Superiority of High Frequency Hypoxic Ischemic EEG Signals of Fetal Sheep for Sharp Wave Detection Using Wavelet-Type 2 Fuzzy Classifiers

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***Abstract*— There is approximately a 6-8 hour window that exists from when a hypoxic-ischemic insult occurs, *in utero,* before significant irreversible brain injury occurs in new born infants. The focus of our work is to determine through the electroencephalogram (EEG) if such a hypoxic-ischemic insult has occurred such that neuro-protective treatment can be sought within this period. At present, there are no defined biomarkers in the EEG that are currently being used to help classify if a hypoxic ischemia insult has occurred. However, micro-scale transients in the form of spikes, sharps and slow waves exists that could provide precursory information whether a hypoxic-ischemic insult has occurred or not. In our previous studies we have successfully automatically identified spikes with high sensitivity and selectivity in the conventional 64Hz sampled EEG.**

This paper details the significant advantage that can be obtained in using high frequency 1024Hz sampled EEG for sharp wave detection over the typically employed 64Hz sampled EEG. This advantage is amplified when a combination of wavelet Type-2 Fuzzy Logic System (WT-Type-2-FLS) classifiers are used to identify the sharp wave transients.

By applying WT-Type-2-FLS to the 1024Hz EEG record and to the same down-sampled 64Hz EEG record we demonstrate, how the sharp wave transients detection increases significantly for high resolution 1024Hz EEG over 64Hz EEG. The WT-Type-2-FLS algorithm performance was assessed over 3 standardised time periods within the first 8 hours, post occlusion of a fetal sheep, *in utero*.

1024Hz EEG results demonstrate the algorithm detected sharps with overall performance rates of 85%, 92%, and 87% in the Early/Mid and Late-latent phases of injury, respectively as compared to 25%, 55% and 31% in the 64Hz EEG. These results demonstrate the power of Wavelet Type-2 Fuzzy Logic System at detecting sharp waves in 1024Hz EEG and suggest that there should be a movement toward recording high frequency EEG for analysis of hypoxic ischemic micro-scale transients that does not occur at present.

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I. Introduction

A major cause of brain injury in preterm infants is due to hypoxia-ischemia [1]. This is caused when the brain becomes starved of oxygen which can occur during a difficult delivery in child birth, resulting in Cerebral palsy and major handicap [2, 3]. It has been shown in the fetal sheep model of hypoxic-ischemia that the electroencephalogram (EEG) [2, 3] exhibits a 6-8 hours post insult period, known as the 'latent phase' after which epileptiform activity [2, 4] of high amplitude appears (shown in, Figure 1B). There are three distinct regions that are delimited in the latent phase period. These are known as the Early-latent, Mid-latent, and Late-latent phases which follow each other chronologically in the whole latent phase period. A very successful neuro-protective hypothermia treatment has been developed by world leaders in our team, Gunn et.al [5], that inhibits the epileptiform activity that leads Cerebral palsy and major handicap in newborns. However, such a treatment must be administered before the end of the late-latent phase to avoid brain-injury occurring.

One of the main issues that exists at present, is that there are no defined biomarkers in the EEG that are currently being used to help classify if a hypoxic-ischemic insult has occurred [6]. However, micro-scale transients with very similar profiles in the form of spikes, sharps and slow waves [4, 7] exists that could provide precursory information whether a hypoxic-ischemic insult has occurred or not. Hence, an automated recognition scheme of such embedded transients in the latent phase may prove beneficial in the identification of hypoxia-ischemia [4-6].

Time-frequency techniques such as the short-time Fourier (STFT) and Haar wavelet transform have provided some initial success in the detection of spike transients [4, 6-10] in the 64Hz sampled EEG. The Wavelet Transform (WT) method is a flexible time-frequency multi-resolution method for decomposing a signal into different frequency scales which has been employed for edge-detection in the EEG [4, 8, 9].

In Type-1 and Type-2 Fuzzy logic systems (FLS), a rule-base is derived from fuzzy set theory [10, 11] and have been employed for biomedical classification, epileptic seizure detection, and spike sorting problems as well [13-18]. In a FLS, human knowledge is imparted via logic rules [10] to the classifier where Type-2 FLS are mostly utilized in order to find a solution for nonlinear problems [11].

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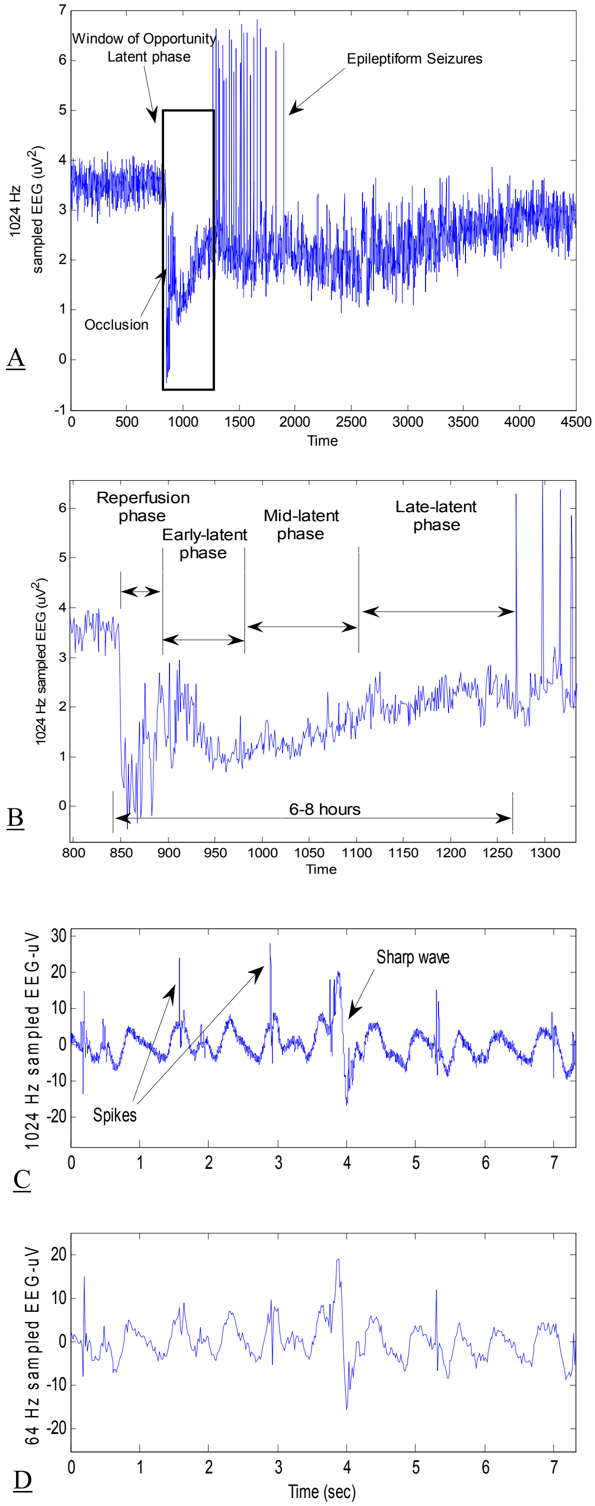

Figure 1. The Latent phase of injury after hypoxic insult (A, B) A sample 7 sec section of the original 1024 Hz signal and the down-sampled 64 Hz EEGs in this phase (C, D)

A fusion method of wavelet pre-processing combined with Artificial Neural Networks (ANNs) has been shown to improve the performance of prediction in the EEG spike detection [19] over application of ANNs performed separately. Such combinational approaches help to separate transients into a several series of wavelet-scales enabling ANNs to identify important details more easily than in the raw EEG time-series.

This work details the significant advantage that can be obtained in using high frequency 1024Hz sampled EEG for sharp wave detection over the typically employed 64Hz sampled EEG when a combination of Mexican hat wavelet Type-2 Fuzzy Logic System (WT-Type-2-FLS) classifiers are used to identify the sharp wave transients.

Firstly, the Wavelet Transform (WT) decomposes the normalized and de-meaned high frequency signal into multiple scales. Secondly, the general features of the signals are extracted in higher scales. Then, an expert interval Type-2 Fuzzy system is used to differentiate the sharp waves from the rest of the transients. The obtained results confirm the superiority of employing high frequency EEG recordings for the sharp detection in comparison with using the conventional low resolution sampled data (Figure 2).

II. Methods

A. Data acquisition

The fetal sheep EEG data sets used were approved by the Animal Ethics Committee of The University of Auckland. A sheep model was used as a maturation of a human brain at 27-30 weeks of gestation coincides with a sheep gestation of 103 days. Fetal asphyxia is applied by obstruction of the umbilical cord for 25 minutes as 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 rate of 1024 Hz, described in [4]. EEG instrumentation and hardware limitations in the in utero environment restricted us to examine up to 1024 Hz. The 1024 Hz data was then down-sampled to 64Hz to provide a second lower resolution dataset to test the hypothesis of improved prediction performance at high resolution sampling rates (Figure 1). All the sharp wave transients among the Early, Mid, and Late latent phase from the left EEG channel recordings were initially identified manually by an expert. (i.e. a sharp wave having an amplitude >20 μV and duration 70-250 ms). In this study, sharp wave detection was carried out on three 10 min durations of: 1) the Early-latent phase; 2) the Mid-latent phase, and 3) the Late-latent (Figure 1), after; 0.75 hour (h), 3.0 h and 6.3 h respectively.

B. Mexican hat wavelet decomposition

The Continues Wavelet Transform (CWT) employs localized basis functions, over Fourier Transform methods, to pick out localized frequency features that exist within a time-domain signal and decomposes the initial signal to several time-series of different wavelet-scales (*m*) in the wavelet-domain.

A sample CWT of a signal $s(t)$ is shown below:

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t)\varphi^{*}\left(\frac{t-b}{a}\right) dt \quad (1)$$

Here $\varphi(t)$ represents the mother wavelet, "*" denotes

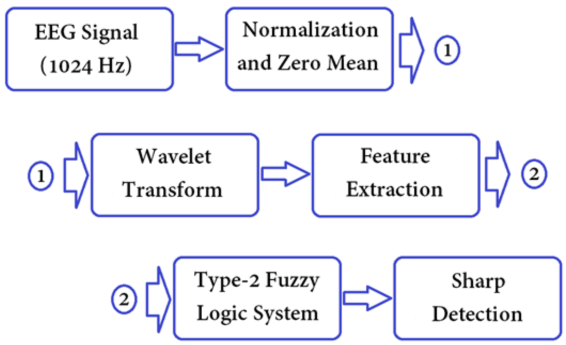

Figure 2. Suggested method for sharp wave detection

complex conjugate, and a, b are the dilation and translation factors of the mother wavelet. In this work, a Mexican hat wavelet was employed as it was found that its profile provided good correlation when applied to the sharp-wave transients. It was found that a Mexican hat wavelet scale of 32 provided a good identification of the sharp-wave transients at 1024 Hz when used in conjunction with the Type 2- FLS (Figure 4, 5).

C. Feature extraction

Using the Mexican hat wavelet scale 32 coefficients we then proceeded to extract the following features that would be fed into the Type 2-FLS as the input Membership Functions (MF) parameters of the system. The features used are described below:

1- Amplitude of the local Maxima and Minima.
2- Amplitude difference of all local extrema
3- Wave duration.
4- Slope before and after local extrema.

D. Fuzzy Inference System

The idea of a Fuzzy Logic System (FLS) is to design a flexible architecture which models human reasoning about the problem at hand. A FLS embeds the knowledge of an expert in the field into Membership Functions (MFs). Typically, a FLS 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. Defining a Footprint of Uncertainty (FOU) in an interval Type-2 fuzzy enables one to handle the uncertainties of a nonlinear problem (Figure 3). A simple structure of a Type-2 fuzzy Multi Input Single Output (MISO) rule could be represented as:

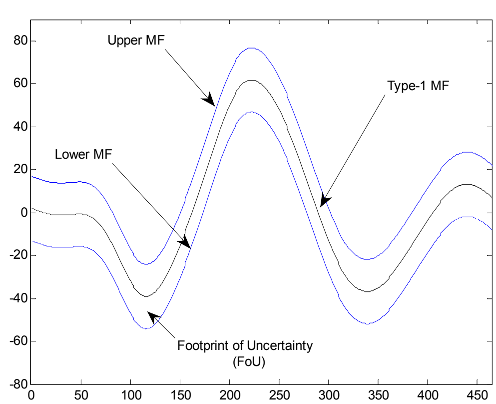

Figure 3. A sample defined Type-2 MF and the FOU

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

$$Then\ \ B_1^l \leq z_1 \leq B_1^h \qquad (2)$$

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 [12]. The features of the extracted scale 32 wavelet from section (II.C) were used as the inputs of the Type-2 Fuzzy system. After de-fuzzification, the output of the Type-2 Fuzzy would identify the potential detection of a sharp-wave.

III. RESULTS

The results from both the 1024Hz sampled and the 64Hz sampled hypoxic-ischemic EEG datasets were then assessed. The performance of the WT-Type-2-FLS was evaluated using the sensitivity, selectivity and overall performance measure [4] described in equations (3-5) respectively.

$$Sensitivity = \frac{TP}{TP + FN} * 100 \qquad (3)$$

$$Selectivity = \frac{TP}{TP + FP} * 100 \qquad (4)$$

$$Overall\ performance = \frac{(Sensitivity + Selectivity)}{2} \qquad (5)$$

Where, a: true positive (TP) occurs when a detection was both identified by the algorithm and an expert, correctly; a false positive (FP) occurred when a correct detection occurred by the algorithm and not by an expert and a false negative (FN) occurred when a spike was identified by an expert and not by the algorithm.
In this study, the expert identified 33, 5, and 35 sharp waves manually in the early, mid and late latent phases, respectively.

TABLE I
Algorithm Performance – Early-latent phase

Signal sampling rate	Sensitivity (%)	Selectivity (%)	Overall Performance (%)
64 Hz	33.33	22.00	27.67
1024 Hz	90.91	78.95	84.93

TABLE II
Algorithm Performance – Mid-latent phase

Signal sampling rate	Sensitivity (%)	Selectivity (%)	Overall Performance (%)
64 Hz	60.00	50.00	55.00
1024 Hz	100.00	83.33	91.67

TABLE III
Algorithm Performance – Late-latent phase

Signal sampling rate	Sensitivity (%)	Selectivity (%)	Overall Performance (%)
64 Hz	27.78	33.33	30.56
1024 Hz	96.97	76.19	86.58

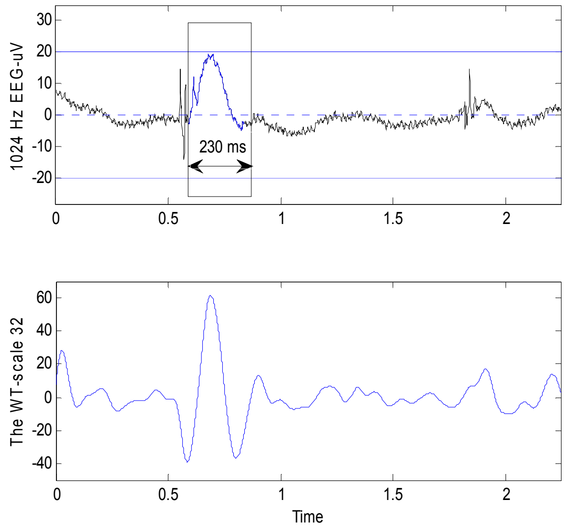

Figure 4. 1024 Hz sampled EEG from left channel and the corresponding Mexican hat wavelet coefficients in scale 32

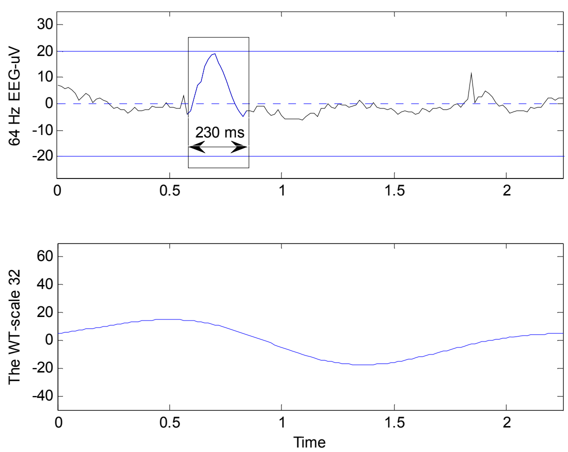

Figure 5. 64 Hz sampled EEG from left channel and the corresponding Mexican hat wavelet coefficients in scale 32

Table I-III, show the performance of the (WT-Type-2-FLS) algorithm for sharp detection for the two different sampling rates of 1024 Hz and 64 Hz. It was found that the proposed WT-Type-2-FLS method detected sharps in 1024 Hz signal with the overall performance of 84.93%, 91.67%, and 86.58% in the Early, Mid, and Late latent phases, respectively. In contrast, the sharp detection for the lower resolution sampling rate of 64Hz was 27.67%, 55% and 30.56% for the Early, Mid, and Late latent phases, respectively.

IV. Conclusion

This paper details the significant advantage to be had in the detection of sharp-waves using the WT-Type-2-FLS method on recorded hypoxic-ischemic EEG signals at high sampling rates 1024 Hz signal as opposed to the conventional 64Hz sampling rates used in clinical study.

The WT-Type-2-FLS algorithm performance was assessed over 3 standardised time periods within the first 8 hours, post occlusion of a fetal sheep, *in utero*. 1024Hz EEG results demonstrate the algorithm detected sharps with overall performance rates of 85%, 92%, and 87% in the Early/Mid and Late-latent phases of injury, respectively as compared to 25%, 55% and 31% in the 64Hz EEG. These results demonstrate the power of Wavelet Type-2 Fuzzy Logic System at detecting sharp waves over noise and distinguishing sharp waves from epileptiform activity in 1024Hz EEG, accurately and suggest that there should be a movement toward recording high frequency EEG for analysis of hypoxic ischemic micro-scale transients that does not occur at present.

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