FRAMEWORK FOR DIAGNOSING LASSA FEVER USING FUZZY ASSOCIATIVE MEMORY

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ABSTRACT

Lassa fever has continued to be a threat to mankind especially in the developing countries as a result of scares resources for curbing its spread. In this paper, fuzzy-logic was used to develop a Mamdani-type fuzzy inference system for the diagnosis of Lassa fever. Based on the expert's knowledge applied, eleven symptoms were fuzzified which generated 729 rules while the centroid method was employed for defuzzification. Some of the symptoms were qualitative while others were quantitative. Consequently, both objective and subjective judgment were applied in forming the rules. The resulting FIS is a transparent rule-based system that can be easily understood and tuned by human users. The framework was designed using MATLAB 7.01 version on a Windows OS platform.

INTRODUCTION

Lassa fever (LF), an endemic disease in West Africa, is an infection caused by -Lassa virus - a single stranded RNA virus. LF is a type of viral haemorrhagic fever with very high mortality rate in hospitalized patients. The natural host of the disease is a rat known as mastomysnatalensis common in endemic areas. The incubation period is 6 to 21 days (Schmitz, *et al* 2002, Eze, *et al* 2010, Ibekwe 2012). There are at least 12 different types of viral haemorrhagic fever which includes LF, Rift valley fever, and Crimean-congo, Marburg and Ebola haemorrhagic fever occur in Africa (Bek, *et al* 2012) as epidemics and newly emerging infections are of increasing concern, threatening the health of people around the world and even affecting travel and trade in the global village. These epidemics continue to challenge health systems in countries with limited resources with the potential of creating new pandemics (Salter and Kamara 2003). As a result of this, both the public and private organizations are involved with the research for finding a lasting solution.

However, the application of computer technology in medical diagnosis has being on the increase. Despite the fact that these fields, in which the computers are used, have very high complexity and uncertainty rate, the use of intelligent systems such as fuzzy logic, artificial neural network and genetic algorithm have been rewarding. In the domain of Lassa fever, the application of artificial intelligence has not been widely used for the diagnosis of the disease. Motivated by the need of such an important tool, in this study, we decided to apply the use of fuzzy logic to develop a fuzzy expert system for the diagnosis of Lassa fever.

The authors illustrated how fuzzy logic control works using eleven input variables as the symptoms and one output variable to determine the diagnostic condition of a patient. A mamdani fuzzy type model was employed to develop a reasoning mechanism for eleven variables and the method of centroid of area was used to derive a better result compared to the classical methods.

Fuzzy Sets: Description

Classical set is a set with a crisp boundary, suitable for various applications. It has been proven to be an important tool for mathematics and computer science, but do not reflect the nature of human concepts and thoughts, which tend to be abstract and imprecise. In contrast to a classical set, a fuzzy set is a set without a crisp boundary. The transition between inclusion and exclusion in a fuzzy set is smooth and gradual, characterized by membership functions that give fuzzy sets flexibility in modeling commonly used linguistic expression (Jang, *et al* 1997), with the advantage in areas where precise mathematical description of the control process is impossible (Agboola, *et al.* 2010). A fuzzy set A, in X is defined as a set of ordered pair:$A = \{(x, \mu_A(x)) | x \epsilon X\}$,(x)being the Membership Function (MF) and the MF maps each element of X to a membership grade (or membership value) between 0 and 1. The membership degree $\mu_A(x)$ quantifies the grade of membership of the element x to the fuzzy set. That is $\mu_A : X \rightarrow [0,1]$, where X is the universe of discourseand maybe discrete (ordered or unordered) object or continuous space. Obviously, the definition of a fuzzy set is a simple extension of the definition of a classical set in which the characteristic function is permitted to have any value between 0 and 1. The values 1 and 0 means x is a member or nota member of the fuzzy set respectively; while values between 0 and 1 characterize fuzzy members, which belong to the fuzzy set partially.

Fuzzy Rules and Reasoning

Fuzzy rules and fuzzy reasoning are the backbone of fuzzy inference systems, which are the most important modeling tool based on fuzzy set theory. The extension principle is the basic concept of fuzzy set theory that provides a general procedure for extending crisp domains of mathematical expressions to fuzzy domains. Conventional techniques for system analysis are intrinsically unsuited for dealing with humanistic systems, whose behaviour is strongly influenced by human judgment, perception, and emotions. This is a manifestation of what might be called the principle of incompatibility. As the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance become almost mutually exclusive characteristics. Because of this, the concept of linguistics variables as an alternative approach to modeling human thinking – an approach that, in an approximate manner, serves to summarize information and express it in terms of fuzzy sets instead of crisp numbers. A linguistic variable is characterized by a quintuple (x, T(x), X, G, M) in which x is the name of the variable; T(x) is the term set of x – that is, the set of its linguistic values or linguistic terms; X is the universe of discourse; G is a syntactic rule which generate the terms in T(x); and M is a semantic rule which associates with each linguistic value A its meaning M(A), where M(A) denotes a fuzzy set in X. Fuzzy reasoning, also known as approximate reasoning is an inference procedure that derives conclusion from a set of fuzzy if - then rules and known facts described as: Let$A, A'$and B be fuzzy sets of X, X, and Y, respectively. Assume that the fuzzy implication $A \rightarrow B$ is expressed as a fuzzy relation R on X * Y. Then the fuzzy set B induced by "$x \ is \ A'$"and the fuzzy rule "if x is A then y is B" is defined by Jang, *et al* (1997) as:

$$\mu_{B'}(y) = max_x min[\mu_{A'}(x), \mu_R(x, y)] = \vee_x[\mu_{A'}(x) \wedge \mu_R(x, y)],$$

or,

$$B' = A' o \ R = A' o \ (A \rightarrow B)$$

According to Agboola, *et al* (2010), a rule human knowledge in the form of "IF- THEN" rules, has been adapted to build fuzzy rule-based systems, whose antecedents and consequence or both are fuzzy. They opined that there is no agreed classification of fuzzy rule modes and a single rule might involve a combination of several different classification types.

METHODOLOGY

We propose a technique to design a Fuzzy Associative Memory (or known as fuzzy inference system) of Mamdani type applying the centroid method for the diagnosis of Lassa fever.

Fuzzy associative memory

The fuzzy associative memory (fuzzy inference system) in Jang *et al* (1997) framework was adopted for the design of the system based on the concept of fuzzy set, fuzzy if-then rules and fuzzy reasoning – also known as approximate reasoning in that the process is to draw a conclusion provided that the fuzzy implication $A \rightarrow B$ is true. The basic components of the fuzzy associative memory (fuzzy inference system) consists of three conceptual components:

a. a rule base containing a set of fuzzy rules,
b. a database which defines the membership functions used in the fuzzy rules, and ,
c. a reasoning mechanism which performs the inference procedures.

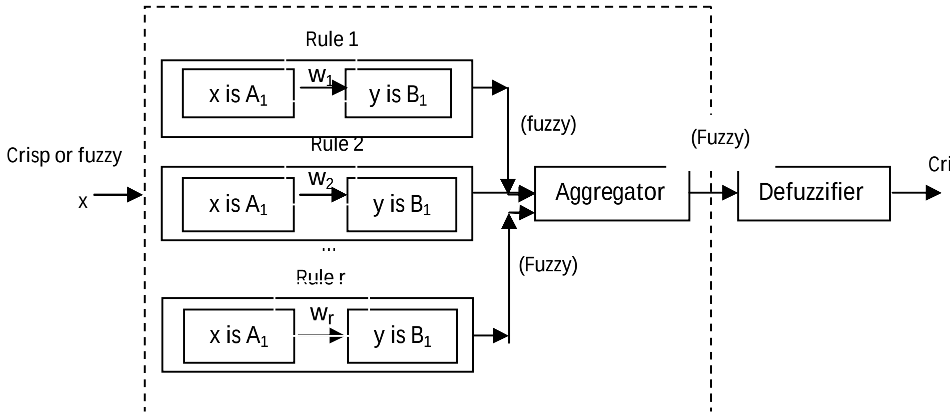

Figure 1. Block diagram for a fuzzy inference system (Jang, *et al* 1997).

According to Chen and Pham (2001), and Yin (2006), the fuzzy reasoning includes four steps (Figure 1):

a. **Fuzzification**: find the degree of similarity between the input function and the membership function
b. **Inference**: combine the degree of similarities from different membership functions using fuzzy AND or OR operators to form a firing strength of the rule. The inference combines the firing strengths of the rules.
c. **Aggregator**: apply the firing strengths to the consequent membership function to generate a qualified consequent membership function
d. **Defuzzification**: aggregate all the qualified consequent membership functions to produce a crisp output.

Fuzzy Sets

The input variables used for the system are the eleven symptoms of Lassa fever: headache, somnolence, seizures, tremor, restlessness, bleeding, neck stiffness, coma, fever, hearing defect and urine. In considering these symptoms, some are qualitative while others are quantitative; we applied objective and subjective judgment. This divides the possible range of values (linguistic values) into the corresponding fuzzy sets namely: Absent (A), Present (P) Low (L), Mild (M), and High (H) in describing our membership function of the symptoms (input variables) and are described as follows:

$$\mu_{headache}(x) = \begin{cases} 0 & x \leq 0.2 \quad Low \\ \frac{(x-0.2)}{(0.6-0.2)} & 0.2 < x < 0.6 \ mild \\ 1 & x \geq 0.6 \quad high \end{cases}$$

$$\mu_{\text{Somnolence}}(x) = \begin{cases} 0 & if \mu_{\text{Somnolence}} \leq 0.4 \quad Absent \\ 1 & if \mu_{\text{Somnolence}} > 0.4 \quad Present \end{cases}$$

$$\mu_{\text{Seizures}}(x) = \begin{cases} 0 & if \mu_{\text{Seizure}} \leq 0.4 \quad Absent \\ 1 & if \mu_{\text{Seizure}} > 0.4 \quad Present \end{cases}$$

$$\mu_{\text{Tremor}}(x) = \begin{cases} 0 & if \mu_{\text{Tremor}} \leq 0.4 \quad Absent \\ 1 & if \mu_{\text{Tremor}} > 0.4 \quad Present \end{cases}$$

$$\mu_{\text{Restlessness}\,(x)} = \begin{cases} 0 & if \mu_{\text{Restlessness}} \leq 0.4 \quad Absent \\ 1 & if \mu_{\text{Restlessness}} > 0.4 \quad Present \end{cases}$$

$$\mu_{fever}(x) = \begin{cases} 0 & x \leq 36.5 \quad low \\ \frac{(x-36.5)}{(37.5-36.5)} & 36.5 < x < 37.5 \ mild \\ 1 & x \geq 37.5 \quad high \end{cases}$$

$$\mu_{bleeding} = (x) \begin{cases} 0 & x \leq 0.2 \quad Low \\ \frac{(x-0.2)}{(0.5-0.2)} & 0.2 < x < 0.5 \ mild \\ 1 & x \geq 0.5 \quad high \end{cases}$$

$$\mu_{coma}(x) = \begin{cases} 0 & x \leq 3.0 \quad low \\ \frac{(x-3.0)}{(6.5-3.0)} & 3.0 < x < 6.5 \ mild \\ 1 & x \geq 6.5 \quad high \end{cases}$$

$$\mu_{\text{Neck Stiffness}}\,(x) = \begin{cases} 0 & if \mu_{\text{Neck Stiffness}} \leq 0.4 \quad Absent \\ 1 & if \mu_{\text{Neck Stiffness}} > 0.4 \quad Present \end{cases}$$

$$\mu_{\text{Hearing Defect}}(x) = \begin{cases} 0 & x < 0.2 \quad Low \\ \frac{(x-0.2)}{(0.5-0.2)} & 0.2 < x < 0.5 \ mild \\ 1 & x \geq 0.5 \quad high \end{cases}$$

$$\mu_{\text{Urine Output}}(x) = \begin{cases} 0 & x < 0.2ml \quad low \\ \frac{(x-0.2)}{(0.5-0.2)} & 0.2ml < x < 0.5ml \ mild \\ 1 & x \geq 0.5ml \quad high \end{cases}$$

Fuzzy Rule Base

The rule base in the study is defined according to the knowledge of the experts. A typical fuzzy logic IF-THEN rule is of the form:R1: IF x_1 is A_1 THEN y is B where A & B are linguistic values defined by the fuzzy sets on universe of discourse X and Y, respectively. The fuzzy rule base forms the heart of the fuzzy associative system due to the rules used to obtain the fuzzy output. In this study, 729 heuristic rules were generated from the fuzzy inference system based on our expert's knowledge.

Defuzzification

The centroid method was used in the defuzzification unit to convert the fuzzy values into the crisp values for human understandability of the system and is given in equation 1 as follows:

$$Z_{COA} = \frac{\int_z \mu_A(Z)zdz}{\int_z \mu_A(Z)dz} \quad (1)$$

Where (z) is the aggregated output, MF This method is the most widely adopted defuzzification strategy.

System Implementation

Matlab 7.10 was used to implement the system design. The Mamdani method in the fuzzy logic toolbox was used to develop the rules and applying the centroid of area as the defuzzification method. The range of fuzzy values of the various symptoms generated 729 fuzzy rules with its corresponding output values.The various input and output membership functions are shown in Figures 2 and 3 respectively.

Testing and Evaluation

Figure 4 shows the surface viewer depicting the diagnostic result for bleeding and headache while Figure 5 shows the fuzzy rules generated. The data used in this study was collected from Irrua Teaching Hospital and based on the expert's knowledge, the symptoms variables were fuzzified. The system has 11 input MFs and one output MF. These MFs can either increase or decrease within their respective ranges used. With the range of values heuristically fixed for the detection of the disease, we were able to diagnose the possibility of the disease which of course can be used to compliment the effort of the medical doctors. The output MF in Figure 3 indicate that 0<x<0.4 indicate “no Lassa fever”, 0.1<x<0.9 indicate “suspected Lassa fever”, while 0.6<x<1 indicate “Lassa fever”. When the system was run, it satisfied these range of values.

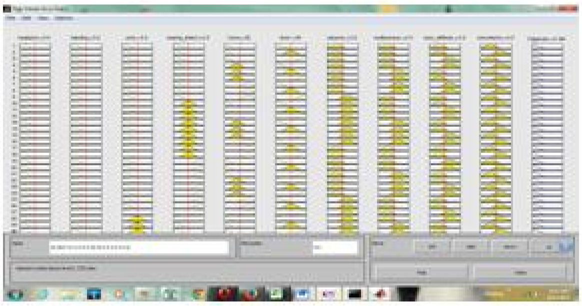

Figure 2: Rule view of both input and output

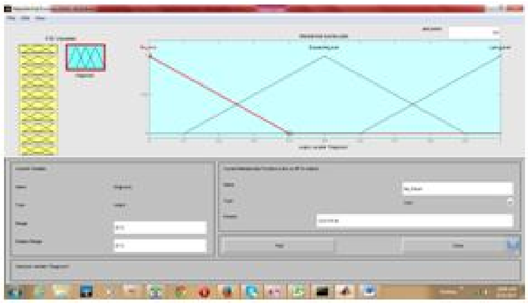

Figure 3: Diagnostic Result MF graph

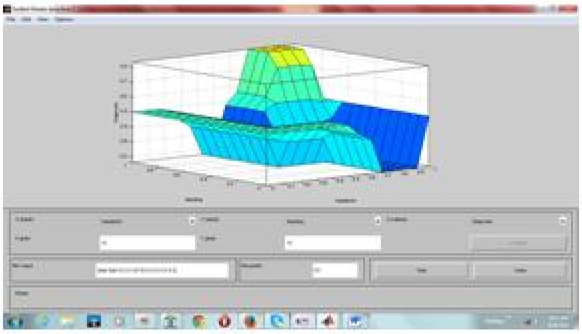

Figure 4: Surface viewer of Diagnosis, bleeding and headache.

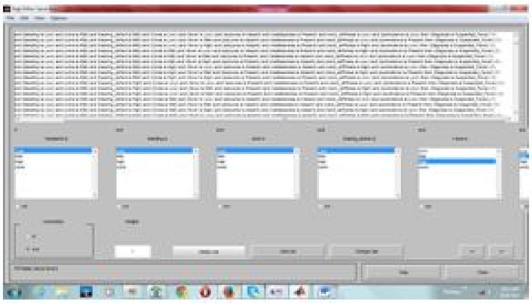

Figure 5: Rule Base of system

CONCLUSION

This system was designed using the expert’s knowledge of the subject matter. The ability of the expert to interpret imprecise and incomplete sensory information comes to bare in this study. Although, the fuzzy inference system has a structured knowledge representation in the form of fuzzy if-then rules where the membership function and the consequent part of the system were pre-assigned, it lacks the adaptability to deal with changing external environments. In the nearest future, we hope to adapt the capability of neural network learning concepts in the fuzzy inference system so as to enable learning and adaptability, thereby concentrating on only the rules that fires and consequently reducing the number of rulesdrastically.

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