Using Type-2 Fuzzy Logic Systems for Spike Detection in the Hypoxic Ischemic EEG of the Preterm Fetal Sheep

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***Abstract*— Perinatal hypoxia is a major cause of brain injury in preterm babies. Thus, neuro-protective treatments play a pivotal role during the first 6-8 hours post hypoxic-ischemic insult. However, at present it is not possible to determine which infants are suffering from hypoxic ischemia. Recent investigations suggest that there are high frequency micro-scale transients exist in the first 6-8 hours of a hypoxic ischemic EEG which could be utilized as the useful benchmarks for the prediction of hypoxia. Type-2 Fuzzy Logic Systems (Type-2 FLS) have the capability to handle inherent uncertainties in nonlinear signals. This paper describes the application of a Type-2 FLS to detect spikes in the preterm fetal sheep electroencephalogram (EEG) after asphyxia *in utero*. The Type-2 FLS differentiates each detected event in terms of its spikiness and specifies the potential events based on their degree of similarity to an EEG expert definition of a standard spike. An adaptive thresholding method has been employed in order to increase the spike detection ability of the purposed system. The sensitivity and selectivity verify enhanced performance of the Type-2 FLS for spike detection in fetal sheep EEG signals with a 98.1% and 93.7% respectively which are significantly improved in comparison to our previous methods.**

I. Introduction

Hypoxia before or during child birth plays a major role in the evolution of brain injury in preterm infants [1]. The electroencephalogram (EEG) is one of the main diagnostic tools used for the identification of neurophysiological disease and brain disorders [2]. In the EEG, when a hypoxic insult occurs, there is a 6-8 hours post insult period, called latent phase, before high amplitude epileptiform activity starts to appear (Figure 1) [3]. The latent phase can be broken down into three distinct subsections called the Early, Mid, and Late latent phase. The detection of hypoxic precursors within the latent phase would enable clinicians to increase the efficiency of further treatment [4]. At the moment, there are no exact biomarkers in the EEG defining if hypoxia has occurred or not [4]. However, high frequency micro-scale transients occur in the hypoxic ischemic EEG signal during the latent phase after hypoxia. Most of the transients are categorized among the epileptiform seizures; the different forms of which are classified as spikes, sharp waves, and slow waves with low amplitudes and high frequencies (less than 400 ms). Such transients may occur separately, in multiples, or as complexes [3, 4] and could be considered potential biomarkers of the injury. Hence, recognition of such embedded transients in the latent phase may prove beneficial in the identification of hypoxia [4-9]. Signal processing methods have shown the capability for EEG feature extraction [4, 8, 10]. A variety of signal processing techniques such as autocorrelation, time-frequency, and the wavelet transform have been used for EEG investigation [4, 6, 10, 11]. This paper is concerned with detecting the spike transients effectively in the EEG signal using fuzzy methods. The idea of fuzzy logic and fuzzy set theory, first described by Lotfi-Zadeh [12], has been employed for biomedical signal analysis. Specifically, the mathematical framework of the type 2 fuzzy conceptual reasoning allows one to handle a large portion of inherent uncertainties of a system, spontaneously [13]. In a fuzzy system, knowledge of a human expert in the field is described in linguistic terms in the rulebase of the fuzzy system [9, 12]. Thus, a system`s behaviour can be modelled using logic rules. Type-1 and Type-2 FLSs have been used in a variety of applications such as signal processing, pattern recognition, data analysis and classification, automatic control, epileptic seizure detection, and spike sorting [14-22]. The Type-2 FLS is mostly utilized in order to find a solution for nonlinear problems [23].

The spikes, sharps, and complexes have very similar shape profiles to each other (namely, similar degrees of fuzziness) [24]. A Type-2 FLS approach allows us to differentiate between such similarity degrees of fuzziness. In this paper, logical rules are firstly derived to classify what we consider as an ideal spike in the EEG of a preterm fetal sheep. Secondly, the Type-2 FLS assesses each shape profile in terms of its spikiness and determines whether it falls into the spikes group or not. Finally, we demonstrate the total performance of the Type-2 FLS is significantly more reliable than our previous methods.

II. Methods

A. Data acquisition

The EEG data sets in this study were recorded and approved by the Animal Ethics Committee of The University of Auckland [4]. Normally, a human`s brain matures between 27-30 weeks of gestation. This is the time which is coincided with a sheep gestation of 103 days. At that time, a

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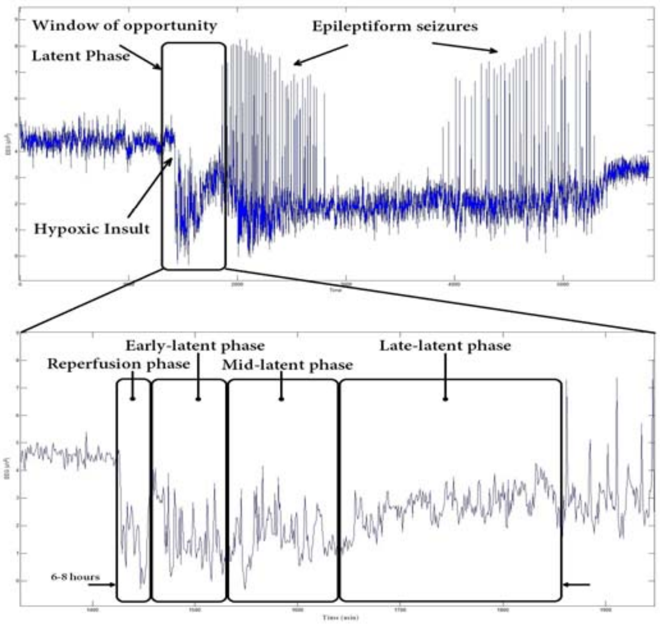

Figure 1. The Latent phase of injury after hypoxic insult

fetal asphyxia is applied by obstruction of umbilical cord for 25 minutes. Measurements of the blood composition and the completion of umbilical cord occlusion are reported in [4]. Under the afore-mentioned conditions, 8 hours post-asphyxia of the fetal EEG has been recorded and digitized at a sampling frequency of 64Hz, described in [4]. The algorithm performance was assessed over data sets with lengths of 38400 points (10 minutes). Normalization and de-meaning processes were performed on the recorded signal. An adaptive thresholding method was employed to make the algorithm EEG/Phase independent. Then, the signal features of the spikes were used in an interval Type-2 FLS membership function for final reasoning (Figure 3). In this study, spike activity detection was carried out on three 10 min durations within the latent phase after; 0.5 hour (h), 3.0 h and 6.2 h. Basically, the latent phase consists of 1) the Early-latent phase, 2) the Mid-latent phase, and 3) the Late-latent recovery phase (Figure 1). Severe EEG amplitude damping and cerebral hypoperfusion occur in the first phase. The maximum number of transient activities were observed in the mid-latent phase and also advanced metabolic deterioration commences in this interval. In addition, the total number of transients reduced in the last phase. The late-latent phase occurs exactly before the high amplitude epileptiform seizures start appearing.

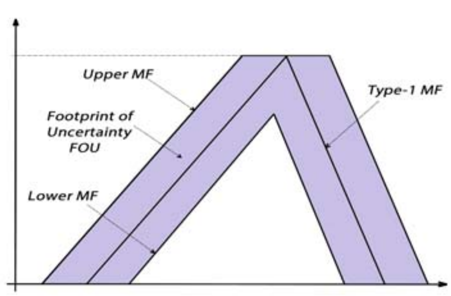

Figure 2. Footprint of Uncertainty in Type-2 FIS Membership Function

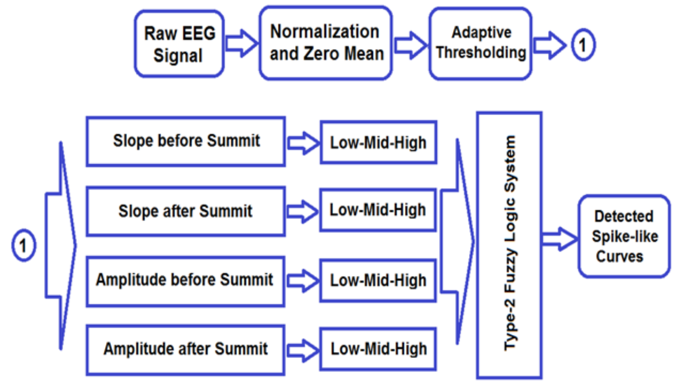

Figure 3. EEG processing by means of Type-2 Fuzzy Logic System

Initially, all the transients of the latent phase from the left EEG channel recordings were identified manually by an expert and also categorized into groups of the high frequency low amplitude transients; spikes (<70 ms), sharps (70–250 ms), slow waves (250-400 ms), and complexes (sharp waves followed by several spikes associated with slow waves) [24].

B. Fuzzy Inference System

Human reasoning about external environments is mostly approximate (analogue) rather than exact (digital). For example we say "it`s cloudy without specifying the percentage of cloudiness". The idea of a Fuzzy logic Inference System (FIS) is to design a flexible architecture which models this behaviour. As a powerful decision making system, FIS, embeds the knowledge of an expert in the field into Membership Functions (MFs). The rulebase of such a system consists of logical fuzzy rule sets which approximates human reasoning. Typically, a FIS is structured on a set of primary IF-THEN logical rules. In such a system, each rule maps multiple inputs from input MFs to one or more outputs on output MFs. In the Type-2 FLS, the union of all possible primary MFs consist of a bounded region that is called Footprint of Uncertainty (FOU) (Figure 2). This region increases the ability of the FLS to detect signals whose generic form varies within same range. A simple structure of a Type-2 fuzzy Multi Input Single Output (MISO) rule could be represented as:

$$If\ A_1^l \le x_1 \le A_1^h\ and \ldots and\ A_p^l \le x_p \le A_p^h$$

$$Then\ \ B_1^l \le z_1 \le B_1^h \qquad (1)$$

Here, x_i, z_1 are the membership values and $A_i^h, A_i^l, B_1^h, B_1^l$ are the upper and lower Type-2 input/output MFs [13]. In particular, slopes before and after the summit and amplitudes before and after the summit were employed as the Type-2 FLS inputs in a potential spike point. A triangular region of likelihood was defined in our method to locate an ideal spike as the Type-2 MFs (Figure 2). In particular, we characterize an ideal spike if it has an amplitude of greater than 20 μV and a duration of less than 70 ms (Frequency greater than 14.3 Hz). Membership functions of the Type-2 FLS were

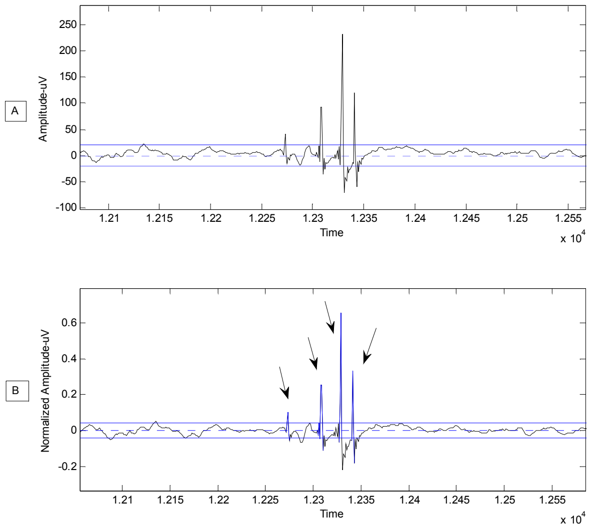

Figure 4. A section of raw EEG singnal in the Early-latent phase (A) and the corresponding Type-2 FLS correct detections (B)

configured considering the above description for an ideal spike. We also define a skew criterion (left, right, and center) of spikes. A sample of the detection boundaries for the detected spikes in the Early-latent phase is depicted in Figure 6a-c. The Type-2 FLS was employed to defuzzify the similarity of a detected sharp to an ideal spike in the EEG signal with epileptic seizures in the background (Figure 3). A sample segment of the early-latent phase and the correct detections are depicted in Figure 4. The suggested network demonstrated a good ability in the detection of multiple spikes which were close together in different situations in time (Figure 5), effectively increasing the algorithm performance.

III. RESULTS

The performance of the discussed algorithm has been assessed using the sensitivity (2) and the selectivity (3) [4]. Also the overall performance of the algorithm, the average of sensitivity and selectivity, is evaluated (4);

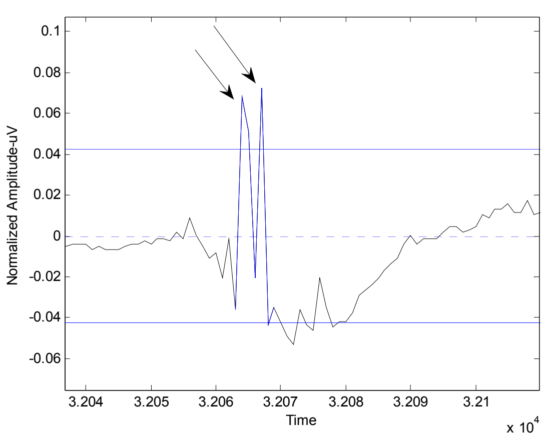

Figure 5. Detected spikes which are very close together in time

TABLE I
ALGORITHM PERFORMANCE – Early-latent phase

	Sensitivity (%)	Selectivity (%)	Overall Performance (%)
Haar Wavelet [4]	80.3	79.2	79.8
STFT [6]	82.1	78.4	80.3
Type-2 FLS detector	98.1	93.7	96.0

TABLE II
ALGORITHM PERFORMANCE – Mid-latent phase

	Sensitivity (%)	Selectivity (%)	Overall Performance (%)
Haar Wavelet [4]	81.8	82.8	82.3
STFT [6]	89.8	88.8	89.3
Type-2 FLS detector	95.5	95.5	95.5

TABLE III
ALGORITHM PERFORMANCE – Late-latent phase

	Sensitivity (%)	Selectivity (%)	Overall Performance (%)
Haar Wavelet [4]	66.3	77	71.7
STFT [6]	78.4	71.6	75
Type-2 FLS detector	73.6	81.7	77.7

$$Sensitivity = \frac{TP}{TP + FN} * 100 \quad (2)$$

$$Selectivity = \frac{TP}{TP + FP} * 100 \quad (3)$$

$$Overall\ performance = \frac{(Sensitivity + Selectivity)}{2} \quad (4)$$

A spike detection is called true positive (TP) when the spike is detected by both the algorithm and an expert; a false positive (FP) is when a spike is detected by algorithm and not by an expert and a false negative (FN) is when not detected by the algorithm and identified by an expert. In addition, the Type-2 FLS was compared against our previous methods for spike detection is the same specimen of Haar wavelet [4] and STFT [6].

The authors identified manually 213, 88, and 73 spikes in three distinct 10 min segments of the early, mid and late latent phases, respectively. The algorithm performance was calculated according to the equations (2), (3), and (4). Tables (I-III) illustrate the superiority of the Type-2 FLS detector for spike detection purposes over our previous methods. The Type-2 FLS demonstrated excellent ability in the correct detection of 209 spikes among the total number of 213 spikes in the Early-latent phase. As a result, the proposed Type-2 FLS model has detected the spikes with the overall performance of 96.0%, 95.5% and 77.7% in the Early, Mid, and Late latent phases, respectively. The maximum and minimum boundaries of all the detected spikes from three different groups over the selected segment of the Early-latent

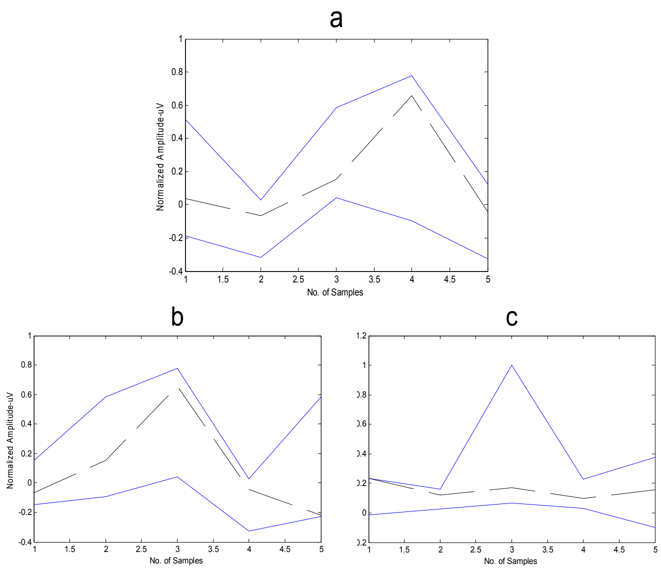

Figure 6. Three different MFs of the detected spikes in Early-latent phase. The solid lines indicate the maximum and minimum extrema of the MFs and the dashed lines indicate a sample spike detection.

phase and a sample spike in each category are depicted in figure 6a-c. These figures depict the adapted FOUs of all the true positive spike detections. In other words, a huge proportion of different spike profile shapes in a 64Hz sampled EEG can be detected using the defined MF areas of the suggested interval Type-2 FLS classifier.

IV. Conclusion

In this paper, a new method based on the Type-2 FLS has been represented for the spike identification in a preterm fetal sheep EEG signal during the latent phase of the injury after hypoxic-ischemia. Dealing with the uncertainty issues of the detection, the discussed method has shown considerable capability in the recognition of spikes from the other similar transients. The best performances (sensitivity and selectivity) were achieved for the benchmark sheep with higher number of transients in the 3 specific 10 minutes of early-, mid-, and late-latent phase, respectively; Namely, with overall performance of 96.0%, 95.5% and 77.7% were obtained for the sensitivity and selectivity factors in the Early-, Mid-, and Late-latent phase, respectively. In the late-latent phase, detection of the sharp waves with those who were appeared around 70 ms have effectively incremented the number of false positive detections and caused a marginal reduction in the algorithm performance. The Type-2 FLS algorithm has demonstrated enhanced performance in the detection of single spikes in the fetal sheep EEG signals as well as multiple spikes which are located very close to each other in time. However, in some rare cases the algorithm misinterpreted a detection of rare sensitive spikes.

References

[1] J.M. Dean, S.A. George, G. Wassink, A.J. Gunn, and L. Bennet, "Suppression of post-hypoxic-ischemic EEG transients with dizocilpine is associated with partial striatal protection in the preterm fetal sheep," Neuropharmacology, vol. 50, (no. 4), pp. 491-503, 2006.

[2] Gluckman PD, Pinal CS and Gunn AJ. Hypoxic-ischemic brain injury in the newborn: pathophysiology and potential strategies for intervention. Seminars in Neonatology, 6(2):109-120, 2001.

[3] M. Thoresen, "Hypothermia after Perinatal Asphyxia: Selection for Treatment and Cooling Protocol," The Journal of Pediatrics, vol. 158, (no. 2, Supplement 1), pp. e45-e49, 2011.

[4] Walbran, Anita C., et al. "Spike detection in the preterm fetal sheep EEG using Haar wavelet analysis." Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE. IEEE, 2011.

[5] Gabor AJ, Seyal M. Automated interictal EEG spike detection using artificial neural networks. Electroencephalogr Clin Neurophysiol 1992; 83(5):271–80.

[6] Walbran, Anita C., et al. "A semi-automated method for epileptiform transient detection in the EEG of the fetal sheep using time-frequency analysis."Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE. IEEE, 2009.

[7] Webber WRS, Litt B, Lesser RP, Fisher RS, Bankman I. Automatic EEG spike detection: what should the computer imitate? Electroencephalogr Clin Neurophysiol 1993; 87(6):364–73.

[8] Kalayci, Tulga, and Ozcan Ozdamar. "Wavelet preprocessing for automated neural network detection of EEG spikes." Engineering in Medicine and Biology Magazine, IEEE 14.2 (1995): 160-166.

[9] Balasubramanian, Karthikeyan, and Iyad Obeid. "Fuzzy logic-based spike sorting system." Journal of neuroscience methods 198.1 (2011): 125-134.

[10] Adeli H, Zhou Z, Dadmehr N. Analysis of EEG records in an epileptic patient using wavelet transform. J Neurosci Methods 2003; 123(1):69–87.

[11] Hazarika N, Chen JZ, Tsoi AC, Sergejew A. Classification of EEG signals using the wavelet transform. Signal Process 1997; 59(1):61–72.

[12] L.A. Zadeh, Fuzzy sets, Inf. Control 8 (3) (1965) 338–353.

[13] Liang, Qilian, and Jerry M. Mendel. "Interval type-2 fuzzy logic systems: theory and design." Fuzzy Systems, IEEE Transactions on 8.5 (2000): 535-550.

[14] Ajiboye, Abidemi Bolu, and R. Fff Weir. "A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control." Neural Systems and Rehabilitation Engineering, IEEE Transactions on 13.3 (2005): 280-291.

[15] Mitchell, Harvey B. "Pattern recognition using type-II fuzzy sets." Information Sciences 170.2 (2005): 409-418.

[16] Aarabi, A., R. Fazel-Rezai, and Y. Aghakhani. "A fuzzy rule-based system for epileptic seizure detection in intracranial EEG." Clinical Neurophysiology 120.9 (2009): 1648-1657.

[17] C.A. Pena-Reyes, M. Siper, A fuzzy-genetic approach to breast cancer diagnosis, Artif. Intell. Med. 17 (1999) 131–155.

[18] D. Nauck, R. Kruse, Obtaining interpretable fuzzy rules from medical data, Artif. Intell. Med. 16 (1999) 149–169.

[19] J.S.R. Jang, ANFIS: adaptive network based fuzzy inference system, IEEE Trans. Syst., Man Cybern. 23 (3) (1993) 665–683.

[20] Mendel, Jerry M. "Uncertainty, fuzzy logic, and signal processing." Signal Processing 80.6 (2000): 913-933.

[21] Ross, Timothy J. Fuzzy logic with engineering applications. John Wiley & Sons, 2009

[22] I. Virant-Klun, J. Virant, Fuzzy logic alternative for analysis in the biomedical sciences, Comput. Biomed. Res. 32 (1999) 305–321.

[23] M. Sugeno, T. Yasukawa, A fuzzy-logic based approach to qualitative modeling, IEEE Trans. Fuzzy Syst. 1 (1) (1993) 7–31.

[24] Bennet, L., L. Booth, and A. J. Gunn. "Potential biomarkers for hypoxic–ischemic encephalopathy." Seminars in Fetal and Neonatal Medicine. Vol. 15. No. 5. WB Saunders, 2010.