Fuzzy-logic Based Information Fusion for Image Segmentation

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Abstract— **This work presents an information fusion mechanism for image segmentation using multiple cues. Initially, a fuzzy clustering of each cue space is performed and corresponding membership functions are produced on the image coordinates space. The latter include complementary as well as redundant information. A fuzzy inference mechanism is developed, which exploits these characteristics and fuses the membership functions. The produced aggregate membership functions represent objects, which bear combinations of the properties specified by the cues. The segmented image results after post-processing and defuzzification, which involves majority voting. A fuzzy rule based merging algorithm is finally proposed for reducing possible oversegmentation. Experimental results have been included to illustrate the steps and the efficiency of the algorithm.**

I. INTRODUCTION

Information fusion is the process that combines information taken from various sources or at different time instances. By combining several "viewpoints", this process aims at increasing the knowledge and the robustness of the system. The fusion of information can be achieved in the data level, in the feature level or in the decision level, depending on the application. In image processing, some oftenly encountered approaches for data fusion are based on Bayesian theory, Dempster-Shafer evidence theory and fuzzy logic. In the current approach, fuzzy logic is used for fusing several cues in order to segment images. Although the conducted experiments concern image segmentation, there isn't any limitation that can restrict the use of the developed fusion mechanism in other applications.

Segmentation comprises a fundamental process in image analysis and is used in numerous research areas. As a result many segmentation techniques have been proposed in the literature [1]–[3]. Recent techniques using information fusion and fuzzy logic have been developed from the medical imaging community (e.g. [4]–[6]). Another method, which concerns unsupervised segmentation of color images using fuzzy rules, is presented in [7]. Fuzzy rules are also used in [8] for fusing features extracted from range and intensity images.

The current approach is based on an inference mechanism which achieves fusion of any number of cues. The different cues, which are selected for the segmentation of an image, include depth, motion vectors, color, texture etc. The information contained in the various cues may be complementary or redundant. Consider, for example, a man walking in front of a wall which has the same color as his shirt. Segmenting this image based on color will give erroneous results as it will be difficult to distinguish between the wall and the shirt. However, in depth information, a human figure is depicted in front of the wall. Similarly, if motion was taken into account, a moving figure would be perceived against the static wall. In this example, in the color-depth pair of cues, complementary information is found, while in the depth-motion pair, redundant information is contained at a significant degree. The objective of our fusion mechanism is to benefit both from the complementarity and the redundancy of the fuzzy clustering information extracted from the various cues.

In the next section, the issues concerning the extraction of fuzzy clustering information from each cue are discussed. The fusion mechanism is described in section 3, while the defuzzification process is described in section 4. Section 5 describes an algorithm for merging neighboring segments. The experimental results are presented in the following section and the final conclusions of the approach are stated in the last section.

II. FUZZY CLUSTERING

Fuzzy clustering of each cue space is performed using for example the fuzzy c-means (FCM) algorithm. The FCM algorithm has been frequently used for segmenting images (e.g. [9]–[11]). A fuzzy clustering method is considered to evolve more smoothly to the global minimum whereas a crisp method bears more risk to get stuck in a local minimum [12].

In the current approach, a fuzzy clustering algorithm was chosen instead of a crisp one, in order to exploit the different degrees of membership in the clusters. In fuzzy clustering, a pixel belongs to all clusters with different membership values, while in crisp clustering a pixel is either a member of a cluster or not. The degree of membership $u_{i(x)}$ of a pixel x in the ith cluster of a cue is indicated by the membership function $\mathbf{u}_i$, which maps every pixel of the image to the interval [0,1]. The membership functions are depicted as grayscale images (Figure 3, Figure 5), where the brighter the intensity value of a pixel, the bigger its membership to the cluster represented by the grayscale image is. The number of clusters, namely the number of membership functions, is given as input to the fuzzy clustering algorithm.

III. INFORMATION FUSION

Although the cues vary in the information content, they refer to the same scene, the same objects. Thus, similarities between the membership functions resulting from different cues should be evident, even in cases where a different number

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of membership functions is derived from each cue. Such similarities increase the possibility that the objects of the scene have been correctly detected. The objective is to increase the certainty of the clustering in such cases without losing the advantage of complementarity between the various cues.

Assuming that from each cue C_p, where $p = 1, ..., N$, applying the fuzzy clustering algorithm result M_p different membership functions. We form all the possible combinations consisting of N membership functions where each one belongs to a different cue. Thus, the number S of all possible combinations is given by $S = \prod_{p=1}^{N} M_p$.

Each one of the N membership functions of a N-tuple, represents objects with certain characteristics, which are specified by its cue (e.g. grey, far away, static objects). Fusing the N membership functions, a new aggregate membership function will be derived, which will represent objects with a combination of the initial characteristics. The first step is to find the clustering information which the membership functions of a N-tuple share in common. For this reason, the intersection between the membership functions of a N-tuple is obtained using,

$$T_x^J = \mathcal{I}\big(u_{J_{1(x)}}, ..., u_{J_{N(x)}}\big), \tag{1}$$

where $J = [J_1, ..., J_N]$ is member of the cartesian product $M_1 \mathrm{x} M_2 \mathrm{x} ... \mathrm{x} M_N$ and is one of the S possible combinations, $u_{J_{p(x)}}$ is the degree of membership of the pixel x in the p membership function of the J combination and $\mathcal{I}$ is any t-norm function. Having a membership function $\mathbf{u}_{J_p}$, we would like to estimate its involvement to the common clustering information of the N-tuple $\mathbf{T}^J$. This estimation is achieved by using the Lukasiewicz implication [13],

$$\mathcal{J}(a, b) = \min(1, 1 - a + b). \tag{2}$$

Thus, a function $\mathbf{R}$ is produced, which indicates how much the membership $u_{J_{p(x)}}$ of a pixel x implies its membership T_x^J in the intersection.

$$\mathbf{R}(u_{J_{p(x)}}, T_x^J) = \min(1, 1 - u_{J_{p(x)}} + T_x^J) \tag{3}$$

Instead of having a function $\mathbf{R}$ for each membership function, it would be more flexible to have just a number indicating how much the p membership function of the J N-tuple implies the intersection $\mathbf{T}^J$. Thus, similarity factors are produced using,

$$R_{J_p} = \frac{1}{n} \sum_x \mathbf{R}(u_{J_{p(x)}}, T_x^J), \tag{4}$$

where n is the number of pixels.

The aggregate membership functions are derived using the inference mechanism depicted in Figure 1 and expressed by the following formula,

$$F_x^J = \mathcal{U}\Big(\mathcal{I}(u_{J_{1(x)}}, R_{J_1}), ..., \mathcal{I}(u_{J_{N(x)}}, R_{J_N})\Big), \tag{5}$$

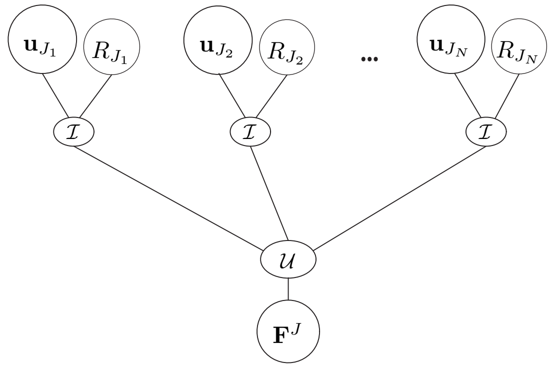

Fig. 1. The inference mechanism.

where $\mathcal{I}$ is any t-norm function and $\mathcal{U}$ is any t-conorm function. Various t-norm (intersection) and t-conorm (union) functions exist with certain properties [13]. The standard t-norm/t-conorm pair consists of the min/max functions.

A further processing step is applied to the aggregate membership functions $\mathbf{F}^J$, in order to become less noisy and smoother. It consists of iteratively applying the following formula:

$$\tilde{F}_x^J = \mathcal{U}_{m \epsilon H}\Big(\mathcal{I}\big(W_m, F_{x+m}^J\big)\Big), \tag{6}$$

where H is a $m_1 \mathrm{x} m_2$ neighborhood, $m = [m_1, m_2]$ and W is a $m_1 \mathrm{x} m_2$ window containing weighting factors. This formula is applied iteratively to each membership function $\mathbf{F}^J$ separately until convergence.

IV. Defuzzification

In the defuzzification process, the membership values of a pixel $\tilde{F}_x^J$ are sorted in ascending order for $J = 1, ..., S$. The sorted values are replaced by integers ranging from 1 to S. Then, each $\tilde{\mathbf{F}}^J$ membership function is replaced by an ordering function $\mathbf{L}^J$. A majority voting algorithm is applied within a neighborhood H according to:

$$V_x^J = \sum_{m \epsilon H} W_m L_{x+m}^J \tag{7}$$

Defuzzification takes place using the max t-conorm function.

$$V_x = \arg\ max_J\big(V_x^J\big) \tag{8}$$

V. Merging

In spite of the fact that the aggregate membership functions produced from fusion are much more than the initial ones, the final result in principle is not oversegmented. For those cases, where less segments are required, a merging algorithm based on fuzzy rules is proposed.

The criteria of merging neighboring segments are based on the similarity of the corresponding regions in the cue images and on the size of the segments. Rules of the form,

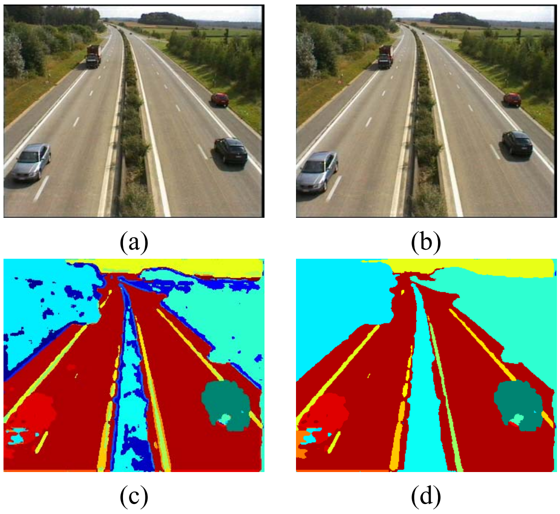

Fig. 2. (a),(b) Two consecutive frames of the “road” sequence. (c) The segmentation result. (d) The result after merging.

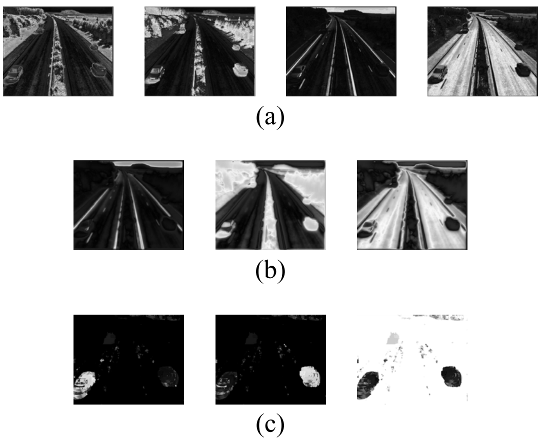

Fig. 3. The membership functions of cue (a) color, (b) texture, (c) motion vectors.

$$\textit{If } S_c \textit{ is } high \text{ AND } size \textit{ is } small, \textit{then } merge \textit{ is } high$$

where S_c represents the similarity between the two segments with respect to the color cue, can be used. The antecedent of a rule can have so many parts as the number of cues plus one. Conventional fuzzy inference is used to take the final decision about merging or not.

The number and the type of If-Then rules depend on the application scenario and on the characteristics of the particular objects that are to be identified from the segmentation.

VI. Experimental Results

Two of the experiments conducted using the current approach, are presented. Though the number of cues chosen in both experiments is three, any number of cues can be used.

The first experiment concerns the image “road” depicted in Figure 2. The membership functions resulted from the FCM algorithm, while their number is assigned ad hoc. The three cues used for this experiment were: color (rgb color space) having four membership functions, texture and motion vectors with three membership functions each (Figure 3). The motion vectors were calculated using two consecutive frames of the “road” sequence. The result from our fusion algorithm is depicted in Figure 2c and the result from the merging algorithm is shown in Figure 2d.

The second experiment was conducted on the “tsukuba” image. This image and its depth image can be seen in Figure 4. The membership functions produced from FCM using color (rgb), texture and depth information are illustrated in Figure 5. The segmented image (Figure 4c), contains the objects depicted in the depth image as well as objects in the background, which resulted from the other two cues.

VII. Conclusions

In this approach, the segmentation of images into meaningful regions is achieved by fusing the fuzzy clustering information extracted from multiple cues. There is no limitation for the number of different cues and no prior knowledge about the image content is necessary.

Initially, a fuzzy clustering of each cue space is performed and corresponding membership functions are produced on the image coordinates space. The membership functions coming from different cues are fused using a fuzzy inference mechanism. The complementary and the redundant information extracted from the different cues is exploited, in order to divide the image into meaningful regions without being over-segmented. The aggregate membership functions, which derive from fusion, represent objects, which bear the combination of the characteristics specified by the cues. The segmented image is produced after post-processing and defuzzification. Finally, a merging algorithm is proposed based on fuzzy rules, which are set by the user according to his intentions.

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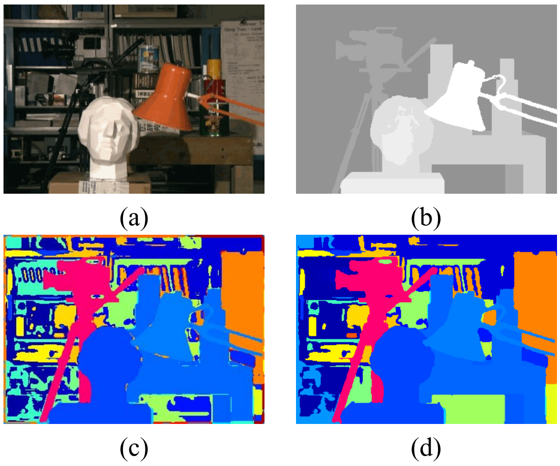

Fig. 4. (a) The “tsukuba” image. (b) Its depth image. (c) The segmentation result. (d) The result after merging.

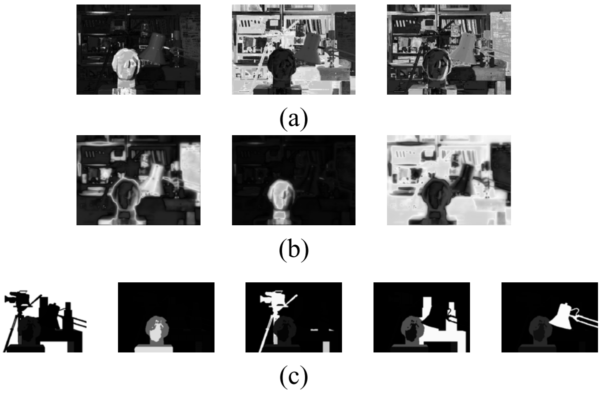

Fig. 5. The membership functions of cue (a) color, (b) texture, (c) depth.

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