Semantic Analysis of Medical Images Using Fuzzy Inference Systems

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***Abstract*— Medical images carry information in a special data format about an organ and the related pathologies. Physicians must decipher this information from the image. This paper suggests a framework for analyzing the image on the semantic level using linguistic data. The framework implements several numerical algorithms to extract the physical features of the existing objects. The semantic interpretation for identifying the organs and possible pathologies from the found physical features is done using fuzzy inference systems. The clinical testing of the framework is a work in progress but the laboratory results are promising.**

Keywords-medical image processing; fuzzy systems; linguistic interpretation

I. INTRODUCTION

Medical images are one of the most basic and common medical diagnosis tools. The most common medical image formats are the X-ray images, the computer tomography images (CT), magnetic resonance images (MRI), the ultrasound images, angio CT, PET (Positron emission tomography) scan, and so on. For a trained eye they can describe accurately the internal organs of a human being and indicate the presence of pathologies. The first step in any medical image interpretation is the segmentation of the image. The trained eye can segment and analyze the image on the cognitive level. In contrast computers need specific algorithms for this task from the first step down to the last. The first step generally in image analysis is the segmentation process. By segmenting the image, the interested areas are separated from the background of the image. The next step is the feature extraction from the found objects. The interested physical features are the shape descriptors, the size of the object, its histogram and the location of the object. These concepts are used in medical image analysis where the objects in the medical image represent different organs and associated pathologies.

In the past years, several medical image analysis frameworks were developed [1]-[3]. One of the shortcomings of the frameworks is the lack of possibility to interpret the segmented object on the cognitive level. This paper proposes a framework that can analyze the object from the image on the semantic level. The physical features of the objects which are recorded using numerical values are transformed into "spoken language". For this process, fuzzy algorithms are implemented [4]. By using fuzzy inference systems coded in XML files [5], the framework can be adapted for different situations. Section two describes the methods which were used to extract numerical and semantic data from the medical image as well as several of the inference rules. Section three presents the case study of the pilot experiment and the first results.

II. USED METHODS

The coding of the information in medical images varies from one image type to another. The majority of the images use shades of gray to represent the reflectivity of the scanned object. For a computer to decode the information, specific methods must be used. The first step is to separate the objects found in the image from the background. The second step is to extract the numerical data from the image segments. These numerical data represent the physical features of the object. For analyzing the image on the semantic, level the numerical data must be converted in to linguistic data. This is done using a fuzzy inference system. This part will present the methods used by the framework to create linguistic results from regarding the data found in the image.

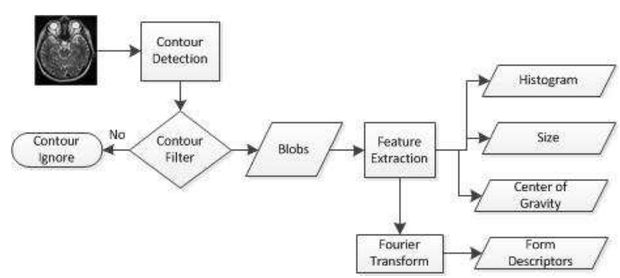

Figure 1. Segmentation workflow

A. Segmentation Process

The segmentation process is a mixed segmentation process. Figure 1 shows the diagram of the segmentation process. First, the image is segmented using a manual segmentation which selects the area of interest. To the selected zone of interest, first the Otsu thresholding algorithm is applied [6]. Statistics are calculated for the two classes of intensity values (foreground and background) that are separated by an intensity threshold.

Figure 2. The segmented blob, the contour and the masked image

The criterion function is σ_{Bi}^2/σ_T^2 for every intensity, i = 0,..,I-1, where σ_{Bi}^2 is the between-class variance, σ_T^2 is the total variance and I = 256, the maximum of the intensity gray level. The intensity that maximizes this function is the optimal threshold. By using this technique a mask image is created and is applied to the selected zone of interest.

The masked image is subjected to the second part of the segmentation process.

The first step in the interpretation process was to identify the threshold value for the segmentation. The formula for computing the threshold value is:

$$T_{\mathrm{sh}} = \mathrm{H}_{sg} + k \tag{1}$$

T_{sh} is the threshold value for which the segmentation process takes place. H_{sg} is the global histogram of the medical image, and k is a factor to control the threshold value. k is defined empirically. The best results are obtained for k = 8-10. These values were determined empirically using several test images.

The second part of the segmentation process is an automatic segmentation which records the existing objects from the masked image. The found objects are called "blobs" shown on Figure 2. These blobs have several physical features. These features are the area recorded in pixels, the location recorded by the center of gravity, the histogram on 3 channels and the bounding rectangle.

The shape of the blob is recorded using the Fourier transformation which provides the frequency components of the contour. These frequency components can be used to identify the shape of the organ.

B. Feature Extraction

The characteristics that are useful for the interpretation of the object are the shape of the object, the histogram value, the size of the object and the location of the object in the image.

For classifying the shape of the object, the Fourier transform can be used [7]. Each pixel from the contour of the object can be located by its Cartesian coordinates. These two coordinates are used to write the complex function of the object:

$$f(r) = x_r + j\,y_r \tag{2}$$

where r = 1… N-1 pixels. Fourier transform gives us the frequency components that make up the outline. This representation reduces the problem of analyzing the shape outline from 2D to 1D. The one-dimensional discrete Fourier transform of the function $f(r)$ is:

$$F(n) = 1/N \sum_{r=0}^{N-1} f(r) * e^{-j2\pi 2\pi r} \tag{3}$$

Excluding F (0), Fourier components do not depend on location of the analyzed shape, thus providing an efficient way to classify contours. To produce a more reliable shape, you can use a 'low pass' filter on the Fourier components, to remove the fine special structures. By computing the Fourier components of a closed contour and by ignoring the first component, the remaining components can be used for contour identification.

The size of the object is represented by the pixels found inside the blob. At this step, the physical size of the blob is measured in units of pixels. For a correct size determination the pixel size must be known.

In the case of DICOM (Digital Imaging and Communications in Medicine standard), images the pixel size can be computed from:

$$PixelSize = \frac{DOFV}{512} \tag{4}$$

The DFOV (display field of view) settings are 16, 20 and 50 for pediatric, head and whole body acquisition, respectively. The typical size of a CT image is 512 x 512 [8]. In case of non-DICOM medical images a segmented fuzzy inference system is proposed which is presented in section 3.

The color detection algorithm is based on determining the mean and variance of the pixel [9]. These methods were modified to take in account only one color plane as the majority of the medical images are in gray scale. The interesting features are the mean or average level of the gray level in the image and the variance or the contrast of the colors.

First, the image is converted into a gray scale image. For each pixel in the image the following algorithm is used:

$$G(x,y) = 0.2989R(x,y) + 0.587G(x,y) + 0.114B(x,y) \tag{5}$$

The coordinates of the pixels are noted using (x, y) is a sub-image of a specific size centered in (x, y). The mean value of the sub-image can be computed using:

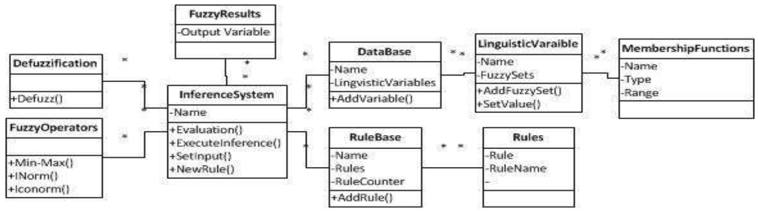

Figure 3. UML Class diagram of the fuzzy inference system

$$G_{ms} = \frac{1}{N} \sum_{(s,t) \varepsilon S_{xy}} G(s,t) \qquad (6)$$

The variance is:

$$G_{vs} = \frac{1}{N} \sum_{(s,t) \varepsilon S_{xy}} \left| G_{ms} - G(s,t) \right| \qquad (7)$$

The N is the total number of pixels in the sub-image. When all the values were calculated a color descriptor vector can be computed:

$$V = [L, W, G_{ms}, G_{vs}] \qquad (8)$$

L and W represent the length and width of the sub-image. This color descriptor contains enough information for suitable color recognition.

The shades of gray represent solid and fluid objects. Than the black objects have a higher absorbance ratio then the white objects. This means that black objects are soft objects and the white spots represent solid objects like bones or calcifications.

The location of the object is recorded using the Cartesian coordinate system in pixels of the center. If the position of the object related to other objects (if it is vital e.g., in case of a tumor) it must be verified if the center of the second object is inside or not of the boundary of first objects and if the boundaries overlap each other or one boundary is inside or not of the other.

C. The Interpretation Process

The found physical features are converted to linguistic features using the fuzzification process. The linguistic features or fuzzy variables are used to identify the selected object. The selected object can be an organ or a malformation of the organ. The object can represent other malformations caused by other malformations or they can indicate other pathologies. The fuzzy variable is a collection of several linguistic features of the same type.

By using several fuzzy variables, which cover all the physical feature types, an inference engine is created. The suggested framework implements a rule based expert system. The rules are created in such a manner that they will cover as many possible options as they can.

These rules are very similar to the natural language communication. They can be compared with some clear instructions coming from one person to another. In their general form they have an antecedent and a consequence separated by the "THEN" statement. The antecedent is a conjunction of several fuzzy terms (using the statement IS) and several logical operators (AND, OR, NOT) between them.

For example: "*IF Size IS Long AND Histogram IS Black AND Size IS Small AND Location IS Head THEN Diagnosis IS Normal-Ventricle*"

The software implementation of the framework is done using visual C# programming language and AForge open source programming framework [10]. The framework was modified to load the fuzzy inference system from an XML (eXtensible Markup Language) file. This permits an easy and fast reconfiguring of the inference system.

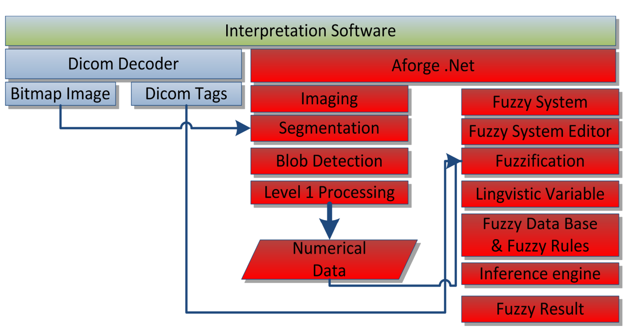

Figure 4. Framework Arhitecture

III. TESTS AND RESULTS

The proposed architecture of the framework, shown on figure 4, is constructed to allow the interpretation of any type of medical image which is in the DICOM format [11], by applying minimal changes to the major parts of the interpretation system.

The framework is constructed from the combination of two open source software. The first open source software decodes the DICOM files and separates the DICOM TAGs (metadata referring to the patient and to the imaging device) from the image itself. The second open source software implements the segmentation and feature extraction process, as well as the interpretation software. The UML Class diagram of the interpretation process is presented in the figure 3. The interpretation software was modified to permit the loading of the fuzzy inference system from an XML file and the editing of the inference system as well. New rules and linguistic variables can be created. This permits an easy change and adaptation of the inference system, without stopping or decompiling the framework.

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For the initial testing of the framework and the fuzzy inference system, we have considered the case of a 74 year old male with a confirmed malignant brain tumor.

For the initial numerical data acquisition, magnetic resonance image sets were chosen in the axial plane from the head section. Each image slice has a thickness of 5 and the space between the slices is 6.5. For testing the framework and the inference engine, the middle slices of the acquisition set were selected, slice 6 to slice 9. These slices contain the most useful data for building an inference system and a rule base.

The physical features of the found objects are presented in the table below:

TABLE I. OBJECT FEATURES

Object Name	Slice nr	Histogram	Size mm^2	Location (x , y)
Damaged ventricle	6,7,8,9,	132,150, 144, 112	6.14, 6.8, 6.8, 5,	250-118,
Normal Ventricle	6,7,8,9,	27, 29,-	2.5, 2.9,-	162-228 and 262-228
Brainmater	6,7,8,9,	76, 85, 82, 75	5.4, 4.8, 7, 3,15	Inside the cranium
Fragments	6,7,8,9,	54, 53, 49,43	0.5, 1, 0.9	Inside the cranium
Bones	6,7,8,9,	150, 155, 1.92	4.5, 3.6, 1,25	Inside the cranium

Using these numerical values the following linguistic variables and fuzzy rules were created:

a) Histogram: has a range from 0 to 255, where 0 from 50 is for the Black label, 40-70 stands for Dark, 70-90 DarkGray, 90-150 is Gray, 150-200 LightGray and 180 to 200 stands for White.

b) Size: has a range from 0 to 10, where 0 from to 1 is for the VerySmall label, 1-5 stands for Small, 4-7 Normal and 6 to 10 stands for Big.

c) Location: has a range from 0 to 512 on two axes (horizontal and vertical) to position the investigated objects center of gravity.

d) Shape: describes the shape of the invetigated object making use of the Fourier descriptors.

e) The Fuzzy Rules: in total 13 fuzzy rules were created to correctly identify the malformations and the soraunding tissues. Several rules that recognize the ventricular malformation are presented below:

<Rule12>IF Size IS Long AND Histogram IS Black AND Size IS Small AND Location IS Head THEN Diagnosis IS Normal-Ventricle</Rule12>

<Rule13>IF Size IS Round Histogram IS Gray AND Size IS Big AND Location IS Head THEN Diagnosis IS Abnormal-Ventricle</Rule13>

The first results are promising. Because the testing of the framework is a work in progress, the case of only one patient was tested. For the image set from which the numerical data was collected to build the inference system and the fuzzification process had a success rate of 100%. For the other image sets from the same patient but from the other image acquisition planes, coronal and sagittal the success rate dropped by 10%. New unforeseen situations had appeared for which new rules hade to be made.

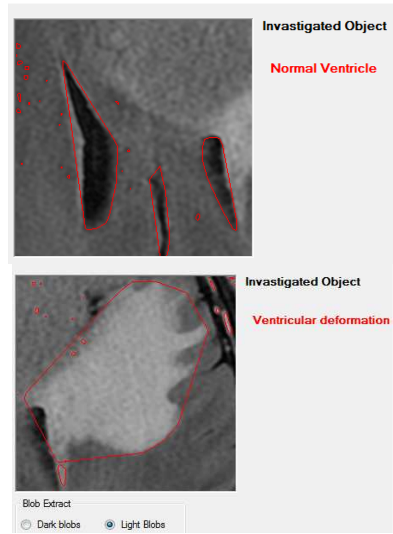

Figure5. A normal ventricle and a ventricular deformation

IV. CONCLUSIONS

The clinical testing of the framework is a work in progress. The numerical and the semantic level of the framework are completed. The used software architecture offers a high level modularity and adaptability to the framework. The framework can be adapted to new and different situations, new ideas and new conditions associated to a diagnosis. Unlike neural networks, where the learning mechanism is based on training data sets, this system permits the medical staff to create the inference rules and to debug the system in case of an error.

The first tests have promising results. For the image sets from the axial data acquisition plane the inference system had a 100% rate of success for identifying the tissue types, the organs and the malformation produced by the brain tumor. When testing the inference system for the other data acquisition planes the accuracy has dropped due to minor differences between the numerical data obtained from the axial plane and the other planes. However these tests were done in laboratory conditions to test the primary functions of the framework. The next step is to test the framework in real life clinical conditions using heterogeneous image sets from different clinical domains. A more complex testing of the framework to build the rules for the other body sections is scheduled for April 2012.

The described method has the advantage to decrease the number of clinical errors in imagistic interpretation. The medical staff will have a suggestion about the diagnostic, in this way reducing the stress level for patients and for the medical staff too.

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REFERENCES

[1] S. Li, T. Fevens, and A. Krzyzak, "A SVM-based framework for autonomous volumetric medical image segmentation using hierarchical and coupled level sets," *International Congress Series 1268, doi:10.1016/j.ics.2004.03.349*, pp. 207– 212, 2004

[2] J. Rivera-Rovelo and E. Bayro-Corrochano, "Medical image segmentation, volume representation and registration using spheres in the geometric algebra framework," *Pattern Recognition 40*, pp. 171 – 188, 2006.

[3] Y.M. Zhu and S.M. Cochoff, "An object-oriented framework for medical image registration, fusion, and visualization," Computer Methods and Programs in Biomedicine 82, pp. 258–267, April 2006.

[4] L.A. Zadeh, "Fuzzy sets", Information and Control, 8 pp. .338-353,1965.

[5] N. Gal and V. Stoicu-Tivadar, "XML as a Cross-Platform Representation for Medical Imaging with Fuzzy Algorithms," EFMI Special Topic Conference, EFMI STC, Lasko, Slovenia, April 2011, pp. 83-86.

[6] X. Xu, S. Xu, Lianghai Jin, and E. Song, "Characteristic analysis of Otsu threshold and its applications", *Pattern Recognition Letters*, Volume 32, 7, 1 May 2011, pp. 956-961.

[7] W. Duan, F. Kuester, Jean-L. Gaudiot, and O. Hammami, "Automatic object and image alignment using Fourier Descriptors", *Image and Vision Computing*, Volume 26, Issue 9, 1 September 2008, pp. 1196-1206.

[8] V.S. Smith, L.G. Shapiro, D. Hanlon, R.F. Martin, J.F. Brinkley, A.V. Poliakov, G.A. Ojemann, and D.P. Corina, "Evaluating Spatial Normalization Methods for the Human Brain," *27th Annual International Conference of the Engineering in Medicine and Biology Society*, 2005. IEEE-EMBS 2005, April 2006, pp. 5331-5334.

[9] N. Wang, and G. Wang, "Shape Descriptor with Morphology Method for Color-based Tracking" *International Journal of Automation and Computing* 04(1), pp. 101-108, 2007.

[10] http://www.aforgenet.com/ <retrieved: 01, 2012>

[11] O. S. Pianykh, "Digital Imaging and Communications in Medicine (DICOM)", 2008 Springer-Verlag Berlin Heidelberg, ISBN 978-3-540-74570-9.

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