Experimental Proposal On Fuzzy Logic And Image Processing Algorithms For Medical Diagnosis

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Abstract

The proposal of this article studies the experimental design process of few fuzzy logic systems and image processing algorithms used predominantly in the method for the early diagnosis of glaucoma in medical fields. The few fuzzy logic with fuzzy expert systems are also mentioned for retrieving image processing algorithms, with the help of this experimental setup the early diagnosis of glaucoma can be identified along with several impaired diseases which might be occurred due to determination of dose etc., so that the design is helpful for the physicians to diagnosis and treat the patients with the images captured through image processing methods and to correct dimension accordingly to open or wide angles of glaucoma. Thus, the paper studies the experimental setup made for fuzzy logic operation by the fuzzy expert system to solve the robustness of glaucoma.

Keywords: Fuzzy logic, Fuzzy expert system, Glaucomatous, Robustness etc.

1. Introduction

Fuzziness quantifies vagueness and ambiguity, as opposed to crisp memberships. The types of uncertainty in images are manifold, ranging over the entire chain of processing levels, from pixel based grayness ambiguity over fuzziness in geometrical description up to uncertain knowledge in the highest processing level. The interrelation of a few such "fuzzy" properties sufficiently characterizes the object of interest. Fuzzy image processing is an attempt to translate this ability of human reasoning into computer vision problems as it provides an intuitive tool for inference from imperfect data. Fuzzy image processing is special in terms of its relation to other computer vision techniques. It is not a solution for a special task, but rather describes a new class of image processing techniques. It provides a new methodology, augmenting classical logic, a component

of any computer vision tool. A new type of image understanding and treatment has to be developed. Fuzzy image processing can be a single image processing routine, or complement parts of a complex image processing chain.

During the past few decades, fuzzy logic has gained increasing importance in control theory, as well as in computer vision. At the same time, it has been continuously attacked for two main reasons: It has been considered to lack a sound mathematical foundation and to be nothing but just a clever disguise for probability theory. It was probably its name that contributed to the low reputation of fuzzy logic. Meanwhile, fuzzy logic definitely has matured and can be considered to be a mathematically sound extension of multivalued logic. Fuzzy logical reasoning and probability theory are closely related without doubt.

2. Related studies

Fuzzy logic plays an important role in some medicine areas, to predict the response to have treatment with citalopram in alcohol dependence , to analyze diabetic neuropathy, to detect early diabetic retinopathy , to determine appropriate lithium dosage, to calculate volumes of brain tissue from magnetic resonance imaging (MRI), to analyze functional MRI data, to help the physicians to decide fast and efficiently about the dose of the medicine to treat the 200 dialysis patients, to characterize stroke subtypes and coexisting causes of ischemic stroke, to improve decision-making in radiation therapy, to regulate of nicardipine infusion for hypertension control during anesthesia , to determine flexor-tendon repair techniques, to detect breast cancer, or prostate cancer, lung cancer, to assist the diagnosis of central nervous systems tumors (astrocytic tumors), to discriminate benign skin lesions from malignant melanomas, to visualize nerve fibers in the human brain, to represent quantitative estimates of drug use, to study the auditory component in schizophrenia and etc depends on modern technical experts.

Because medical diagnostic investigations are very complex, it would be very difficult to cover this connection to describe this situation using crisp logical operations. When a doctor starts treatment of a patient he uses his personal experience, knowledge from books, and mental ability. So, the goal of the fuzzy intelligent system is to imitate behavior of a doctor and give him consultation. In this paper, we showed some of our applications in different areas of medicine.
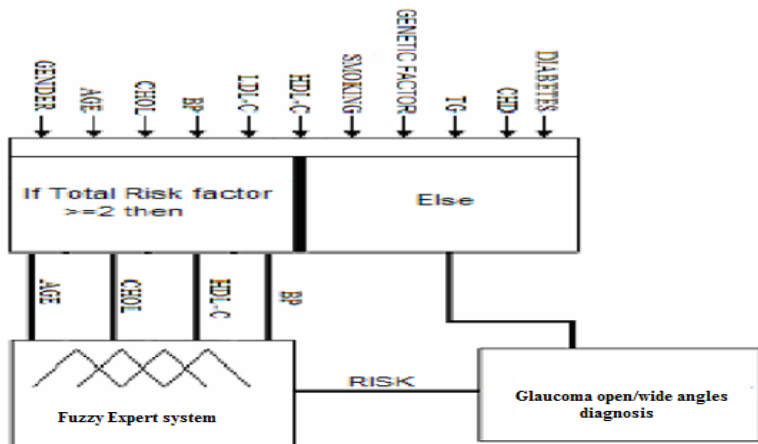
Fig 1: Fuzzy Expert System for early detection of Glaucoma diagnosis

3. Experimental Setup

The two basic components of fuzzy systems are fuzzy sets and operations on fuzzy sets. Fuzzy logic defines rules, based on combinations of fuzzy sets by these operations. This section is based on the basic works of Zadeh,

$$A = \{x_1, x_2, \dots, x_n\} \qquad \{1\}$$

Crisp sets. Given a universe of discourse X = {x}, a crisp (conventional) set A is defined by enumerating all elements x ∈ X

$$f_A : X \longrightarrow \{0,1\}, \quad f_A = \begin{cases} 1 \text{ if } x \in A \\ 0 \text{ if } x \notin A \end{cases} \qquad \{2\}$$

that belong to A. The membership can be expressed by a function fA, mapping X on a binary value, thus, an arbitrary x either belongs to A, or it does not, partial membership is not allowed. For two sets A and B, combinations can be defined by the following operations:

$$\begin{aligned} A \cup B &= \{x \mid x \in A \text{ or } x \in B\} \\ A \cap B &= \{x \mid x \in A \text{ and } x \in B\} \qquad \{3\} \\ \bar{A} &= \{x \mid x \notin A, \ x \in X\} \end{aligned}$$

Additionally, the following rules have to be satisfied:

$$A \cap \bar{A} = \varnothing, \quad \text{and} \quad A \cup \bar{A} = X \qquad \{4\}$$

A common notation for fuzzy sets, which is perfectly suited for fuzzy image processing, has been introduced by Zadeh [26]. Let X be a finite set $X = \{x_1,\dots,x_n\}$. A fuzzy set A can be represented as follows:

$$\mu_A(x) + \mu_B(x) + \dots \neq 1 \qquad \{5\}$$

For infinite X we replace the sum in Eq. (22.7) by the following integral:

$$A = \frac{\mu_A(x_1)}{x_1} + \dots + \frac{\mu_A(x_n)}{x_n} = \sum_{i=1}^{n} \frac{\mu_A(x_i)}{x_i} \qquad \{6\}$$

The individual elements $\mu_A(x_i)/x_i$ represent fuzzy sets, which consist of one single element and are called fuzzy singletons.

$$A = \int_X \frac{\mu_A(x)}{x} dx \qquad \{7\}$$

4. Fuzzy logic application on Image processing

In computer vision, we have different theories, methodologies, and techniques that we use to solve different practical problems (e. g., digital geometry, mathematical morphology, statistical approaches, probability theory, etc.). Because of great diversity and complexity of problems in image processing, we always require new approaches. There are some reasons to use fuzzy techniques as a new approach. We briefly describe two of them; the most important reason why one should investigate the potentials of fuzzy techniques for image processing is that fuzzy logic provides us with a powerful mathematical framework for representation and processing of expert knowledge. Here, the concept of linguistic variables and the fuzzy if-then rules play a key role. Making a human-like processing possible, fuzzy inference engines can be developed using expert knowledge. The rule-based techniques, for example, have the general form, If condition A1, and condition A2, and ... , then action B.

In real applications, however, the conditions are often partially satisfied (e.g., the question of homogeneity in a neighborhood cannot always be answered with a crisp yes or no). Fuzzy if-then rules allow us to perform actions also partially.
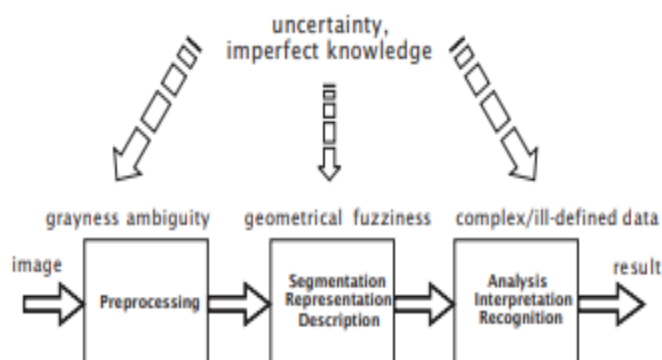
Figure 2: Fuzzy logic application on Image processing

These and many other similar questions arise during image processing—from low-level through high-level processing—and are due to vagueness and ambiguity. There are many reasons why our knowledge in such situations is imperfect. Imprecise results, complex class definitions, different types of noise, concurring evidences, and finally, the inherent fuzziness of many categories are just some sources of uncertainty or imperfect knowledge. Distinguishing between low-level, intermediate-level, and high-level image processing, the imperfect knowledge is due to grayness ambiguity, geometrical fuzziness, and imprecision/complexity. Fuzzy techniques offer a suitable framework for management of these problems.

5. Fuzzy image topology

To use the fuzzy logic in image processing applications, we have to develop a new image understanding. A new image definition should be established, images and their components (pixels, histograms, segments, etc.) should be fuzzified (transformation in membership plane), and the fundamental topological relationships between image parts should be extended to fuzzy sets (fuzzy digital topology).

6. Fuzzy Rules and Sets

The "IF-THEN" rules are validated by ophthalmologists. Having a medical meaning, they already differentiate between free glaucoma persons vision, glaucomatous and glaucoma-suspected ones. The fuzzy engine includes six rules.

We defined fuzzy membership expressions for the input parameters (Age, Diabetic retinopathy, Cholesterol level, HDL) and output parameter that is glaucomatous risk ratio. For example, fuzzy membership function for glaucomatous patient is presented as formulas (1) and membership graphic for this fuzzy value according to the formulas (1) is shown in the **Fig. 3**. So, for example, for Diabetic retinopathy or BP level sure value (let z) fuzzy membership expressions will be as:

$$\mu_{Low}(z) = \begin{cases} 1 & z < 100 \\ \dfrac{(130-z)}{30} & 100 \leq z < 130 \end{cases}$$

$$\mu_{Middle}(z) = \begin{cases} \dfrac{(z-100)}{30} & 100 \leq z < 130 \\ 1 & 130 \leq z \leq 140 \\ \dfrac{(155-z)}{15} & 140 \leq z < 155 \end{cases}$$

{8}

$$\mu_{High}(z) = \begin{cases} \dfrac{(z-130)}{15} & 130 \leq z < 145 \\ 1 & 145 \leq z \leq 180 \\ \dfrac{(220-z)}{40} & 180 \leq z < 220 \end{cases}$$

$$\mu_{veryhigh}(z) = \begin{cases} \dfrac{(z-145)}{55} & 145 \leq z < 200 \\ 1 & z \geq 200 \end{cases}$$

For Glaucomatous Risk value (let R) fuzzy membership output expressions will be as:

$$\mu_{VeryLow}(R) = \begin{cases} 0 & R < 1 \\ \frac{(5-R)}{5} & 0 \le R < 5 \end{cases}$$

$$\mu_{Low}(R) = \begin{cases} \frac{(R-2)}{3} & 2 \le R < 5 \\ \frac{(15-R)}{10} & 5 \le R < 15 \end{cases}$$

$$\mu_{Middle}(R) = \begin{cases} \frac{(R-5)}{10} & 5 \le R < 15 \\ \frac{(25-R)}{10} & 15 \le R < 25 \end{cases} \qquad \{9\}$$

$$\mu_{High}(R) = \begin{cases} \frac{(R-15)}{5} & 15 \le R < 20 \\ \frac{(35-R)}{10} & 20 \le R < 35 \end{cases}$$

$$\mu_{VeryHigh}(R) = \begin{cases} \frac{(R-25)}{10} & 25 \le R < 35 \\ 1 & R \ge 35 \end{cases}$$

1. IF the vertical ratio belongs to the normal class AND the horizontal ratio belongs to the normal class THEN the patients normal.
2. IF the vertical ratio belongs to the normal class AND the horizontal ratio belongs to the glaucoma-suspected class THEN the patient is normal.
3. IF the vertical ratio belongs to the glaucoma-suspected class AND the horizontal ratio belongs to the normal class THEN the patient is normal.
4. IF the vertical ratio belongs to the glaucomatous class AND the horizontal ratio belongs to the glaucomatous class THEN the patient is glaucomatous.
5. IF the vertical ratio belongs to the glaucomatous class AND the horizontal ratio belongs to the glaucoma-suspected class THEN the patient is glaucomatous.
6. IF the vertical ratio belongs to the glaucoma-suspected class AND the horizontal ratio belongs to the glaucomatous class THEN the patient is glaucomatous.
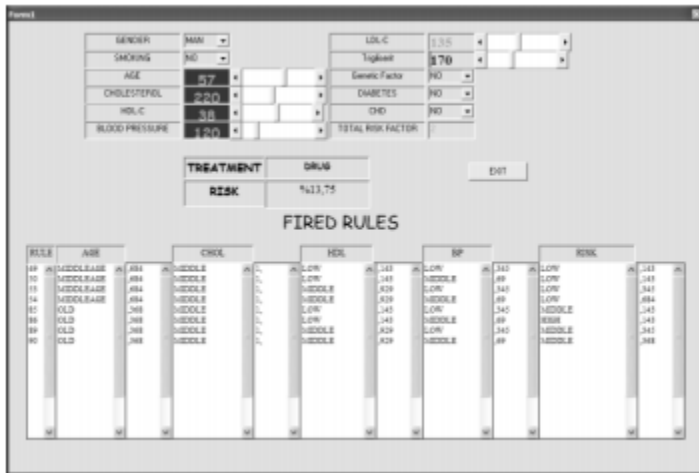
Figure 3: Ratio and calculation of the glaucomatous shows risk ratio

As represented in Fig.3 for the glaucomatous patient with age 57 years, with confirmation of risk factors of Diabetic retinopathy and Cholesterol 220 mg/dl, blood pressure 120 mm/Hg and HDL-C 38 mg/dl. So, as designed systems with few fuzzy set of rules represents that such systems can be very useful for physicians for decision through the image processing techniques.

7. Fuzzification and Defuzzification

In order to reverse the process of fuzzification, we use defuzzification to produce a crisp answer from a fuzzy output feature. Depending on the selected fuzzy approach, there are different ways to defuzzify the results. And the reputed images of the glaucomatous shown in Fig 4.
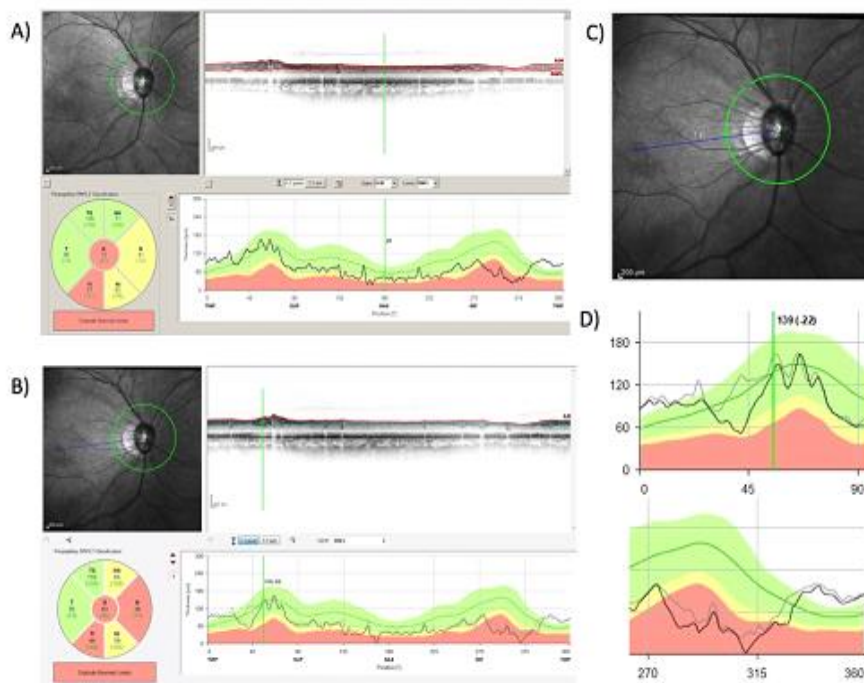
Figure 4: Preprocessing, contour detection and the glaucomatous detection results

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