Fuzzy propositions determination using veracities or how to relate fuzzy logic and probability theories for segmentation

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Abstract – In medical imaging, and more generally in medical information, researches go towards fusion systems. Nowadays, the steps of information source definition, pertinent data extraction and fusion need to be conducted as a whole. In this work, our interest is related to the esophagus inner and outer wall segmentation from ultrasound images sequences. We aim to elaborate a general methodology of data mining that coherently links works on data selection and fusion architectures, in order to extract useful information from raw data. In the presented method, based on fuzzy logic, some fuzzy propositions are defined using physicians a prior knowledge. The use of probability distributions, estimated thanks to a learning base, allows the veracity of these propositions to be qualified. This promising idea enables information to be managed through the consideration of both information imprecision and uncertainty. In the same time, the benefit provided when a prior knowledge source is injected into a fusion based decision system, can be quantified. By considering that, the fuzzyfication process is optimized relatively to a given criteria using a genetic algorithm. We conclude this paper with some preliminary results and outline some further works.

Keywords: Segmentation, data mining, information fusion, veracity, probability, genetic algorithms.

1. Introduction

In medical imaging and precisely in ultrasound image processing, segmentation studies are often based on the use of a prior knowledge given by the physicians experience. Knowledge based systems appear to be promising approaches for segmentation. By this way researchers aim to imitate human ability for segmentation and thus, hope to increase the algorithms robustness. At the present day, we can first consider that the most knowledge based works do not describe clearly how a prior knowledge are defined and how is the possibility to evaluate their gain objectively. Secondly, the most of these works are based on only one knowledge source, which is the local contour information. Rare studies make use of different knowledge sources to solve the segmentation problems. Different manners exist to include these knowledge sources in a segmentation system, but usually the combination of theses information is not clearly presented.

In this work, we introduce a method that is able to quantify the gain that a prior knowledge can contribute to performance of a segmentation system. After a brief description of the applicative aspect of this work in section 2, the problematic of this study is described. Then, the main considered principles are exposed in section 4. The architecture for evaluating a prior knowledge will follow. Some preliminary results are then presented in section 5. Finally, conclusions and further works close this paper.

2. Acquisition And Pre-Processing

As previously mentioned, the goal of this study is to achieve the segmentation of esophagus outer wall using sequences acquired with the echoendoscopic imaging system Olympus EU-M3. The catheter, topped with an ultrasound transducer, is introduced into the patient mouth and progress along the esophagus lumen, toward the cardia. Ultrasound waves are emitted in the progression transversal plane and, thanks to reflections, an image reconstruction is possible. The catheter progression is mechanically controlled using a developed acquisition system so, images can be captured with a constant spacing (Figure 1).

Figure 1: Acquisition system elements encompasses ultrasound catheter (a) and mechanical control (b), enabling to obtain the data volume (c).

In Figure 2, the difficulties represented by this kind of images can be appreciated. Their quality depends mainly on two phenomena: the speckle noise (due to the ultrasound imaging approach) and multiple waves reflections [1][2], called “harmonics” (due to the transducer outer-sheath, which preserves esophagus wall from sensor rotations).
Although the multi layer nature of the esophagus wall, the fine structure can be analyzed with this diagnosis procedure. This explains the efficiency of endosonography in medical “staging” of esophagus tumors, which typically appear between the different layers composing the esophagus wall.

Three primary steps compose the proposed pre-processing. As esophagus has a structure of pseudo-cylinder, or more precisely of generalized cylinder, a “cartesian to polar” conversion is operated in order to simplify significantly the detection stage. The second step consists on the detection and the attenuation of harmonics, which perturb detection processing. Third, sequence photometry equalization is operated. This stage is accomplished as follows: images bias is evaluated inside the main harmonic (which the position is known) and is subtracted.

4. Fuzzy proposition qualification

Fuzzy logic is an efficient mathematical tool [3], which eases the manipulation and the fusion of imprecise and heterogeneous concepts such as for example position, size, intensity and so on. In our particular case, we can define several primitives, by using a prior knowledge, which denote (with a given ambiguity) that a pixel belongs to the esophagus wall.

4.1 Fuzzy image/field concept

We introduce, first, the useful concept of fuzzy images. A fuzzy image is defined as the transformation of an original image (considered as a MxN array of gray level associated with each pixel) into an image with the same dimensions but in the way that each pixel is associated with a value denoting the reliability of possessing a fuzzy property:

\[
P: \text{MxN} \rightarrow [0;1] \quad I(i, j) \rightarrow \mu_P(I) \tag{1}
\]

where \(\mu_P(I)\) reflects the appropriateness or the validity of the fact that the pixel \(I\) possesses the fuzzy property “\(P\)”. Concerning the application of the esophagus wall detection, four fuzzy images are defined. Similarly to [1][2], the following concepts are represented in terms of fuzzy images (i.e., images where gray levels corresponding to membership values of the considered pixels to a given concept):

**Harmonics:** Before starting any echoendoscopic processing method, the characteristics of the harmonics (i.e., their positions as well as their gray level distributions) must be known. Otherwise, they will impinge on the extraction of useful information. The contrast between esophagus lumen...
and harmonics is used to determine the position of the first harmonic. Other harmonic positions are then estimated by using a predefined model [4][5]. Thus, the fuzzy harmonics image \( \mu_c \) can be constructed as follows: the membership value is arbitrary fixed to 0.3 for harmonic pixels and to 1.0 for the others.

**Region:** Due to the acquisition system, a strong contrast defines two different regions, which can be easily distinguished: esophagus lumen (appears in black) and tissue area (appears usually brilliant). This information is very precious for the computation of inner wall belief image. The cartesian to polar transformation eases image clustering. An image \( \mu_c \) where each gray level corresponds to a membership value to esophagus lumen is attributed.

**Contour:** The concept of a contour is a strong information on the presence of the esophagus inner and outer wall. A gradient operator, defined by two 5x5 convolution masks and similar to Sobel operator, is used to estimate contours in the data volume. After having normalized the gradient volume by a S-Shape function, we obtain an image \( \mu_c \) where pixel gray levels correspond to the membership values to the contour concept.

**Intensity:** Given the fact that a hyper-echoic tissue (for example the inner and outer wall) appears as brilliant in an ultrasound image, the gray level intensity is an important feature to consider. An image \( \mu_i \) where each pixel level denotes the appropriateness of the concept “being brilliant”, is obtained by normalizing the original image with a S-Shape function.

In addition, we may complete these information and particularly the contour and intensity concepts by the notion of information connectedness. This notion is fundamental in this study, because the anatomical structures are continuous objects and then, the features that characterize these objects are also continuous when they are observed with an ultrasound imaging system. For example, the intuitive contour concept is both local and global. As a consequence, the local gradient needs to be completed by global information. The notion of fuzzy connectedness that have been first introduced in [6] gives an interesting answer to this lack. The concept of the \( \chi \)-connectedness [7] is defined as below:

\[
C_{\chi}(p) = 1 - \min_{a \in \Omega} \max_{i \in \Omega} |\mu(a) - \mu(p)| \tag{2}
\]

where \( L(a,p) \) is a path linking \( a \) and \( p \), \( \mu \) a fuzzy field and \( \chi^H(p) = 1 - |\mu(p) - \mu(a)| \) a transform of the fuzzy field. The \( \chi \)-connectedness concept is exploited through the use of a filter. It aims at erasing non-connected information and increase the strength of well-connected information. In this filter, the local fuzzy field connectedness is evaluated by considering all paths passing at a given position. At each position, a degree of connectedness is associated. The final value attributed to the considered pixel is given by the mean of the fuzzy field median calculated on each path, weighted by the connectedness strength.

### 4.2 Probability of a fuzzy event

In this work, in order to characterize esophagus wall, we focus our interest on the two following fuzzy propositions:

- “Esophagus wall is brilliant”
- “Esophagus wall is a contour”

These propositions are defined by using physicians a prior knowledge:

- Due to their acoustic impedance, inner wall and outer are hyper-echoic that means they have a high ability to reflect ultrasound. They appear “brilliant” in ultrasound images.
- Inner wall is located between esophagus lumen and mucous those are hypo-echoic, as a consequence, it corresponds to a well-defined contour.
- Outer wall is situated between second mucous and internal tissues that are hypo-echoic in comparison, also it appears as a contour in non-pathologic cases but the contrast is less important than inner wall.

Our interest is to introduce a notion of veracity of these fuzzy propositions, which are defined by using a prior knowledge. In order to quantify this notion of veracity objectively, a possible approach is to consider the problem from the probabilistic point of view. For this purpose, the following problem model is introduced. Our approach lies on the closed world assumption where the possible events are grouped in the set \( \Omega = \{W_1, W_2, ..., W_N\} \). The possible events correspond in our particular case, to inner wall, outer wall and other tissues. In this context, we assume that it is possible to consider information exclusivity and exhaustivity. That means in this study we have:

\[
\sum_{i=1}^{N} p(W_i) = 1 \quad \text{and} \quad \forall i \neq j, W_i \cap W_j = \emptyset \tag{3}
\]

From now onwards, we can commonly consider the problem from the Bayes point of view. Given a stochastic vector of features labeled \( X(i,j) \), which attributes at each pixel \( (i,j) \) a set of features, we can express the following conditional probabilities:

\[
p(W_i/X(i,j) = x) = \frac{p(W_i \cap X(i,j) = x)}{p(X(i,j) = x)} \tag{4}
\]

and

\[
p(X(i,j) = x|W_i) = \frac{p(W_i \cap X(i,j) = x)}{p(W_i)} \tag{5}
\]

This leads to the commonly used Bayes expression given by:

\[
p(W_i/X(i,j) = x) = \frac{p(X(i,j) = x|W_i) \cdot p(W_i)}{p(X(i,j) = x)} \tag{6}
\]
In this expression, we call a posteriori probability the first member and a priori probabilities the others. The last member can usually be estimated from a learning base. In general, such a learning base of \( n \) elements associates to each case a vector of features (Figure 4).

![Figure 4: The concept of learning in the case commonly encountered in problems of Supervised Bayes classification](image)

Now, if the features vector is an imprecise event, it is necessary to deal with fuzzy features. More concretely, this case is encountered when an object is defined by one or more fuzzy proposition as for example “being brilliant”, “being a contour” or “being tall”. In this case, it is possible to talk in terms of fuzzy events probabilities. Such fuzzy propositions are associated to a membership function by taking its values in the interval \([0;1]\). In this kind of problematic, we consider the belief space and not the feature space. The expression (6) can be modified in order to express the a posteriori probability to observe the class \( W_i \) knowing a membership value as in (7).

\[
\begin{align*}
\Pr(W_i | \mu(i,j)) &= \frac{\Pr(\mu(i,j) = \mu(W_i)) \cdot \Pr(W_i)}{\Pr(\mu(i,j) = \mu)} \\
\end{align*}
\]  

(7)

In this expression, a prior probabilities have the following signification:

- \( \Pr(W_i) \) is the probability of each class \( W_i \). This probability is directly estimated for each class from the predefined learning base.
- \( \Pr(\mu(i,j) = \mu) \) represents the probability distribution to observe a given membership value on the learning base. This probability distribution is directly estimated from the learning base histograms.
- \( \Pr(\mu(i,j) = \mu | W_i) \) or \( p_2 \) corresponds to the probability to observe a given membership value, corresponding to a given concept, knowing the class \( W_i \). This means that the distribution of probabilities can be estimated by the exploitation of the membership value histogram on the class \( W_i \). This estimation is achieved by using the learning base defined before.
- \( \Pr(\mu(i,j) = \mu | P) \) corresponds to the probability to classify a given pixel in the class \( W_i \), knowing its membership value to the concept \( P \). In other terms, this probability gives the appropriateness of the considered fuzzy set defined by \( \mu_P \) to characterize the class \( W_i \).

In order to estimate these probabilities, we introduce the following learning base:

\[
B = \{\{\mu_{P_i} | W_i\}_i \in \{1, ..., n\}\}
\]

where \( \{P_i\} \) is a set of fuzzy propositions and \( \{\mu_{P_i}\} \) the associated membership function. In order to interpret this set of proposition, we have to associate a membership function at each proposition (Figure 5). This step is fundamental and must be attentively conducted.

![Figure 5: General scheme of a learning base when any fuzzy propositions are used in order to characterize objects designated to be classify. How to characterize a degree a veracity of these propositions for each class? What are the best membership functions that characterize the considered propositions?](image)

The consideration of a learning base enable to established a relation between fuzzy feature space and decision space through the concrete definition of membership functions. We have to answer the two following questions: which fuzzy function has the best power to characterize an object, and at the same time, how can the fuzzy proposition veracity be defined, considering a given object?

### 4.3 Veracity of a fuzzy proposition

Given the fuzzy proposition \( P \) (based on a fuzzy concept) and an associated membership function \( \mu_P \), an example of belief probability distribution can appear as in Figure 6.

![Figure 6: An example of membership values distribution probabilities. The light bars correspond to a prior probabilities on the considered object. The dark ones correspond to the a posteriori probabilities to observe the object when considering a given belief.](image)
In this graph, we can notice that high membership values are preponderant on a posteriori probability distribution. This means that given a membership value, the probability to observe the considered class is significant. On the other hand, by examining a prior distribution of membership values on object 1, we can see that the probability to observe high beliefs is low. In this case, the chosen membership function is not sufficient. This example corresponds to a case where the membership function is not correctly estimated or simply where the initial proposition is false. Through the consideration of the last example, it becomes possible to outline a criterion that the membership function must satisfy, in order to efficiently corresponds the initial fuzzy proposition, if this one has a minimum of veracity:

- The a posteriori belief distribution of probability must be the highest as possible. This means that the maximum of the a posteriori probability \( p_m = p(W|\mu(i,j) = \mu) \) must be considered in the criteria.
- These probabilities must correspond to significant membership values. Thus, we must include the corresponding membership value in the final criteria which is defined as follows:

\[
\mu_m = \text{argmax}\left[p(W|\mu(i,j) = \mu)\right]
\]  
(8)

- On each learning objects, the beliefs distribution of probability must give more importance to high membership values. This means that this distribution of probability must be skewed toward the high membership values. An estimation of skewness \( \kappa \) of the distribution considered in this work is given by (9),

\[
\kappa = \frac{\overline{\mu} - \tilde{\mu}}{\sigma_{\mu}}
\]
(9)

where \( \overline{\mu}, \tilde{\mu} \) and \( \sigma_{\mu} \) denote the mean, the median and the standard deviation of the \( \mu(i,j) \) distribution.

- Finally, the distribution \( p_i \) must be the more uniformly distributed as possible, to preserve sufficient information during all the process. As a consequence, the consideration of the entropy \( S \) (10) will ensure that data will not be reduced to only one value.

\[
S = - \sum_i p_i \log(p_i)
\]
(10)

In considering these constraints, we can define a final criteria which can also be considered as a veracity measurement of the fuzzy proposition \( P \). The searched membership function must maximize this criteria, which is defined in general as follows:

\[
\Gamma(p_m, \mu_m, p_i) = f(p_m)g(\mu_m)h(\kappa)S(p_i)
\]
(11)

where \( f \) is an increasing function of \( p_m \), \( g \) is an increasing function of the membership value \( \mu_m \) associated with \( p_m \), \( h \) and \( i \) are respectively increasing functions of the beliefs distribution skewness and entropy. The considered functions are all chosen in the bounded interval \([0;1]\). To conclude this paragraph, the searched membership function is as (12).

\[
\mu_m = \text{argmax}\left[\Gamma(p_m, \mu_m, p_i)\right]
\]
(12)

5. Genetic processing

Several optimization techniques are encountered in order to maximize a given criteria. The optimality has to be considered as a function of a given criteria. Among existing stochastic optimization techniques, two families can be distinguished: genetic algorithms [8] and simulated annealing algorithms [9]. The choice of a stochastic approach is justified by two arguments:

- The fixed objective is to develop an algorithm independent from arbitrary or “operator dependant” initialization as needed in deterministic optimization models like dynamic model approaches, for example.
- We only have weak a priori information on the solution position and the search space is large and noisy. We need a method, which can apprehend the search space in its integrity.

We propose here genetic algorithms in order to find optimal membership functions corresponding to fuzzy propositions.

In the particular case of this study, we parameterize the membership function by a SShape function \( S_{a,b,c} \) which depends on three parameters \( a, b \) and \( c \). A representation of \( S \) is given on Figure 7.

![Figure 7: S-Shape function graphical representation. The three parameters a, b and c, respectively define low membership values, intermediary membership values and high membership value.](image)

A set (or a family) of random solutions \( \{G_i\} \) (called chromosomes) is initially computed in the search space \( \Omega \), which is a bound by the maximum value authorized for the given scalar feature in the entire learning base.

First solution elaboration step being ended, three kinds of operators are now applied on each chromosome. During the reproduction stage, best chromosomes are duplicated, in order to build the new chromosomes set. The likelihood of duplication depends on values of the fitness function that are computed on each chromosome. The role of such an operator is to favorite the best solutions in comparison with others. Several crossovers, which correspond to chromosomes melting, are operated on \( \{G_i\} \). The main advantage of this kind of operator is to speed up the algorithm convergence. Mutations operated on \( \{G_i\} \) ensure that the search space is always taken into account. Therefore, chances that the coefficients being stabilized in a local minimum are reduced. Mutations can be accomplished with uniform or non-uniform likelihood rule. In our
particular case, a uniform likelihood has been chosen. At each generation, the best solution, corresponding to the best set of fuzzy function parameters relative to (12), is retained from the original solutions set. The genetic progress is stopped, when the standard deviation of the fitness function on each chromosome is less than a threshold (Figure 8). This one is a percentage of the mean error value in the chromosome set/family. In the case where this condition is not realized, the genetic process is stopped after a given number of iterations $N_{gen}$.

Figure 8: State of convergence of the genetic algorithm. On this graph, the bars represent the mean of fitness function evaluate on the chromosome family. The state of convergence is represented through the associated segments, which length depends on fitness values standard deviation.

It is important to notice that genetic algorithms do not give the optimal solution but simply a set/family of sub-optimal solutions. In our particular case, we use parameters histogram in order to choose the best solution. An example of such an histogram is given in Figure 9. Finally, we compute the parameters histogram, in order to choose the best solution.

Figure 9: Obtained histogram after genetic evolution simulation. This case represents the histogram the S-Shape $b$ parameter.

6. Experiments and discussion

This section presents first experiments obtained from real sequences acquired in the gastroenterology service of the Brest center hospital (France). The set of possible events is composed of three elements $\Omega = \{W_1, W_2, W_3\}$, where $W_1$=“inner wall” $-$ $W_2$ = “outer wall” and $W_3$=“others tissues”. The condition of exhaustivity and exclusivity needed in the context of probably formalism is assumed.

The constituted learning base is composed, for instance, of two hundred images of non-pathologic cases issues from three complete examinations acquired on real patients. A prior considered in this paper are simple: esophagus walls are hyper-echoic, so they appear with high gray levels on ultrasounds slices. Moreover, these anatomical structures correspond to interfaces, so they belong to high gradient areas. Two fuzzy propositions are associated with this a prior knowledge: $P_1$=“local gradient is high” and $P_2$=“gray level is high”. The veracity of these two concepts is evaluated by using the learning base described before. The best translation of these fuzzy propositions is found as defined in section 4 and 5. Finally, the effect to consider the connectedness information is tested through the reevaluation of statistics after the filtering of images as described in section 4.

Figure 10: Evaluation of the fuzzy proposition $P_1$ on the esophagus inner wall. Results on (a) and (c) are obtained by considering a membership function $\mu_{\xi_1}$, which corresponds to a simple normalization of gray levels. Results on (b) and (d) are obtained by considering a membership function $\mu_{\xi_{1opt}}$, which corresponds to the optimization of (12).

Figure 11: Evaluation of the fuzzy proposition $P_2$ on the esophagus outer wall. Results on (a) and (c) are obtained by considering a membership function $\mu_{\xi_2}$, which corresponds to a simple normalization of gradients levels. Results on (b) and (d) are obtained by considering a membership function $\mu_{\xi_{2opt}}$, which corresponds to the optimization of (12).

Figure 12: These experiments illustrate the gain that can bring the use of the connectedness information. (a) and (c) corresponds to $P_1$ on inner wall, whereas (b) and (c) corresponds to $P_2$ on outer wall.
This veracity makes use of the probability. Results have given elements to quantify the fuzzy propositions veracity. Some preliminary results obtained with this approach, we can notice that results are better on information connectedness is injected. Even if the influence of posteriori probabilities can be strongly increased, when the reliability. As we can notice see on Figure 12.a better anatomical structure in increasing probabilities of the information connectedness to discriminate “brilliancy information”. The second point concerns the anatomical structure appears significant, in comparison with the “contour” information. Respectively, in Table 2, the ability of the “contour information” has to separate outer wall from others anatomical structure appears significant, in comparison with “brilliancy information”. The second point concerns the utility of the information connectedness to discriminate better anatomical structure in increasing probabilities reliability. As we can notice see on Figure 12.a and 12.c, a posteriori probabilities can be strongly increased, when the information connectedness is injected. Even if the influence of this a priori is less significant on “brilliancy” information, we can notice that results are better on Figure 12.b and 12.d.

### Table 1

<table>
<thead>
<tr>
<th>Statistics</th>
<th>$\mu_{P_1}$</th>
<th>$\mu_{P_1,opt}$</th>
<th>$\mu_{P_2}$</th>
<th>$\mu_{P_2,opt}$</th>
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<td>0.1</td>
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<tr>
<td>$\mu_m$</td>
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<td>0.9</td>
<td>1</td>
<td>0.8</td>
</tr>
<tr>
<td>$\kappa$</td>
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<td>-0.3</td>
<td>-2.5</td>
<td>-0.1</td>
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<td>$S$</td>
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<td>2.80</td>
<td>2</td>
<td>2.5</td>
</tr>
<tr>
<td>Veracity</td>
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<td>0.28</td>
<td>0.003</td>
<td>0.004</td>
</tr>
</tbody>
</table>

The Figure 10 and Figure 11 presents the obtained histograms for the cases of esophagus inner and outer walls. We can appreciate how it is possible to increase the reliability of a priori through the optimization of membership functions using a learning base. The Figure 10.a, 10.c and Figure 11.a, 11.c present the obtained histograms with non-optimal membership functions, whereas Figure 10.b, 10.d and Figure 11.b, 11.d correspond to optimized membership functions. With these results, it is possible to conclude on two primary points. Considering first the defined veracity of fuzzy proposition, a priori of the physicians concerning the hyper-echoic aspect of esophagus wall, cannot be directly used through the fuzzy proposition “being brilliant” to characterize esophagus inner wall. As we can see in Table 1, the brilliancy proposition cannot well discriminate inner esophagus wall of the other anatomical structures in comparison with the “contour” information. Respectively, in Table 2, the ability of the “contour information” has to separate outer wall from others anatomical structure appears significant, in comparison with “brilliancy information”. The second point concerns the utility of the information connectedness to discriminate better anatomical structure in increasing probabilities reliability. As we can notice see on Figure 12.a and 12.c, a posteriori probabilities can be strongly increased, when the information connectedness is injected. Even if the influence of this a priori is less significant on “brilliancy” information, we can notice that results are better on Figure 12.b and 12.d.

### 7. Conclusion

Some preliminary results that obtained with this approach, give elements to quantify the fuzzy propositions veracity. This veracity makes use of the probability. Results have shown, for some simple examples of fuzzy propositions, that a blink use of a priori knowledge given by physicians is not always sure. More particularly, the esophagus inner wall appears to be clearly a contour but is not as hyper-echoic as it was initially expected. The filtering based on fuzzy connectedness could, as we have shown, improve perceptibly the fuzzy propositions veracity.

In this work, a priori knowledge has been evaluated before any fusion process. The next step of this study will be continued on optimizing the fuzzy function after the a priori knowledge has been combined in a fusion process. In this manner, it will be possible to optimize fuzzy propositions by taking into account the fusion process. At this level, the gain of such a consideration should be directly evaluated on segmentation and 3D reconstruction of esophagus inner and outer wall results. These further works aim at verifying if, information sources definition, pertinent data extraction and fusion methods must be processed as a whole, to become really efficient.

### References