Interval-Valued Fuzzy System for Segmentation of Prostate Ultrasound Images

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Abstract— *In this paper we introduce an application of interval-valued systems to the segmentation of prostate ultrasound images. The system classifies each pixel as prostate or background. The input variables are the values of each pixel in different processed images as proximity, edginess and enhanced image. The system has 20 rules and is trained with ideal images segmented by an expert. Interval-valued fuzzy systems have been used due to their potential to capture uncertainty in a more robust way compared to ordinary fuzzy systems.*

Keywords— Interval-valued fuzzy sets, ultrasound image, image segmentation

1 Introduction

Ultrasound images are used in clinical settings to evaluate anomalies, tissues and organs. Ultrasound imaging is a quite common modality due to its low cost, portability and harmlessness to human body. Transrectal ultrasound images of the prostate in male patients are frequently used for both diagnosis and treatment purposes. Detecting the outline of the prostate – prostate segmentation – is therefore the first step regardless the following step is of diagnostic nature or treatment planning as for brachytherapy of prostate cancer.

Ultrasound image segmentation is strongly affected by the lower quality of these images. Speckle noise, shadows and prostate inhomogeneity make the segmentation a complicated task. There exist several methods to segment ultrasound images, a complete review can be found in [12]. Some methods use machine learning techniques to extract the objects/lesions. In those methods ideally segmented images created by an expert radiologist are used to train the system. In [18] reinforcement learning is used to train an agent devoted to segment prostate ultrasound images. Zhang et al. [20] optimize the weights of a weighed wavelet to detect microcalcifications in mamographic images. Neural networks were used in [13] to identify possible injuries in liver images and in [5] a genetic algorithm optimizes the weights of a self-organized neural network (Kohonen net).

One of the problems of the Neural Networks is the black box reasoning. In medical applications it is very useful to know how a certain task has been done the process of segmenting the image. Hence, we propose to use a fuzzy logic system to segment ultrasound images since they provide a convenient way of interpreting the tasks/results.

Due to the complexity of the ultrasound images we are going to use interval-valued fuzzy sets enabling us to represent the uncertainty that is within these images. In [9] Mendel proposes an adaptation of the fuzzy rule learning algorithm to interval type 2 fuzzy rules. Note what he called interval type 2 fuzzy sets are the same as interval-valued fuzzy sets in some cases (when $a = 1$, please see section 2). The objective of this paper is to develop an interval-valued fuzzy logic system (from now IT2FLS following the notation given in [9]) to segment prostates in transrectal ultrasound images.

Why to use interval-valued fuzzy systems instead of classical fuzzy systems? When we design a fuzzy system that is going to be trained using typical machine learning algorithms, we must choose the input variables, the output of our system and the number of rules. If we train the system with the past data, we can understand this process as function fitting problem, in which the fuzzy rule base system is a parametrized function and the training process is the modification of said parameters. This means that the output of the system fits the training data. If the system uses interval-valued fuzzy sets instead of classical fuzzy sets, the number of parameters to define an interval fuzzy rule is larger than the one needed for a classical fuzzy rule. So, in the training process, with the same data, the interval fuzzy system has more parameters, more degrees of freedom, which means it can be adjusted in a better way to the data. Some researchers suggest that this is an advantage compared to ordinary fuzzy systems. Therefore it means that for the same linguistic complexity (number of rules and number of variables) interval-valued fuzzy systems can, at least in theory, achieve better accuracy. We have made a comparative study to verify this hypotheses.

This work is organized as follows: first we present an introduction of interval-valued fuzzy logic systems. In section 3 we review Mendel's algorithm to generate an IT2FLS from training data. Later, in section 4 we present the model that we propose to segment ultrasound images. Finally we show some experimental results, conclusions and future research.

2 Interval-valued fuzzy systems

An interval-valued fuzzy set constitutes that the membership degree of every element to the set is given by a closed subinterval of interval [0,1]. The concept of type 2 fuzzy sets was introduced by Zadeh [19] as a generalization of an ordinary

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fuzzy set. The membership degree of an element to a type 2 fuzzy set is a fuzzy set in [0,1].

An interval type 2 fuzzy set $\overline{\overline{A}}$ in U is defined as

$$\overline{\overline{A}} = \{(u, A(u), \mu_u(x)) | u \in U, A(u) \in L([0,1])\},$$

where $A(u) = [\underline{A}(u), \overline{A}(u)]$ is a membership function; i.e., a closed subinterval is $[0,1]$, and function $\mu_u(x)$ represents the fuzzy set associated with the element $u \in U$ obtained when x is within $[0,1]$; $\mu_u(x)$ is given in the following way:

$$\mu_u(x) = \begin{cases} a \text{ if } \underline{A}(u) \leq x \leq \overline{A}(u) \\ 0 \text{ otherwise} \end{cases},$$

where $0 \leq a \leq 1$.

In [8]–[10], it is proved that an interval type 2 fuzzy set is the same as an interval-valued fuzzy set if $a = 1$.

Example: We can represent an interval-valued fuzzy set by means of an upper bound membership function and a lower bound membership function. In this work, all of the membership functions are going to be represented by a Gaussian function:

$$\mu_k^l(x_k) = exp\left[-\frac{1}{2}\left(\frac{x_k - m_k^l}{\sigma_k^l}\right)\right] \quad \sigma_k^l \in [\sigma_{k1}^l, \sigma_{k2}^l] \qquad (1)$$

In fig. 1 we show the membership function with parameter $m_k^l = 0.4$. We take $\sigma_{k1}^l = 0.05$ to represent the lower bound and $\sigma_{k2}^l = 0.1$ for the upper bound.

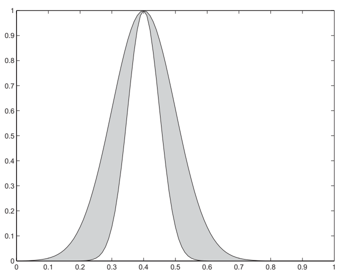

Figure 1: Interval-valued membership function with a Gaussian primary membership function and $m = 0.4$, $\sigma_{k1}^l = 0.05$ y $\sigma_{k2}^l = 0.1$.

An IT2FLS is a rule-based system in which the sets that represent the antecedents and consequents are interval-valued fuzzy sets (or interval type 2 fuzzy sets). In fig. 2 we depict the most important modules of an IT2FLS (see [9]).

The input of the system is a set of values. The fuzzfier transforms the inputs into interval-valued fuzzy sets. Then, the main part of the system, using the rules carries out the inference to generate conclusions, represented by interval-valued fuzzy sets. To use these conclusions (decisions) in the real world, the defuzzifier transforms these sets into crisp values. Commonly, before defuzzification, we can reduce the sets from interval-valued fuzzy sets to classical fuzzy sets, such a way typical defuzzifying techniques could be used to obtain crisp values.

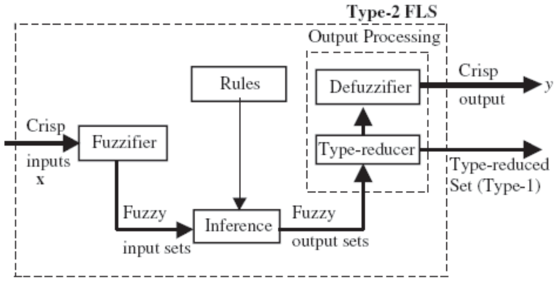

Figure 2: Interval Type 2 Fuzzy Logic System

Considering an IT2FLS with p inputs $x_1 \in X_1, \cdots, x_p \in X_p$ and one output $y \in Y$. Then we assume that the system has M rules in the following way:

$$R^l: \text{ IF } x_1 \text{ is } F_1^l \text{ AND } \ldots \text{ AND } x_p \text{ is } F_p^l, \quad \text{THEN } y \text{ is } G^l \text{ con } l = 1, \ldots, M \qquad (2)$$

where $F_1^l, \ldots, F_p^l, G^l$ are interval-valued fuzzy sets. Each rule is interpreted as an implication:

$$R^l : F_1^l \times F_2^l, \cdots \times F_p^l \rightarrow G^l = A^l \rightarrow G^l \text{ with } l = 1, \ldots, M \qquad (3)$$

R^l is described by the membership function $\mu_{R^l}(\mathbf{x}, y) = \mu(x_1, \ldots, x_p, y)$ where,

$$\mu_{R^l}(\mathbf{x}, y) = \mu_{A^l \rightarrow G^l}(\mathbf{x}, y) = \left[\bigcap_{i=1}^{p} \mu_{F_i^l}(x_i)\right] \bigcap \mu_{G^l}(y) \quad (4)$$

Using the extension of the Zadeh's compositional rule to interval-valued fuzzy sets, the consequent is calculated as follows:

$$\mu_{B^l}(y) = \mu_{A^l \circ R^l}(y) = \bigcup_{x \in X} \left[\mu_{A_x}(\mathbf{x}) \bigcap \mu_{R^l}(\mathbf{x}, y)\right] \quad \text{with } y \in Y, l = 1, \ldots, M \qquad (5)$$

There exist several works regarding the inference with interval-valued fuzzy rules [2, 6], but in this work we are going to use the method proposed by Mendel in [9] (for a more detailed study see [10]).

3 Design of Interval-valued fuzzy systems from data

In this section we show how we can design an IT2FLS from training data.
Given a collection of N pairs of input-output data $(\mathbf{x}^{(1)}, y^{(1)}), (\mathbf{x}^{(2)}, y^{(2)}), \cdots (\mathbf{x}^{(N)}, y^{(N)})$ where $\mathbf{x}^{(t)}$ is the input vector and $y^{(t)}$ is the output value of the t training pair, we define the error of the IT2FLS for the t-th input as:

$$e^{(t)} = f_{s2}(\mathbf{x}^{(t)}) - y^{(t)} \quad t = 1, \ldots, N \qquad (6)$$

where f_{s2} is the output of the IT2FLS. Such a value depends on the parameters that define the interval-valued fuzzy sets of the antecedents and consequents of the corresponding rules (m_k^l, σ_{k1}^l, σ_{k2}^l, y_l^j and y_r^j, with $k = 1, \ldots, p$, for p inputs, $j = 1, \ldots, M$, for M rules). Also y_l^j and y_r^j represent the bounds of the membership function of the consequent after

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the type reduction.
We define the quadratic error of the IT2FLS in t-th input as:

$$E^{(t)} = \frac{1}{2}[e^{(t)}]^2 \quad t = 1, \ldots, N \tag{7}$$

and the performance of the system as

$$E = \sum_{i=1}^{N} E^{(t)} \quad t = 1, \ldots, N \tag{8}$$

The training of an IT2FLS aims at finding the optimal values of the parameters that define the system such that equations (7) or (8) are minimized. If we minimize equation (7) (such a method is explained in [9]), the learning process is done in an incremental way, because the parameters are adjusted iteratively after processing every training pair. If we minimize equation (8), as we have done in this work, the learning process is done as a batch processing, because the parameters are adjusted after processing all of the training pairs. When we process all of the N training pairs and modify the parameters it is called a training epoch. In this work, in every epoch the parameters are adjusted proportional to the error gradient $\frac{\partial E}{\partial m_k^l}$, $\frac{\partial E}{\partial \sigma_{k1}^l}$, $\frac{\partial E}{\partial \sigma_{k2}^l}$, $\frac{\partial E}{\partial y_l^j}$ and $\frac{\partial E}{\partial y_r^j}$.

This quantity is calculated using the *resilient backpropagation* algorithm (RPROP, [14]). This algorithm automatically adjusts its own parameters during the training process, and is very easy to implement and can achieve a high convergence speed.

4 Proposed method

The objective of our method is to classify each pixel of the image. That is, decide if each pixel belongs to the important area (prostate) to segment or if it belongs to the background. Since the size and the position of the prostate are subject to change, the user must select the central point of the region (also called the seed point) to avoid false detections (and to focus on the segmentation itself). Therefore, the method is semi-supervised due to user suppling some relevant information. However, automation of this step is quite possible and has been repeatedly reported in literature.

The IT2FLS that we propose has 5 inputs, one output and consists of 20 rules. The inputs are:

1. pos_i: The distance, in pixels, of the pixel considered from the central point in the horizontal axes.
2. pos_j: The distance, in pixels, of the pixel considered from the central point in the vertical axes.
3. $dist$: The proximity of the pixel w.r.t. to the central point, calculated via a flooding algorithm.
4. edg: Edginess of each pixel.
5. mgr: Average gray level of the pixels neighborhood (e.g. 5×5 neighborhoods) in the enhanced image.

In the following subsections we present the techniques used to obtain the values of enhancement, proximity and edginess.

4.1 *Enhanced image*

The algorithm used to enhance ultrasound images is the one proposed by Sahba et al. [15, 16, 17], in which fuzzy rules such as the following have been used:

IF the pixel does not belong to the prostate,
THEN leave it unchanged
IF the pixel belongs to the prostate AND is dark,
THEN make it darker
IF the pixel belongs to the prostate AND is gray,
THEN make it dark
IF the pixel belongs to the prostate AND is bright,
THEN make it brighter

We use a simplified version of these rules in form of

IF the pixel *belongs* to the object AND is *dark*,
THEN make it *darker*,

or in a even more simple formulation and to save time we can use rules such as:

IF the pixel *belongs* to the object,
THEN make it *darker*,

where the degree of "belonging" of each pixel to the object is a function of its distance to the central point of the object or the inside of an initial/coares segment as proposed by Sahba et al. The main idea of enhancement is to eliminate the noise in the images and enhance the gray levels of selected area (regional contrast enhancement). First the noise is eliminated using a median filter (7×7 or 9×9). Then each pixel is fuzzyfied depending on its intensity with a membership function that is constructed taking into account the mean level of gray of the surroundings and the position of the selected point.

4.2 *Proximity image*

The proximity image represents the proximity of every pixel to the central point (similar to [7, 15, 16]), but taking into account the edges that separate the different regions of the original image. First we calculate the edges of the enhanced image using the Canny algorithm [4]. Then, starting from the central pixel selected by the user the algorithm labels the pixels with their distance to the central pixel step by step. In the first step the neighbors are labeled with distance 1 and so on (Fig. 3). The pixels marked as edge by the Canny edge detector are used as walls and cannot be labeled, so the proximity values generated are related with areas of the image.

4.3 *Edginess*

To create the edginess image, we calculate what is commonly called *false edges*. In [3] we presented a method to obtain false edges by means of t-norms and t-conorms. For every pixel a neighborhood matrix is constructed (3×3, 5×5, etc.). Applying t-norms to the elements of the matrix we obtain a lower bound of an interval. Applying t-conorms we obtain the upper bound of that interval. We called the length of the interval, that is the difference between the upper bound and the lower bound of the interval, false edge. The most known case is obtained when using minimum as the t-norm and maximum as the t-conorm.

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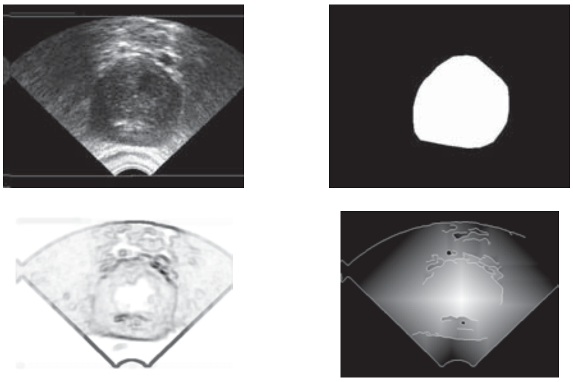

Figure 3: Top left to bottom right: Original image, ideally segmented image, edginess image, proximity image

5 Experimental results

To evaluate the performance of the IT2FLS we have a set of ten prostate ultrasound images with their corresponding ideal segmentation created by an expert. Each image has a central point of the prostate provided by the expert (for many prostate images automated detection of central point is relatively easy [1]). We use two of these images for the training and the other six for the validation. From the two training images we select randomly 200 pixels which are the training data pairs. This training data set is used to adjust the parameters of the system as described in section 3. The data is also split into two groups, the training set (80% of the data pairs) and the validation set (20%). To evaluate the performance of the IT2FLS we use an overlap measure S_A between the areas of the IT2FLS result and the ideally segmented image.

$$S_A = \frac{|Ideal \cap IBF|}{|Ideal \cup IBF|}, \tag{9}$$

where $Ideal$ is the binary image segmented by the expert, IBF is the binary image obtained using our method, $\cap$ and $\cup$ are the intersection and the union between crisp sets, respectively. Due to the initial values of the parameters of the system are selected randomly before training, we can obtain different possible solutions. In Table 1 we show the best ones after 20 trials. In Fig. 4 and 5 we show the binary images obtained by IT2FLS.

Table 1: Area overlap of segmented images with ideally segmented prostates.

Image	1	2	3	4	5	6	7	8	9	10
IVFS S_A(%)	84	61	74	75	77	75	62	64	71	72
Fuzzy S_A	86	67	77	78	77	80	71	72	70	73

Table 2: Percentage of convergence.

System	Percentage of convergence
Fuzzy	90 %
IVFS	30 %

In the experimental results we show that interval-valued fuzzy rule systems perform similar to classical fuzzy systems. The point is that the convergence of IVFS systems is really poor and also the mean performance achieved by these systems is a bit worse than ordinary fuzzy sets. It means that the extra adjustable parameters, if we dont use a specific learning algorithm with the IVFS system, are not worth in this case.

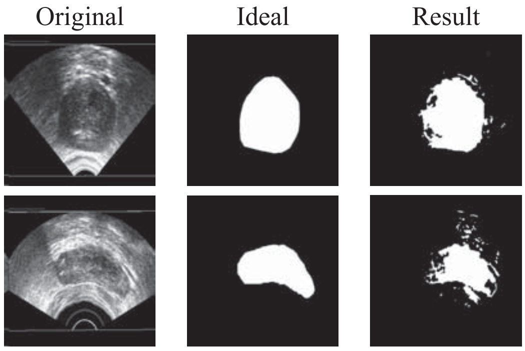

Figure 4: Comparison between ideally segmented images and IT2FLS segmented images used for training.

6 Conclusions and future research

We have proposed a new method to segment ultrasound images using an interval-valued fuzzy system. The system has 5 inputs, 20 rules and one output and can be trained using images previously segmented by an expert. An average overlap of 72% between the segmented area and the ideal segmentation has been reached. Nevertheless the results of the classical fuzzy systems are a bit better than the IVFSs system, mainly due to poor convergence of the learning algorithm.Taking into account the size of the proposed system on one hand and the challenging nature of prostate ultrasound segmentation on the other hand, the results can be regarded as promising.

The results show poor spatial consistency, which could be improved by adding some constraints or rules regarding shape and boundaries of the areas to the system. Also, we want to obtain interval input values to capture the uncertainty existing in the ultrasound images and deal with it via the IT2FLS in order to obtain better results.

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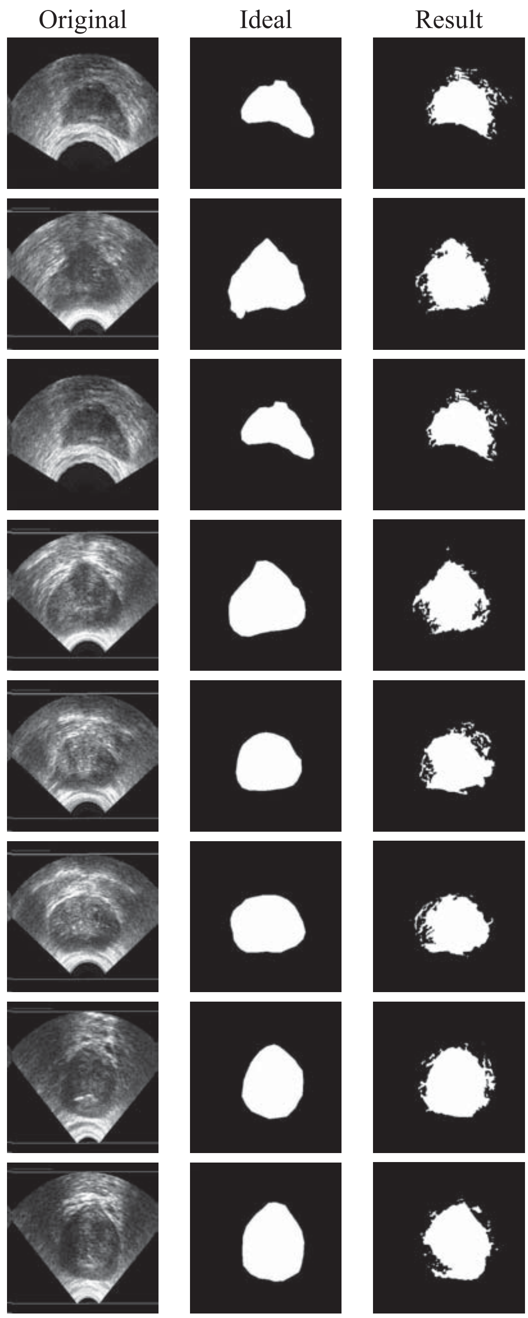

Figure 5: Comparison between ideally segmented images and IT2FLS segmented images. These are test images.