COMPUTATIONAL INTELLIGENCE AND MEDICAL APPLICATIONS

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Summary

We give a brief introduction to computational intelligence application in medicine. We review medical image processing in magnetic resonance images and nondestructive evaluation studies by ultrasonic systems. Primary processes of medical image processing are segmentation, registration and enhancement. In them, automated segmentation is received much considerable attentions. In general, several typical segmentation procedures are known as segmentation via thresholding, segmentation via clustering, supervised segmentation and rule-based segmentation. We discuss how fuzzy logic works in the segmentation procedure. To indicate the achievement, we give a clinical study to diagnose Alzheimer's disease and a study for diagnosing meniscal tears provided by a MRI scanner. As an application of artificial neural network, we describe an identification method for cellular quantity of Bone Marrow Stromal Cells(BMCSs) in an artificial culture bone composed of β-tricalcium phosphate (β-TCP). Composites of BMScs and β-TCP have been increasingly used as bone substitutes and studied as a bone graft model for bone tissue engineering. The number of seeded cells in the composites is a crucial issue for achieving successful bone tissue engineering. This study nondestructively identifies the quantity of BMCSs in the artificial culture bone by artificial neural network.

1. General Introduction

Medical system has evolved at an explosive rate according to the advance of computer and internet technology. Especially, in medical imaging, high-resolution, high-dimensional anatomical information can now be obtained in a routine manner with magnetic resonance imaging (MRI) and X-ray computer-aided tomography (CT), and this visualizing and diagnosis support studies rapidly advanced. In the other medical system, new ultrasonic device, photon microscope device, surgery support system such as DaVinci and Zeus are now practically available in medical institute. In them software used here needs to provide useful and reliable information with high speed computing. Computational intelligence provides a powerful and integrated framework should be solved in them.

Lotfi A Zadeh, he is the father of fuzzy logic, directed the Berkeley Initiative in Soft Computing (BISC) project in the University of California at Berkeley. In it, he defined soft computing, i.e., computational Intelligence, as a consortium of methodologies that exploit a tolerance for imprecision, uncertainty and partial truth. Results are achieved with high tractability, robustness and a good rapport with reality. The main ideas of soft computing were brought forth by the confluence of fuzzy logic, neural computing, genetic algorithm and probabilistic reasoning with the latter subsuming belief networks, evolutionary computing including DNA computing, chaos theory and parts of learning theory. Especially, fuzzy logic based technique provides a powerful framework to medical applications since:

1. Fuzzy logic is well adapted to medicine since the natural spatial interpretation of fuzzy logic leads to efficient representations of imprecise or implicit information or classes in medicine.
2. Fuzzy logic provides a way to represent and manipulate linguistic variables expressed by medical experts.
3. Fuzzy medical model consists of knowledge in medicine or medical experts. This leads a reasonable solution in medical issue, which should be accepted by medical experts in clinical practice.

In the past, a mixture of image processing and Fuzzy Logic aided techniques has led to successful tasks to medical applications.

Section 2 describes a mixture of fuzzy logic and image segmentation with respect to Magnetic Resonance (MR) images. MR imaging is useful for diagnosing human body. There is no completely automatic method for segmenting a given neuro-anatomical structure in a large number of scans because of the complexity of the images. The segmentation of MR images by using fuzzy logic, neural networks, Markov field, statistics, and anatomical knowledge can produce good results for specific problems. A combination of pattern recognition and fuzzy logic techniques can also lead to successful data fusion, and data modification.

Section 2.1 describes an automated procedure for segmenting an MR image of a human brain based on fuzzy logic. An MR volumetric image composed of many slice images consists of several parts: gray matter, white matter, cerebrospinal fluid and others. We mainly describe a procedure for decomposing the obtained whole brain into the left and right cerebral hemispheres, the cerebellum and the brain stem. In it, fuzzy linguistic variable needed in decomposition is introduced, and then, fuzzy if-then rules can represent information on the anatomical locations, segmentation boundaries as well as intensities. Evaluation of the inferred result using the region growing method can then lead to the successful decomposition of the whole brain. We applied this method to 44 MR volumes. The segmented brains were statistically compared with those manually segmented by a physician. Consequently, the method can identify the whole brain, the left cerebral hemisphere, the right cerebral hemisphere, the cerebellum and the brain stem with high accuracy and therefore can provide the three dimensional shapes of these regions to diagnose Alzheimer diseases.

Section 2.2 describes an automated procedure for segmenting menisci in MR images of a human knee aided by fuzzy logic. A three-dimensional (3D) MR volumetric image composed of slice images consists of several parts: bone marrow, meniscus, periarticular liquor, cartilage and others. We employ both T1-weighted and T2-weighted MR images to identify the menisci. After a registration between these images is manually done on a computer display, our procedure aided by fuzzy logic can automatically segment meniscal regions from 3D MR images. Physicians can observe the 3D shapes of meniscal tears from any point of view on the display. We examined five subjects including a normal knee and three injured knees. The all meniscal regions were significantly identified, and these 3D shapes were displayed. Thus, this method can provide useful information for diagnosing meniscal tears.

Section 3 describes an artificial neural network identification method for cellular quantity of Bone Marrow Stromal Cells in β-TCP. The system was made by an ultrasonic device and the software with a feed forward three layer neural network with back propagation learning scheme. This network has two inputs such as amplitude and frequency. Amplitude is obtained from the magnitude of ultrasonic wave, and frequency is calculated from frequency domain obtained by applying cross-spectrum method. The network has 23 outputs for 24 samples on Leave One Out Cross Validation. After 5000 learning, the artificial neural network identified the cell quantity in artificial culture bone, and it classified the quantity to one of three classes. These classes are obtained by dividing the range of cell quantity to three intervals. A comparison was done with the multiple linear regression. The neural network identified the cellular quantity and its class with higher accuracy than the multiple linear regression.

Section 4 discusses the conclusions and perspectives of future medical systems aided by computational intelligence.

2. Fuzzy Logic and Medical Image Processing

2.1. Three-dimensional Human Brain Image Segmentation from MR Images

Introduction

In this section, we describe an automated method for segmenting the whole brain and then to decompose it into the left and right cerebral hemispheres, the cerebellum and the brain stem. To do this, we employed fuzzy logic techniques including fuzzy membership functions used in fuzzy knowledge representation with fuzzy linguistic variables and the fuzzy inference to obtain information on neuro-anatomical locations, segmentation boundaries and intensities. To perform a thorough validation, we used 50 brain MR volumetric images (a total of 6,200 slices) obtained under different conditions for segmentation of the whole brain and 44 brain MR volumetric images (a total of 5,456 slices) out of the 50 MR volumetric images for decomposition of the whole brain into the above-mentioned regions.

2.1.1. Outline of Segmentation Procedure

We obtained MR volumetric images from a Signa Advantage 1.5 Tesla MRI Scanner (General Electric Co.) using a circularly polarized head coil as both the transmitter and receiver. The image acquisition method was coronal 3D SPoiled GRadient echo (SPGR) with TR = 14 ms, TE = 3 ms and flip angle = 20 degrees. The Field of View (FOV) was 220 mm. The matrix was 256 by 256. Each of the volumes was made up of 124 separate slices whose thickness was 1.5 mm. Voxel size was $0.86\times0.86\times1.5\ \mathrm{mm}^3$. We constructed the MR volumes of the human brain, which consisted of voxels. In the system, the images appeared as, and were treated as, intensity $124\times256\times256$ images. The intensity value for all voxels of all intracranial structures ranged between 0 and 255.

2.1.2. Segmentation of Whole Brain by Threshold Finding

We employed a region growing with three conditions to segment the whole brain. First, two intensity thresholds, Th_1 and Th_2, are determined from the intensity histogram of a human brain MR volume. The thresholds Th_1 and Th_2 are determined to extract white matter and gray matter, respectively. The details of the determination method were shown in Y. Hata et.al. "Automated segmentation of human brain MR images aided by fuzzy information granulation and fuzzy inference," IEEE Trans. Syst., Man, Cybern. C, vol. 30, no. 3, pp. 381-395, Aug. 2000. Second, an edge voxel image is obtained by using the standard Sobel operator. Third, monotonicity of the intensity, i.e., white matter to gray matter intensity change, is evaluated. $C(t)$ denotes a voxel at coordinate C in the MR volumes at t-th step in the region growing process. In this notation, in the following step $(t+1)$, the voxels adjacent to $C(t)$ are referred to as $C(t+1)$. Let $I(C(t))$ denote the intensity of voxel $C(t)$.

Step 1: Assume that the 124 two-dimensional MR images are arranged in order along the *z*-axis as shown in Figure 1. We randomly select a voxel being larger than or equal to Th_2 of the 68921 nearby voxels in the volume (110+20, 150+20, 60+20). This is repeated until a voxel is found that satisfies the intensity condition.

Step 2: Region growing starts from the starting voxel decided in Step $1(t=t_0)$. White matter is extracted by including voxel $C(t_1)$ if $I(C(t_1))>Th_2\,(t_1>t_0)$.

Step 3: Region growing starts from the final voxels obtained in Step 2. Then, gray matter is extracted by including $C(t_2)$ if each of the following three conditions is met:

1) $Th_2 > I(C(t_2)) > Th_1$,
2) $C(t_2)$ is not included in the edge region, and
3) $I(C(t_2-1)) \ge I(C(t_2))$ with respect to $t_2\,(t_2>t_1)$.

Step 4: When the region growing in Step 3 is finished, the selected voxels will constitute the whole brain.

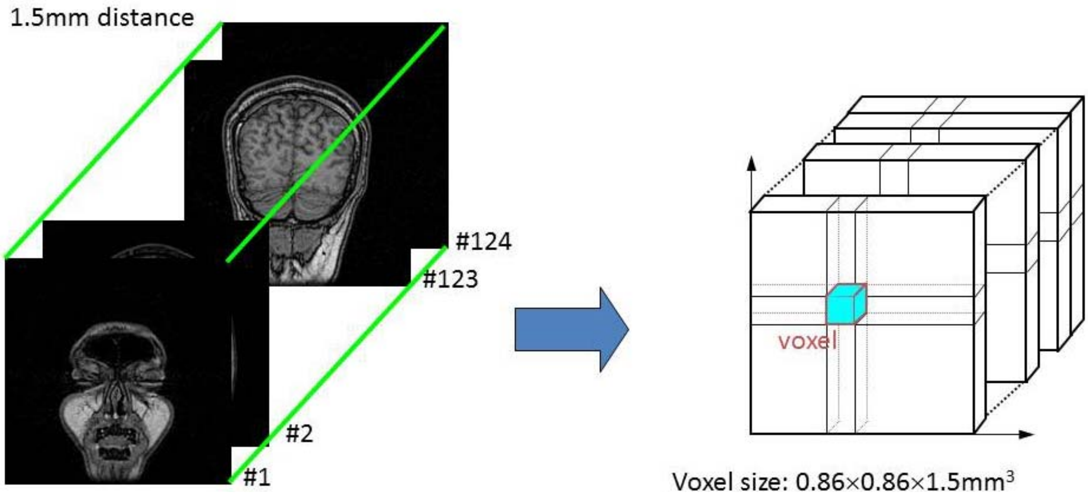

Figure 1. Human brain MR image

2.1.3. Decomposition of whole Brain to Left and Right Cerebral Hemisphere, Cerebrum, and Brain Stem by Fuzzy Inference

A. Representation by Fuzzy if-then Rules

Generally, the fuzzy if-then rule is expressed by " if A then B", in which A and B are fuzzy subsets. A fuzzy relation R from A to B is a fuzzy subset of the Cartesian product $U \times V$ where $A \in U$ and $B \in V$. The conditional statement " if X is A then Y is B" is represented by the fuzzy relation R, and it is widely used as min in fuzzy control applications.

$$\mu_R = \min\left(\mu_A(u), \mu_B(v)\right): \ u \in U \text{ and } v \in V \ , \tag{1}$$

If x is a fuzzy subset of U, then the fuzzy subset y of induced by V is denoted by $y = x \circ R$ and is defined as follows:

$$\begin{aligned} \mu_y(v) &= \max_{u \in U} \min(\mu_x(u),\ \mu_R(u,\ v)) \\ &= [\bigvee_{u \in U}(\mu_x(u) \wedge \mu_A(u))] \wedge \mu_B(v) \end{aligned} \tag{2}$$

Generally, we can calculate the center of gravity of $\mu_y(v)$ as the inference result. The above fuzzy if-then rule is called a min-max center of gravity method or the Mamdani method.

In this chapter, we consider various types of information. The information can be represented by membership functions $\mu_A(x_{mn})$ and $\mu_B(Y)$ for the input membership functions $\mu_A(x_{mn})$ below,

$$\mu_y(Y) = [\bigvee_{m \times n \ \in M \times N}(\mu_{A'}(X_{mn}) \wedge \mu_A(X_{mn}))] \wedge \mu_B(Y) \tag{3}$$

where X_{mn} denotes the spatial coordinate of (m,n) th-pixel and Y denotes the degree with respect to the information of the pixel X .

B. Decomposition Method

For the obtained brain volumes, assume the center of gravity of the brain region is the origin and then its coordinate system is defined in Figure 2. Our portions of interest are: the left cerebral hemisphere (LCH), the right cerebral hemisphere (RCH), the cerebellum (CB) and the brain stem (BS).

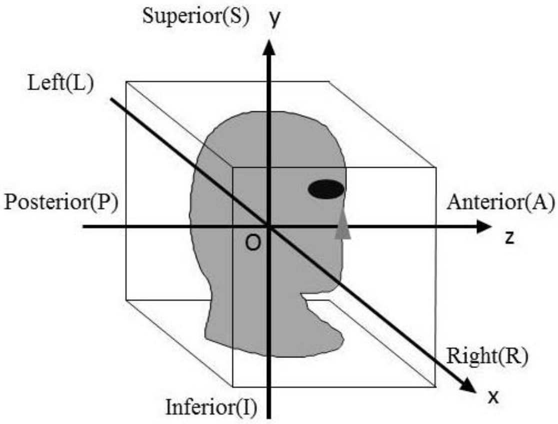

Figure 2. Coordinate system of human brain MR image

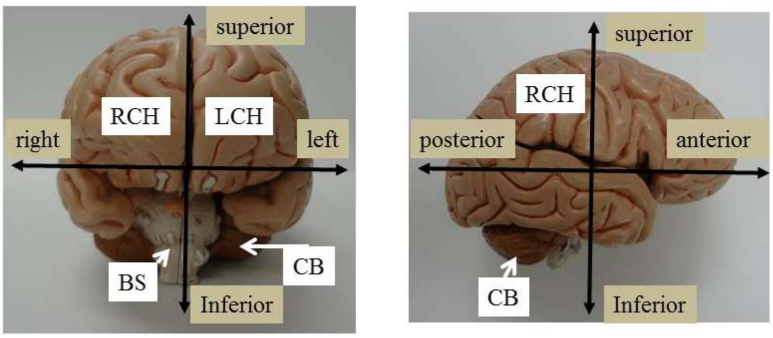

Figure 3. Locations of LCH, RCH, BS and BS

<Information needed to obtain the portions of LCH, RCH, CB and BS.>

(1) Location information:

i. Belongingness: The “right” and “left” cerebral hemispheres have explicit labels of “right” and “left”, respectively. Their labels show their belongingness in location of human head. In addition, cerebellum and brain stem locate under LCH and RCH. Figure 3 shows these relations. These locations are tabulated in Table 1.

ii. Boundary: Boundary information derived from their locations provides boundary edge between portions.

(2) Contour information: Euclidean distance from back ground provides sparse contact boundary edge between portions

(3) Intensity: Brain voxel has either gray or white matter intensity.

Brain portion	***x***	***y***	***z***
Left cerebral hemisphere	left	superior	any
Right cerebral hemisphere	right	superior	any
Cerebellum	any	inferior	posterior
Brain stem	middle	inferior	middle

Table 1. Location Table of brain portions

<Expression by the linguistic rule>

(1) Location information:

i. Belongingness: We can derive the following linguistic rule from Table 1. The notation μ_i denotes fuzzy membership degree of location with respect to $i,\ i \in \{LCH,\ RCH,\ CB$ and $BS\}$.

If x = left AND y = superior THEN the belongingness to LCH (denoted by μ_{LCH}) is high.

If x = right AND y = superior THEN the belongingness to RCH (μ_{RCH}) is high.

If y = inferior AND z = posterior THEN the belongingness to CB (μ_{CB}) is high.

If x = middle AND y = inferior AND z -middle THEN the belongingness to BS (μ_{BS}) is high.

ii. Boundary: The voxels in boundary between μ_i and μ_j have similar belongingness, and the belongingness of μ_i and μ_j are not small, where $j \in \{LCH,\ RCH,\ CB$ and $BS\}$.

(2) Contour information: Euclidean distance: The distance between each of voxels and background region (non-brain region) is short in boundary between portions.

(3) Intensity: The voxel with gray matter intensity is near to boundary, and the voxels with white matter is far from boundary.

<Fuzzy if-then rule and defined fuzzy membership functions>

(1) Location information:

i. Belongingness: Table 2 tabulated the fuzzy if-then rule. From this table, we can derive the following fuzzy if-then rules with fuzzy membership functions shown in Figure 4(a). First column of Table 2, left cerebral hemisphere (LCH), we can derive “If x =NEGATIVE THEN μ_{LCH} is *VH*. This rule is represented for a voxel (x, y, z) as follows:

IF x is NEGATIVE THEN μ_{LCH} is *VH*

IF x is ZERO THEN μ_{LCH} is L

IF x is POSITIVE THEN μ_{LCH} is *VL*

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Biographical Sketches

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His research interests are in medical system, health monitoring system, fuzzy system and Immune system. He received 13 international awards such as the Franklin V. Taylor Best Paper Award (IEEE SMC 2009), Biomedical Wellness Award (SPIE Defense, Security, and Sensing 2010) etc. He is an Editor-in-chief: International Journal of Intelligent Computing in Medical Sciences and Image Processing, USA and 5 Journal editors such as IEEE Systems Journal, Automation and Soft Computing Journal, Applied Soft Computing Journal. He serves as Chair of IEEE SMC TC Medical Informatics, and IEEE CIS Task Force Fuzzy Logic in Medical Sciences.

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