This is the Accepted Manuscript version. This version is defined in the NISO recommended practice RP-8-2008 http://www.niso.org/publications/rp/


Copyright

Items in ResearchSpace are protected by copyright, with all rights reserved, unless otherwise indicated. Previously published items are made available in accordance with the copyright policy of the publisher.

© World Scientific Publishing Company

For more information, see General copyright, Publisher copyright, SHERPA/RoMEO.
ROBUST WAVELET STABILIZED ‘FOOTPRINTS OF UNCERTAINTY’ FOR FUZZY SYSTEM CLASSIFIERS TO AUTOMATICALLY DETECT SHARP WAVES IN THE EEG AFTER HYPOXIA ISCHEMIA

HAMID ABBASI
Department of Engineering Science, The University of Auckland
Auckland, New Zealand
h.abbasi@auckland.ac.nz

LAURA BENNET
Department of Physiology, Faculty of Medical and Health Sciences
The University of Auckland
Auckland, New Zealand
l.bennet@auckland.ac.nz

ALISTAIR J. GUNN
Department of Physiology, Faculty of Medical and Health Sciences
The University of Auckland
Auckland, New Zealand
aj.gunn@auckland.ac.nz

CHARLES P. UNSWORTH*
Department of Engineering Science, The University of Auckland
Auckland, New Zealand
c.unsworth@auckland.ac.nz

Currently, there are no developed methods to detect sharp wave transients that exist in the latent phase after hypoxia-ischemia (HI) in the Electroencephalogram (EEG) in order to determine if these micro-scale transients are potential biomarkers of HI. A major issue with sharp waves in the HI-EEG is that they possess a large variability in their sharp wave profile making it difficult to build a compact ‘Footprint of Uncertainty’ (FOU) required for ideal performance of a Type-2 Fuzzy logic system (FLS) classifier. In this article, we develop a novel computational EEG analysis method to robustly detect sharp waves using over 30 hours of post occlusion HI-EEG from an equivalent, in utero, preterm fetal sheep model cohort. We demonstrate that initial wavelet transform (WT) of the sharp waves stabilizes the variation in their profile and thus permits a highly compact FOU to be built, hence, optimizing the performance of a Type-2 FLS. We demonstrate that this method leads to higher overall performance of 94%±1 for the clinical 64Hz sampled EEG and 97%±1 for the high resolution 1024Hz sampled EEG that is improved upon over conventional standard wavelet 67%±5 and 82%±3 respectively and fuzzy approaches 88%±2 and 90%±3 respectively when performed in isolation.

Keywords: EEG, Hypoxic-Ischemic Encephalopathy (HIE), High frequency micro-scale seizures, sharp wave detection, Type-2 Fuzzy, Wavelet transform, Machine learning, Automatic detection

* Corresponding author.
1. Introduction

Hypoxia-ischemia (HI) at birth can lead to acute HI encephalopathy (HIE) and ultimately to brain injury. The risk of injury is much higher in babies born preterm \(^1\)-\(^3\). Importantly, injury evolves over time, and many brain cells die over hours to days after an HI insult \(^3\),\(^4\). This delay in injury offers a window of opportunity for neuroprotective treatments. Pre-clinical animal studies in term fetuses and neonates have shown that after a severe HI insult, there is restoration of oxidative metabolism in a “latent” phase lasting around 6 hours. This is followed by a secondary loss of oxidative metabolism lasting around 48-72 hours, during which time most brain cells die \(^2\),\(^4\). The timing of these phases is broadly similar for the preterm brain \(^5\),\(^6\). Cerebral hypothermia is now used clinically for term infants with evidence of moderate to severe HIE \(^2\),\(^4\),\(^7\), but animal studies show that it is only effective if started during the latent phase of recovery \(^2\),\(^4\). Clinically, despite starting cooling early after birth, only one baby in every 6-8 benefits from hypothermia \(^7\). This, largely, reflects the fact that many babies are born with brain injury which has evolved beyond the latent phase \(^6\).

However, currently, we do not have reliable biomarkers which can allow us to determine the phase of injury and thus which babies will benefit from treatment \(^5\). Such biomarkers would also help refine the use of hypothermia for term infants, and for the development of new neuroprotection therapies for term and preterm babies. Electroencephalographic (EEG) monitoring is increasingly used to assess the neurological well-being of newborn infants \(^3\). Two lead amplitude-integrated EEG (aEEG) recordings are most commonly used to assess newborn EEG. Although aEEG readily identifies large amplitude seizures it does not readily allow for detection of more subtle low amplitude high frequency events \(^3\) which our preclinical animal studies have shown are important \(^3\),\(^6\). A number of other pre-clinical and clinical studies have been conducted on existence of HI transients along the EEG which have shown a correlation between events and outcomes \(^8\)-\(^10\). Our pre-clinical observations in preterm fetal sheep after asphyxia, using raw signals from two lead EEG recordings, have shown that high frequency epileptiform transients (spikes, sharps and slow-waves) \(^5\),\(^11\),\(^12\) occur primarily in the latent phase peaking around 2-3 hours after the end of HI \(^5\),\(^13\),\(^14\) and that numbers of latent phase transients correlate with neurological outcome \(^5\),\(^6\). Thus, transient identification and quantification in the latent phase of injury may provide useful biomarkers for identifying and assessing preterm infants who have been exposed to HI (Figure 1). The present study addresses ways of automatic detection of sharp wave epileptiform transients in the EEG after HI. In contrast, the majority of research to date has focussed on automatic diagnosis of neurological disorders \(^15\) as well as automatic detection of spike waves for seizure detection, in the epileptic EEG, summarized in papers involving prediction with linear and nonlinear methods \(^16\), wavelet methods \(^17\),\(^18\), spike sorting techniques \(^19\), kernel methods \(^20\),\(^21\) and neural network prediction \(^22\)-\(^24\) with some cot side systems being available \(^25\). HI induced seizures have been studied in several animal models, reviewed in \(^26\) with morphological operators being used to improve automated spike wave detection in seizures \(^27\) and unsupervised methods \(^28\) from the HI EEG of the neonatal rat. We have previously reported the utility of short-time Fourier (STFT), Haar and Reverse Bi-orthogonal wavelet transform (WT) and Type-2 fuzzy logic system (FLS) classifiers for spike transient identification \(^11\),\(^12\),\(^29\),\(^30\) in the EEG sampled at 64Hz from preterm fetal sheep. Automated detection methods since 2011 have been reported to improve the accuracy of seizure detection in the HI EEG of human neonates \(^31\). These studies have demonstrated that quantitative EEG (qEEG) measures such as relative delta power, skewness, kurtosis, amplitude, and discontinuity can be used to separate between HIE grades. A neonatal HI EEG research group, Temko et.al, have applied support vector machines (SVMs) to discriminate between seizure and non-seizure EEG epochs \(^32\),\(^33\), and probabilistic modelling to improve the prediction of seizures in the EEG of neonates exposed to HI \(^34\),\(^35\).
By contrast, our work differs by being concerned in the identification of HI sharp wave epileptiform transients in the latent phase of the EEG, before high amplitude seizures occur. There is no current method for the accurate identification and quantification of sharp wave transients in the EEG after HI. Fetal sheep EEG data are often collected at a relatively low sampling rate of 64Hz, which could also limit the accurate detection and quantification of transients 5, 11, 12, 29. This is in comparison to human models which use the clinical sample rates of 64Hz have been employed in 36, 37 and recently higher sample rates of 256Hz employed in 32, 33. We have recently presented preliminary results of how the WT-Type-2-FLS method can detect sharp wave transients at a conference 38. This paper presents, for the first time, a WT-Type-2-FLS method to accurately detect and quantify epileptiform sharp wave transients in the EEG recorded after HI and determines a suitable wavelet for both typical clinical 64Hz sampling of the EEG and high, research-based sampling at 1024Hz.

Current work is performed using over 30 hours of data collected after HI induced by a period of umbilical cord occlusion from a cohort of preterm-equivalent, anaesthetized fetal sheep, studied in utero. This provided more than 5000 individual sharp waves for analysis, which is larger than studied in most previous studies 39. We demonstrate that a significant performance gain can be achieved using the developed WT-Type-2-FLS method over standalone wavelet or fuzzy methods.

2. Data Acquisition

2.1. Experimental procedures

All the animal procedures for acquisition of the data sets were approved by the Animal Ethics Committee of the University of Auckland and in accordance with the Animal Welfare Act (1999) of New Zealand. Data used in this study were obtained from preterm fetal sheep at 0.7 gestation (equivalent to a 27-30 week human in terms of brain maturation) 40. Under general anesthesia and using aseptic techniques, five fetal sheep were instrumented with catheters and electrodes as previously described 5, 13. For the purposes of this study, 4 EEG electrodes (two on the left side of the head, two on the right side of the head), plus a ground electrode were used in the measurement of fetal EEG (made in-house from AS633-5SSF wire; Cooner Wire, Chatsworth, CA, USA). These electrodes were placed through burr holes onto the dura over the parasagittal parietal cortex (5 and 10 mm anterior to bregma and 5 mm lateral). A standard montage was not used rather one electrode was used to measure the potential difference relative to the second electrode on the left side of the head, and similarly this was performed for the two electrodes on the right side of the head. The data sets used in the study were drawn from the differential set of electrodes on the left side of the head. Burr holes were filled with surgical bone wax and the electrodes secured with cyanoacrylate glue. A reference electrode was sewn over the occiput. We use EEG recorded from the extradural space because the fetus is highly active and suspended in an electrolyte solution similar to plasma, that is to say, the amniotic fluid. In this unique environment extradural recordings provide a far superior signal to surface recordings with minimal movement artifact. We anticipate that higher-frequencies recorded on the extradural surface may have greater resolution than surface EEG, as suggested by 41. These issues are much less important in the postnatal environment where preterm infants are not able to move much. A silicone occluder was placed around the umbilical cord, for later inflation to produce HI. Fetuses were returned to the uterus, and ewes and their fetuses were allowed five days to recovery from surgery and anesthesia before experiments began. Fetuses were studied at 103.4±0.6 days (term =147 days). On the day of experiment fetal HI was induced by complete occlusion of the umbilical cord for 25 minutes 5, 13. The occluder was then released, fetuses returned to normoxic conditions, and the fetal EEG was studied during the first 6 hours of recovery (the latent phase).

2.2. Data collection

EEG data were continuously recorded through two channels using Labview (Labview for Windows, National Instruments, TX, USA) and digitized at a sampling frequency of 1024 Hz. For reliable high resolution EEG sampling, EEG signals were recorded via leads through a head-stage with an overall gain of 10,000 which aided primary noise reduction of the signal. Analogue signals were then processed with a 6th order low-pass Butterworth anti-aliasing filter, with cutoff frequency of 512 Hz and a high-pass filter of 1.6 Hz. EEG signals were saved at 1024 Hz. Since the study was conducted in utero there was no need to have an additional notch filter to filter out 50Hz. The recorded data were then decoded and extracted into Matlab for analysis. In order to compare the performance of the WT-Type-2-FLS to typical sampling rates in fetal sheep
Robust Wavelet Stabilized FOU for Type-2 Fuzzy Classifiers

In this paper, we demonstrate how the initial application of a suitably chosen wavelet transform can be used to stabilize the transformed sharp wave profiles considerably. This then allows for a robust FOU to be built that can be subsequently passed to a Type-2-FLS classifier resulting in high performance in comparison to the direct application of wavelet and fuzzy methods separately to the original sharp waves in post-HI EEG recordings.

3. Methods
In this section, we introduce wavelet transform (WT) methods and fuzzy logic system (FLS) classifiers. This is followed by an overview of our developed WT-Type-2 FLS classifier and the feature extraction necessary to provide reliable identification of sharp waves in high and low frequency sampled post-HI EEG signals.
3.1. The Wavelet Transform

The Wavelet Transform (WT) is a flexible time-frequency multi-resolution technique that can decompose a signal into different frequency scales 46. 47. Wavelet techniques have broad application in medical and biomedical fields such as monitoring fetal and adult heart rate variability, ECG feature extraction and diagnostic assessment and frequency decomposition of ultrasound images 47-49. They have been extensively applied to analysis of epileptiform activity 17, brain MRI 50, diagnosis of ADHD 51, Alzheimer’s diseases 52-55 and autistic spectrum disorder 56. Although, some recent works, based on the metaheuristics and enhanced probabilistic neural network, have shown enhancements for combination of classifiers and cluster ensembles 57-60, but wavelet techniques are highly useful for many facets of signal processing, such as: edge detection, approximation, compression, de-noising and classification 61. The Continuous Wavelet Transform (CWT) of a signal \( s(t) \) is defined as

\[
CWT(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t)\phi^*\left(\frac{t-b}{a}\right) dt \tag{1}
\]

Where \( \phi(t) \) represents a basis function known as the ‘Mother wavelet’, ‘\(^*\)’ denotes complex conjugate, and \( a, b \) are the dilation and translation factors of the mother wavelet 61. 62. The two key properties of wavelets are ‘dilation’ where the mother wavelet becomes “stretched” to different scales and “translation” where the scaled wavelet is shifted in time. It is the “dilating and translating” of a chosen mother wavelet that allows one to correlate it with similar hidden events in a signal. This discloses the frequency and location of the desired event in time and helps one to detect specific shape profiles.

3.2. Justifying an appropriate wavelet basis

Initial determination of an appropriate wavelet family was made by visually inspecting the similarity that a wavelet had to a sharp wave. On observation of a typical sharp profile, Daubechies and Gaussian wavelet families intuitively came to mind. We then narrowed this choice down further, by determining which wavelet in the family provided the highest cross-correlation 63 and the lowest minimum Shannon entropy 61 to the sharp wave at both 64Hz and 1024Hz sampling rates. For completeness, this was performed on the Daubechies and Gaussian wavelet families 64 for the wavelets with vanishing moments 1-3 with software written in Matlab.

The normalised cross-correlation was determined for every sharp wave profile against each individual wavelet in the Daubechies and Gaussian wavelet families, for vanishing moments 1-3. The ‘average normalised cross-correlation’, figure 3(A) was then determined for each individual wavelet in the Daubechies and Gaussian wavelet families, for vanishing moments 1-3 from all the normalized cross-correlations of every sharp wave profile. The Minimum Shannon entropy criterion 61, S, was also used to assess how similar the wavelets in the Daubechies and Gaussian wavelet families, figure 3(B), for vanishing moments 1-3 were to the sharp waves.

As one can observe from Figure 3(A) and figure 3(B) both the Gaussian 2 and Daubechies 2 wavelet provided the highest cross-correlations and minimum Shannon entropies for both the 1024Hz and 64Hz versions of the sharp wave signals. It was found that scale 15 of Daubechies 2 corresponded to the temporal length of the 64Hz sharp waves and scale 32 corresponded to the temporal length of the 1024Hz sharp waves. Thus, we would hypothesise that Gaussian 2 and Daubechies 2 wavelets would be reasonable and logical choice for sharp wave detection. This is also in agreement with the ‘general rule of thumb’: that the number of vanishing moments of the wavelet should tally with the same number of vanishing moments as a sharp wave respectively (namely, 2). In section 4.1, we initially assess how the Gaussian 2, scale 32 and Daubechies 2, scale 15 wavelets perform (i.e. a wavelet-only approach) when directly applied at different magnitude threshold values (0.4-0.7) in the 64Hz and 1024Hz sampled HI EEG.

3.3. Fuzzy Inference Systems

Fuzzy logic systems (FLS) 65 provide a framework to embed human observed priories via a set of logic rule-bases 66 known as Type-1 and Type-2 Fuzzy Logic Systems (FLS) 65. 66. FLSs have been used in biomedical classification of epileptic seizure and spike sorting applications 29. 67-71 as well as diagnosis of autism spectrum disorder and ADHD 72,73. Fuzzy Logic Systems (FLS) 47, 74, 75 are structured on a set of primary IF-THEN logical rules which are used to embed the knowledge of an expert into the FLS’s Membership Functions (MFs).

In such a system, each rule maps multiple inputs from input MFs to one or more outputs on output MFs. Type-1 FLS are very specific and do not accommodate variance of the signal of interest well, which is a common
problem in real-world data and when noise is present. The Type-2 FLS overcomes the issues encountered in Type-1 FLS by employing a Footprint of Uncertainty (FOU), namely a region which accounts for the variance that exists in the signal of interest. In this study, the FOU consists of all the MFs that represent a collection of sharp waves identified by an expert. Thus, a typical format of a Type-2 fuzzy Multi Input Single Output (MISO) rule for a Type-2 fuzzy classifier for the detection of sharp waves is represented as:

\[
\text{If } f(LMF) \leq f(W(signal)) \leq f(UMF),
\]

\[
\text{Then } \text{Class is 'Sharp wave detected'}
\]

\[
\text{Else } \text{Class is 'Not Sharp wave'}
\]

Where, \(LMF\) and \(UMF\) are the lower and upper Type-2 input MFs, respectively. Several Type-2 Fuzzy rules are then defined by an expert in the rule-base of the purposed Type-2 FLS classifier. In this study, these rules are executed, known as ‘firing, on the wavelet decomposition of the post-HI EEG and the output of the Type-2 FLS classifier identifies whether a detection of a sharp-wave has occurred.

3.4. The WT-Type-2-Fuzzy classifier

In this article, we hypothesize that the wavelet transform of the raw sharp waves will provide a more robust FOU than a FOU based directly on the raw sharp wave profiles themselves, hence, significantly improving the performance of Fuzzy Type-2 classifier. As will be discussed later in section 4.2, the FOUs built from the sharp waves directly had large variance and were not robust. Thus, we hypothesize that stable FOUs could be obtained by performing an initial wavelet transformation using an appropriate wavelet basis and using the transformed signal to indirectly build compact FOUs. Thus, all that would be necessary would be to visually identify a suitable wavelet scale that provided a smooth compact transformation.

3.5. Performance measures

For the sensitivity and selectivity criteria, equations 3 to 5 were used to evaluate the performance of the WT-Type-2-FLS classifier, defined as:

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100
\]

\[
\text{Selectivity} = \frac{TP}{TP + FP} \times 100
\]

4. Results

In this section, we present performance results for the detection of sharp waves in the post-HI EEG of the preterm fetal sheep using the following methods:

(i) Conventional Wavelet Performance – performance of Gaussian 2, scale 32 and Daubechies 2, scale 15 wavelets applied directly to the post-HI EEG of the fetal sheep for varying magnitude threshold values (detailed in section 4.1).

(ii) Conventional Type-2 Fuzzy Performance – performance of Type-2-Fuzzy classifier applied to FOUs built directly from the raw sharp waves themselves of the post-HI EEG of the fetal sheep (detailed in section 4.2).
(iii) Performance of the developed WT-Type-2-Fuzzy classifier where the FOUs are indirectly built up from the wavelet transformations of the sharp waves of the post-HI EEG of the fetal sheep (detailed in section 4.3).

4.1. Conventional Wavelet Performance

We initially assessed how the Gaussian 2, scale 32 and Daubechies 2, scale 15 wavelets performed when directly applied at different magnitude threshold values in the 64Hz and 1024Hz sampled HI EEG. Results from the wavelet-only approach are presented in figure 4.

Figure 4 shows the average overall performance, using the recordings from all 5 sheep, of the wavelet-only approach for different threshold levels for the Daubechies 2, scale 15 wavelet applied to the 64Hz EEG (dotted line-red squares) and the Gaussian 2, scale 32 wavelet applied to the 1024Hz EEG (solid line-blue circles). It can be seen that the average overall performance increases to a maximum of 67.4% ± 4.7 for the Daubechies 2, scale 15 wavelet of the 64Hz EEG and 82.1% ± 3.0 for the Gaussian 2, scale 32 wavelet of the 1024Hz EEG when the threshold value is 0.5 and decreases thereafter. Hence, the best detector of sharp waves using a standard wavelet-only approach would be the Gaussian 2, scale 32 wavelet when used on a 1024Hz sampled EEG. It was found that higher numbers of false positives (FP) and false negatives (FN) contributed to the reduced overall performance of the wavelet-only method.

4.2. Conventional Type-2 Fuzzy Performance

FOUs were constructed directly from sharp waves by defining an envelope around the mean to build an FOU, for all the different combinations of the sheep cohort, shown in Figure 5(A) for the 64Hz sampled EEG, and Figure 5(B) for the 1024Hz sampled EEG. FOUs constructed directly from the sharp waves did not provide stable and consistent FOUs, as shown in figure 5(A-B), which should lead to a low performance of the Type-2-FLS classifier due to large variance in the FOU. Figure 10(A), highlights the low performance expected of the Type-2-FLS using the FOU’s defined using 1,2,3 and 4 sheep (where the method of building a robust FOU is described in detail in section 4.4) due to the large variance FOU’s of Figure 5(A-B).

4.3. The Developed WT-Type-2-Fuzzy Performance

Smooth compact transformations were observed for the Gaussian 2 wavelet at scale 3 for the 64Hz sampled post-HI EEG, figure 6(B) and at scale 32 for the 1024Hz sampled post-HI EEG, figure 6(H). For the Daubechies 2 wavelet, smooth compact transformations were observed at scale 3 in the 64Hz sampled post-HI EEG, figure 7(C), however, no smooth compact support was observed for the 1024Hz sampled post-HI EEG, figure 7(F-H).

FOUs were then built from wavelet transformations of the sharp waves for the scales that were identified as having smooth compact wavelet transformations. Figure 8 shows the FOUs obtained from the Gaussian 2 transformations for scale 3 at 64Hz and scale 32 at 1024Hz. As can be seen, the FOUs built from the wavelet transformations of the sharp waves, figure 8(B), are highly compact and should result in a good Type-2 FLS performance. Figure 9(A) shows the FOUs obtained from the Daubechies 2 transformation for scale 15 at 64Hz. As can be seen, the FOUs built from this selected scale is also highly compact and should result in a good Type-2 FLS performance. We have also included the FOU of a highly irregular wavelet transformation, figure 9(B), which corresponds to Daubechies 2, scale 32 at 1024Hz shown in figure 7(H), to highlight how this leads to a non-stable FOU which should yield a poor classification performance. The developed WT-Type-2-Fuzzy system then took particular features from the FOUs, described above, to build a fuzzy rule-base that could be then passed to the Type-2-Fuzzy classifier. We define 2 features of the FOU: the function that defines the envelope of the upper bounds of all the wavelet transformed sharp waves, denoted as the Upper Membership Function (UMF), and the function that defines the envelope of the lower bounds of all the wavelet transformed sharp waves, denoted as the Lower Membership Function (LMF). In this manner, the wavelet transformed (W) EEG was passed to the Type-2-Fuzzy classifier and performance was measured against an experts prior identification of the sharps waves in the EEG.

4.4. Building a robust FOU

We next addressed the question of how many sharp waves are necessary to build a suitable FOU that was sufficiently reliable to predict the unseen sharp waves to a high degree of accuracy. In addition, one consideration of the nature of this work is the experimentally difficulty, expense and time required to obtain data from the sheep model in utero (described in section 2.2). Thus, obtaining an FOU from as few sheep as possible would be highly
desirable. Our approach to tackling this issue was to build separate FOU’s from the whole latent phases of sheep 1, 2, 3 and 4. The constructed FOUs could then be tested out on the remaining sheep whose latent phase was not used in building the FOU’s. For example, the top row of Figure 5(A) depicts the FOU’s constructed from the raw sharp waves that existed in the entire latent phase for each of the 5 sheep. Thus, the FOU for sheep fetus 1 in figure 5(A) could be considered to be our training set and the prediction performance of this FOU could be estimated by essentially validating it on the average number of sharps correctly detected in the latent phases of the remaining sheep fetus’s 2, 3, 4 and 5. In addition, this approach could be ‘bootstrapped’ by then using the FOU of sheep fetus 2 and validating it on the average number of sharps correctly detected in the latent phases of the remaining sheep 1, 3, 4, and 5. Furthermore, FOU’s were then constructed of 2 sheep, 3 sheep and 4 sheep (as shown in figure 5, rows 2-4) and tested on the remaining sheep and permutating in a similar manner as described above for 1 sheep. The bootstrapped results from using the raw sharp wave profiles (Figure 5) as well as the wavelet transformed envelopes (Figures 8 and 9) are given in sections 4.2 and 4.3 for the different FOUs, respectively.

5. Discussion

Figure 10(A) highlights the Type-2-FLS classifier’s overall bootstrapped performance, using training sets consisting of 1-4 sheep, when passed the FOUs built from

Fig. 4. The Average Overall Performance (for 5 sheep) using a standard wavelet-only approach for different threshold values. Gaussian 2, scale 32 wavelet applied to 1024Hz EEG (solid line-blue circles), Daubechies 2, scale 15 applied to 64Hz EEG (dotted line-red squares).

Fig. 5. Typical FOUs defined for the Type-2-FLS using all the raw sharp waves for all the different combinations of the sheep cohort for: (A) 64Hz sampled EEG, (B) 1024Hz sampled EEG.
the raw sharp waves themselves (where the dotted line represents the 64Hz sampled EEG and the solid line the 1024Hz EEG). Similarly, Figure 10(B) highlights how the Type-2-FLS overall bootstrapped performance, using training sets consisting of 1-4 sheep, when passed the FOUs built from the wavelet transformed sharp waves (where the dotted lines again represents the 64Hz sampled EEG and the solid lines the 1024Hz EEG). It can be seen that the Type-2-FLS classifier performance improved in all cases as the FOUs were built by increasing the sheep cohort to 4.

The best performing Type-2-FLS classifier occurred when the FOUs were built from Gaussian 2, scale 32 wavelet transformations of the sharps waves for a 1024Hz sampled EEG. This provided an excellent overall performance of 97%±1, as shown in Figure 10(B). This was followed by a Type-2-FLS classifier, where the FOUs were built from Daubechies 2, scale 15, wavelet transformations of the sharp waves for a 64Hz sampled EEG, with an overall performance of 94%±1, Figure 10(B). It should be noted that both these Type-2-FLS classifiers were the ones identified as having the most stable compact wavelet transformed FOU in Figures 8(B) and 9(A) respectively. The third performing Type-2-FLS classifier used FOUs built from Gaussian 2, scale 3, wavelet transformations of the sharp waves for a 64Hz sampled EEG, with an overall performance of 93%±1, Figure 10(B). The fourth and fifth performing Type-2-FLS classifiers, were the ones where the FOUs were built from raw sharps waves for the 1024Hz and 64Hz sampled EEGs, with overall performance of 90%±3 and 88%±2, respectively, Figure 10(A). The sixth performing Type-2-FLS classifier involved FOUs built from Daubechies 2, scale 32, wavelet transformations of the sharp waves from the 1024Hz sampled EEG, with an overall performance of 83%±2, Figure 10(B). As mentioned in 4.3, this corresponded to a highly irregular, non-stable FOU that should yield a poor classification performance.

For standard equivalent wavelet-only detection, described in Section 4.1 - Figure 4, the performance was found to be 67%±5 for the Daubechies 2, scale 15 wavelet for the 64Hz EEG compared to the 94%±1 for a WT-Type-2-FLS classifier, where the FOUs were built from Daubechies 2, scale 15, wavelet transformations of the sharps waves for the 64Hz sampled EEG. Similarly, for wavelet-only detection, the performance was found to be 82%±3 for the Gaussian 2, scale 32 wavelet of the
Robust Wavelet Stabilized FOU for Type-2 Fuzzy Classifiers

Gaussian 2 Wavelet FOU

Fig. 8. FOU obtained from: (A) Gaussian 2, scale 3 at 64Hz and (B) the Gaussian 2, scale 32 at 1024Hz

Daubechies 2 Wavelet FOU

Fig. 9. FOU obtained from: (A) Daubechies 2, scale 15 at 64Hz (B) Daubechies 2, scale 32 at 1024Hz
1024Hz EEG compared to 97%±1 for a Type-2-FLS classifier, where the FOUs were built from Gaussian 2, scale 32, wavelet transformations of the sharp waves from the 1024Hz sampled EEG.

Thus, it is evident that the robust performance of the Type-2-FLS classifier was dependent on building a compact FOUs, strongly supporting our hypothesis that a FOU built from a suitable chosen wavelet transformation of the sharp waves provides superior performance over FOUs built from raw sharp waves alone.

The work presented here is concerned specifically on the automatic detection of sharp wave epileptiform transients in the latent phase of the EEG of hypoxic ischemic fetal sheep model, which differ in amplitude and duration to sharp waves detected in conventional human EEG. To this end the technique is unique and novel as no other group to date has developed detection methods specifically for this type of sharp wave in this HI animal model as human HI EEG has been concerned primarily with improving the accuracy of seizure detection in the HI EEG of human neonates.

The only work to date in this area has been our published preliminary results of a more simplified version of the WT-Type-2-FLS method at conference level. This paper presents, for the first time, a WT-Type-2-FLS method to accurately detect sharp wave transients in the EEG recorded after HI and determines a suitable wavelet for both typical clinical 64Hz sampling of the EEG and high, research-based sampling at 1024Hz.

Here we showed that the simplified version of the algorithm which only used certain feature points in the FOU, rather than the whole envelope which we perform in this paper, provided an average overall performance rate of 88% for the detection of sharp waves over the whole latent phase using a Gaussian 2 wavelet. This is in comparison to the 97% obtained here using the whole envelope, thus, providing an improvement of 9% over the simpler method for 1024Hz sampled EEG. The simplified version of the WT-Type-2-FLS method performed even more poorly for the 64Hz sampled EEG providing an average overall performance rate of 37% for the detection of sharp waves over the whole latent phase using a Gaussian 2 wavelet. The performance was dramatically improved upon in the more detailed work presented here obtaining a 94% overall performance using a Daubechies 2 wavelet and the whole envelope as the FOU. Thus, providing an improvement of 57% over the simpler method for 64Hz sampled EEG.

6. Conclusion

In this article, we demonstrate, for the first time, that it is possible to robustly detect sharp wave epileptiform transients accurately in over 30 hours of post-HI EEG for the in utero preterm fetal sheep. It was shown that this is possible through initial wavelet transformation of the sharp waves, which serves to stabilize the variation in their profile, and thus permits a highly compact FOU to be built, which in turn optimized the performance of a Type-2 FLS classifier. We demonstrated that this method leads to higher overall performance for both a 64Hz sampled EEG and a high resolution 1024Hz sampled EEG.
EEG, compared with both conventional standard wavelet and fuzzy approaches undertaken in isolation. This study shows that the developed wavelet stabilized FOU method for Type-2-FLS classifiers can be exploited for the identification of epileptiform sharp wave transients during the latent phase of recovery from severe HI in a preterm-equivalent large animal. It should be noted that whilst we have optimized the developed detection method to identify the particular signatures of the sharp wave epileptiform transient in the preterm fetal sheep model, since the approach is generic, it would be possible to adapt the method to detect other forms of epileptiform transient activity and to human models in both children and adults. We believe that this highly automated approach will be valuable for future studies to determine if these micro-scale epileptiform transients are biomarkers of HI.

Acknowledgements

- The work was sponsored by the Health Research Council of New Zealand (HRC grant number 12/613).
- We would also like to acknowledge the contribution of NeSI high-performance computing facilities to the results of this research. URL https://www.nesi.org.nz.

References

sparse representation. *International Journal of Neural Systems*, 24(04), 1450015.
64. Daubechies, I. (1992). *Ten lectures on wavelets* SIAM.
