

A NEURO-FUZZY SYSTEM TO SUPPORT IN THE DIAGNOSTIC OF EPILEPTIC EVENTS AND NON-EPILEPTIC EVENTS USING DIFFERENT FUZZY ARITHMETICAL OPERATIONS

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Abstract – Objective: To investigate different fuzzy arithmetical operations to support in the diagnostic of epileptic events and non epileptic events. **Method:** A neuro-fuzzy system was developed using the NEFCLASS (NEuro Fuzzy CLASSification) architecture and an artificial neural network with backpropagation learning algorithm (ANNB). **Results:** The study was composed by 244 patients with a bigger frequency of the feminine sex. The number of right decisions at the test phase, obtained by the NEFCLASS and ANNB was 83.60% and 90.16%, respectively. The best sensibility result was attained by NEFCLASS (84.90%); the best specificity result were attained by ANNB with 95.65%. **Conclusion:** The proposed neuro-fuzzy system combined the artificial neural network capabilities in the pattern classifications together with the fuzzy logic qualitative approach, leading to a bigger rate of system success.

KEY WORDS: epileptic events, non epileptic events, artificial neural network, fuzzy logic.

Um sistema neuro-difuso para auxiliar no diagnóstico de eventos epiléticos e eventos não epiléticos utilizando diferentes operações aritméticas difusas

Resumo – Objetivo: Investigar diferentes operações aritméticas difusas para auxiliar no diagnóstico de eventos epiléticos e eventos não-epiléticos. **Método:** Um sistema neuro-difuso foi desenvolvido utilizando a arquitetura NEFCLASS (NEuro Fuzzy CLASSification) e uma rede neural artificial com o algoritmo de aprendizagem backpropagation (RNAB). **Resultados:** A amostra estudada foi de 244 pacientes com maior frequência no sexo feminino. O número de decisões corretas na fase de teste, obtidas através do NEFCLASS e RNAB foi de 83,60% e 90,16%, respectivamente. O melhor resultado de sensibilidade foi obtido com o NEFCLASS (84,90%); o melhor resultado de especificidade foi obtido com a RNAB (95,65%). **Conclusão:** O sistema neuro-difuso proposto combinou a capacidade das redes neurais artificiais na classificação de padrões juntamente com a abordagem qualitativa da logica difusa, levando a maior taxa de acertos do sistema.

PALAVRAS-CHAVE: eventos epiléticos, eventos não epiléticos, rede neural artificial, lógica difusa.

Although the development of a methodology for a project of *neural-fuzzy systems* (NFS) is an activity which has been sought for two decades, it has not obtained yet a systematic procedure which may be applied to problems of different fields. This has caused the rise of several proposals which are used in special situations. The proposed article fits in this profile, with the particular feature of not seeking a general architecture, like the other proposals,

but of doing an analysis about some decisions of a prior level to the architecture itself to be utilized through fuzzy logic theory and artificial neural network

Fuzzy logic is the science of thinking and reasoning it, is an extension of binary theory that does not use crisp definitions, the fuzzy logic is a method that uses the concept of fuzziness. The properties of the *artificial neural network* (ANN) in tuning rule based fuzzy system that ap-

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proximate the way human reasoning. The synergy of ANN and fuzzy logic takes the advantages from both methodologies for learning, known as NFS.

The main contribution of the work consists of a performance analysis of different fuzzy arithmetic operations. To evaluate the proposal effectiveness, an NFS is proposed to support in the diagnostic involving the *epileptic events* (EE) and the *non epileptic events* (NEEs). Through the application and analysis of these operations, it can attain a bigger or smaller system hit rate.

METHOD

The implemented models use Mamdani's inference method which is based on the *Perceptron Multilayer* (MLP) model through the reprogramming modified algorithm¹.

In order to analyze the different arithmetic operations, the NFS have been developed. The first model has been implemented with the NEFLASS with *max/min* fuzzy pattern arithmetic operations to solve problems of pattern classifications. It can be used to determine the class or correct category from an entry pattern, which correspond to group symptoms presented by the patients².

The second model, implemented by *DELPHI 7.0* language, uses an *artificial neural network with backpropagation learning algorithm* (ANNB) based on the MLP modified algorithm, through the choice of AND/OR operators in the intermediate layer and the AND/OR in the output layer.

The network learning process consists of updating the synaptic weights, using the *Einstein's Product* fuzzy arithmetical operation for AND neurons and the *Einstein's Sum* fuzzy arithmetical operation for OR neurons, implemented with the fuzzy neuron proposed by Kwan-Cai^{3,4}.

In the NFS implementation a ANNB with fourteen input units, representing the symptoms showed by the patients and two output units is used, corresponding to an EE or NEE. The NFS input contains quantitative values, which means, quantity of presented symptoms by the patient during an EE or NEE.

In this research, the case base is subdivided into a training base and a test base, both containing parameters come from patients with EEs and NEEs. The case base is composed of two hundred and forty-four patients. Out of this total, 105 showed EEs and 139 showed NEEs. From the 244 cases which have been analyzed, 122 have been chosen at random for the composition of the training base, i.e., 52 patients with EEs and 70 patients with NEEs. The remaining cases were used in implementing the test base in the total amount of 53 patients with EEs and 69 patients with NEEs. The sample period was from March 2002 to May 2006.

The biggest frequency of patients is in the female sex belonging to a lower social class. The kind of sample was not chosen at random, selection of convenience. At the samples collection, it was used the interview technique (directed and non directed) and observation with a medical expert.

The NFS training process is interrupted when the system reaches the smallest *square mean error* (SME) approximating

the NFS exit with a desirable one, which means, the exit given by the medical expert (golden standard). The fixed error criterion was chosen because it has been opted not to use a validation set due to the small number of examples which integrate the case base.

In case of the NFS given exit be different from the one given by the medical expert, the NFS receive new values of synaptic weights and the web is trained to try again. In both models, the NFS was trained with 1,000 epochs. The goal is focused on finding the sufficient number of fuzzy rules which may correctly classify a set of input patterns, involving the EE and NEEs. The group of rules was elaborated together with the medical expert that tries to represent the biggest number of symptoms showed by the patients. When the NFS does not find the rule that satisfies the entrance characteristics (symptoms showed by patients) the NFS automatically generates the correspondent rule.

The variables of the entrance at the NFS, correspondents to epileptics patients data used in the training and test network are registered according to the *epilepsy neurological tracking* (ENT)⁵. The variables of the entrance in non epileptic patients were implemented altogether with the medical expert. It was by means of ENT that one has determined the variables which integrate the data collection system. After the interview phase, the patients' data were analyzed and, patients with non-existent data were excluded from training and test phase of NFS to support in the diagnostic of epileptic events and non epileptic events.

The model of development of the NFS to support in the clinical diagnosis of the epileptic crises was based on the classification criteria of *International League against Epilepsy* (ILAE/81)⁶.

According to Nassar⁷, the evaluation of the expert systems occurs by means of two phases: (1) evaluation of the performance system and (2) internal evaluation of the knowledge base. In this research, the implemented statistic analyses include the performance evaluation of the learning models and the internal evaluation of the knowledge base, both of them being applied in the NFS test phase.

In evaluating the performance of the models, one has chosen the hypothesis test which is grounded on an experimental situation. The hypothesis test for proportions has been chosen in view of the goal to compare the *t-norms* and *t-conorms* fuzzy arithmetical operations with the fuzzy pattern arithmetical operations which were implemented with the NEFLASS architecture, in order to either accept it or reject it⁸.

The research project has been approved by the Ethics Committee of research of the Passo Fundo University.

Epilepsy

The World Health Organization (WHO) defined epilepsy as a *disturbance of the brain, of varied etiologies, characterized by the consequent recurring crises to the excessive discharge of the cerebral neurons*, including the epilepsy in the mental upset chapter. People with epilepsy suffer from stigma and when left without treatment, suffer from serious dysfunctions. The treatment for epilepsy is frequently under the responsibility of mental health professionals, due to the great prevalence and the rel-

ative absence of specialized neurological services, especially in countries under development⁹.

The epilepsy is the most common neurological disease in population in general. One of the main worries of the psychiatrists involving this pathology is the consideration of an epilepsy diagnosis in psychiatrists patients¹⁰. Due to this reason, nowadays, researches have been developed including neurology and psychiatric aspects of epilepsy looking for an integration theory-practice between the two medical experts¹¹.

Due to the uniformity lack in the classification of the epilepsies the ILAE established an international committee to try to standardize it. They looked for the criteria in the information that can be obtained from the patients (history and clinical exam) and in the characteristics of the electroencephalogram. The first step to the diagnosis is to define if the episodes are truly epileptic or non epileptic. The history must include the description of the initial symptoms, the critical manifestations and the after critical symptoms¹². At this way, it is necessary the investigation of different qualifying systems that serve as a supportive architecture to the diagnosis involving EEs and NEEs.

After an analysis of the main features involving epilepsies and performed along with the medical expert, one has been chosen, among the variables which involve the definition of EEs and NEEs, fourteen determining features which integrate EEs and NEEs^{5,6,12-14}.

The features which attack NEEs are: (1) conversion classical symptoms, including pharyngeal spasms, digestive disturbances, contractions, body ache and paralysis; (2) sensibility disturbances (anesthesia) and sensory activity disturbances; (3) emotional factors (4) behavioral, convertible, dissociatable disturbances including panic, flights, depersonalization, somatization, hypochondria and simulation; (5) swoons and (6) disturbances, including sleep, arrhythmical endocrinal movements and fever crisis.

The features that involve the EEs are: (7) partial signs and symptoms; (8) during fainting they saw something; (9) during fainting they heard something; (10) during fainting they bit their tongue; (11) during fainting they hurt themselves; (12) duration of crises (13) after critical events, including mental confusion, sleepiness, paralyzes, vomiting and body ache; (14) generalized tonic, clonic, tonic-clonic, absence seizure (petit mal), atonic signs and symptoms. The symptoms described, including EEs and NEEs, integrate the NFS entrance variants (fuzzy neuron), registered according to the *epilepsy neurological tracking* (ENT)⁵ and was based on the classification criteria of *International League against Epilepsy* (ILAE/81)⁶.

The research is based on the main hybrid learning algorithms found in literature¹⁵⁻²³, among others.

Learning models

Initially, the NEFLASS architecture implements a rule base generated to meet, for each pattern in the training set; a rule which best classifies it. If a rule with an identical antecedent does not exist in the rule base, then this rule will be created. After all the patterns have been processed, the rule base will be complete²⁴.

The NEFLASS present fourteen entry units, one hundred forty-nine fuzzy rules and three exit units. The system has *feed forward* network architecture with three layers called C₁, C₂ e C₃. The layer C₁ represents the numeric entry of (x_1, x_2, \dots, x_{14}) values, describing the features of the input patterns to be classified symptoms presented by the patients

The Layer C₁ selects the *input* patterns. Each x_i *input* patterns meets its (μ) pertinence function according to its respective fuzzy set. In layer C₂ the fuzzy rules for classification are implemented by using E operator through the *t-norms* (*min*) function. This layer contains one mode for each IF-THEN fuzzy rule.

The fuzzy rules for classification are implemented in the following way:

$$\text{IF } (x_i \text{ igual } A_{ir}) \text{ E} \dots \text{ E } (x_n \text{ igual } A_{nr}) \text{ THEN class } C_{jr} \quad (1)$$

where,

x_n represents the features of the input patterns;

r represents the rule number ($r = 1, 2, \dots, R$);

$A_{ir} = 1, 2, \dots, n$ are fuzzy sets representing linguistic descriptions of the of the patterns features (sometimes, often, always) and

$C_{jr} =$ defines the name of the output class, where $j \in \{1, 2\}$, represents the occurrence of an EE or NEE, respectively.

The C₃ layer represents the exit units, one for each class (EE or NEE). The weights of the connections C₂ e C₃ layers are fixed in 1. Each unit in C₃ layer calculates its entry value as the sum of the exit weights of these units in layer C₂.

The second implemented model is related to the utilization of *Einstein's Sum/Product* fuzzy arithmetical operations³, as shown in Fig 1.

Layer 1: each node of this layer represents linguistic features of the input patterns. It is the layer which receives the data from the external environment and converts the patterns into fuzzy categories. The layer 1 presents fourteen input patterns.

Layer 2: the function in the layer 2 nodo is to perform antecedent matching of the inputs against the fuzzy sets they represent and compute a similarity measure known as the *membership value* (MV).

Layer 3: each node in this layer represents the IF part of the network fuzzy rule-base using the *Einstein's Product* fuzzy arithmetical operation. Each rule computes the degree of current inputs fulfillment of the with respect to the antecedents of the fuzzy rule;

Layer 4: each node in this layer represents the THEN part of the rules using the *Einstein's Sum* fuzzy arithmetical operation that hold the consequent of the fuzzy rules in layer 3;

Layer 5: this layer represents the output of the NFS, representing an EE or NEE.

The network is trained following from: (1) an training and test base; (2) an initial rules base with one hundred and forty-nine fuzzy rules which were implemented jointly with the medical expert who accompanies the research development.

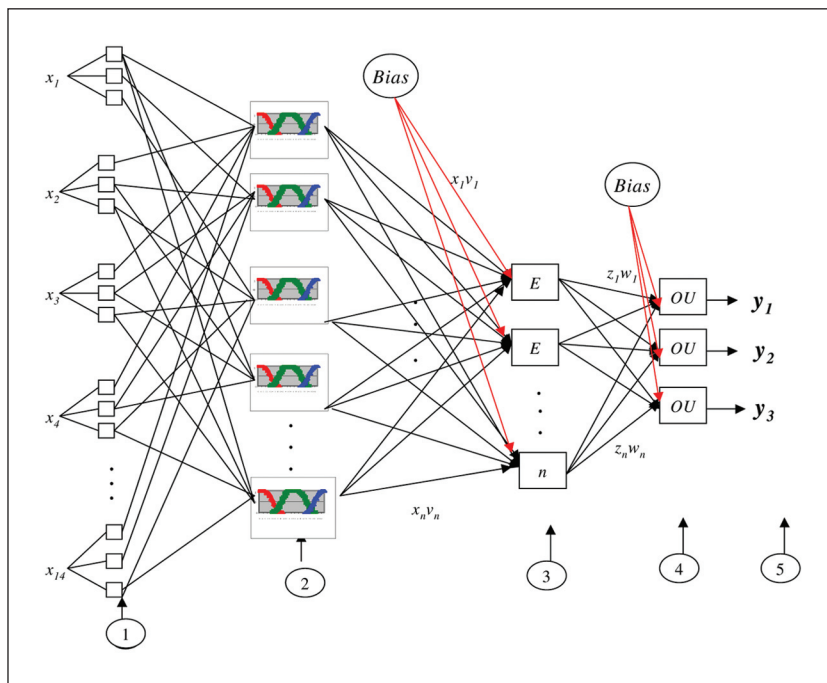


Fig 1. Artificial neural network with backpropagation learning algorithm.

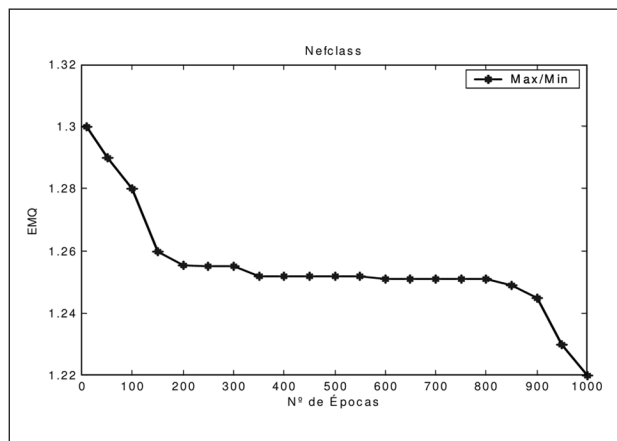


Fig 2. Max/Min fuzzy pattern arithmetic operations.

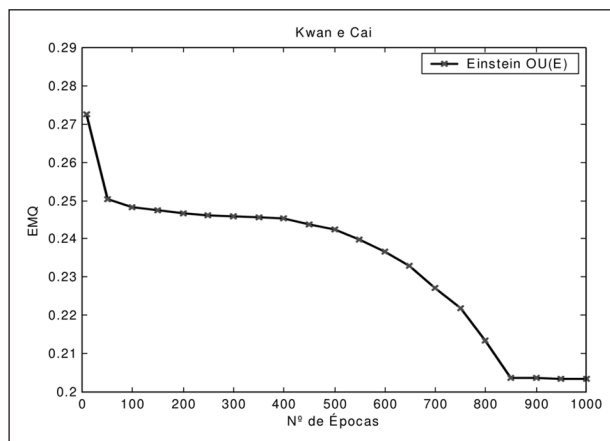


Fig 3. Einstein's Product/Sum fuzzy arithmetical operations.

RESULTS

After implementing the different fuzzy arithmetical operations, SME results by epoch, variation of the SME absolute rate and hit percentage in the training phase are described.

In the *max/min* fuzzy pattern arithmetic operations implemented with the NEFCLASS, SME remained between the values [1.30; 1.22], presenting a SME average of 1.22 and an SME absolute rate variation of 0.002 (Fig. 2). The number of right decisions at the training and test phase, presented by the NEFCLASS, was 83, 60%. It was noticed that SME decreased to the epoch of 200; afterwards, the learning remained stable, and only from the 850 epochs that learning returned to present better results.

SME referring to *Einstein's Product/Sum* fuzzy arith-

metical operations remained between the [0.27; 0.20] values, with a SME average of 0.21 and a SME absolute rate variation of 0.001 (Fig 3). The number of right decisions at the training and test phase, presented by the ANNB, was 90, 16%. It was noticed that SME minimized gradually close to the 850 epochs, and afterwards, learning remained stable until the end of training.

DISCUSSION

Only the results related to NEFCLASS architecture were confronted with literature, because up to now it has not been found references to the consulted literature related to the exploration of the different fuzzy arithmetical operations which are proposed for the research. The found

results, using the *max/min* fuzzy pattern arithmetic operations with NEFLCLASS, prove their similarity, by showing percentage hits which are compatible with the consulted literature. Conde, Ramos and Vasconcelos investigated two neuro-fuzzy systems: (1) breast cancer and (2) diabetes mellitus which presented a hit percentage of 98.28% and 76.72%, respectively²⁵. Serhatlioglu et al. investigated diabetes mellitus in (left and right) ophthalmic arteries and in the carotid arteries, obtaining a hit percentage of 85.0%, 87.5% and 85.0%, respectively^{26, 27}. Nauck and Kruse explored a neuro-fuzzy system in order to diagnose breast cancer by presenting a hit percentage of 96.5%²⁴.

For the sensibility and specificity percentiles related to NFS in order to diagnose visual glaucoma, it found hit percentiles of 96.0% and 93.4%²⁸.

The architecture explored in this research showed smaller results: 84.90% and 82, 60%, respectively.

In conclusion, from the implementations which were done NEFLCLASS and the ANNB, one has noticed that the *max/min* fuzzy pattern arithmetic operations and the *Einstein's Product* fuzzy arithmetic operation stayed at stable rates of hit, both in either the training phase and the network test phase. The ANNB presented a smaller SME than NEFLCLASS model in the test phase.

From the results presented in the internal validation of the knowledge base, the best sensibility result was attained by means of *max/min* fuzzy pattern arithmetic operations (84, 90%). The best specificity result was attained by using the fuzzy neuron proposed by Kwan-Cai by means of *Einstein's Product/Sum* fuzzy arithmetic operations (95.65%). The best percentiles of positive predictable value was attained by means of Kwan-Cai's fuzzy neuron by using the *Einstein's Product/Sum* fuzzy arithmetic operations (93.61%). As negative predictable value, the NEFLCLASS architecture, along with Kwan-Cai's fuzzy neuron presented similar results (87.69% and 88.00%), respectively.

After applying the hypothesis test to proportions, it was verified that NEFLCLASS is similar to ANNB architecture, presenting a value "p" of 0.3438 and 0.4705 respectively in relation to specificity and positiveness predictable value, an ANNB architecture was better than the NEFLCLASS architecture, showing a value "p" of 0.00053 and 0.00043, respectively.

The development of an NFS based on the utilization of these fuzzy arithmetic operations is justified, given the importance that involves the handling of different operations in the fuzzy rules base, leading to a bigger or smaller system hits rate. This technique could be used widely in a variety of medical areas.

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