A SELF-ORGANIZED MULTI AGENT DECISION MAKING SYSTEM BASED ON FUZZY PROBABILITIES: THE CASE OF APHASIA DIAGNOSIS

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Abstract. Aphasia diagnosis is a challenging medical diagnostic task due to the linguistic uncertainty and vagueness, large number of measurements with imprecision, inconsistencies in the definition of Aphasic syndromes, natural diversity and subjectivity in test objects as well as in options of experts who diagnose the disease. In this paper we present a new self-organized multi agent system that diagnoses different types of Aphasia based on fuzzy probabilities. In the proposed multi agent system, the characteristic of self organization is employed as both a decision making feature selection paradigm as well as a mechanism to estimate the probability mass functions of Aphasia factors. The estimated probability mass functions are involved in fuzzy probability calculation of different types of Aphasia. The performance and robustness of the proposed method is compared with several earlier approaches. While the proposed method requires more of the available test parameters, the comparison clearly shows the superiority of the proposed method in terms of accuracy as well as robustness.

1. Introduction

In any complex decision making process, the issue of an appropriate paradigm to handle uncertainties/information is as important as the problem of recognizing the appropriate decision parameters and their interaction. Most of the current approaches for uncertainty modeling and analysis are either based on probability theory or fuzzy logic. There are however many systems where both of these uncertainty types co-exist and their interaction significantly influences model performance. For such systems, a source of uncertainty is usually the lack of knowledge and complete information [21]. Under such circumstances, uncertainty should rather be modeled by a combined paradigm of probability theory and fuzzy logic. Several reasons that justify this combination are that probability theory is unable to analyze the problems that deal with fuzzy data and quantifiers. Indeed it is unable to deal with linguistic knowledge of experts and generally it is not able to calculate and analyze imprecise probabilities [63]. Fuzzy probability [62], in contrast, is an appropriate paradigm for modeling and analyzing such uncertainties. In this framework probability theory is complemented with an extra dimension of uncertainty provided by fuzzy set theory [46,47].

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Current applications of fuzzy probabilities can be divided in two main fields of risk assessment and decision making [48]. In the area of risk assessment and reliability, fuzzy probabilities have been widely applied in Breast cancer risk assessment [48], pedestrian collisions risk assessment [46], fuzzy fault trees to assess the fault risk [13, 14, 27], reliability assessment for pressure piping [68], risk assessment of natural hazards [26] and reliability enhancement by combining expert opinions [59]. Also in the decision making field, fuzzy probabilities have been employed in perception based theory [64], optimal decision fusion [56,57], inference by aggregation [45], information retrieval [21] and inventory control [8].

In addition to an appropriate paradigm for handling information, recognizing the effective factors as well as their interaction can also significantly influence the final outcome. Unfortunately, recognizing all of the effective factors and the precise amount of their effectiveness is not trivial. In other words, it is always probable that some of the effective factors have not been considered or the percentage of their effectiveness has not been adjusted properly. Having statistical characteristics, fuzzy information and the effective factors in any phenomenon can be helpful for the determination of that phenomenons probability of occurrence.

In 1968, Zadeh [61] modified the elementary concepts of probability theory in a more general setting in which the probability of fuzzy events could be calculated by employing the probability mass function and fuzzy membership function of the intended variable. Further study in this field resulted in the development of fuzzy probabilities [62]. Fuzzy probability theory as a generalized form of probability theory can deal with experts linguistic knowledge, incomplete information and fuzzy data to calculate fuzzy probabilities which are mostly in the form of fuzzy sets. As indicated in [62], fuzzy information induces fuzzy probabilities. Therefore due to fuzzy information employment in probability calculation of a fuzzy event [61], this imprecise probability can be considered as a fuzzy probability [36]. Here the probability of a fuzzy event which is calculated based on both fuzzy and statistical information is also called fuzzy probability.

As indicated in [35], self organizing networks can be employed to estimate probability mass functions based on statistical data. Based on these pioneering works, and in order to efficiently choose parameters and to reduce time complexity, we employ multi agent systems to estimate fuzzy probabilities of a fuzzy variable. Hence, we propose to address the complexities of a decision making process by employing a combination of fuzzy probability, multi-agent systems and self-organizing approaches.

Multi agent systems (MAS) are distributed computational systems with intelligent autonomous agents. In a MAS, agents cooperatively or competitively coordinate their tasks to reach their goals while the agents may be the same or different [28]. MASs are mainly employed to solve the problem where the environment is open, dynamic, uncertain or complex [58]. In a cooperative multi agent system, agents are able to divide a problem to several sub problems and share their knowledge with each other [58]. Result sharing is one the most important capabilities of a multi agent system where each agent shares its local result obtained based on its local data with other agents. The aggregation of all these local results creates a global result with a high level of confidence. Result sharing increases the confidence level in the total result and ensures the precision of the final solution [46,47,48]. Self organization is the other capability that can be found in MASs. Self organized multi agent system (SOMAS) is a type of MASs where the MAS spontaneously arranges its structure and its agents in a purposeful manner, under appropriate conditions, without being guided or managed by an outside source to solve its problem.

Multi agent systems have been widely applied in decision making problems. A multi agent robot soccer system which makes intelligent decisions through compounded artificial neural networks is presented in [23]. In 2009 Gao et al. developed an agent-based intelligent system for decision making in chemical process industry [16]. Ghijsen et al. introduced decision making frameworks that enable the agents of a system to select the best coordination mechanism (centralized and decentralized) in a given situation [18]. Tatari et al. introduced a Fuzzy-probabilistic multi agent system for breast cancer risk assessment and insurance premium assignment [48]. In the field of economics, MASs have been employed for decision making of several applications such as reordering in a parallel supply chain [42], employing fuzzy group decision making model for financial multiceria decision making [60], employing internet-based multi agent system for strategic decision making [33] and agent based simulation of consumer purchase decision making [66]. In the field of SOMASs we can refer to [43] where a SOMAS is applied for emergent timetabling and in [7] a SOMAS has been employed for flood prediction. Also self organized approaches have been introduced for simulation and assignment of agricultural grounds [12] and for localization and tracking [17].

Multi agent systems are applicable in various areas of medical sciences such as health monitoring [11,31,24,52,77], medical diagnosis [19,29,32,33,53], electronic medicine [39,49,51], risk assessment [10,34,49], medical services [15] and medical information systems [40]. In the mentioned fields, disease diagnosis is a kind of decision making which is mostly accompanied by uncertainty, because it is usually impossible to determine all the effective factors and the percentage of their effectiveness on the final diagnosis.

Scientists have extended the use of fuzzy logic theory in designing disease diagnosis and decision making systems for different diseases. The areas in which medical applications are developed for fuzzy illness modeling [20] and fuzzy disease diagnosis are: heart and cardiovascular disease diagnosis [65], abdominal pain [50], tropical diseases [1], neurological diseases [55], malaria diagnosis [54], diagnosis and treatment of diabetes[44], diagnosis of lung and liver diseases [38], prostate diseases [41], etc. The other areas of medical applications are found to be in: x-ray mammography [25], interpretation of mammographic and ultrasound images [37] and electrographic investigation of human body [30].

In the proposed method, we employ self-organization in estimating the probability mass functions of the effective features and designing a self-organized multi-agent system that can automatically arrange its organization to have an optimal performance in the decision making process. In the process of decision making by a self-organized multi-agent system, we use fuzzy probability as a suitable approach to model and handle the uncertainty by employing the estimated mass functions and fuzzy data. In summary, we introduce a self-organized multi-agent system that decides based on fuzzy probabilities, where we demonstrate the applicability of this method on the problem of Aphasia diagnosis.

This paper is organized as follows. In Section 2, Aphasia disease and the employed database are introduced. Section 3 illustrates the procedure of extracting the probability mass function of Aphasia factors by employing the self organizing networks. The proposed self organized multi agent system which decides about Aphasia diagnosis based on fuzzy probabilities is explained in Section 4. The obtained results of the proposed approach and its comparison with previous methods can be found in Section 5. Finally, conclusions are drawn in Section 6.

2. Aphasia Literature Survey and Database

Aphasia is an acquired impairment of language processes including receptive and expressive modalities which is caused by the malfunction of specific areas in the brain primarily responsible for the language function [36]. Strake, head injury and cerebral tumors may be the reasons of such brain damage [36]. Four major types of Aphasia syndromes are Anomic, Broca (also called Motor or Expressive Aphasia), Global (also called Total Aphasia) and Wernicke (also called Sensory or Receptive Aphasia).

Aphasia syndromes diagnosis is a difficult medical diagnosis because in addition to the variety of experts opinions and medical tests other sources of complexities exist due to linguistic data vagueness and uncertainties in different Aphasia syndromes definitions and varying in precision of medical tests [36]. Due to the existing complexities, diagnosis of aphasia types are time consuming and error-prone. In the 4 mentioned types of Aphasia, so many of the disease features are joint. Because of the overlap in the boundaries of clusters in feature space, classes taxonomies are more probabilistic rather than crisp [22]. So far several hybrid intelligent methods have been applied for aphasia diagnosis, such as artificial neural networks [4,5], fuzzy logic and fuzzy clustering [3,6,9], and genetic-fuzzy algorithms. In [2] a hierarchical fuzzy rule based method (two-layered fuzzy rule-based system) is proposed for Aphasia diagnosis, this method has employed a fuzzy hierarchical system where product operation is the inference engine of the system. In [36] a fuzzy classifier is introduced for Aphasia diagnosis which benefits from a fuzzy probability estimator as its inference engine. It should be emphasized that the authors of [36] have just employed an estimator for calculating the fuzzy probabilities of four major types of Aphasia.

We have employed a database which is supplied based on Achen Aphasia Test (AAT) which is common in German speaking countries. In this database, previously used in [36,2], information files of 265 Aphasia patients exist, where based on the result of 30 different tests (features), available in Table 1, 146 patients are diagnosed with one of four major types of Aphasia (Anomic, Broca, Global, Wernicke). This specific group (146 patients) forms our statistical database while others profiles are either in other types of Aphasia or are undecided profiles. By classifying these 146 patients in 4 major types of Aphasia, we realize that 24, 33, 42, 47 patients are respectively infected by Anomic, Global, Broca, Wernicke. In this order 4 statistical sub societies with different populations (database size $SD_{d_l,i}(l \in [1,4], i \in [1,30])$) are determined for 4 major types of Aphasia.

$SD_{Anomic,i} = 24, SD_{Broca,i} = 33, SD_{Global,i} = 42, SD_{Wernicke,i} = 47,$
$SD_{Anomic,i} + SD_{Broca,i} + SD_{Global,i} + SD_{Wernicke,i} = 146$

Code	Test	Score Range
	Spontaneous speech	
P0(X1)	Communicative behavior	0 - 5 [points]
P1(X2)	Articulation and prosody	0 - 5 [points]
P2(X3)	Automatized language	0 - 5 [points]
P3(X4)	Semantic structure	0 - 5 [points]
P4(X5)	Phonologic structure	0 - 5 [points]
P5(X6)	Syntactic structure	0 - 5 [points]
T0(X7)	Token test	0 - 100 [%]
T1-T5(X8-X12)	Token subtests	0 - 10 [points]
N0(X13)	Repetition	0 - 100 [%]
N1(X14)	Single phonemes	0 - 30 [points]
N2(X15)	Monosyllabic nouns	0 - 30 [points]
N3(X16)	Loan and foreign words	0 - 30 [points]
N4(X17)	Compound words	0 - 30 [points]
N5(X18)	Sentences	0 - 30 [points]
C0(X19)	Written language	0 - 100 [%]
C1(X20)	Reading aloud	0 - 30 [points]
C2(X21)	Selecting/combining on dictation	0 - 30 [points]
C3(X22)	Writing on dictation	0 - 30 [points]
B0(X23)	Confrontation naming	0 - 100 [%]
B1(X24)		0 - 30 [points]
B2(X25)		0 - 30 [points]
B3(X26)		0 - 30 [points]
B4(X27)		0 - 30 [points]
V0(X28)	Comprehension	0 - 100 [%]
V1(X29)	Auditory for words and sentences	0 - 60 [points]
V2(X30)	Reading for words and sentences	0 - 60 [points]

Table 1. AAT Subsets [4]

In the self organized multi agent system which is introduced in the following, the agents try to calculate the fuzzy probabilities of each type of Aphasia based on the mass functions of disease factors and the available data. Therefore we need to estimate the mass functions of each Aphasia feature for any type of Aphasia based on the available database.

3. A Self Organized Network for Probability Mass Function Extraction of Aphasia Features

By classifying the main database of the Aphasia patients to 4 databases of Anomic, Broca, Global and Wernicke databases, we can estimate the mass functions $pdf(f_i|d_l)$, where $i = 1, 2, ..., 30$ is the Aphasia feature index and $l = [1 : Anomic], [2 : Broca], [3 : Global], [4 : Wernicke]$ indicates one of the four types of Aphasia. Assumptions of a particular form about a feature probability mass function (such as being Normal, Uniform, Weibul,), introduce the potential to deviate from reality. This can be constructed as a basic point where this work departs from most of the traditional techniques of decision making. Here, we utilize self-organizing networks to directly calculate the required mass functions. Self-organizing networks calculate the probability mass functions $pdf(f_i|d_l)$, through estimating how probable the feature f_i of a patient can be equal to an integer amount between 0 and c_i, provided that the patient is affected by the l^{th} Aphasia type ($l = 1, 2, 3, 4$),where c_i is the upper bound of the feature. Here we employ 120 self organizing networks to learn and estimate the required 120 mass functions. We propose to use Kohonen model of self organizing networks, which is an unsupervised model, to estimate the probability mass functions $pdf(f_i|d_l)$. In the proposed model for estimating any of the probability mass functions, we use a one dimensional network including a number of cells aligned in an even topology as shown in Figure 1, where in our database, the inputs are also scalar. The number of network cells (N) is determined based on the corresponding bounds of any feature and appropriate resolution which is needed, where N is $N = c_i \times n, f_i \in [0, c_i], n \gg 1$. For example if $c_i = 100$ and $n = 10$,the network has $N = 1000$ cells.

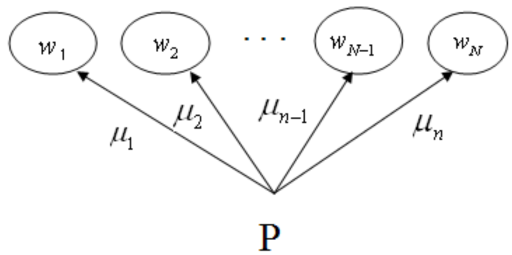

FIGURE 1. One Dimensional Topology of the Proposed Self-organizing Network (P= Input Data for the Network, w_i =Weight of the i^{th} Cell ($i = 1, ..., N$), μ_i =Learning Rate of Each Cell, O = Each Network Cell)

Network cells compact the received information, where each cell represents r number of entered data to the network. In any network which corresponds to the estimation of $pdf(f_i|d_l)$, r is defined as $r = (SD_{d_l,i} \times 1000)/(c_i \times n)$, where $SD_{d_l,i}$ is the size of the database for the l^{th} type of Aphasia and the i^{th} feature. For estimating $pdf(f_i|d_l)$, i.e. the mass function of the i^{th} feature of the l^{th} type of Aphasia, we first assign random and uniform weights from the range of the considered feature f_i to any cell ($w_j \in [0, c_i], j \in [1, N]$), then we enter the data of the feature f_i from the l^{th} type of Aphasia database one by one into the constructed network. After a new datum becomes available, the network finds the most similar cell to the entered datum; the resemblance criterion is based on the Euclidean distance $d(w_i, p)$ between the entered datum ($P \in R$) and the cells weights ($w_i \in R$).

$$d(w_i, p) = |w_i - p|, \qquad p \in R, w_i \in R \tag{1}$$

In this order, the cell which has the least distance from the new datum is chosen as the winning cell. In the next step the weights of the cells which are in the neighborhood of the winner cell must be alerted, where the winner cell is in the center and others are in its neighborhood. We employ a method where the weights of the network cells move toward the input at different rates. These learning rates, $0 \leq \mu \leq 1$, are determined such that the winning cell has the highest learning rate and the learning rate decreases for the neighbor cells by getting farther from the winner. Also, any cell learning rate is decreased as time passes. It should be noted that this method is more accurate but more time consuming in comparison with methods where the only cells inside a specific radius around the winning cell move their weights toward the input by the same learning rates. Based on the mentioned procedure all the inputs enter the network and by any datum entry the network corrects the cells weights. Due to the limited number of input data in the available database, all the inputs enter the system again and again for n_{train} epochs. The more the epochs of input entry, n_{train}, the higher the precision of the probability mass function. Therefore by reentering the inputs for limited times, or in the other words by sufficiently training the network, all the weights will converge to their true values.

After the weights converged, we can estimate the required probability mass function. First we round the estimated weights to integer weights. Afterwards we consider f_i range as $[0, c_i]$, we can determine how many cells among the network cells have the weights equal to $0, 1, 2, ..., c_i$ and the numbers of these cells are shown by $s_0, s_1, ..., s_{c_i}$, respectively. Finally by calculating the $s_0/N, s_1/N, ..., s_{c_i}/N$ amounts where N is the total number of cells, we have estimated how probable the feature f_i of a patient can be equal to an integer amount between 0 and c_i, provided that the patient is affected by the l^{th} Aphasia type ($l = 1, 2, 3, 4$). Now we can obtain a histogram where $0, 1, 2, 3, ..., c_i$ are the x-coordinates and correspondingly $s_0/N, s_1/N, ..., s_{c_i}/N$ are the y-coordinates of the histogram points, it is clear that the obtained histogram is the probability mass function $pdf(f_i|d_l) = f_{A_i^{d_l}}$ for the i^{th} feature from the l^{th} type of Aphasia. The resulting probability mass function is shown in Figures 2.

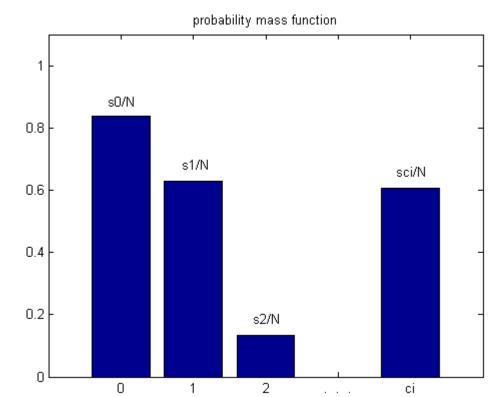

FIGURE 2. Histogram of Probability Mass Function

While no specified assumption is considered about the probability mass functions types, studying the shape of the obtained mass functions verifies that no specific distribution can reasonably fit the calculated mass functions in the case of Aphasia diagnosis. As an example, the probability mass function $pdf(N4|Broca)$ estimated by a self organized network (SON) with N=1000 cells through $n_{train} = 1000$ training epochs, is shown in Figure 3. In the mentioned network, the learning rate (LR) is adjusted as below:

$(Max(LR) = 0.85 \quad for(1-99)epochs), (Max(LR) = 0.8 \quad for(100-199)epochs),$
$(Max(LR) = 0.75 \quad for(200-299)epochs), (Max(LR) = 0.7 \quad for(300-399)epochs),$
$(Max(LR) = 0.65 \quad for(400-499)epochs), (Max(LR) = 0.6 \quad for(500-599)epochs),$
$(Max(LR) = 0.55 \quad for(600-699)epochs), (Max(LR) = 0.5 \quad for(700-799)epochs),$
$(Max(LR) = 0.49 \quad for(800-899)epochs), (Max(LR) = 0.48 \quad for(900-1000)epochs).$

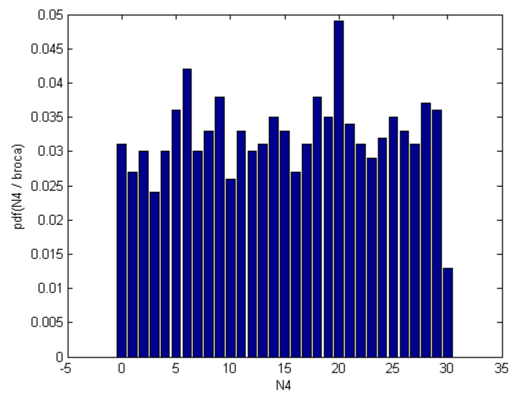

FIGURE 3. The Estimated Probability Mass Function $pdf(N4|Broca)$ by SON

The procedure of probability mass function generation is depicted in Figure 4. It should be noted that the number of cells and the learning rates in any feature network is adjusted in a way to prevent the formation of dead cells in the network. A dead cell is one whose weights are not adjustable with respect to the network inputs.

4. A Self Organized Multi Agent System for Aphasia Diagnosis

Here we propose a self organized multi agent system (SOMAS) which is able to automatically organize the appropriate structure of the MAS to have the best performance in Aphasia diagnosis. The agents in this self organized system are equipped with the probability mass functions of Aphasia types which are calculated through the above Kohonen self organizing networks. Therefore the MAS has employed self organizing methods as a helpful aid in its own structure and as the agents knowledge to improve its performance.

The proposed self organized multi agent system for Aphasia diagnosis initially contains 30 feature agents which are considered as the cells of the proposed self organized multi agent network. Any of the 30 feature agents in our SOMAS is representative for one of the 30 features of Aphasia which exists in the database. Any feature agent that corresponds to the $i^{th} (i = 1, 2, ..., 30)$ feature f_i is equipped with 4 probability mass functions of its own i^{th} feature for 4 different types of Aphasia $pdf(f_i|d_1), pdf(f_i|d_2), pdf(f_i|d_3), pdf(f_i|d_4)$. Additionally each feature agent has the statistical data of its own feature from the four Aphasia type sub databases. These statistical data and their corresponding probability mass functions are the

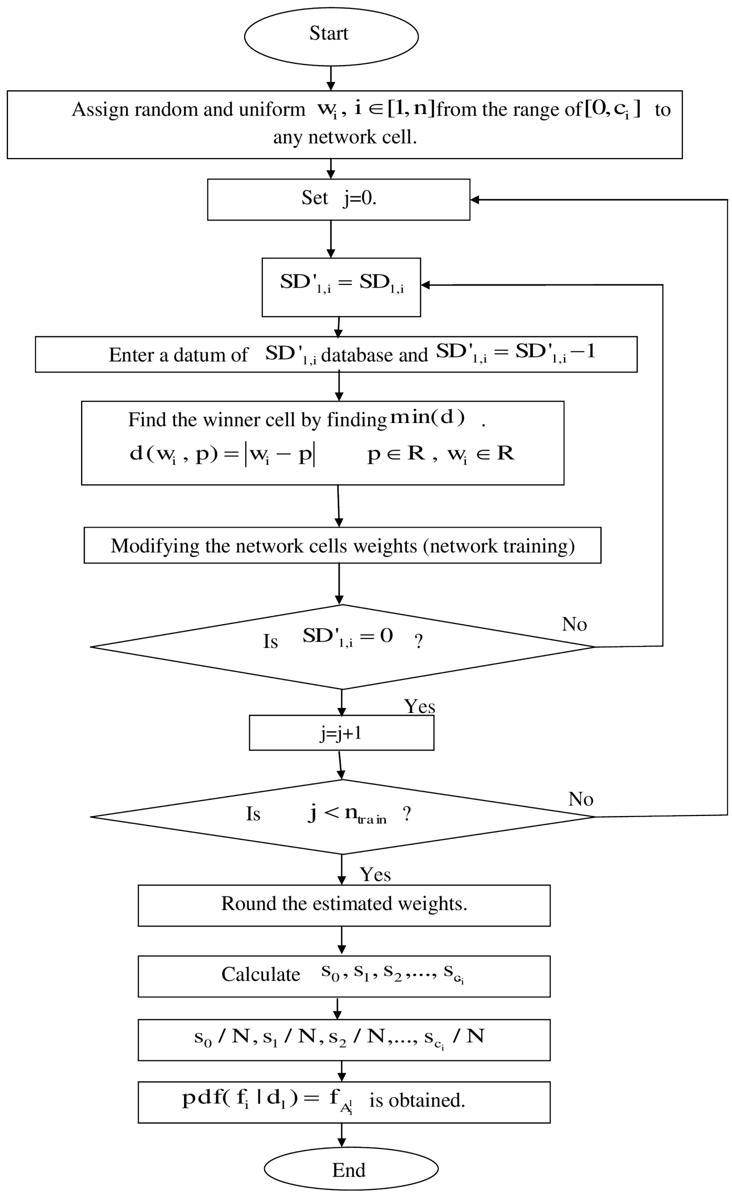

FIGURE 4. Probability Mass Function Estimation Through the Self Organizing Network

knowledge of each feature agent which helps it to organize the structure of the MAS and to diagnose different types of Aphasia correctly.

The proposed multi agent system is designed in a way that can automatically employ the appropriate number of feature agents to diagnose different types of Aphasia with the highest possible performance. To organize the system, each feature agent tries to evaluate its own performance based on its local data and knowledge. Any feature agent is a fuzzy agent that tries to diagnose the Aphasia type based on four fuzzy rules and a fuzzy probability inference engine. To evaluate its performance, each feature agent divides any of its feature sub databases of Aphasia types to two random halves, one testing set and one training set. Each feature agent calculates the average and standard deviation of its training sets which are respectively shown by $\bar{x}_i^{d_l}$ and $S_i^{d_l}$ as below

$$\bar{x}_i^{d_l} = \frac{1}{n_i^{d_l}} \sum_{j=1}^{n_i^{d_l}} x_{ij}^{d_l}, \quad S_i^{d_l} = \frac{1}{n_i^{d_l} - 1} \sum_{j=1}^{n_i^{d_l}} (x_{ij}^{d_l} - \bar{x}_i^{d_l})^2 \tag{2}$$

where $x_{ij}^{d_l} \in N$(the set of natural numbers), $i = 1, 2, ..., 30$ is the feature index of each feature agent, $l = 1, 2, 3, 4$ is the index of each type of Aphasia, $j = 1, ..., n_i^{d_l}$ is the index of the patients, and $n_i^{d_l}$ is the total number of the patients in the training database of the l^{th} type of Aphasia for the i^{th} feature. It should be noted that $\bar{x}_i^{d_l} \in R$ and $S_i^{d_l} \in R$. In order to avoid loss of information, each feature agent employs its statistical parameters ($\bar{x}_i^{d_l}$,$S_i^{d_l}$) to construct 4 triangular fuzzy sets $A_i^{d_l}, (l = 1, 2, 3, 4)$.

Along with probability distributions (probability mass functions), possibility distributions of Aphasia features which are in the form of triangular fuzzy sets are later employed in the construction of fuzzy probabilities.

It should be mentioned that authors, in their earlier work, had chosen trapezoidal membership functions $\mu_{A_i^{d_l}}(x_i; a_i^{d_l}, b_i^{d_l}, c_i^{d_l}, d_i^{d_l})$ where $a_i^{d_l} \leq b_i^{d_l} \leq c_i^{d_l} \leq d_i^{d_l}, a_i^{d_l} = [\bar{x}_i^{d_l} - 3S_i^{d_l}], b_i^{d_l} = [\bar{x}_i^{d_l} - S_i^{d_l}], c_i^{d_l} = [\bar{x}_i^{d_l} + S_i^{d_l}], d_i^{d_l} = [\bar{x}_i^{d_l} + 3S_i^{d_l}]$,($\bar{x}_i^{d_l}$,$S_i^{d_l}$) are respectively the statistical mean and standard deviation), since it seemed to cover the data feature space better than a Gaussian membership function and provided a better fit to the distributions of the records as follows.

$$\mu_{A_i^{d_l}}(x_i; a_i^{d_l}, b_i^{d_l}, c_i^{d_l}, d_i^{d_l}) = \begin{cases} (x_i - a_i^{d_l})/(b_i^{d_l} - a_i^{d_l}) & a_i^{d_l} \leq x_i < b_i^{d_l} \\ 1 & b_i^{d_l} \leq x_i \leq c_i^{d_l} \\ (x_i - d_i^{d_l})/(c_i^{d_l} - d_i^{d_l}) & c_i^{d_l} < x_i \leq d_i^{d_l} \\ 0 & x_i \in N - \{a_i^{d_l} \leq x_i \leq d_i^{d_l}\} \end{cases} \tag{3}$$

However, trapezoidal membership functions lead to double diagnosis in some cases, and hence in this work, triangular membership functions are recommended. The triangular membership functions $A_i^{d_l}$ can be obtained as below, where $a_i^{d_l} \leq b_i^{d_l} \leq c_i^{d_l}, a_i^{d_l} = [\bar{x}_i^{d_l} - 3S_i^{d_l}], b_i^{d_l} = [\bar{x}_i^{d_l}], c_i^{d_l} = [\bar{x}_i^{d_l} + 3S_i^{d_l}]$.

$$\mu_{A_i^{d_l}}(x_i; a_i^{d_l}, b_i^{d_l}, c_i^{d_l}) = \begin{cases} (x_i - a_i^{d_l})/(b_i^{d_l} - a_i^{d_l}) & a_i^{d_l} \leq x_i < b_i^{d_l} \\ (c_i^{d_l} - x_i)/(c_i^{d_l} - b_i^{d_l}) & b_i^{d_l} < x_i \leq c_i^{d_l} \\ 0 & x_i \in N - \{a_i^{d_l} < x_i < c_i^{d_l}\} \end{cases} \tag{4}$$

After that each feature agent forms its 4 fuzzy sets $A_i^{d_l}(l = 1, 2, 3, 4)$, by employing fuzzy probability through four fuzzy rules, it can decide about the Aphasia types and can evaluate its performance based on its testing sets ($x_i^{d_l}$ $\in$any of the four Aphasia testing sets). The general format of 4 fuzzy rules in any feature agent is as below:

Rule (1): if $x_i^{d_l}$ is $A_i^{d_1}$ then diagnosis is Anomic with fuzzy probability $P(A_i^{d_1})$.
Rule (2): if $x_i^{d_l}$ is $A_i^{d_2}$ then diagnosis is Broca with fuzzy probability $P(A_i^{d_2})$.
Rule (3): if $x_i^{d_l}$ is $A_i^{d_3}$ then diagnosis is Global with fuzzy probability $P(A_i^{d_3})$.
Rule (4): if $x_i^{d_l}$ is $A_i^{d_4}$ then diagnosis is Wernicke with fuzzy probability $P(A_i^{d_4})$.

The fuzzy probabilities $P(A_i^{d_l}), l = 1, 2, 3, 4$ are calculated based on the definition which was expressed by Zadeh for the probability of fuzzy events [61]. According to this definition, the fuzzy probability of event A is as follows

$$P(A) = \int_A f(z)dz = \int_R \mu_A(z).f(z)dz = E[\mu_A(z)] \tag{5}$$

where z is a random variable, $f(z)$ is the mass function of z , $\mu_A(z)$ is the membership degree of z in the fuzzy event A and $E[.]$ shows the expected value. Here in the case of Aphasia diagnosis, the estimated features probability mass functions are discrete, therefore according to the above definition, we can calculate the fuzzy probabilities $P(A_i^{d_l})$ by employing $f_{A_i^{d_l}}$ mass functions and $A_i^{d_l}$ triangular feature membership functions as follows:

$$P(A_i^{d_l}) = \mu_{A_i^{d_l}}(x_k).f_{A_i^{d_l}}(x_k) = E[\mu_{A_i^{d_l}}(x_k)], \quad k \in [1, n_{test_l}] \tag{6}$$

where k is the index of the patients in the testing set of the i^{th} feature in the l^{th} type $l = 1, 2, 3, 4$ of Aphasia and n_{test_l} is the total number of patients in any corresponding testing set. Figure 5 illustrates the process of fuzzy probability computing of the $l^{th}, l = 1, 2, 3, 4$ type of Aphasia based on the $i^{th}, i = 1, 2, ..., 30$ feature. The computed fuzzy probability will be used in the fuzzy probability inference engine of the corresponding feature.

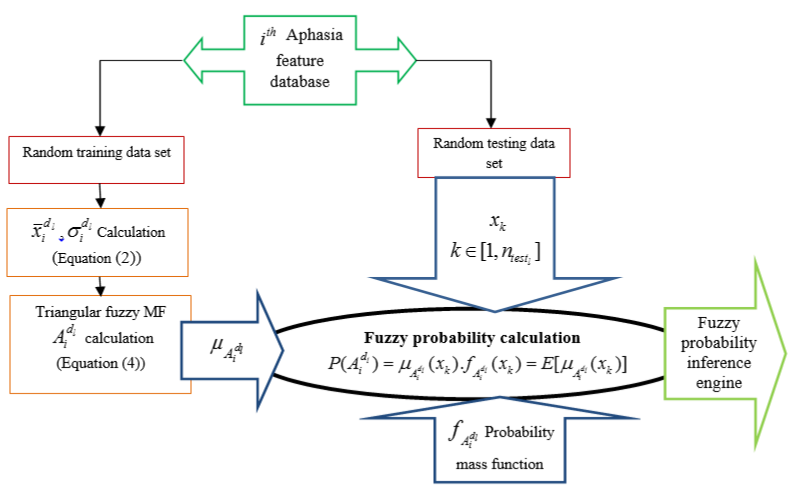

Figure 5. Fuzzy Probability Calculation of the l^{th} Type of Aphasia Based on the i^{th} Feature

Finally each feature agent chooses a type of Aphasia for its final diagnosis which has the highest fuzzy probability among four calculated fuzzy probabilities. As depicted in Figure 6, each feature agent evaluates its local performance in diagnosing

4 different types of Aphasia based on its own training and testing sets and calculates the average of its correct diagnosis through 50 episodes based on 50 random training and testing sets. It should be mentioned that the definition of fuzzy probability in Equation (6) is derived from Equation (5) which was first introduced by Zadeh [61].

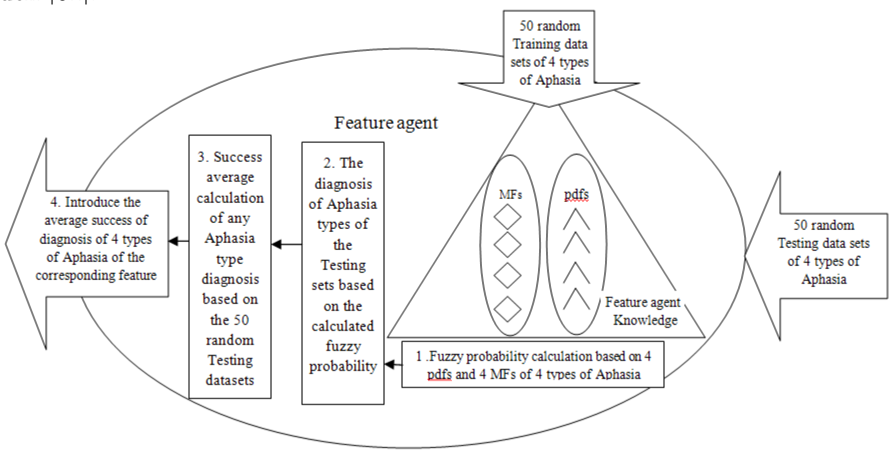

Figure 6. The Inner Calculation of any Individual Feature Agent

After each feature agent computes the average of its success in the 4 types of Aphasia diagnosis based on different testing and training sets, the two feature agents which have the highest average percentage of success will be selected by the network (Max1 and Max2 in Figure 7) also 4 other feature agents except the two best feature agents will be selected (Rand1,..., Rand4 in Figure 7).

These 4 feature agents are selected by a random mechanism where probability of their selection is based on their average performance in proportion to the sum of all 30 features average performances. Equivalent forms of the selected features are then placed in the category which is called the winner feature agents group (see Figure 7). In the next step any member of the winner agents group tries to choose and add a new feature agent (among 30 feature agents) to its features through result sharing and interacting by all of these 30 feature agents. In this order any of the previous members of winner agents group adds a new feature among the 30 feature agents to its previous feature that through their collaboration the highest average percentage of success is obtained. Figures 8 and 9 depict an instance of the first and second updating of winner agents group members, respectively.

This member updating will continue until the system can recognize the best member of winner agents group which contains the best feature agents for Aphasia diagnosis. Once the members of winner agents group have updated their features by adding a new feature to their previous feature agents in any episode (each episode contains the process of updating the 6 members of winner agents group), system recognizes a member which has the maximum success average in Aphasia diagnosis among the 6 members. We expect to have an increase in the maximum success average among these six members in comparison with the previous maximum success

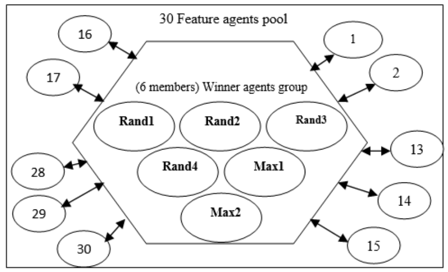

FIGURE 7. Member Selection of the Winner Agents Group

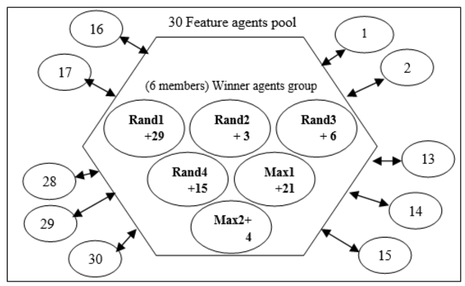

FIGURE 8. First Updating of Winner Agents Group Members

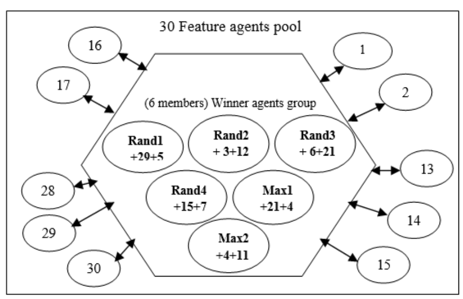

FIGURE 9. Second Updating of Winner Agents Group Members

average from the last updating. Although despite our desire we may see a decrease in the maximum success average in back to back episodes. In this case we ignore these decreases if the number of back to back episodes where we face decreases, n_D , is less than $m(m > 1)$. In this way, the system gives its members this chance to improve their performance through back to back episodes and if this decrease continues more than m back to back episodes we would stop the feature updating of the winner agents members. In this problem we have considered $m = 3$. After we stopped the member updating by facing 3 back to back decreases of maximum success average in 3 back to back winner members updating, we choose one of the members of winner agents group which has the highest maximum success average at the episode where we came across the first decrease in the maximum success average. We keep the chosen member as the final winner agent group and omit other members from the winner agents group. Also the features which are encompassed by the chosen member (final winner agent group) will construct the optimal feature agents which should be involved in the SOMAS to have an accurate diagnosis of Aphasia types.

Therefore the cycle for updating the members of the winner agents group members (as depicted in Figure 10) will continue until the MAS can automatically choose the efficient and sufficient member of the winner agents group that contains appropriate feature agents and omit the rest of the members to automatically organize an optimal structure for the MAS.

This collaboration and interaction happens when each feature agent shares its result by the members of winner agents through employing fuzzy rules and fuzzy probabilities. As an instance, member 1 of the Winner Agent Group (WAG) interacts with each of the 30 feature agents based on the following fuzzy rules and fuzzy probabilities.

Rule (1): if $x^{d_l}_{winnermember1}$ is $A^{d_1}_{winnermember1}$ with fuzzy probability $P(A^{d_1}_{winnermember1})$ and $x^{d_l}_i$ is $A^{d_1}_i$ with fuzzy probability $P(A^{d_1}_i)$ then diagnosis is Anomic with fuzzy probability $P^{d_1}_{i,wm1})$.

Rule (2): if $x^{d_l}_{winnermember1}$ is $A^{d_2}_{winnermember1}$ with fuzzy probability $P(A^{d_2}_{winnermember1})$ and $x^{d_l}_i$ is $A^{d_2}_i$ with fuzzy probability $P(A^{d_2}_i)$ then diagnosis is Broca with fuzzy probability $P^{d_2}_{i,wm1})$.

Rule (3): if $x^{d_l}_{winnermember1}$ is $A^{d_3}_{winnermember1}$ with fuzzy probability $P(A^{d_3}_{winnermember1})$ and $x^{d_l}_i$ is $A^{d_3}_i$ with fuzzy probability $P(A^{d_3}_i)$ then diagnosis is Global with fuzzy probability $P^{d_3}_{i,wm1})$.

Rule (4): if $x^{d_l}_{winnermember1}$ is $A^{d_4}_{winnermember1}$ with fuzzy probability $P(A^{d_4}_{winnermember1})$ and $x^{d_l}_i$ is $A^{d_4}_i$ with fuzzy probability $P(A^{d_4}_i)$ then diagnosis is Wernicke with fuzzy probability $P^{d_4}_{i,wm1})$.

$$P^{d_l}_{wm} = \sum_{i=1}^{v} \mu_{A^{d_l}_i}(x_i).f_i(x_i), (v \leq 30, l = 1, 2, 3, 4) \quad (7)$$

where v is the total number of selected agents in each member. Also the average performance of any interaction is calculated based on diagnosis of 4 types of Aphasia through 50 random training and testing sets. In the preceding rules, we assumed that there is just one agent in any member of the winner agents group while it can be more than one agent in any member of winner agents group that requires adding their fuzzy sets to the antecedence and consequence parts of the rules. In this order the feature agents which are sufficiently eligible for organizing the MAS in Aphasia diagnosis are chosen. The final selected agents automatically organize the optimal multi agent system which can accomplish the process of Aphasia diagnosis through result sharing. Apparently result sharing is done by the interaction and collaboration of the feature agents of the SOMAS and employment of appropriate fuzzy rules and fuzzy probability calculation (Equation (7)).

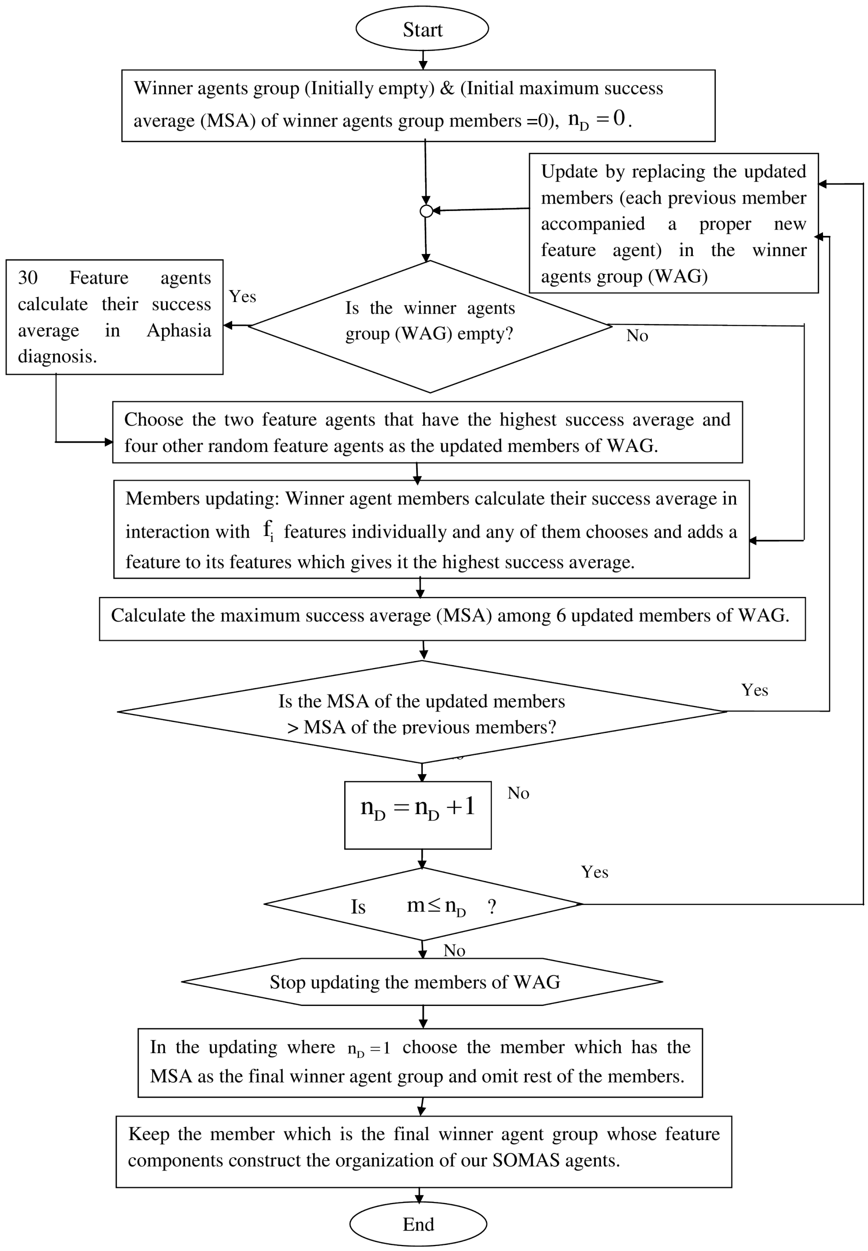

Figure 10. The Schematic Representation of SOMAS Working

5. The Results of the Proposed SOMAS Employment in Aphasia Diagnosis

By employing the SOMAS for performing the feature agents selection procedure, it is concluded that use of the interaction and result sharing of P5, T4, B1, B3, N5, N1 features (introduced in Table 1) lead to the highest average percentage of success in Aphasia diagnosis, where additional use of any other feature agent only deteriorates the maximum success average in Aphasia diagnosis. Therefore a MAS which consists of 6 feature agents for P5, T4, B1, B3, N5 and N1 is automatically generated. The fuzzy rules for the aggregation and result sharing processes for these six agents are as follows:

Rule(1): if $x_6^{d_l}$ is $A_6^{d_1}$ and $x_{11}^{d_l}$ is $A_{11}^{d_1}$ and $x_{24}^{d_l}$ is $A_{24}^{d_1}$ and $x_{26}^{d_l}$ is $A_{26}^{d_1}$ and $x_6^{d_l}$ is $A_6^{d_1}$ and $x_{18}^{d_l}$ is $A_{18}^{d_1}$ and $x_{14}^{d_l}$ is $A_{14}^{d_1}$ then diagnosis is Anomic with fuzzy probability $P_{6,11,24,26,6,18,14}^{d_1}$.

Rule(2): if $x_6^{d_l}$ is $A_6^{d_2}$ and $x_{11}^{d_l}$ is $A_{11}^{d_2}$ and $x_{24}^{d_l}$ is $A_{24}^{d_2}$ and $x_{26}^{d_l}$ is $A_{26}^{d_2}$ and $x_6^{d_l}$ is $A_6^{d_2}$ and $x_{18}^{d_l}$ is $A_{18}^{d_1}$ and $x_{14}^{d_l}$ is $A_{14}^{d_1}$ then diagnosis is Broca with fuzzy probability $P_{6,11,24,26,6,18,14}^{d_2}$.

Rule(3): if $x_6^{d_l}$ is $A_6^{d_3}$ and $x_{11}^{d_l}$ is $A_{11}^{d_3}$ and $x_{24}^{d_l}$ is $A_{24}^{d_3}$ and $x_{26}^{d_l}$ is $A_{26}^{d_3}$ and $x_6^{d_l}$ is $A_6^{d_3}$ and $x_{18}^{d_l}$ is $A_{18}^{d_1}$ and $x_{14}^{d_l}$ is $A_{14}^{d_1}$ then diagnosis is Global with fuzzy probability $P_{6,11,24,26,6,18,14}^{d_3}$.

Rule(4): if $x_6^{d_l}$ is $A_6^{d_4}$ and $x_{11}^{d_l}$ is $A_{11}^{d_4}$ and $x_{24}^{d_l}$ is $A_{24}^{d_4}$ and $x_{26}^{d_l}$ is $A_{26}^{d_4}$ and $x_6^{d_l}$ is $A_6^{d_4}$ and $x_{18}^{d_l}$ is $A_{18}^{d_1}$ and $x_{14}^{d_l}$ is $A_{14}^{d_1}$ then diagnosis is Wernicke with fuzzy probability $P_{6,11,24,26,6,18,14}^{d_4}$.

And any of the fuzzy probabilities $P_{6,11,24,26,6,18,14}^{d_l}, (l = 1,2,3,4)$ is calculated as follows

$$P_{6,11,24,26,6,18,14}^{d_l} = \sum_{i=6,11,24,26,6,18,14} \mu_{A_i^{d_l}}(x_i).f_{A_i^{d_l}}(x_i), (l = 1,2,3,4) \tag{8}$$

In the hierarchical fuzzy rule base method [2] and fuzzy probability estimator method [36] after selecting one feature this feature would not be omitted from the pool of features and could be selected again, therefore for having a fair comparison we do not omit the winner feature agents from the society of feature agents in a way that they could be chosen again.

For evaluating the results of the proposed method, we investigate and compare our results with the results of the latest methods in the field of Aphasia diagnosis using the same database: back propagation neural networks addressed in [2,36], hierarchical fuzzy rule based approach [2] and fuzzy probability estimator approach [36]. For having a fair comparison, all the methods have been iterated for 50 folds on different random training and testing sets from the same database. The topology of the neural networks addressed in [36] contains a multilayered preceptron which contains an input layer, a hidden layer and an output layer. The inputs of neural network are the measurements of P1, P5, N0 and C1 and the outputs are the four classes of Anomic, Broca, Global, Wernicke and 4-5-4 are respectively the number of neurons from the input layer to the output layer and respectively utilizes sigmoid-sigmoid-linear activation functions. Also the back propagation with momentum is

	SOMAS with fuzzy probability	Fuzzy probability estimator approach	Fuzzy hierarchical rule based approach	Neural networks
Average for 50 fold cross validation	88.56	86.13	84.88	83.47
Number of used Features	6	3	3	4
Average of column's standard deviations	2.13	9.38	9.28	11.06
Maximum gained accuracy	94.49	94.46	95.55	91.86

Table 2. Comparing SOMAS with Fuzzy Probability Approach with Other Methods

the learning method of the neural network [36]. The results of this implementation for 50 random distributions of different testing and training sets are depicted in Table 3. Due to the obtained results the average percentage of success in the 50 iterations is 83.47%. In the Table 4 we can see the results of hierarchical fuzzy rule based method [2] (a two-layered fuzzy rule-based system), this method has employed a fuzzy hierarchical system for Aphasia diagnosis and has employed the product inference engine. In this method the average percentage of success in 50 iterations is 84.88% by employing three P5, N4, B0 features. In the latest employed method, fuzzy probability estimator [36], the average percentage of success through applying 3 features of P5, N4, B0, is 86.13% (refer to Table 5). The detailed results of 50-fold running the self organized multi agent system which decides based on fuzzy probabilities are shown in Table 6. The average percentage of success in the proposed method by employing six feature agents P5, T4, B1, B3, N5, N1, is 88.56%.

It should be illustrated that the differences between the proposed method and fuzzy probability estimator method are that in the proposed method we employ a self organized multi agent system to automatically and stochastically do the feature selection procedure. In this method we stochastically allow 5 random features in addition to the first best feature to improve their performances in the group of winner agents while in the probability estimator approach, just the first best feature had this opportunity to improve itself in any updating. Furthermore, in the inference part of the fuzzy rules instead of using fuzzy probability estimator addressed in [36], we could obtain the real amount of fuzzy probabilities through employing probability mass functions calculated by self organizing networks. Also we employed triangular membership functions (MFs) instead of trapezoidal MFs to solve the problem of double diagnosis of Aphasia types in some of the cases while employing trapezoidal MFs.

Other ability of the proposed SOMAS that decides based on fuzzy probabilities is the automatic feature selection in this system which can easily save time and energy. Also it can decrease the future updating expenses while the designed system is still applicable for Aphasia diagnosis in both cases of adding new efficient features and new patients information, to update the database.

Fold number	Anomic	Broca	Global	Wernicke	Mean (of all classes)	Standard deviation (of all classes)
1	66.67	71.43	68.75	78.26	71.28	5.05
2	75.00	47.62	87.50	73.91	71.01	16.77
3	75.00	71.43	100.00	91.30	84.43	13.51
4	100.00	80.95	87.50	86.96	88.85	8.00
5	100.00	80.95	81.25	86.96	87.29	8.91
6	91.67	85.71	100.00	69.57	86.74	12.86
7	66.67	90.48	100.00	91.30	87.11	14.29
8	91.67	85.71	81.25	86.96	86.40	4.28
9	75.00	85.71	93.75	91.30	86.44	8.34
10	58.33	66.67	81.25	82.61	72.21	11.74
11	50.00	90.48	100.00	86.96	81.86	21.94
12	83.33	90.48	93.75	60.87	82.11	14.81
13	83.33	71.43	68.75	69.57	73.27	6.80
14	75.00	66.67	93.75	91.30	81.68	13.02
15	75.00	71.43	100.00	82.61	82.26	12.71
16	66.67	61.90	93.75	82.61	76.23	14.66
17	75.00	80.95	81.25	95.65	83.21	8.78
18	100.00	66.67	93.75	91.30	87.93	14.64
19	75.00	90.48	93.75	91.30	87.93	8.54
20	75.00	90.48	81.25	60.87	76.90	12.43
21	100.00	80.95	93.75	69.57	86.07	13.56
22	83.33	90.48	93.75	86.96	88.63	4.49
23	75.00	90.48	93.75	100.00	89.81	10.63
24	83.33	80.95	93.75	91.30	87.34	6.16
25	66.67	71.43	93.75	86.96	79.70	12.76
26	75.00	100.00	93.75	69.57	84.58	14.60
27	91.67	76.19	100.00	91.30	89.79	9.92
28	66.67	61.90	100.00	60.87	72.36	18.60
29	83.33	85.71	87.50	69.57	81.53	8.16
30	50.00	71.43	62.50	86.96	67.72	15.55
31	91.67	80.95	100.00	78.26	87.72	10.03
32	91.67	95.24	81.25	95.65	90.95	6.71
33	75.00	66.67	100.00	95.65	84.33	16.05
34	83.33	95.24	93.75	60.87	83.30	15.86
35	75.00	85.71	100.00	78.26	84.74	11.12
36	75.00	71.43	93.75	78.26	79.61	9.83
37	91.67	76.19	75.00	86.96	82.45	8.16
38	83.33	95.24	81.25	73.91	83.43	8.85
39	75.00	80.95	93.75	86.96	84.16	8.04
40	91.67	80.95	100.00	65.22	84.46	15.01
41	91.67	95.24	93.75	65.22	86.47	14.24
42	100.00	90.48	87.50	52.17	82.54	20.93
43	91.67	76.19	93.75	86.96	87.14	7.83
44	83.33	90.48	93.75	73.91	85.37	8.79
45	83.33	90.48	93.75	100.00	91.89	6.94
46	75.00	85.71	93.75	78.26	83.18	8.35
47	91.67	95.24	81.25	86.96	88.78	6.06
48	91.67	85.71	100.00	82.61	90.00	7.65
49	83.33	57.14	100.00	78.26	79.68	17.67
50	91.67	85.71	100.00	86.96	91.08	6.47
Mean of each column	81.00	80.76	91.00	81.13	83.47	11.22
Standard deviation of each column	12.15	11.42	9.21	11.47	5.74	
	Mean of standard deviation of the 4 columns of Anomic, Broca, Global, Wernicke is 11.06.					

Table 3. Neural Network Method Features: P1, P5, N0, and C1

Fold number	Anomic	Broca	Global	Wernicke	Mean (of all classes)	Standard deviation (of all classes)
1	66.67	85.71	100.00	82.61	83.75	13.68
2	91.67	90.48	87.50	69.57	84.80	10.31
3	75.00	90.48	100.00	91.30	89.20	10.40
4	83.33	76.19	87.50	91.30	84.58	6.47
5	91.67	80.95	93.75	78.26	86.16	7.69
6	75.00	90.48	93.75	91.30	87.63	8.54
7	100.00	95.24	100.00	86.96	95.55	6.15
8	50.00	85.71	87.50	91.30	78.63	19.23
9	58.33	95.24	87.50	91.30	83.09	16.81
10	100.00	95.24	87.50	82.61	91.34	7.77
11	66.67	95.24	93.75	82.61	84.57	13.20
12	83.33	80.95	93.75	82.61	85.16	5.81
13	75.00	90.48	75.00	86.96	81.86	8.05
14	75.00	90.48	100.00	86.96	88.11	10.33
15	83.33	85.71	100.00	82.61	87.91	8.17
16	66.67	95.24	87.50	73.91	80.83	12.92
17	75.00	95.24	81.25	82.61	83.52	8.48
18	83.33	71.43	93.75	91.30	84.95	10.05
19	66.67	90.48	87.50	95.65	85.07	12.73
20	50.00	85.71	75.00	95.65	76.59	19.63
21	100.00	80.95	93.75	69.57	86.07	13.56
22	66.67	95.24	93.75	91.30	86.74	13.48
23	83.33	80.95	93.75	95.65	88.42	7.36
24	83.33	90.48	87.50	82.61	85.98	3.69
25	66.67	85.71	87.50	95.65	83.88	12.27
26	83.33	90.48	93.75	69.57	84.28	10.73
27	83.33	61.90	93.75	65.22	76.05	15.10
28	66.67	85.71	93.75	82.61	82.18	11.36
29	66.67	90.48	87.50	82.61	81.81	10.61
30	66.67	90.48	87.50	82.61	81.81	10.61
31	75.00	90.48	93.75	86.96	86.55	8.18
32	91.67	85.71	93.75	86.96	89.52	3.81
33	58.33	100.00	87.50	69.57	78.85	18.52
34	83.33	95.24	87.50	82.61	87.17	5.79
35	66.67	95.24	93.75	82.61	84.57	13.20
36	75.00	80.95	100.00	82.61	84.64	10.75
37	75.00	80.95	81.25	91.30	82.13	6.76
38	83.33	80.95	100.00	82.61	86.72	8.91
39	50.00	85.71	68.75	95.65	75.03	20.04
40	83.33	80.95	100.00	69.57	83.46	12.56
41	83.33	90.48	87.50	82.61	85.98	3.69
42	100.00	76.19	87.50	82.61	86.57	10.08
43	83.33	76.19	93.75	78.26	82.88	7.84
44	58.33	100.00	93.75	82.61	83.67	18.36
45	66.67	76.19	93.75	100.00	84.15	15.41
46	75.00	95.24	87.50	82.61	85.09	8.50
47	91.67	85.71	75.00	73.91	81.57	8.58
48	91.67	90.48	93.75	95.65	92.89	2.29
49	100.00	100.00	87.50	82.61	92.53	8.86
50	100.00	71.43	100.00	86.96	89.60	13.58
Mean of each column	77.50	87.14	90.63	84.26	84.88	10.61
Standard deviation of each column	13.70	8.12	7.17	8.14	4.06	
	Mean of standard deviation of the 4 columns of Anomic, Broca, Global, Wernicke is 9.28.					

Table 4. Fuzzy Hierarchical Method Features: P5, N4, and B0

Fold number	Anomic	Broca	Global	Wernicke	Mean (of all classes)	Standard deviation (of all classes)
1	83.33	85.71	100.00	82.61	87.91	8.17
2	100.00	90.48	87.50	65.22	85.80	14.72
3	66.67	95.24	100.00	91.30	88.30	14.86
4	75.00	76.19	87.50	91.30	82.50	8.14
5	100.00	90.48	93.75	78.26	90.62	9.14
6	91.67	90.48	93.75	82.61	89.63	4.87
7	100.00	95.24	100.00	82.61	94.46	8.21
8	50.00	76.19	87.50	95.65	77.34	19.89
9	58.33	85.71	87.50	95.65	81.80	16.23
10	100.00	90.48	87.50	78.26	89.06	8.96
11	91.67	100.00	93.75	78.26	90.92	9.15
12	83.33	85.71	93.75	82.61	86.35	5.11
13	75.00	80.95	81.25	86.96	81.04	4.88
14	75.00	90.48	100.00	86.96	88.11	10.33
15	83.33	95.24	100.00	78.26	89.21	10.12
16	100.00	95.24	87.50	60.87	85.90	17.47
17	75.00	95.24	81.25	78.26	82.44	8.91
18	83.33	76.19	93.75	95.65	87.23	9.14
19	58.33	85.71	87.50	95.65	81.80	16.23
20	75.00	85.71	81.25	82.61	81.14	4.50
21	91.67	85.71	93.75	69.57	85.17	10.95
22	75.00	95.24	93.75	91.30	88.82	9.36
23	83.33	85.71	93.75	91.30	88.53	4.83
24	100.00	90.48	87.50	78.26	89.06	8.96
25	83.33	95.24	87.50	86.96	88.26	5.01
26	91.67	90.48	93.75	69.57	86.36	11.28
27	83.33	80.95	93.75	65.22	80.81	11.79
28	100.00	90.48	93.75	65.22	87.36	15.28
29	100.00	90.48	87.50	65.22	85.80	14.72
30	66.67	80.95	87.50	91.30	81.61	10.84
31	75.00	80.95	93.75	86.96	84.16	8.04
32	100.00	90.48	93.75	86.96	92.80	5.55
33	83.33	95.24	87.50	69.57	83.91	10.76
34	100.00	95.24	87.50	73.91	89.16	11.40
35	66.67	95.24	93.75	78.26	83.48	13.58
36	100.00	85.71	93.75	65.22	86.17	15.14
37	75.00	85.71	81.25	95.65	84.40	8.69
38	91.67	76.19	93.75	78.26	84.97	9.02
39	50.00	85.71	81.25	100.00	79.24	21.07
40	91.67	95.24	100.00	60.87	86.94	17.71
41	83.33	90.48	87.50	82.61	85.98	3.69
42	100.00	85.71	87.50	69.57	85.69	12.49
43	100.00	80.95	93.75	73.91	87.15	11.86
44	91.67	100.00	93.75	69.57	88.75	13.27
45	58.33	85.71	93.75	100.00	84.45	18.37
46	66.67	95.24	87.50	82.61	83.00	12.07
47	91.67	85.71	81.25	65.22	80.96	11.33
48	100.00	90.48	93.75	86.96	92.80	5.55
49	100.00	100.00	87.50	78.26	91.44	10.58
50	91.67	76.19	100.00	82.61	87.62	10.41
Mean of each column	84.33	88.57	91.00	80.61	86.13	10.85
Standard deviation of each column	14.64	6.60	5.53	10.77	3.70	
	Mean of standard deviation of the 4 columns of Anomic, Broca, Global, Wernicke is 9.38.					

TABLE 5. Fuzzy Probability Estimator Features: P5, N4, and B0

Fold number	Anomic	Broca	Global	Wernicke	Mean (of all classes)	Standard deviation (of all classes)
1	83.33	80.95	93.75	87.50	86.38	5.60
2	100.00	90.48	100.00	87.50	94.49	6.47
3	83.33	85.71	93.75	83.33	86.53	4.94
4	83.33	80.95	100.00	83.33	86.90	8.80
5	83.33	85.71	100.00	87.50	89.13	7.44
6	83.33	85.71	100.00	83.33	88.09	8.01
7	83.33	71.43	100.00	83.33	84.52	11.74
8	83.33	90.48	100.00	79.17	88.24	9.12
9	83.33	95.24	100.00	87.50	91.51	7.50
10	91.67	80.95	100.00	87.50	90.03	7.97
11	83.33	76.19	100.00	87.50	86.75	9.98
12	75.00	85.71	100.00	87.50	87.05	10.24
13	83.33	95.24	100.00	79.17	89.43	9.79
14	83.33	80.95	100.00	83.33	86.90	8.80
15	83.33	85.71	100.00	87.50	89.13	7.44
16	83.33	80.95	93.75	87.50	86.38	5.60
17	83.33	85.71	100.00	87.50	89.13	7.44
18	83.33	76.19	93.75	87.50	85.19	7.37
19	83.33	90.48	100.00	87.50	90.32	7.08
20	83.33	80.95	100.00	79.17	85.86	9.57
21	83.33	90.48	100.00	83.33	89.28	7.89
22	83.33	80.95	100.00	87.50	87.94	8.48
23	100.00	85.71	93.75	87.50	91.74	6.49
24	83.33	95.24	100.00	87.50	91.51	7.50
25	91.67	80.95	100.00	87.50	90.03	7.97
26	83.33	74.43	100.00	79.17	84.23	11.12
27	100.00	85.71	100.00	87.50	93.30	7.76
28	83.33	90.48	93.75	83.88	87.86	5.09
29	83.33	90.48	93.75	87.50	88.76	4.43
30	91.67	90.48	100.00	83.33	91.37	6.83
31	91.67	85.71	93.75	87.50	89.65	3.69
32	91.67	85.71	100.00	87.50	91.22	6.36
33	83.33	90.48	100.00	83.33	89.28	7.89
34	83.33	85.71	100.00	87.50	89.13	7.44
35	83.33	85.71	100.00	87.50	89.13	7.44
36	83.33	85.71	100.00	83.33	88.09	8.01
37	83.33	71.43	100.00	87.50	85.56	11.78
38	83.33	85.71	93.75	87.50	87.57	4.45
39	83.33	90.48	100.00	87.50	90.32	7.08
40	83.33	76.19	100.00	87.50	86.75	9.98
41	83.33	76.19	100.00	83.33	85.71	10.10
42	83.33	80.95	100.00	87.50	87.94	8.48
43	83.33	85.71	100.00	83.33	88.09	8.01
44	83.33	90.48	100.00	87.50	90.32	7.08
45	75.00	90.48	100.00	87.50	88.24	10.31
46	83.33	85.71	93.75	87.50	87.57	4.45
47	83.33	90.48	100.00	83.33	89.28	7.89
48	83.33	85.71	100.00	87.50	89.13	7.44
49	83.33	90.48	100.00	83.33	89.28	7.89
50	83.33	85.71	100.00	83.33	88.09	8.01
Mean of each column	84.83	85.10	98.75	85.59	88.56	7.76
Standard deviation of each column	2.13	2.68	2.52	5.08	4.96	
	Mean of standard deviation of the 4 columns of Anomic, Broca, Global, Wernicke is 3.10.					

Table 6. SOMAS Based on Fuzzy Probability, Features: P5, T4, B1, B3, N5, N1

Table 2 compares the performance of the proposed method with neural network [2], hierarchical fuzzy rule based [2], and fuzzy probability estimator [36] methods. As it can be seen in Table 2 the average percentage of success in the proposed method in 50 iterations is 88.56% while this percentage is 83.47, 84.88 and 86.13 in neural network, hierarchical fuzzy rule base and fuzzy probability estimator methods, respectively. The best result in the proposed method is 94.49% while the best result in the artificial neural network, hierarchical fuzzy rule base and fuzzy probability estimator method are respectively 91.89%, 95.55%, and 94.46%. Both of the obtained average percentage and best result in the proposed method ensures a higher precision in comparison with the previous methods. Furthermore the reliability and robustness of the proposed method results are significantly better than other methods since the average of standard deviation of this method (2.13) is considerably lower in comparison with the standard deviation averages of 3 other methods (9.38, 9.28, 11.06).

The proposed SOMAS, benefiting from automatic and stochastic feature selection as well as actual fuzzy probability calculations, shows superiority in comparison with artificial neural networks, hierarchical fuzzy rule base and fuzzy probability estimator methods in terms of a higher average success percentage of 88.56% in 50 trials. Also, the proposed method better ensures the reliability and robustness of diagnosis in comparison with other mentioned methods, due to its lower standard deviation.

6. Conclusion

We propose a general method for decision making under uncertain conditions by integrating the capabilities of fuzzy probabilities, multi agent systems and self organizing systems. The fuzzy probabilities are promoted here as a suitable paradigm for uncertainty handling, particularly when information is scarce and uncertainty is abundant. The resulting system is hence applied to medical diagnosis and specifically determining Aphasia type from interview data. The dual use of self organizing MAS (SOMAS) is shown to successfully approximate the parameters probability mass functions of the decision making process. It also shows the discrimination between effective parameters and the others. Results indicate that using only 6 of the 30 available parameters from interviews can yield to a more accurate and robust diagnosis. The proposed SOMAS with fuzzy probability outplays other previous methods employed for Aphasia diagnosis in the case of mean performance percentage and best performance, also its superior performance is reported in robustness of diagnosis.

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