ScrutiniseIT: A Search-Based Approach to EEG Seizure Detection

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***Abstract*—Seizures are both the most common neurological emergency afflicting neonates and the most difficult to detect clinically. Currently, the monitoring of a multi-channel electroencephalogram (EEG) is the gold standard for seizure detection. The accurate analysis of this physiological data requires a neurophysiologist with expertise in neonatal EEG. The provisioning of this expertise on a continuous basis can be challenging for medical facilities. In this paper, we describe a cloud-based platform capable of supporting clinicians through the creation of expert knowledge repositories. While the platform is considered general purpose, in this work it is applied specifically to neonatal EEG.**

***Keywords*—e-health, Seizure detection, Cloud computing, expert knowledge, search, signal processing, EEG**

I. Introduction

There is a correlation between the quality of care given to a patient and the availability of expert knowledge, particularly that which enables specialist care [1]. Therefore, there is a need for a platform capable of alleviating issues affecting the provisioning of this expert knowledge. We propose a platform that would be capable of broadening the scope of expertise, both human and machine, available to medical centres.

The ScrutiniseIT platform is based on a *scan-and-scrutinise* methodology. It incorporates the scalability benefits of cloud computing, enabling large volumes of physiological data to be continuously analysed for the identification of features of interest. It relies on expert annotations to the data and an algorithm designed to search through existing data repositories. The scan phase of the algorithm runs continually on data streams being acquired. A simple evaluation function is used to determine data segments that warrant closer examination. Upon detection of a potential feature of interest, that section of the stream is more closely scrutinised. The scrutinise phase determines if particular features of interest are present in the candidate signal. This is done within a specified confidence interval.

ScrutiniseIT is a live platform that affords clinicians the ability to collaboratively enhance one another's work. Clinicians annotate new data to highlight the occurrence of interesting features, this data becomes part of the overall annotated data repository. Subsequent processing of the data repository will be influenced by these contributions, thus improving the quality of the system over time.

The remainder of this paper is organised as follows: Section II provides an overview of related work on classification techniques for seizures in EEG, Section III describes the technologies that make up the system and provides details of their implementation, Section IV outlines our proposals for the experimental evaluation of the platform. Finally, our conclusions and future work are discussed in Section V.

II. Related Work

Numerous EEG seizure detection algorithms, using a variety of signal processing techniques, have been described in the literature. In [2], the authors present a neural network based system that operates in five stages: filtering, artifact detection, feature extraction (of both candidate and non candidate data), redundancy and relevance analysis. In [3], the author proposes the use of Discrete Wavelet Transformation, in an effort to find an improved time frequency representation of EEG and improve classification results.

In [4] three algorithms (Celka *et al.*, Gotman *et al.* and Liu *et al.*) for the automated analysis of neonatal EEG are evaluated. The algorithms employ a variety of classification

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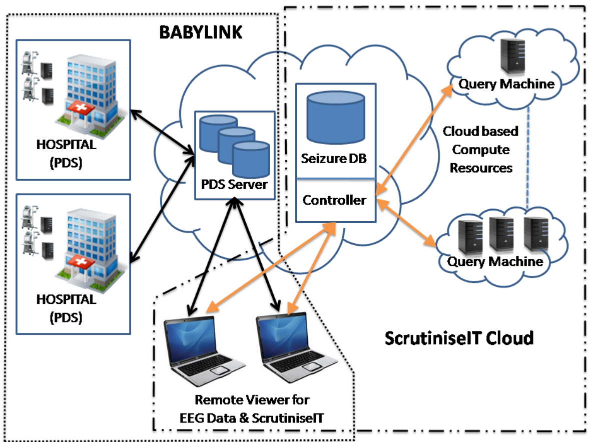

Figure 1. A high level view of the platform showing the BabyLink and ScrutiniseIT components.

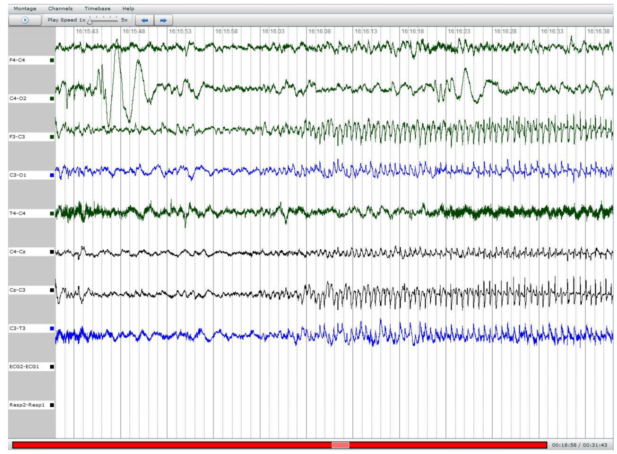

Figure 2. The view of EEG provided to a clinician through the BabyLink viewer. Seizure is visible on channels F3-C3, Cz-C3, C3-01, C3-T3, C4-Cz, so predominantly on the left hemisphere of the brain.

techniques, such as modelling, complexity analysis, rhythmic discharge detection and auto-correlative functions. The algorithms were found to have sensitivities ranging from 42.9% to 66.1% and specificities ranging from 54% to 90.2%.

In [5], it is argued that classifier based approaches are too rigid due to large variance in a neonate's signal frequency, morphology and topography. Instead, the authors attempt to mimic the behaviour of human experts through the creation of an algorithm that recognises the characteristics that enable humans to detect seizures. The algorithm focuses on the background EEG and the recurrence of patterns in the signal as a means of providing automated neonatal seizure detection. While this is an interesting approach, it can be considered a variant of traditional classification techniques.

III. PLATFORM OVERVIEW

The algorithms described in Section II tend to use tried-and-tested signal processing techniques. However, this approach results in a static system that tries to identify seizures based on a single formula that does not change. The platform described in this paper uses a novel search-based approach to seizure detection that relies on comparison with a growing body of historical data. As such, it does not compete with traditional signal processing techniques, although these can be incorporated where appropriate during the matching phase. The platform utilises cloud computing in order to provide a scalable seizure detection service. The processing of EEG can be computationally expensive, availing of cloud infrastructure allows us to employ more resources when necessary. The platform is based on two components, BabyLink and ScrutiniseIT, each of which is described in detail below. An overview of the complete platform is depicted in Figure 1.

A. BabyLink

The Physiological Data Server (PDS), presented in [6], a web-based remote monitoring system that allows physiological data streams to be viewed in near-real-time, while acquisition is ongoing, via a web interface. This forms the core of the BabyLink part of the platform. Users are presented with a continuously updating view of the entire data stream, allowing them to view new data as they arrive or review data transferred earlier. The view presented closely resembles that found in the NICU and offers a similar interface to that seen in a traditional EEG monitoring machine. The only tool required for viewing EEG data using BabyLink is a modern web browser with the commonly available Adobe Flash plugin installed.

BabyLink's remote monitoring functionality was further extended, as described in [7], through the introduction of a facility to annotate data whilst reviewing it. Three top-level annotations were made available; *events*, *comments* and *waveform classifications*. Events indicate occurrences at the acquisition location. Comments are general, free-form text markup of the signal data. Waveform classifications represent a categorisation of a recording segment by a human analyst.

BabyLink also incorporates an agent framework, as described in [8]. This enhances the remote monitoring system by allowing a user-configurable set of agents to perform analysis on physiological signals as they are streamed through the system. The output of the agents assist with the analysts' interpretation of the data being streamed through the provision of alternate visualisations and automatically created annotations.

BabyLink is the gateway from the hospital to the platform. Enabling a clinician to analyse a patients data stream, toggle on or off continuous monitoring, or annotate a segment as a feature of interest. The agent framework enables the continuous acquisition of EEG and transmission of the data in real time, ensuring the that the platform is capable of "scrutinising" it as described in the next section.

B. ScrutiniseIT

ScrutiniseIT uses a *scan-and-scrutinise* approach to seizure detection, in which a candidate EEG is compared to a set of known seizures that have been obtained previously. The EEG data stream is treated as a series of epochs. Each epoch

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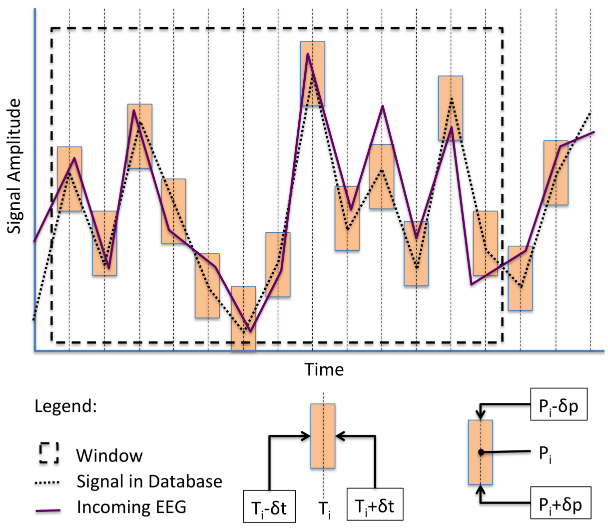

Figure 3. Signal matching in a ScrutiniseIT search.

is examined for potential matches to the database of known seizures. Once a pre-determined threshold has been reached the potential for a match is noted, processing of that epoch ceases, and the process continues by advancing to the next epoch. The size of the epoch is defined by the Window Size (WS) parameter described below. A match occurs when a series of points observed match a similar series in the database.

ScrutiniseIT integrates with BabyLink via the agent framework described in Section III-A. Through the tuning of different parameters, the algorithm can either accelerate its search through the EEG (*scanning*), or perform slower, more detailed, analysis (*scrutinising*). These parameters are:

- **Confidence:** a percentage value indicating a minimum threshold that must be exceeded before a match with a feature of interest is recognised. The higher the confidence specified, the more exacting the match must be before the feature is reported.
- **Window Size (WS):** ScrutiniseIT uses a dynamic sliding window to contextually analyse a candidate signal pattern. Larger windows are used during the scan phase when trying to identify regions of interest in the candidate signal. When such a region is identified, the window size contracts appropriately to scrutinise these regions in more detail in an attempt to report features for a given confidence.
- **Grain Size (GS):** ScrutiniseIT operates by matching turning points in the incoming EEG with similar points in the database of known seizures. The grain size specifies the number of points required for a match to occur and is used to determine when an advance to the next epoch is triggered. The larger the grain size the greater the accuracy of the resulting matches.
- **Threshold Deltas δt, δp** : Matches are compared on each point at time +/- δt, and with accuracy +/- δp.

Figure 3 illustrates the matching process in action. The dotted line shows a sample signal from the database. Each turning point in the signal has a known amplitude which represents a point of interest. The window size being examined is encapsulated by the dashed rectangle. For each point of interest, the boundaries defined by the δt and δp points are shown as a shaded rectangle. The candidate signal is compared against the database of known signals. Although, in this case, the candidate signal exhibits a slightly different form; within the given window there are 11 matches out of 13 possible turning points exhibiting a confidence rating in the order of 84%. If a confidence rating less than 84% had been specified a match would have being reported, if greater than 84% no match would have occurred.

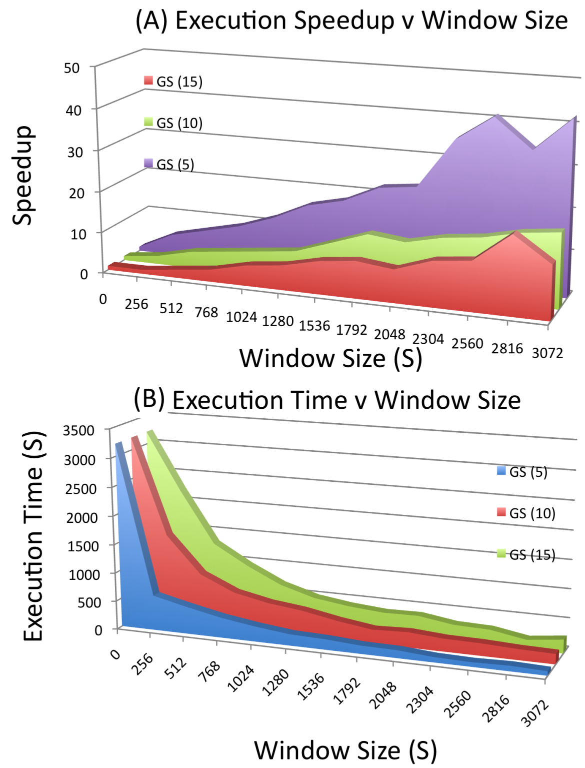

Figure 4. Preliminary results from ScrutiniseIT evaluation.

There is a trade-off between the time taken to process the signal and the search parameters such as window size (WS) and grain size (GS). The data shown in Table I illustrates this, the larger the window size the faster the algorithm executes but the less accurate the match with the points stored in the database, similarly the smaller the grain size, the faster the algorithm executes but the less accurate the match.

Therefore, our initial results show that a larger grain size will yield more accurate matches but at a cost of slower execution time. During our preliminary tests we have observed that for signals containing no known seizures, the number of matches is tiny.

Table I
RESULTS OBTAINED FROM A NUMBER OF SEARCHES ALTERING WS AND GS VALUES. SPEEDUP OBTAINED IS ALSO SHOWN.

WS	GS = 5 Time(s)	Matches	GS=10 Time(s)	Matches	GS=15 Time(s)	Matches	Speedup GS=5	GS=10	GS=15
0	3216	1840	3216	920	3216	613	1	1	1
256	612	176	1536	113	2208	108	5	2	1
512	476	65	898	60	1303	59	7	4	2
768	354	43	634	42	962	40	9	5	3
1024	266	33	511	31	677	32	12	6	5
1280	199	26	441	25	503	25	16	7	6
1536	183	21	329	23	420	21	18	10	8
1792	144	18	244	18	371	18	22	13	9
2048	137	16	268	17	381	16	23	12	8
2304	92	14	224	14	290	14	35	14	11
2560	79	13	216	14	273	13	41	15	12
2816	95	12	189	12	168	12	34	17	19
3072	76	11	178	10	241	11	42	18	13

IV. EVALUATION

Initial tests of ScrutiniseIT have been conducted with a limited database of known seizures. An excerpt of the results from these tests are listed in Table I and depicted in Figure 4. In Figure 4(A) total execution speedup obtained versus selected window size is shown. Three sets of results are shown for different grain sizes. It can be seen that significant speedup can be achieved by selecting a smaller grain size, albeit at the cost of a reduction in the quality of matches. For the tests illustrated in this example, a confidence value of 70% was chosen.

Figure 4(B) illustrates that, as window size is increased, the total execution time is reduced. This is due to the reduced number of epochs that are available for selection. If a significant number of contiguous matches are found, the platform begins the scanning process at the next epoch. So, larger window sizes result in faster, less accurate, searches.

Although the results presented here are preliminary, they are encouraging. To further development, the platform will be evaluated in collaboration with the Neonatal Brain Research Group (NBRG, based in Cork University Maternity Hospital, Cork, Ireland) who have extensive expertise in neonatal EEG and have assembled a data repository consisting of over 800 hours of multi channel EEG containing more than a thousand seizures as well as a validation set comprising 70 neonates (35 seizure/35 non seizure). The main focus of the evaluation will be on the performance of the scan-and-scrutinise algorithm.

V. CONCLUSIONS AND FUTURE WORK

The scan-and-scrutinise approach to seizure detection in neonatal EEG is novel in that:

- Incoming EEG data is compared with a database of known seizures, this is in contrast to more typical approaches that apply generalised formulae.
- The provision of the system as a web service will allow it to evolve over time.

While this is a work in progress, further investigations into the effectiveness of the platform are ongoing, particularly in identifying optimal configurations that balance speed with accuracy.

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