results prove the better performance of the proposed method against other mentioned algorithms. The proposed method achieved image segmentations with minimum energy and error and reaches maximum tanimoto. Hence, by looking at segmented images, the impact of fuzzy in FMRF can be realized. This property makes FMRF model more robust against noise and random data in comparison with MRF which results in homogenous segmentation with uniform regions.

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