Development of an Algorithm for the Automatic Detection of Artifacts in Neonatal Electroencephalography

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“We may feel ill prepared to face the feared changes ahead, yet each of us can look back at our own lives and see countless times that something felt scary, hard and impossible. We were sure we wouldn’t make it, and then we did. This is resilience - the willingness to persist, to learn from the experience, and to try again.”

Sarina Behar Natkin
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Resumo

Todos os dias, bebés recém-nascidos são admitidos em inúmeras Unidades de Cuidados Intensivos Neonatais (UCIN). As causas para estas admissões passam principalmente por nascimentos prematuros ou outros tipos de complicações durante o parto, como é o caso da asfixia.

Visto que quaisquer complicações durante o parto podem levar a Acidentes Vasculares Cerebrais (AVC’s) ou outro tipo de danos no cérebro, os recém-nascidos são admitidos por períodos de tempo que podem chegar às 72 horas. Neste período de admissão, os bebés do hospital pediátrico de Utrecht, nos Países Baixos, são acompanhados por uma equipa de médicos e enfermeiros sempre presente, ao mesmo tempo que são altamente monitorizados, tanto em termos da sua atividade cerebral – através de eletroencefalografia (EEG) – como de outros parâmetros fisiológicos, como o ritmo cardíaco - eletrocardiografia (ECG) -, função respiratória ou mesmo oxigenação cerebral através de espetroscopia do infravermelho próximo (Near Infra-red Spectroscopy – NIRS).

Dadas as longas aquisições dos vários parâmetros fisiológicos, dos quais a atividade cerebral medida através de EEG é tida em especial foco nesta dissertação, é normal que ocorram perturbações nas leituras, sejam essas perturbações de origem fisiológica ou não. Assim sendo, os artefactos, i.e., os períodos de informação de EEG que não representam corretamente a atividade cerebral do indivíduo, corrompem a integridade da aquisição de dados, podendo mesmo levar a decisões erradas no que diz respeito ao diagnóstico do paciente ou a opções terapêuticas. Um dos grandes obstáculos neste campo é o facto de muitos artefactos terem um carácter periódico e altamente rítmico e serem comumente identificados como convulsões pelos algoritmos de deteção de convulsões, levando muitas vezes à administração de medicação excessiva e/ou errada nos pacientes na UCIN.

Atualmente já existem algoritmos de deteção de artefactos em EEG, os quais se baseiam principalmente em características espaciais dos sinais de EEG – às quais não é possível recorrer neste caso, visto que se usam apenas dois canais bipolares – ou na Análise de Componentes Independentes (ICA), a qual separa os sinais de EEG nos diferentes componentes presentes no sinal. Como já foi referido, com apenas dois canais de EEG não se torna viável aplicar esta análise porque o resultado seria demasiado reduzido para ser possível alcançar uma decisão de confiança. Estes algoritmos já desenvolvidos focam-se principalmente nos artefactos mais comumente presentes nos dados, como os da atividade ocular, muscular e cardíaca.

Posto isto, o projeto desenvolvido na presente dissertação propõe um novo método de deteção de artefactos em sinais de EEG neonatal. Atualmente podem ser encontrados no EEG da UCIN sete tipos diferentes de artefactos:

- Ondas Sinusoidais – ondas que se assemelham em tudo à função matemática sinusoidal e que têm uma frequência característica entre os 1.5 Hz e os 3 Hz;
- Ondas tipo PED (*Periodic Epileptiform Discharges*) – estas ondas assemelham-se a ondas características de episódios epiléticos, mas devido ao facto de possuírem uma forma diferente e não terem causa fisiológica conhecida são consideradas como artefactos;

- Ondas Zeta – ondas delta (com frequência inferior a 4 Hz) com uma forma de serra e que se encontram no EEG durante períodos de tempo reduzidos;

- Oscilações de Alta Frequência – embora não tenham uma frequência particularmente alta para os valores que o EEG pode atingir, estes artefactos são caracterizados por uma onda sinusoidal constante com uma frequência entre os 8 Hz e os 11 Hz;

- Atividade Muscular – como o nome indica, a atividade muscular na cabeça dos recém-nascidos pode influenciar a leitura dos elétrodos, introduzindo uma aquisição com maior frequência e de menor amplitud;

- Atividade Cardíaca – o campo elétrico do batimento cardíaco é conduzido até ao escálepe, onde se encontram os elétrodos agulha, influenciando a leitura dos mesmos e levando a um sinal de EEG que se assemelha bastante à de um ECG;

- Movimento/Deslocação dos Elétrodos – Quando os bebés são movidos ou quando se administra algum tipo de medicação pode haver deslocamento dos elétrodos colocados no escálepe e a leitura pode atingir valores demasiado elevados, que não têm justificação fisiológica.

Desta forma, o algoritmo para deteção de artefactos desenvolvido focou-se primeiramente na criação de sete algoritmos individuais, cada um especializado nas características de cada um dos artefactos mencionados acima. Para cada algoritmo individual foi criada uma base de dados de EEG de cinco sujeitos, que serviu para o treino e para o teste de cada algoritmo. O EEG de cada sujeito tinha aproximadamente 30 minutos e eram períodos com uma forte presença de artefactos. Estes períodos foram selecionados especialmente para este projeto e todos os artefactos presentes nos dados foram marcados manualmente por uma médica especializada, de forma a que os algoritmos tivessem um *golden standard* para que fosse possível comparar os seus resultados e otimizar cada algoritmo. Desta forma, foram considerados neste projeto aquisições de EEG de 28 sujeitos diferentes: cinco para cada algoritmo, à exceção do algoritmo para a Atividade Muscular que teve apenas três sujeitos e o do Movimento, que não necessitou de nenhum.

Durante o desenvolvimento de cada algoritmo foram sempre considerados os resultados de Sensibilidade e Especificidade através da comparação com as marcações manuais do *golden standard* da base de dados de treino e teste, de forma a otimizar cada algoritmo e obter sempre os melhores resultados possíveis.

Para os três primeiros artefactos (Ondas Sinusoidais, tipo PED e Zeta) os algoritmos baseiam-se no cálculo da correlação do sinal com uma onda substituta que tem uma forma igual à do artefacto em questão. Quando a correlação for superior a um determinado valor limite definido pelo utilizador, o algoritmo considera a presença desse artefacto, indicando-o no resultado final. Estes valores
limites são diferentes para cada algoritmo devido às características de cada artefato e à forma como cada algoritmo foi desenvolvido. O algoritmo para as Oscilações de Alta Frequência tem como base a compressão no tempo do sinal de EEG, de forma a obter um sinal semelhante ao de aEEG (EEG de amplitude integrada), o qual permite uma identificação mais fácil do artefacto, método este que é utilizado de forma semelhante para o artefacto da Atividade Cardíaca. O algoritmo para a Atividade Muscular baseia-se numa função que calcula a distância entre pontos consecutivos, visto que este consiste num sinal com menor amplitude, mas com variações de valores mais abruptas entre pontos consecutivos, permitindo identificar os períodos de sinal artefactual. Por fim, o algoritmo para o artefacto de Movimento e/ou Deslocalização dos Elétrodos baseia-se no valor máximo absoluto que o EEG pode tomar. Desta forma, no início do algoritmo o utilizador deve introduzir a idade do sujeito em questão e para cada valor (entre 23 e 42 semanas gestacionais) haverá valores máximos e mínimos aceites na literatura como fisiologicamente normal. Se o EEG estiver acima ou abaixo (respetivamente) desses limites, é considerado como artefactual.

Após o desenvolvimento de todos os algoritmos individuais, estes foram combinados num só algoritmo de deteção de artefatos em EGG neonatal. Este algoritmo final requer apenas que o utilizador indique a idade do sujeito em que o EEG foi adquirido e que artefato é que pretende detetar. Desta forma, o algoritmo ainda não é totalmente independente do utilizador, pois confia que o mesmo fará uma rápida avaliação visual do sinal a analisar e que consegue identificar qual o artefacto presente no EEG, permitindo ao algoritmo identificar com maior exatidão os períodos em que os artefatos se iniciam e terminam.

De forma a analisar os resultados finais do algoritmo de deteção de artefatos, foram calculadas as taxas de Verdadeiros Positivos, Falsos Positivos e Falsos Negativos. O algoritmo final, englobando todos os algoritmos individuais, obteve uma taxa de Verdadeiros Positivos de 92,4% ± 7,5%, uma taxa de Falsos Positivos de 34,9% ± 19,8% e uma taxa de Falsos Negativos de 7,7% ± 7,5%.

Como se pode observar pelas percentagens obtidas, o algoritmo conseguiu identificar corretamente mais de 90% dos artefatos presentes nos dados, o que se traduz numa deteção correta e de confiança. A taxa dos Falsos Positivos ainda poderá ser foco de otimização, uma vez que é passível de ser reduzida através de mais dados para treinar e testar os algoritmos, conduzindo então a uma maior precisão dos valores limite que separam os períodos artefactuals daqueles que correspondem a atividade cerebral verdadeira. Já a percentagem dos Falsos Negativos, ou seja, as vezes que o algoritmo não detetou um artefacto quando este estava de facto presente no sinal, não é exessivamente alta e foi considerada reduzida o suficiente pelo pessoal médico quando estes resultados lhes foram apresentados.

O projeto apresentado nesta dissertação propõe então um primeiro passo no desenvolvimento do primeiro algoritmo que considera sete artefatos distintos, pelo que ainda há tópicos que merecem otimização – como os valores limite definidos -, havendo também a necessidade da inclusão de mais dados de sujeitos diferentes para poder treinar e testar os algoritmos individuais, de forma a evitar o sobre-ajuste dos métodos aos dados disponíveis.
Palavras-chave: Deteção de Artefatos; EEG Neonatal
Abstract

Artifacts - erroneous information in the acquisition of the brain activity – in the EEG reading of newborns that are admitted in the NICU is a major problem that can have serious consequences, both in diagnostic and therapeutic-related decisions, as some artifacts can easily be mistaken for seizures, leading to wrongful administration of medication. These artifacts can have various origins and its manual identification in the EEG trace is highly time-consuming, reason why there is the need to develop an algorithm that can automatically detect the artifacts in the EEG acquisitions.

The algorithm developed in this dissertation proposes to detect seven distinct types of artifacts commonly found in neonatal EEG: Sinus waves, PED-Like waves, Zeta waves, High Frequency Oscillations, ECG, EMG and Movement/Electrode Displacement artifacts. Each one of these artifacts has its own specific features that allow it to be identified, usually through a visual assessment of the raw EEG signal, so the overall algorithm is based on seven individual algorithms, each focusing on one artifact, highlighting those characteristics and selecting the periods of data that correspond to artifactual EEG. Each individual algorithm had a training/testing set of data that was selected by an experienced doctor who manually annotated all the artifacts present in the EEG signal, so that the algorithms could have a golden standard to compare its results to. Periods of 30-minute EEG were considered from 28 different subjects as a training/testing set of data – five for each subject, minus EMG that only had three and Movement had none. These periods were selected due to a strong present of artifacts in it.

The final detection algorithm had a True Positive rate of 92.4% (±7.5%) and a False Negative rate of 7.7% (±7.5%). The algorithm still requires user input in the selection of which artifact is to be detected in the data, but this algorithm is the first step in a method that comprises this many different artifacts into one detection tool, reason why there is still room for improvement in the methods developed.

Keywords: Artifact Detection, Neonatal EEG;
# Table of Contents

Acknowledgements – Pt. 1 ................................................................. i
Acknowledgements – Pt. 2 ................................................................. iii
Resumo .............................................................................................. v
Abstract ........................................................................................... ix
Table of Contents ............................................................................. xi
List of Figures ................................................................................... xiii
List of Tables ..................................................................................... xv
List of Abbreviations ......................................................................... xvii
1 Introduction .................................................................................. 1
2 Theoretical Background ................................................................. 3
  2.1 Neonatal Neuro-care in the NICU ................................................ 3
  2.2 Neonatal Electroencephalography .............................................. 4
  2.3 Amplitude-integrated EEG in the NICU ....................................... 4
  2.4 EEG Artifacts ........................................................................... 7
3 State of the Art .............................................................................. 13
  3.1 Artifact Detection ..................................................................... 13
  3.2 Seizure Detection ..................................................................... 15
  3.3 Artifact Removal ...................................................................... 16
4 Methods .......................................................................................... 17
  4.1 EEG Acquisition ...................................................................... 17
  4.2 Manual marking of the artifacts .................................................. 18
  4.3 Detection Method ..................................................................... 19
  4.4 Threshold Selection ................................................................... 25
  4.5 Assembling the Algorithms ....................................................... 26
5 Results ............................................................................................ 29
  5.1 Sinus Wave .............................................................................. 29
  5.2 The other algorithms ................................................................ 37
  5.3 Assembling the Algorithms ....................................................... 43
6 Discussion ...................................................................................... 47
7 Conclusion ....................................................................................... 55
8 Future Work ................................................................................... 57
9 References ....................................................................................... 59
10 Appendices .................................................................................... i
List of Figures

Figure 2.1 – Signal processing from the raw EEG to the aEEG. The scale on the horizontal axis remains constant in all plots. Source: [14] .........................5

Figure 2.2 – Different traces of the neonatal aEEG: A – Continuous Normal Voltage, B/C – Discontinuous Normal Voltage, D - Burst suppression, E – Continuous Low Voltage, F – Flat Trace. Source: patient data .........................6

Figure 2.3 – Seizure pattern detected in the neonatal aEEG (above), with a rhythmic activity visible in the EEG (below). Source: [14] ...........................7

Figure 2.4 – ECG artifacts visible on both left and right raw EEG traces. Source: patient data .................................................................8

Figure 2.5 – Artifacts due to muscle activity on the left raw EEG (above) and HFO artifacts on the right raw EEG (below). Source: patient data .....................9

Figure 2.6 – Artifacts due to movement with large increase of the amplitude. Source: patient data .........................................................9

Figure 2.7 – Sinusoidal artifacts in the right raw EEG. Source: patient data. 10

Figure 2.8 – Periodic Epileptic Discharges in both raw EEG traces, with a clearer shape in the right signal. Source: patient data ..............................11

Figure 2.9 – PED-Like Artifact in both raw EEG traces. Source: patient data ...11

Figure 2.10 – Zeta waves artifacts visible on both raw EEG traces. Source: patient data .................................................................12

Figure 4.1 – Examples of correlation values for different overlapping sinus signals ............................................................21

Figure 5.1 – Raw EEG signal with annotated artifacts ......................................... 30

Figure 5.2 – Correlation matrix with the sin function ..................................... 30

Figure 5.3 – Correlation matrix with the cos function ..................................... 31

Figure 5.4 – Correlation matrix after the combination of the sin and cos matrices ............................................................32

Figure 5.5 – Normalized array with the correlation values ............................. 33

Figure 5.6 – ROC curve with the Sensitivity and Specificity values for all thresholds ............................................................34

Figure 5.7 – Detections array ..................................................................... 35

Figure 5.8 – Detections array after the function joint_peaks ...................... 36

Figure 5.9 – Raw EEG signal with two PED-Like artifacts .......................... 37
Figure 5.10 - Array with the detection of both PED-Like artifacts ...................... 37
Figure 5.11 - Raw EEG signal with two Zeta artifacts ................................. 38
Figure 5.12 - Array with the detection of both Zeta artifacts ......................... 38
Figure 5.13 - Raw EEG signal with one HFO artifact .................................. 39
Figure 5.14 - Array with the detection of the one HFO artifact ....................... 39
Figure 5.15 - Raw EEG signal with two ECG artifacts .................................. 40
Figure 5.16 - Array with the detection of both ECG artifacts ......................... 40
Figure 5.17 - Raw EEG signal with one EMG artifact .................................. 41
Figure 5.18 - Array with the detection of the one EMG artifact ....................... 41
Figure 5.19 - Raw EEG signal with two distinct periods of artifacts due to Movement or Electrode Displacement ................................................................. 42
Figure 5.20 - Array with the detection of both periods of artifacts due to Movement or Electrode Displacement ................................................................. 42
List of Tables

**Table 4.1** – Number of artifactual periods in each set of data .......................... 18
**Table 5.1** - Threshold values for the different artifacts ..................................... 34
**Table 5.2** - Types of artifacts that each algorithm detected ................................... 43
**Table 5.3** - Results of all algorithms, for all subjects ............................................. 45
**Table 5.4** - Mean of the results from all algorithms .............................................. 46
List of Abbreviations

aEEG | Amplitude-Integrated Electroencephalogram
BCI | Brain-Computer Interface
BSS | Blind Source Separation
DWI | Diffusion-Weighted Imaging
CFM | Cerebral Function Monitor
ECG | Electrocardiography
EEG | Electroencephalography
EMG | Electromyography
EOG | Electrooculography
FN | False Negative
GA | Gestational Age
HF | High Frequency
HFO | High Frequency Oscillations
HIE | Hypoxic-Ischemic Encephalopathy
ICA | Independent Component Analysis
LF | Low Frequency
MRI | Magnetic Resonance Imaging
NaN | Not a Number
NICU | Neonatal Intensive Care Unit
NIRS | Near-InfraRed Spectroscopy
PCA | Principal Component Analysis
PED | Periodic Epileptic Discharges
ROC | Receiver Operating Characteristic
aEEG | Amplitude-Integrated EEG
STFT | Short-Time Fourier Transform
TN | True Negative
TP | True Positive
US | Ultrasound
WGA | Weeks of Gestational Age
1 Introduction

The human brain is constantly trying to explain itself.

Neuroscience is one of the most studied fields of science and yet there is so much that is still undiscovered. In an effort to understand the human brain, one must take into account every aspect of its maturation and all the processes that lead to the development of such a complex organ. This is why it is very important to understand not only the adult, matured brain, but also the newborn one - term and preterm.

If sometimes it is complicated enough to explain the mechanisms underlying the adult brain, one can only expect to encounter just as many obstacles with a newborn brain, and then some more due to the constant developmental processes occurring. In the infants admitted to the Neonatal Intensive Care Unit (NICU), brain activity is monitored over periods of several hours - even days - through electroencephalographic (EEG) acquisitions, which allow for a better understanding of all the processes that happen in that time.

Unfortunately, and like any other physiological parameter’s acquisition, it is very hard to obtain only the intended information without artifacts. In this dissertation, artifacts are defined as physiological or non-physiological features [1] that disrupt the data and influence the overall trace on the acquisition, possibly leading to misinterpretations or lack of understanding on the real and correct information of the health state of the patient. As the NICU is no exception, neonatal EEG acquisitions also include artifacts that sometimes may prevent proper conclusions on diagnosis or therapeutic options. This is the reason why there is the need to develop a method that automatically detects these artifacts from the data and avoids the need for the clinical staff or researchers to have to run through all the data and annotate them manually, which is very tiresome and highly time-consuming.

As artifacts can very often mask the true EEG reading of the brain’s activity and lead to misinterpretations, harming the diagnostic process, one must be very careful when analysing the raw EEG. Only experienced clinicians can infer conclusions based on the EEG and/or the amplitude-integrated EEG (aEEG) traces, as it requires a great discerning capacity to be able to separate artifacts from normal brain activity.

In the normal brain activity category, one must also include seizures, as they are present in 4% to 48% of the newborn population in the NICU [2]. The seizure detection algorithms nowadays rely mostly on the rhythmicity of the signal in order to identify an epileptic episode, and unfortunately, some artifacts have a similar morphology as seizures and are characterized by a high degree of repetitiveness. When one considers this fact, it becomes easy to understand the reason why these seizure detection algorithms may have a high rate of false positives [1].
This is the motivation for this dissertation project: to be able to identify artifacts in EEG data without relying solely on its rhythmicity or its repetitive pattern, but also on some more artifact-specific known features, individual to each different type of artifact considered. With this in mind, the algorithm developed here focused on each artifact separately, making the most out of the characteristics that were previously studied and identified.

Automatic detection of different aspects of the neonatal brain’s activity is already built in some devices, but most of them focus on detecting seizure episodes or periods of high electrode impedance, both very different, as the former allows the clinicians to adjust medication and make therapeutic decisions, and the latter informs what periods may not have the best data quality, regardless of being actual brain activity or artifactual periods of data. The development of a method that automatically detects artifacts in neonatal EEG would avoid time-consuming visual assessment of all the data, which can cover a few days, while also being an addition to the signal processing tools that already exist.

As this is the first approach on the project, the algorithm was developed in a basis of trial-and-error, creating novel methods of analysis and artifact detection, comparing those results with manual annotations and calculating basic results of Sensitivity and Specificity, and these methods are all described with a higher level of detail in the following chapter – see Methods. Once each attempt was developed and its results were analysed, the goal was to understand what was being done right and which aspects of the method could be improved, always comparing results within the same artifact’s methods, in order to optimize the detection algorithm.

As one can understand, not all attempts for each artifact’s method could be detailed in this report, so only the successful attempts are detailed and only those results are included in the Results chapter. Following that, a discussion of the algorithm’s results is also included, as well as a Conclusion for this dissertation and some topics to reflect upon when considering the Future Work that can still be done in this project.
2 Theoretical Background

2.1 Neonatal Neuro-care in the NICU

In order to best monitor the changes in the healthcare of neonates, as well as improve the resources for better therapeutic options and research investigations associated with birth asphyxia, brain hemorrhage and hypoxic-ischemic brain injury [3], a variety of measuring techniques can be used. As an example, a newborn admitted to the NICU can be submitted to EEG acquisitions, as well as cerebral blood oxygenation monitoring through Near Infra-Red Spectroscopy (NIRS). Other critical physiological parameters are also measured in the NICU, such as heart rate and blood pressure [4]. Given the neurological stress at birth, the brain’s electrical activity is very carefully monitored through aEEG, which allows for – but not exclusively - seizure detection through a monitoring system [3]. Two-channel EEG suffices in the conditions of the NICU, allowing for an early diagnosis that could otherwise be made later on, when the child started to display learning difficulties. While the aEEG displayed in the Cerebral Function Monitor (CFM) only has two channels, providing less information than a conventional EEG with 16 channels or more, one must consider the benefit of placing only five electrodes at any time and leaving them for long-time acquisitions. This is especially true in the case of premature newborns or babies with suppressed brain activity, where indicators of brain injury may arise during several hours or even days after birth or an hypoxic-ischemic event, allowing for a better monitoring of the brain’s recovery of the background activity and response to medication in the presence of seizures [4].

When it comes to brain imaging, neonatal cerebral ultrasound (US) is usually considered in order to rule out any kind of antenatal injury or some sort of intracranial hemorrhage, while Magnetic Resonance Imaging (MRI) is used to diagnose more subtle white matter lesions in the preterm infant and hypoxic ischemic injury in the full-term infant following perinatal asphyxia or other disorders such as metabolic disorders or strokes [5]. At the same time, Diffusion Weighted Imaging (DWI) can also be useful in the detection of cytotoxic edema, when the MRI if preformed within the first week after delivery and presumed time of insult.

When considering to monitor the newborn’s brain activity for longer periods of time, electroencephalographic data becomes the best approach. In this, one must take into account the hemispheric asymmetry, reason why most acquisitions take into account bilateral fronto-parietal electrodes [6]. Especially in infants with suppressed brain activity the amplitude may be increased due to artefacts and result in a drift of the baseline activity, which must also be taken into consideration, especially in infants with suppressed brain activity, so both the pattern and the amplitude values must be considered carefully in order to avoid an incorrect diagnosis.
The most important reason for the use of continuous EEG in the NICU is the detection of seizures, which can have clinical manifestations (clinical/convulsive seizures) or not (non-clinical/non-convulsive seizures), the latter being the hardest to identify without EEG. These seizures may be the result of acute cerebral edema or some other kind of injury, which can be exacerbated by the seizures [7].

2.2 Neonatal Electroencephalography

In the NICU or in any other health-care facility, EEG is usually the best approach to monitor the brain’s activity, given that it is a powerful and non-invasive tool for diagnosis, research and prognosis on possible injuries to the brain. Most of the times, in the NICU, EEG recordings begin as soon after birth as possible after birth, allowing for a better discernment between normal and abnormal activity throughout the admission and possible reactions to treatment [9].

Given the different states of neural maturation and development, the neonatal nervous system is different from the pediatric one, as well as the adult, with most of the seizures being subclinical, an important reason why continuous EEG is of great value [10]. When it comes to a normal preterm EEG, one must take into account that the third trimester of pregnancy is the one with the biggest developmental changes in the brain [9], which are also visible in the baby’s EEG. In preterms of under 30 weeks of gestational age (WGA) the different patterns of sleep/wake cycling are not yet clearly visible, given that they spend most of their time in a state of quiet sleep. In these patients one can see in the EEG trace various discontinuous patterns, different rhythmic delta, alpha and beta activity, as well as energy bursts and intervals between bursts with variable durations [9].

2.3 Amplitude-integrated EEG in the NICU

Every day extremely premature infants are born, and even in term infants, some complications may arise during birth, such as perinatal asphyxia. In all of these cases, the existence of proper monitoring of the newborn’s cerebral function is critical, hence the increasing interest in the development of the NICU’s equipment.

When it comes to measuring the brain activity of infants that are admitted to the NICU for several days, one can’t expect to analyze approximately 72 hours of data to check the EEG trace and only then be able to run a correct diagnosis. In order to facilitate the observation and make the decision-making process faster, the NICU’s nowadays also consider aEEG as part of bedside monitoring.
This signal is obtained from a normal EEG, but goes through a process of filtering and time compression (Figure 2.1), displaying the difference between the maximum and minimum amplitude in the normal EEG, allowing for an easier and quicker evaluation of the activity in the neonatal brain [11].

This modality of displaying electroencephalographic data is widely used in neonatal cases of hypoxic-ischemic encephalopathies (HIE), seizures, infections, amongst others, and uses only five electrodes (preferably needle because of lower impedance) [7], unlike the American Electrophysiology Guideline [12], that favors the use of 16 channels. The electrodes are placed in bi-parietal positions - P3/F3 and P4/F4 according to the 10/20 system [13].

The display of the information is usually made in a semi-logarithmic scale – linear from 1 to 10 µV and logarithmic from 10 to 100 µV – maximizing the ability to detect changes in the lower frequencies. The signal in the aEEG is amplified and band-pass filtered, which suppresses activity with a frequency lower than 2 Hz and higher than 15 Hz, in order to minimize artifacts originated from sweating, movement, muscle activity and electrical interference [14]. The signal can be further processed, which includes rectification, smoothing and considerable time compression, in order to see the overall evolution of the trace and better identify specific patterns, such as sleep-wake cycles and seizures, the latter being recognized by a shift of both the lower and upper margins in the aEEG.

![Figure 2.1 – Signal processing from the raw EEG to the aEEG. The scale on the horizontal axis remains constant in all plots. Source: [14]](image)

The signal displayed on the bedside monitor can then be visually evaluated and different patterns can be recognized and classified, according to [14] (Figure 2.2):

A - Continuous Normal Voltage (CNV) – continuous activity with a lower margin between 7 µV and 10 µV and upper margin between 25 µV and 50 µV;
**B/C** - Discontinuous Normal Voltage (DNV) – discontinuous background with various ranges of amplitude, but with a lower margin under 5 $\mu$V and upper margin over 10 $\mu$V;

**D** - Burst Suppression (BS) – discontinuous background activity with a minimum activity around 0 $\mu$V and bursts that are greater than 25 $\mu$V;

**E** - Continuous Low Voltage (CLV) – continuous background activity but with an upper margin around 5 $\mu$V;

**F** - Flat Trace (FT) – isoelectric (inactive) background activity.

![Different Traces of Neonatal aEEG](image)

**Figure 2.2** - Different traces of the neonatal aEEG: A – Continuous Normal Voltage, B/C – Discontinuous Normal Voltage, D – Burst Suppression, E – Continuous Low Voltage, F – Flat Trace. Source: patient data.

With this long-duration data visualization, aEEG is a very powerful tool for the diagnosis of HIE, but its assessment requires training in detecting actual brain activity, given that artifacts may arise and contaminate the actual data [15]. Movement, which has a much higher amplitude, may contaminate the data and be seen in the aEEG, as well as muscular shivering, sometimes caused during hypothermia. Another thing that the clinical staff must be able to recognize are seizures, which are identified by an increase in amplitude, visible in the aEEG, and a progressive change in frequency, visible in the EEG (Figure 2.3). These seizures are caused by excessive and spontaneous electrical activity of clusters of neurons that are responding to instabilities in the normal brain function [1].

The aEEG allows the time-locked synchronized visualization with the raw EEG, the former having a window of approximately three hours of recording and the latter one of only 10 seconds. This form of display enables the identification of artifacts that were not described in the newborn population [16], which could lead to misinterpretations on the development of the infants, as well as their outcomes [17] [18].
Unfortunately, and despite all efforts to minimize the presence of artifacts in the data, the NICU itself is a suboptimal environment, as the researchers have less control over the conditions of the acquisition, creating a higher risk of recording artifactual signals [19].

![Figure 2.3 - Seizure pattern detected in the neonatal aEEG (above), with a rhythmic activity visible in the EEG (below). Source: [14]](image)

### 2.4 EEG Artifacts

As the aEEG is time-compressed, it is mainly used to evaluate the background pattern, sleep-wake cycles and the presence of seizure episodes, given their amplitude shift in the aEEG, as shown in Figure 2.3. In the raw EEG however, artifacts are more easily seen, especially in babies with suppressed brain activity, where artifactual physiological or non-physiological information can have a higher influence and juxtaposition in the brain’s activity.

In order to further understand artifacts and how to identify them, a brief explanation on each type is followed.

#### 2.4.1 Electrocardiogram

An electrocardiogram (ECG) is the measurement of the heart’s electrical activity and is one of the parameters acquired in the NICU.

In infants with highly suppressed brain activity, ECG artifacts occur when the high electrical cardiac field affects the surface potentials on the scalp, near the electrodes, interfering with the EEG reading [20] [21]. As one can expect, the more suppressed the brain activity, the easier it is to see the
infant’s ECG on the EEG. The time grid on the screen allows the visual assessment of a highly periodic signal of smaller amplitude that a seizure (which is also periodic but with an evolution in frequency and/or amplitude), as one can see in Figure 2.4.

![Figure 2.4](image)

**Figure 2.4** – ECG artifacts visible on both left and right raw EEG traces. Source: patient data.

### 2.4.2 Electromyogram

The EEG activity can often detect electromyographic (EMG) activity, picked up because of the muscles’ electrical activity [22]. This activity can also occur due to the eyes’ muscle movement, but those artifacts are not seen in the NICU because of two reasons: first, the infants spend most of their time with their eyes closed, in a state of quiet sleep, and second because the electrodes used are usually parietally placed, far away from the influence of the eye’s movement.

These artifacts are usually characterized by a small amplitude in suppressed infants, as well as a signal with a shape that appears to be much more like a stochastic signal and without a specific frequency, as it can be seen by the upper half of **Figure 2.5** (in the left raw EEG).
2.4.3 Movement and Electrode Displacement

When the infant is moved or the electrodes are displaced, the artifacts that are mainly present in the raw EEG are characterized by a higher amplitude than any than any brain activity measured, and is usually over 100 µV (Figure 2.6), sometimes reaching 400 µV. These artifacts can also be detected by a very irregular shape and by some time points that don’t have an actual value (due to the amplifier’s saturation), as the electrodes couldn’t read information from the brain’s activity due to the movement at that time.

2.4.4 High Frequency Oscillations

High Frequency Oscillations (HFO) are small amplitude waves that can occur in the suppressed EEG. They have a well defined shape and do not translate into any specific brain process or kind of activity, like in the lower
half of Figure 2.5, on the right raw EEG. This type of artifact usually has a frequency range of 8 – 11 Hz, which is higher than the normal ventilation frequency, hence its name. Within this range, the frequency can also depend on the subject.

2.4.5 Sinusoidal Waves

Sinusoidal Waves are sine-shaped waves in the EEG recordings [2] that do not have a well-defined source but are characteristic to the head’s position in the incubator and might be related to respiration, in infants who are on a ventilator. These waves can have variable frequency (between 1.5 and 3 Hz) and amplitude, but are usually smooth and easily identifiable (Figure 2.7 – right raw EEG).

![Figure 2.7 – Sinusoidal artifacts in the right raw EEG. Source: patient data.](image)

2.4.6 Periodic Epileptiform Discharges

Periodic Epileptiform Discharges (PED) are specific periodic EEG patterns defined as a bisynchronous sharp wave complex occurring in periodic intervals between 0.5 and 4 seconds [23] (Figure 2.8). They can be lateralized, bilateral or generalized and in adults typically occur in the setting of some sort of neurological injury [24], such as stroke or HIE. PEDs are not considered artifacts, as their origin is well known and studied [23] [24] [25], but nonetheless, these physiological features are included in this chapter because there is a type of artifact – PED-Like (Figure 2.9) – that is believed to be related to PED due to a similar shape but without the peak at the end of every cycle [2]. This waveform’s origin is unknown, and therefore considered as an artifact on the neonatal EEG.
2.4.7 Zeta Waves

Zeta waves are characterized by sharp spikes with variable phase followed by similar waves (Figure 2.10) [26]. These waves are distinct, sharply contoured delta waves [27] that have been reported to have a high correlation with structural brain lesions in adults [26][28], but unfortunately there is still very little that is known about these waves, reason why they are considered artifacts. These waves can have a higher amplitude, as they are considered “slow” delta waves, and they don’t usually last for long periods of time, reason why it is only possible to see a few periods at a time [2].
Figure 2.10 – Zeta waves artifacts visible on both raw EEG traces. Source: patient data.
3 State of the Art

3.1 Artifact Detection

Automatic artifact detection algorithms for electroencephalographic data must be highly specific to the different types of data it aims at, and for the same reason, different analysis methods must be employed according to each artifact’s features. This type of analysis can be divided into two categories: one where the artifacts are removed from the original data, allowing for post-processing and analysis, and the other where the algorithms only detect the artifactual data without actually removing it, keeping the original signal intact.

The interest in performing this detection automatically is constantly increasing, especially in the last two decades, as EEG has more and more applications, such as the field of Brain-Computer Interfaces (BCI), or as a diagnostic tool for various neurological conditions. Another reason for this rapid interest is the fact that with more applications to the EEG, longer acquisition times are set in order, and it is time consuming for a clinician or a researcher to go through large amounts of EEG data to select the periods that do not present the data quality that is required. Unfortunately, nowadays, that is the scenario in most cases, but several algorithms are being developed in order to avoid this tiresome ordeal.

Unfortunately, given that the needle electrodes capture a mixture of signals from different brain regions, as well as other non-cerebral sources (through volume conduction), the EEG signal can never be expected to have only the true raw signal, and thus its feature cannot be simply averaged out or filtered, in most cases [1].

Different algorithms are proposed to detect different artifacts, such as ocular muscle movement [29]–[31], muscular activity [28] [29], ECG/pulse activity [1] or even electric interference, known as power line [34]. Not all of these artifacts are common to neonatal EEG, as mentioned in the previous chapter, but these algorithms are pointed out to reinforce the idea that each artifact has its very specific characteristics and that one algorithm can’t consider all artifacts as only one kind. Most algorithms use adaptive filters, reference signals (such as the case of the ocular movement or the ECG), wavelet transforms or Blind-Source Separation (BSS) techniques, such as Independent Component Analysis (ICA), which is also used for the removal of the artifacts [35].

An example of that is the ADJUST (Automatic EEG artifact Detection based on the Joint Use of Spatial and Temporal features) algorithm [36], which combines spatial and temporal features to detect the artifacts automatically. Especially in studies with children that can move freely, artifacts are a very common occurrence, increasing the amplitude of the EEG trace and making the acquisition unusable for research. For that purpose, ICA
is used to detect the independent components (IC’s) on the EEG, but its use is limited: the selection of the IC’s is almost just as time-consuming and has a subjective factor that comes along with the decider [36]. With this in mind, this algorithm characterizes the artifact-related IC’s by previously known stereotyped features (temporal and spatially) and then combines them in order to identify the artifacts. The artifactual features considered in this algorithm are ocular movements (blinks, vertical and horizontal) and a generic artifact class – discontinuity – for capturing anomalous activity, which is characterized by empty (NaN) data points. This algorithm was then tested through the comparison of its results and manually classified artifacts, where the analysis revealed that ADJUST’s performance was equivalent to the manual classification by experts, possibly saving time in the analysis and giving an opportunity for further improvements and addition of extra artifactual features in future detection models.

While this was tested in adult EEG, the same did not occur for neonatal acquisitions, where the traces can be quite diverse, given the different patterns that one can find when going through the data: normal background, seizure, slow waves, sharp waves, rhythmic spikes or even discontinuity [35]. The brain maturation and development is supported by a process that is mainly driven by energy bursts, which are easily seen in the neonatal EEG trace given their sudden increases in amplitude from the background activity. However, high energy artifacts can mimic these bursts, making it difficult for the clinician to differentiate burst from artifactual activity. A study on the detection of bursts, which had as groundwork previous models [34] [35], allowed for the identification of bursts in single channel acquisitions [35], where the segments of data were classified according to a model that identifies artifactual data. This model resorted to wavelet decomposition and ICA to test the dataset previously available and was able to obtain a greater accuracy in the results in the detection of bursts and artifacts, when comparing to the previous model.

Other methods of detection have been set in order, such as line length [39]. While most algorithms are based on amplitude changes to detect artifactual data, line length consists on the running sum of the absolute differences between the data samples within a defined time window, thus increasing the value of the line length if the variance of the signal increases. This method allows for the detection of high frequency features, such as the energy bursts with the same accuracy as the manual detection performed by clinicians. Another advantage of this algorithm is the possibility to adapt the threshold every 150 seconds, given that multiple factors, but specially medication, can have an almost immediate influence on the EEG pattern. This algorithm also proved to be just as accurate with only two channels as with a full-head EEG, allowing for the method to be applied not only in research but also in every hospital as a method for analysis on the background EEG.

A General Artifact Detection System (GADS), based on two steps and regardless of the patient, is proposed in [40]. The first step consists in differentiating artifactual data with large amplitude from that caused by
electrode displacement (resulting in a lack of acquired values) or higher impedance. The second and final step aims at detecting smaller artifactual manifestations, such as muscular activity, movement or periodic features. These two stages were proposed in a machine learning process, which means that a series of features from neonatal epochs were submitted through a classifier and that classifier returned a simple output stating if the epoch was artifactual or not, based on a threshold. Pre-processing techniques were also used, such as high-pass filtering, notch filtering and segmentation of the original signal into several epochs [40]. The features used in this system were the mean, median and variation of amplitude, mean frequency, bandwidth, three frequency-bands energies and a ratio of maximum energy to mean energy. For ECG and pulse artifact two other features were included in the analysis, given its repetitive nature: peak frequency and spectral distortion [40].

The correlation coefficient has been used previously as a method to quantify the changes in the filtered adult EEG signal after ICA was applied to remove certain artifactual components [41], providing a measure of the distortion by the suppression of the artifacts. ICA was preferred for this method, over digital filtering, given that digital filters may alter the morphology of the original signal, meaning that the filtered result may not always be true to the actual brain activity one wishes to measure. The comparison between the efficacy of ICA and of filtering was demonstrated by the use of correlation coefficients as an objective quantifier of results.

### 3.2 Seizure Detection

Seizures, clinical or non-clinical, are very common in preterm newborns admitted in the NICU with HIE [6], and they are characterized by an increase in the lower and upper margin of the aEEG trace [1] [14].

In [42] autocorrelation was used to characterize activity with a certain periodicity as electrographic seizure in the EEG. This periodicity was then scored according to spectral analysis, allowing for a bedside tool for the online detection of seizures as they occur in the neonate.

A different algorithm was developed in [43], which had the objective of also detecting artifactual activity that could be mistaken for seizures, assisting for the online detection of epileptic activity in the bedside aEEG monitor. In this study, the authors only considered seizures with 60 seconds or more, even though most seizures last for five to ten seconds, given that in the aEEG the activity is time-compressed and the episodes would not be recognizable. In this algorithm, the detection method was based on the sudden increase of the lower boundary of the signal, as a new lower boundary was defined every ten seconds of the signal. Changes in this margin were detected as of interest through a determined threshold higher than the reference
boundary in those 60 seconds. The algorithm was then evaluated by comparing its results with the manual comparison by two observers and obtained results with high sensitivity (rate of true positives).

3.3 Artifact Removal

The issue with the removal of artifacts is that one can never know the true original form of the EEG signal without any sort of artifacts or noise [44]. This means that without a “true” example of the data, it is not possible to know for sure the accuracy of the artifact removal technique.

Depending on the purpose of the analysis, sometimes it’s easier to remove the artifacts from the EEG data rather than to simply detect them, like in cases where there is no need to recover the original EEG and the acquisition can simply be deleted [45].

In cases of ocular movement or pulse, the artifactual data can be detected through a reference signal – electrooculography (EOG) or ECG, respectively – through different methods, and then removed from the original signal.

Most algorithms use BSS techniques to detect the specific pattern of the artifact to remove it, like ICA [1] [41] [46] [47], Principal Component Analysis (PCA) [45] or constrained ICA [48] (which can be spatial or temporal and implies prior knowledge on the source signal, making it a semi-blind source separation), but other methods can be applied, such as filtering specific frequencies [49] or wavelet analysis [50].

A study on the removal of neonatal artifacts [51] uses wavelet-enhanced ICA, where wavelet decomposition is used on the IC’s with the advantage that it allows for the retaining of a residual neural signal in the components marked as artifactual, minimizing the loss of information on actual brain activity. Unfortunately, in this method, the artifacts were identified only based on their high amplitude and short duration in time, which comprises only a small portion of all artifacts that can be found on the neonatal EEG.
4 Methods

The current chapter focuses on the description of the algorithms developed throughout this project.

As decided in the beginning of the project, the development of the detection algorithm will consist of the assembling of seven different detection algorithms, each focusing on a specific artifact.

All algorithms were developed on MATLAB 2016b (The MathWorks, Inc., Natick, Massachusetts, USA).

As previously introduced, the artifacts to be considered in this project are:
- Sinus Waves with Low Frequency (LF): 1.5 – 2.5 Hz;
- High frequency Oscillations (HFO): 8 – 11 Hz;
- PED-Like;
- Zeta Waves;
- ECG activity;
- EMG activity;
- Movement/Electrode displacement.

This chapter will consist of an introduction to the manual markings of the artifacts in the raw data, followed by an explanation of each algorithm’s method and their assembly.

Although the algorithms have different methods for the detection of the artifacts (see Appendices I to V), there are some parts that share the same logic. For that matter, the general backbone of the algorithms is:
- Detection Method
- Threshold Selection

The first topic, the core of each algorithm, will be explained for each different algorithm, and the definition and selection of the threshold shares the same reasoning for all the artifacts as well. Whilst not a part of the algorithms itself, the artifacts must be marked on the data before training and/or testing the algorithm, reason why there is a sub-chapter dedicated to explaining how this procedure is done (even though it’s outside the algorithm).

4.1 EEG Acquisition

The EEG signals that were used as training and testing set were not acquired as a part of this project, and therefore the author took no part in the process. Nevertheless, for the sake of clarifying, it becomes relevant to explain how the data were acquired.
All EEG signals were acquired in the NICU of the Wilhelmina Children’s Hospital, University Medical Center Utrecht, The Netherlands. A total of 28 subjects were considered for this project (five subjects for each of the first five artifacts pointed out before, except the EMG one that only considered three subjects). Subjects’ age and gender were not discriminated.

The EEG montage in the NICU consists of five needle electrodes placed on the newborns’ scalps, in the F3/P3 and F4/P4 positions (following the 10/20 EEG system adapted for neonates [13]) and one for reference on the forehead, resulting in two bipolar channels. The signals considered for the algorithms were raw, only with the pre-processing for the bipolar channels’ signal, and the sampling frequency was 64 Hz, meaning that one second of acquisition consisted of 64 data points.

### 4.2 Manual marking of the artifacts

Given that the algorithm needs a golden standard to evaluate its results, all the data considered in this project was first selected by an experienced aEEG reader, in order to have training and testing data with both artifactual and non-artifactual EEG traces. This assessment consisted of the selection of data with approximately 30 minutes where there was a large amount of artifactual periods mixed with normal brain activity. The aEEG reader created a database where for each type of artifact there was data from five different subjects and for each subject the artifacts were marked with the beginning and end time of each artifactual period in those 30 minutes of data. These periods of artifactual data could have a varying duration, lasting for at least a few seconds, depending on the type of artifact. Also, the number of each type of artifact in each set of data (from all five subjects) can vary, as can be seen in Table 4.1.

<table>
<thead>
<tr>
<th>Artifact</th>
<th>Number of artifacts in data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sinus</td>
<td>167</td>
</tr>
<tr>
<td>PED-Like</td>
<td>104</td>
</tr>
<tr>
<td>Zeta</td>
<td>145</td>
</tr>
<tr>
<td>HFO</td>
<td>221</td>
</tr>
<tr>
<td>ECG</td>
<td>84</td>
</tr>
<tr>
<td>EMG</td>
<td>16</td>
</tr>
</tbody>
</table>

As one can see, the Movement/Electrode Displacement artifact is not included in this table. Due to the fact that the algorithm for this type of artifact depends only on the absolute value of the EEG signal, regardless of the subject’s condition or any other features, it was not necessary to gather training and testing data.
The data is then exported from BrainZ and loaded into MATLAB, where the time points for the beginning and end of each artifactual period were saved as an independent variable, so that they could be used throughout the algorithms. This allowed for a comparative analysis between the manual markings of the artifacts and the algorithms’ results.

### 4.3 Detection Method

#### 4.3.1 Sinus, PED-Like and Zeta Waves

These three artifacts are included in the same sub-chapter due to the fact that their algorithms follow the same line of thought in its methods.

The diagram in Appendix I summarizes the method in this type of algorithm, which will now be further explained.

For every algorithm, the first step is always the definition of the most important variables. In this case, that includes loading the EEG signal, defining the sampling frequency ($fs = 64$ Hz), signal length and beginning and end times of the artifacts in the data from the golden standard.

For all three algorithms included in this sub-chapter, the overall idea is to find the artifacts based on the correlation coefficient between the signal and a surrogate waveform with a fundamental frequency and with a shape very much like the artifacts’. For that reason, it is important to shed a light on the correlation definition. The MATLAB function `correcoef` consists on the computation of the Pearson correlation coefficient (4.1), measuring the linear dependence of two different variables. This value of dependence can vary between -1 and 1, where -1 means a total negative linear correlation, 0 means an absence of correlation and 1 a positive linear correlation. Considering that A and B are different variables, like the EEG signal and the surrogate, the coefficient for a specific surrogate’s frequency at a specific time point $i$ is given by:

$$
\rho(A,B) = \frac{1}{N - 1} \sum_{i=1}^{N} \left( \frac{A_i - \mu_A}{\sigma_A} \frac{B_i - \mu_B}{\sigma_B} \right)
$$

(4.1)

where $\mu$ and $\sigma$ represent the mean value and standard deviation of each variable (in index). The result of this function call is a square matrix (4.2) where:

$$
\mathbf{r} = \begin{bmatrix}
\rho(A,A) & \rho(A,B) \\
\rho(B,A) & \rho(B,B)
\end{bmatrix}
$$

(4.2)
Given that both \( \rho(A, A) \) and \( \rho(B, B) \) represent the correlation of the variables with themselves, the main diagonal of the matrix is always 1. The other two values are equal to each other because the Pearson correlation coefficient is symmetrical, so \( \rho(A, B) = \rho(B, A) \). For this reason, only the second value from the first row is considered for the analysis.

With this in mind, it becomes relevant to clarify the method behind the correlation analysis for these three algorithms.

### 4.3.1.1 Sinus (LF)

As previously introduced, this type of artifact consists on a sinusoidal-shaped wave with a variable frequency, but still within the range of 1.5 – 2.5 Hz. Considering this special feature, the surrogate wave for this artifact was created with the \( \text{sin} \) and \( \text{cos} \) functions from MATLAB (Appendix VI), given that between the two functions there is a phase difference of 90° and therefore they are able to cover more of the variability of the artifact within the same frequency value. This method consisted on the creation of several surrogate waves with a length of five seconds, all with different frequencies from 0.02 Hz up to 3 Hz, with a frequency step of 0.02 Hz, meaning that there are 150 different surrogates for the \( \text{sin} \) function, and another 150 for the \( \text{cos} \) function, in an attempt to cover as much of the variability of the artifact as possible.

Each surrogate is now a sliding window that runs across the whole length of the raw signal, calculating the correlation coefficients between the surrogate and every period of five seconds of signal, with a time step of 10 points (or 10/64 of a second), meaning that there is an overlap of \( \text{fs} \times 5 - 10 = 310 \) time points (approximately 97% of the window length). Hence, for each step, the correlation between the surrogate and a portion of 5 seconds from the signal will be calculated and saved.

In order to save all the correlation values, a new matrix is created for the \( \text{sin} \) surrogate and another for the \( \text{cos} \), in which the rows correspond to all the 150 frequencies considered and the columns to each time point considered for the correlation.

Following this method, the next step is to combine the two matrices in order to get the best results possible. After considering several ways of combining both matrices, the method that provided the best results was found to be the one that considers a varying shift (from 1 to 10 points) between each row of the matrices. From, Figure 4.1 which shows a simple example of this method, one can see that with a slight shift of the two different surrogates (\( \text{sin} \) and \( \text{cos} \)) the absolute value of the correlation can be optimized (i.e., higher), and the shift is never over 10 points because otherwise that could change the time identification of the artifacts in the EEG signal.
Given this method, within each different shift, it calculates the square of the sum of the absolute value from each row from both matrices, i.e., only rows corresponding to the same frequency are added. This step considered the absolute values because a negative correlated surrogate and raw signal can also indicate the presence of a sinus artifact, but with a phase difference. After this, the algorithm considers the shift that produced the highest (therefore, the best) values and stores that result into the corresponding row of the final matrix. This way, different rows may have been combined with different shifts because of the maximum values that were possible to achieve.

Once the matrices are combined, the result is one single matrix with all the values for every frequency and time step. As a first visual assessment, the matrix can be plotted according to a color scheme where high values can be easily distinguished both in the time and the frequency domain.

The next step in the selection of the artificial periods consists on saving the maximum value for each time point, i.e., for each column the maximum value is considered from all frequencies, corresponding to the frequency that was the most correlated to the sinus artifact present in the data.

This results of this process is a single array corresponding to the maximum values of the whole matrix, and those values are then divided by the maximal value from that array, in order to normalize the whole correlation array and having all values between 0 and 1, which will make future analysis easier to compare.

4.3.1.2 PED-Like

The detection method for this artifact (Appendix VII) is slightly different than the previous, given that Periodic Epileptiform Discharges don’t have a well-defined or simple shape.
For this reason, the best surrogate was created by selecting examples of this artifact in real EEG data. Given that one surrogate couldn’t explain the whole variability of the artifact, which is a physiological characteristic, four different surrogates from four different subjects were considered.

After this, the detection method is very similar to the one discussed for the Sinus (LF) artifact. Every surrogate has a length of two seconds and then that surrogate is “stretched” up to 33%, 67% and 100% more of its own length, meaning that for every surrogate there are three other copies but with different frequencies, in case the artifact had a different frequency than the segments considered as surrogate. This way, there are 16 (4*4) different surrogates for the correlation matrix in this algorithm, in which all of them work as sliding windows that go through the signal with a time step of 5 time points, always calculating the correlation coefficient between the surrogate and the signal.

The final result, like in the previous artifact, are four different matrices, one for each surrogate. For this algorithm, the combination of the matrices is different: in this case the algorithm analyses which of the matrices has the most values above 0.8 (a value that decided as indicating of high correlation) and considers that matrix as the one that best detected the artifact, given that more high correlation values indicate a stronger presence of artifacts with the surrogate’s shape in the raw data. After that, the algorithm multiplies all values of that matrix by 2 and adds that to the sum of the square of the other three matrices, because those matrices still store important information about artifacts that may have slight distinct features and are therefore covered by the other surrogates. The result of this process is a matrix with the same dimensions, where the maximal values for each time point are saved into a single array that is later normalized, like in the previous algorithm.

### 4.3.1.3 Zeta Waves

The method for this type of artifact (Appendix VIII) is mostly similar to the one for the PED-Like. The only function that could resemble the Zeta Waves is the sawtooth but that does not take into account all the variability if the artifact because the function would still need to be adjusted to match the artifact. For that reason, in this algorithm the surrogates were also exported from the raw signal of several subjects, allowing the analysis to take into account four different surrogates, all with a length of two seconds. In this case, the frequency of the surrogates was not altered because that variability was already taken into account in the surrogates selected from the data. Once the surrogates are loaded, the correlation coefficients with the raw signal are calculated and saved.

For the case of this type of artifact, the result of the correlation between each sliding surrogate and the signal is only one array and not a correlation matrix, because there was no variation of the frequency. The combination of
the results was simply the sum of the four arrays, resulting in one single array that was also normalized, meaning that all its values are between zero and one.

4.3.2 HFO

The first approach on the algorithm (Appendix IX) for this type of artifact was in all ways similar to the one for the Sinus (LF), but unfortunately that method could not detect artifacts where they were present. This is probably due to the fact that the frequency range in this artifact is broader and there might be frequency shifts within the same artifactual period, which does not allow for a proper detection with the method described previously.

With that in mind, and after a discussion with the medical staff, it was discussed that the HFO artifacts are visually identified not only in the raw EEG, but also in the aEEG, by a shift in both the upper and lower margins.

Following this line of though, and given that the aEEG algorithms are not open-source, the algorithm for this artifact includes an aEEG-like algorithm, but with less specifics and less computational load. This part of the algorithm calculates the difference between the maximal and the minimal value of the raw EEG in a 1-second window, thus yielding a signal that resembled the time-compressed aEEG. This way, and given that the HFO artifact has a small amplitude, the resulting array has lower values whenever the artifact is present. After that the signal is normalized (by dividing all the values by its maximum) and inverted between zero and one, meaning that the end array is the result of 1 – aEEG. This is done because for future analysis and threshold selection it is preferable if the periods of the resulting array corresponding to artifactual EEG have higher values than the periods of normal brain activity.

4.3.3 EMG

This artifact is characterized by a trace with a small amplitude and a frequency higher than normal for a neonatal EEG. Knowing that the high frequency is one of the major features of muscular activity, one would consider frequency analysis as a first attempt. Unfortunately, the frequency band of the normal EEG can sometimes overlap with the artifact’s frequency, reason why classical filtering cannot be applied in this artifact, because that could mean the loss of important information regarding the normal EEG activity.

With this in mind, another approach was set in place (Appendix XI). Given the main characteristics of EMG artifact, this algorithm takes into account that more amplitude shifts in the data (due to the high frequency) translates into a higher distance between consecutive points, so it considers a function
that calculates the difference between the values of consecutive points. After this, the resulting distance function is averaged in a window of seven seconds because this artifact can last for long periods of time. This way, whenever the EMG artifact is present the resulting normalized array will have higher values, thus distinguishing the artifactual periods from the ones with normal brain activity.

4.3.4 ECG

The method in the algorithm for this artifact (Appendix X) is based on the algorithm for the EMG activity, meaning that it also takes into account the distance between consecutive points and an averaging within a window of five seconds. The difference in this algorithm comes in two parts: the first is that this is an artifact with a very small amplitude, where the QRS complex is represented by a short peak, hence the distance between points is actually smaller than average whenever the artifact is present. The second aspect is that the averaging window in this case is only of five seconds, because after further analysis this was the window length that provided the best results.

Due to the first difference, after the final array is normalized, it is subtracted from 1, like in the HFO artifact, resulting in a normalized array where the higher values represent the periods of signal with artifactual data.

4.3.5 Movement and Electrode displacement

This artifact is separate from the others since it does not need any correlation method and, therefore, the threshold used does not depend on the signal processing methods in the algorithm.

As stated in the literature [52], the maximal activity for the normal neonatal EEG takes different values depending on the infant’s gestational age (GA), in weeks. With this in mind, this algorithm (Appendix XII) only requires that the user inserts the GA of the signal’s subject as an input and then for each different age from 23 up to 42 weeks GA the algorithm associates that with a specific value for the maximal (and minimal) activity that’s physiologically accepted. If the activity in the EEG is above this maximal value (or below the minimal) or if it is not a number (NaN) due to electrode displacement, the algorithm will consider it an artifact.
4.4 Threshold Selection

As stated in the methods described above, the result of every algorithm is a single normalized array, with a length relatively the same size as the raw signal and with all its values between zero and one.

The methods in each algorithm all aimed at artifactual periods with higher values than the average normal EEG, so the problem that poses now is how to separate the artifactual periods from the ones with actual brain activity. This separation will rely on the definition of a threshold, a number between zero and one that indicates that any values above that threshold (in the normalized array) represent artifactual periods in the EEG, and any values below represent real non-artifactual brain activity.

To find the best threshold for each different subject (because each sample of signal from each patient has its own characteristics), all thresholds between zero and one, with a step of 0.01 are tested. This testing is done resorting to an ROC (Receiver Operating Characteristic) Curve, which is a plot of two different variables:

- Sensitivity (4.3) – or true positive rate, calculated by:

\[
Sensitivity = \frac{TP}{(TP + FN)}
\]  

(4.3)

where the True Positives (TP) are defined as all the periods of signal that the algorithm detects as artifactual (meaning, above the considered threshold) and False Negatives (FN) as all the periods of artifactual data that the algorithm did not consider artifactual but, in fact, correspond to artifacts in the data.

- Specificity (4.4) – or true negative rate, calculated by:

\[
Specificity = \frac{TN}{(TN + FP)}
\]  

(4.4)

where the True Negatives (TN) are all the periods of signal that the algorithm did not classify as artifact, i.e., the algorithm classifies them as actual brain activity and are below the considered threshold, and the False Positives (FP) are all the periods of actual brain activity that the algorithm considered as artifact but are in fact periods of non-artifactual brain activity.

This method of analysis takes into account the binary classification of the data. In this part of the algorithm, if the resulting array is above the current threshold, it’ll be converted into a 1, meaning that the algorithm is classifying that as part of an artifact, and if it is below the threshold it’ll be converted into a 0, i.e., not an artifact.
Considering this method, for each threshold out of the 100 different between 0.01 and 1, results one sensitivity and one specificity values, meaning that the final result is two different arrays with 100 values each: one for the sensitivity values and another for the specificity. The ROC Curve is, as previously stated, the plot of these two arrays. On the vertical axis is the sensitivity and on the horizontal one is $1 - \text{specificity}$. The purpose of this plot is to find which threshold does the best separation between artifacts and brain activity, i.e., which threshold optimizes both sensitivity and specificity simultaneously. The chosen criteria for the threshold selection was the distance to the upper left corner of the plot, where sensitivity = 1 and $1 - \text{specificity} = 0$, or specificity = 1 as well. The threshold that was plotted the closest to this corner, was the one selected as the best threshold to separate the artifacts in that subject’s detection algorithm.

### 4.5 Assembling the Algorithms

After all the algorithms are developed, it’s time to move on to the next step and assemble all the smaller algorithms into one larger detection algorithm.

The first attempt on the assembling of the algorithms consisted on the loading of the signal and then all the small algorithms would run, one at a time, and have its own detection result. After this, the logic behind it was based on the fact that the algorithm with the most detections (length of overall artifactual periods over signal length) would indicate that its artifact was the one present on the data, and therefore the overall algorithm would be able to not only detect the artifacts, but also classify them.

The second attempt was decided after a discussion with the clinical staff. Given that a doctor usually does a quick preview of the raw file before performing any analysis, this method of combining all the algorithms considers the decision of the user as an input: before running the detection algorithm, the user decides which artifact he/she wants to detect and inserts that as an input on the algorithm. This way the user has the freedom to choose which artifact is to be detected and the overall algorithm only runs one out of the seven smaller algorithms within. Once the algorithm is finished, the result is a plot of the raw signal with coloured bars that represent the beginning (green) and the end (red) of each artifactual period in the data.

Once all the classifications were done, the method had to be compared to the manual annotations – the golden standard that was available – in order to assess if the algorithm was detecting the artifacts as it should be. This evaluation of the algorithm’s performance considered three different classifications:
True Positive (4.5) – when the algorithm detects an artifact where there is indeed an artifact. This rate is calculated when dividing the number of artifacts correctly detected by the algorithm by the overall number of artifacts in the data (through the manual markings):

\[
\text{True Positive} = \frac{\# \text{artifacts detected}}{\# \text{artifacts in data}} \tag{4.5}
\]

False Positive (4.6) – when the algorithm detects an artifact in a period of signal that is actually non-artifactual brain activity. This is the quotient between the number of wrong detections of artifacts and the total number of detections made by the algorithm:

\[
\text{False Positive} = \frac{\# \text{wrong artifacts detected}}{\# \text{detections}} \tag{4.6}
\]

False Negative (4.7) – this indicates the rate of artifacts that the algorithm didn’t detect, i.e., the artifacts that the algorithm considered as normal brain activity. This rate is given by dividing the number of undetected artifacts by the total number of artifacts in data (by the manual markings):

\[
\text{False Negative} = \frac{\# \text{artifacts undetected}}{\# \text{artifacts}} \tag{4.7}
\]

These three different types of classification evaluate of the algorithm’s performance, allowing for its optimization upon training and testing with the data available.

In consideration of further implementation of the developed algorithm into different systems that are currently used in the NICU, Appendix XV focuses on a brief explanation of Use Cases, which were approached in the beginning but not fully developed throughout the project.
5 Results

In this chapter the results obtained from the methods previously described are presented. To ease the interpretation process, the results for every step of only one algorithm will be presented, given that most methods follow the same logic. After that, an example of every algorithm’s result will be presented. The results for both approaches in assembling the smaller algorithms are also included, which demonstrate why the first approach (running all individual algorithms at once) was not optimal for the purpose of this project. The results for the three classification criteria (True Positive, False Positive and False Negative) are also presented, as a way of demonstrating the overall results of the final algorithm.

5.1 Sinus Wave

5.1.1 Detection Method

When considering all the different algorithms detailed before, one can understand that the algorithm for the Sinus Wave artifact is the most complex one, given the different matrices created and their combination method. With this in mind, this chapter will go through a detailed explanation of the results for each step of this algorithm, clarifying the output of every process within the algorithm. The results for the other artifacts’ algorithms will also be considered afterwards, given that all methods must be accounted for, but with less detail, due to the similarities between the methods.

In order to simplify the walkthrough of the logic for the Sinus Wave algorithm, this chapter will focus on a small portion of signal from the 30 minutes long sample of data from one subject. This way, it is possible to see a plot of the raw signal with three artifactual periods within just a few seconds, like in Figure 5.1.

In this sample of signal it is possible to observe three periods of non-random activity, different from normal signal acquired with the EEG. These artifactual periods are characterized by a periodic and rhythmic activity, like described in a previous chapter, and also by a smaller amplitude when compared to the rest of the signal, as one can see by the comparing these with the periods not marked as artifacts. These artifactual periods are approximately 15 seconds long, with intervals between them of around 5 seconds.
The green and red bars, marking the beginning and end of each artifact respectively, aid the visual interpretation and identification of the artifacts in the EEG signal.

Regarding the correlation method, it is relevant to consider the importance of the \( \sin \) and \( \cos \) correlations, given the phase difference between the two functions, accounting for a larger variability of the signal in question. For that reason, in this chapter it is presented the matrix resulting from the correlation with both functions, in Figure 5.2 and Figure 5.3.
In both figures one can see the same bars that were marking the artifactual periods in the raw signal, for the same sample of EEG trace. These figures indicate the resulting matrices after the correlation coefficients with each function are calculated, and are then plotted according a colour map, which goes from -1 (dark blue) to 1 (bright yellow) - the possible extreme values that one can obtain from the correlation function. On the vertical axis of the matrices, one can find the different frequencies considered for the correlation: 0.02 Hz up to 3 Hz, with a frequency step of 0.02 Hz. This way of displaying the results allows the observer to identify the frequencies that resulted in higher correlations with the raw signal. For the purposes of this analysis, both extremely high and extremely low correlation values were considered as indicators of the presence of an artifact given due to the reason explained in the Methods. According to this, it is possible to observe yellow (high) and dark blue (low) colours in most of the artifactual periods (between the green and red bars), specially in the area corresponding to 1.4 – 1.5 Hz, allowing the user to also extrapolate the approximate frequency of the artifact in question.

It is also possible to observe high and low values of correlation coefficients for other frequencies - around 0.5 Hz outside artifactual periods and 2.7 Hz within the same periods – but those possible artifactual values are eliminated once the combination method is applied to both matrices, resulting in the matrix in Figure 5.4.

In this Figure 5.4, considering the colour scale changes from 0 (dark blue) to 1 (bright yellow), it is possible to understand that the correlation values within the artifactual periods are indeed the ones with the highest values within the matrix, highlighted by the bright colours within these periods. This
scale has a minimum of zero because in the combination process all values are converted into their absolute values.

Another factor that should be considered is that outside the artifactual periods there are still some relatively high values, but these are much more scattered in the frequency domain, indicating that these values do not relate to this artifact, which has a specific and somewhat constant frequency.

Once this matrix is obtained, and following the methods described before, the algorithm selects the maximum value of every time point, i.e., the highest value from all frequencies in that point. This is done because if we are in the presence of an artifact, it indicates the frequency that correlated the best with that artifact, and if not, the value will be low for all the frequencies considered anyway. This way the result is an array just as long as the matrix and the original signal itself that is then normalised, meaning that all the values of the array are comprised between zero and one, as it can be observed in Figure 5.5.

In this normalised array (from the same segment of signal and from the same correlation matrices) is evidently shown that the artifactual periods are indeed characterized by higher correlation values than normal brain activity periods. With this type of analysis, it becomes clear that the artifactual periods have certain characteristics that differ from non-artifactual signal, and those features can be evidenced thanks to this correlation method.

![Figure 5.4 - Correlation matrix after the combination of the sin and cos matrices](image)
5.1.2 Threshold Selection

The problem that arises now, is how to separate these two classifications: artifactual and non-artifactual. Thanks to the difference in values in this normalised array, one can define a threshold that separates the two different periods of signal. Given that higher values are found in the portions of signal with artifacts, everything above that said threshold shall be considered as artifact, and everything below as normal brain activity. That can later be translated into the raw signal and help in identifying the artifacts in the data. With this in mind, it is now necessary to define the threshold that best preforms the separation between artifactual and non-artifactual signal. This was done with the aid of a ROC (Receiver Operating Characteristic) curve.

As previously explained in detail, this curve allows the analysis of every threshold between zero and one (because the array is normalised) with a threshold step of 0.01 (thus considering 100 different thresholds) and calculating the sensitivity (true positive rate) and the specificity (true negative rate) obtained with every threshold. In the specific case for the subject considered in this chapter, the ROC curve obtained can be found in Figure 5.6.

Once the curve was obtained, the selection of the best threshold was needed, and the criteria for this selection was discussed with the clinical staff. The final decision on this matter relied on the fact that the best threshold is the one that maximizes both sensitivity and specificity at the same time, meaning that it is the one that’s closest to the upper left corner (sensitivity = specificity) of the ROC plot. Considering these criteria, the algorithm also calculated the distance between every point in the curve and the upper left corner, and in the end, the smallest distance was the one that indicated the best threshold.
For the case of this particular subject presented here in this chapter, the best threshold was found to be 0.54, but each different subject has a different threshold, because of various features unique to each signal, like the exact frequency, the result after the combination of the correlation matrices, or even the threshold step for the ROC curve. Despite all of these factors, the thresholds for each different type of artifact are always within a certain range, allowing the user to have some guidance as to which value to choose for the threshold, as it can be seen in Table 5.1.

Table 5.1 - Threshold values for the different artifacts

<table>
<thead>
<tr>
<th>ARTIFACT</th>
<th>THRESHOLDS’ RANGE [0 - 1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>WAVE</td>
<td>0.49 - 0.55</td>
</tr>
<tr>
<td>PED-LIKE</td>
<td>0.68 - 0.78</td>
</tr>
<tr>
<td>ZETA</td>
<td>0.76 - 0.80</td>
</tr>
<tr>
<td>HFO</td>
<td>0.81 - 0.94</td>
</tr>
<tr>
<td>ECG</td>
<td>0.52 - 0.81</td>
</tr>
<tr>
<td>EMG</td>
<td>0.09 - 0.30</td>
</tr>
</tbody>
</table>

After analysing the values in the table, one can see that for the first four algorithms the thresholds are all within a certain and short-limited range: for the wave’s algorithm, the thresholds are around 0.5, for the PED-Like’s its around 0.7, same as for the Zeta algorithm, and the HFO is around 0.9. The last two algorithms have wider ranges, and therefore in these cases the selection of the threshold should be performed with caution. One must keep in mind that all algorithms were trained and tested on 5 subjects each, except the EMG one, that only had 3 subjects, so these ranges are referring to those subjects’ thresholds without any statistical calculations, i.e. mean, median, minimum or maximum. Once every subject’s threshold is determined, it is
time to perform the actual separation between brain activity and artifacts. This part of the algorithm takes the newly-found threshold into account into the normalised array and performs a binary operation. Any time point value equal or below the threshold is turned into a zero (0) and any value above is turned into a one (1), resulting into a binary array like the one in Figure 5.7.

![Figure 5.7 – Detections array](image)

This figure refers to the portion of signal from the same sample as before, with the same markings, but this time the plot is binary, as one can see from the values and the scale on the vertical axis. The artifactual periods in the array have a comb-like, very spiky shape because the high values in the array from Figure 5.5 were also sharp-like and even in the high-values areas, some parts were below the threshold, resulting in this shape. Because of this feature that was present in many different arrays, even for different artifacts and different subjects, a function was created in order to join peaks (Appendix XIII) that were too close together. This way, it becomes possible to obtain a smoother result like the one in Figure 5.8.
As one can see, after joining of the peaks, separate artifactual periods that are too close apart were merged and considered as only one period of artifactual data, but after convening with the medical staff this was not posed as an obstacle, given that all three manually marked periods in this example are contemplated in the detection result from the algorithm.

This final binary array is then considered the final detection result. Regarding the algorithm’s results presentation, it is still left to be decided, given that that decision is up to the medical staff’s preferences: it can either be done by a plot of the raw signal with bars marking the beginning and the end of the detection periods (much like the manual markings) or some sort of a report that is written after the algorithm has run, stating in text the beginning and end times of the artifactual periods, in ‘hh:mm:ss’ format, according to the time of the acquisition of the signal.

**Figure 5.8 - Detections array after the function joint_peaks**

Error! Reference source not found.
5.2 The other algorithms

In regards to the other artifacts, the methods may differ, as detailed before, but the result follows the same logic. Because of that, the results for every step of the other algorithms will not be included in this chapter, as the logic behind it has already been explained, but a sample of each artifact and its algorithm’s result will be included here, as to show the reader that all the different algorithms are indeed detecting the artifacts. Such results can be found from Figure 5.9 up to Figure 5.20.

![Figure 5.9 - Raw EEG signal with two PED-Like artifacts](image)

![Figure 5.10 - Array with the detection of both PED-Like artifacts](image)
In this set of examples, it is possible to see that the different algorithms can indeed detect the artifactual periods, even though the beginning and end times of the manual markings and of the detections don't always match. Despite that, the samples here included can translate the algorithms' results as an artifact detection method. This provides a new insight into the analysis that can be performed in this type of neonatal acquisitions, possibly helping the clinical staff and reducing the time-consuming task of manually identifying the artifacts.

Figure 5.11 - Raw EEG signal with two Zeta artifacts

Figure 5.12 - Array with the detection of both Zeta artifacts
Figure 5.13 - Raw EEG signal with one HFO artifact

Figure 5.14 - Array with the detection of the one HFO artifact
Figure 5.15 - Raw EEG signal with two ECG artifacts

Figure 5.16 - Array with the detection of both ECG artifacts
Figure 5.17 - Raw EEG signal with one EMG artifact

Figure 5.18 - Array with the detection of the one EMG artifact
Figure 5.19 - Raw EEG signal with two distinct periods of artifacts due to Movement or Electrode Displacement

Figure 5.20 - Array with the detection of both periods of artifacts due to Movement or Electrode Displacement
5.3 Assembling the Algorithms

With the aforementioned proof that the separate algorithms are in fact detecting the artifacts, it is time to assemble them and with that create the overall detection algorithm.

This assembling process went through two different approaches: the first one, where all algorithms run and there is a selective criteria to determine the artifact present, and a second one where only one (instead of all seven) algorithm runs. In order to justify the reason why the second attempt was necessary, it will be first demonstrated the results of the first attempt, and then the results from the second.

As it was described in the Methods chapter, the criteria for the first approach on the overall algorithm’s development was to run all separate algorithms and then the one with the most detections was the one referring to the artifact present in the signal. Following that logic, Table 5.2 shows the artifacts present in the respective signals in the rows and the separate algorithms in the columns.

The table easily shows that each specific artifact is not being entirely detected by its own algorithm, when all the algorithms run at the same time. As one can see, the signals with a Wave artifact where being mostly detected by the algorithm for the HFO artifact, meaning that the user can’t even be sure that the artifacts that were “detected” by this algorithm are indeed artifacts and not real brain activity. This problem can be found for most of the artifact, except the HFO and the EMG artifacts, as it can be seen in the table that these are the only ones with a check mark solely on the same artifact and algorithm.

<table>
<thead>
<tr>
<th>ARTIFACTS</th>
<th>WAVE</th>
<th>PED-LIKE</th>
<th>ZETA</th>
<th>HFO</th>
<th>ECG</th>
<th>EMG</th>
</tr>
</thead>
<tbody>
<tr>
<td>WAVE</td>
<td>√</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>PED-LIKE</td>
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<td></td>
<td>√</td>
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<tr>
<td>HFO</td>
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<td></td>
<td></td>
<td>√</td>
<td></td>
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<tr>
<td>ECG</td>
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<td>EMG</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>√</td>
</tr>
</tbody>
</table>

Bearing this problem in mind, another approach on the overall algorithm had to be thought. After discussing the issue with the medical staff, it was possible to reach the conclusion that the physician that is analysing the data always has an overview of the overall signal, in order to make sure that everything is in order,
allowing the user to identify the artifact that is present in the data. As such, the second – and final – approach on the developing of the final algorithm is based on the fact that only one out of the seven specific algorithms runs.

This new approach means that the user is the one that selects which artifact he/she wants to detect in the signal, given that usually, per subject, there’s only one type of artifact. Alongside with the selection of the artifact to detect, the user also has the freedom to choose the threshold that shall separate artifactual data from actual brain activity, thanks to the thresholds from Table 5.1, which remain the same for this final algorithm.

Finally, with the final detection algorithm developed, it is time to demonstrate the overall results from every algorithm for every subject, given that the plots previously presented only display a small sample of the efficacy of the independent algorithms. Table 5.3 gives us the results for every test performed on the subjects, for the optimal thresholds taken from the ROC curves for each subject.
Table 5.3 - Results of all algorithms, for all subjects

<table>
<thead>
<tr>
<th>WAVE ARTIFACT</th>
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<th>FALSE NEGATIVE</th>
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<td>92.0</td>
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<td>#2</td>
<td>91.2</td>
<td>24.4</td>
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<table>
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<td></td>
<td>#1</td>
<td>100.0</td>
<td>52.9</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>#2</td>
<td>81.3</td>
<td>33.3</td>
<td>18.7</td>
</tr>
<tr>
<td></td>
<td>#3</td>
<td>92.6</td>
<td>16.7</td>
<td>7.4</td>
</tr>
<tr>
<td></td>
<td>#4</td>
<td>80.0</td>
<td>20.0</td>
<td>20.0</td>
</tr>
<tr>
<td></td>
<td>#5</td>
<td>100.0</td>
<td>25.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>EMG ARTIFACT</th>
<th>SUBJECT</th>
<th>TRUE POSITIVE</th>
<th>FALSE POSITIVE</th>
<th>FALSE NEGATIVE</th>
</tr>
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<tbody>
<tr>
<td></td>
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<td>100.0</td>
<td>80.0</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>#2</td>
<td>77.8</td>
<td>12.5</td>
<td>22.2</td>
</tr>
<tr>
<td></td>
<td>#3</td>
<td>100.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
By observing Table 5.3 one can see that the True Positive (TP) rate has the highest values, always above 80% with a few exceptions. Following this rate is the False Positive (FP) rate, with lower values than the TP but still higher than the False Negative (FN) rate, which translates the percentage of artifacts that were not detected by the algorithms. As one can see, the last column in the table has a few values of 0.0%, which means that in those cases the algorithms in question detected all the artifacts present in the data.

In order to get an easier overview of the results presented above, Table 5.4 presents the mean and standard deviation of all the three criteria.

<table>
<thead>
<tr>
<th>CRITERIA</th>
<th>MEAN ± STANDARD DEVIATION (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRUE POSITIVE</td>
<td>92.4 ± 7.5</td>
</tr>
<tr>
<td>FALSE POSITIVE</td>
<td>34.9 ± 19.8</td>
</tr>
<tr>
<td>FALSE NEGATIVE</td>
<td>7.7 ± 7.5</td>
</tr>
</tbody>
</table>

This table considers the overall performance of the algorithm, regardless of the artifact it’s detecting. As such, the artifact due to movement or electrode displacement is not included here because that artifact, as it was previously explained, does not need any training or testing, relying only on an absolute threshold stated in the literature [52].
6 Discussion

In this chapter, a critical overview of the results it will be included, with a discussion of what they mean and how they can be interpreted as parts of the whole that is this project. The logic of this chapter shall be the same as the previous one — Results — in order to keep the same line of thought and ease the process of discussing the algorithm’s steps.

After considering the State of the Art and all the methods previously attempted by other research groups, three methodological conclusions were reached:

- Independent Component Analysis (ICA) should not be performed in this set of data because one only has access to two different channels in the EEG, which would mean that this analysis could only have an output of two different components, which was not reliable enough to discern artifacts from normal data;

- Even though some artifacts have a specific frequency range, classical filtering is also not the best approach due to the fact that these frequency ranges could be overlapping with the normal EEG’s frequency range, and one does not want to remove important data from the EEG trace;

- Basic subtraction of the EEG trace with ECG, EMG or respiration/ventilation signals could not be done due to the fact that these acquisitions were not available for every subject, and therefore the algorithm could not rely on additional physiological signals in order to detect these types of artifacts.

Therefore, the first topic to mention in this chapter is the sample of raw EEG chosen to illustrate the steps of the algorithm for the Sinus (LF) artifact. As seen in Figure 5.1 one can see that the sample translates the problem in question: very often the raw EEG signal contains artifactual periods that mask the real brain activity and may lead to erroneous conclusions regarding diagnosis and treatment of seizures. In this portion of signal one can see three artifactual episodes in the data, clearly separated, but close enough to provide an insight on how accurately the algorithm is able to identify separate episodes of artifactual data. Another feature that can be identified is that this specific artifact usually has a smaller amplitude when comparing to the brain activity on the EEG, whilst being less stochastic and therefore more periodic.

When this portion of signal goes through the correlation process, the first result resembles Figure 5.2 and Figure 5.3, showing the matrices of correlation between the raw periods of signal (periods of 5 seconds) and the sliding window that is the surrogate (created from the sin and cos functions in MATLAB). Each column of these matrices correspond to a time point, from the beginning to the end of the acquisition, and each row corresponds to a different frequency considered to the surrogates, from 0.02 to 3 Hz, with a frequency step of 0.02 Hz.

One might argue that this method is very similar to the Short-Time Fourier Transform (STFT) that can be performed also in MATLAB with the aid of the function spectrogram. There are two different reasons why this function was not
used in this algorithm: first, because this function, with the same parameters (sliding window of 5 seconds – 5x64 time points –, overlap of 5x64-10 = 310 time points) did not provide results as good as the ones presented previously, as the artifacts could not be identified in the resulting matrix, whether in the time domain and the frequency domain. The second reason is because spectrogram is an in-built function from MATLAB, and as it was discussed previously, the end-goal of this algorithm is to be implemented in SignalBase and eventually in the bedside monitors in the NICU. As none of these systems have MATLAB within or even have the chance to do so, one cannot resort to such complex functions when thinking about the future of the project. When the method for this artifact’s algorithm was developed the STFT was not considered, but once the original method proved effective the similarities between both processes were noticed and therefore the results were compared, in order to see if STFT should be considered in the analysis. As mentioned before, the STFT did not perform a separation between artifactual and non-artifactual periods of EEG as effectively as the method developed, reason why the function spectrogram from MATLAB was not considered for this algorithm.

Focusing again on Figure 5.2 and Figure 5.3, it is possible to observe that there are in fact different patterns in the matrices within the areas marked as artifactual. For most of the length of these periods and between the frequencies 1.2 Hz and 1.5 Hz there are patterns composed by really high and really low correlation values, as one can see in the colour bar on the right side of the matrices. Something worth noticing in these colour bars is that the extreme values of -1 and 1 are never reached or even considered in the bars, given that the computational process of correlation never really reaches a perfect result, which is expected because there is also a certain variability associated with the artifact, given that it is still part of an EEG measurement. For that reason, the maximal values in these matrices are always around ±0.9, which are considered values high/low enough to indicate a high correlation. Outside these areas in the matrices, most of the values are around 0, indicated by a green-ish colour in the overall plot, excepting some other random high/low values that are later eliminated when these matrices are combined, as one can see in Figure 5.4.

In this figure it is presented the result of the combination of the sin and cos correlation matrices. The periods of higher and lower correlation values are now consistently higher than the rest of the matrix, an analysis that’s aided by the colour bar on the right of the plot. The values in this matrix are not normalized, but it is still possible to understand that the periods of artifactual data do indeed possess higher values between the green and the red bars and also always within the same frequency range, another feature that indicates that we’re in the presence of an artifact of Sinus (LF) and not just some random and periodic activity from the brain. A characteristic that can be seen in this example is that the start of the high values in the matrix don’t match exactly with the beginning of the artifactual period, i.e., there’s always a small lag between both features. This can be understood when considering the fact that the surrogate window has a length of five seconds, so the higher correlation values cannot commence when only a portion of the raw signal matches the surrogate, thus the delay.
In this same matrix, it is also possible to observe slightly higher values also around 2.8 Hz, but still not as high as the ones mentioned before. As one can see, this frequency value is approximately the double of the frequency range for the highest values, meaning that the surrogate with a higher frequency might be having a correlation higher than usual even though it is not the same frequency of the artifact, given that one cycle of a surrogate with 3 Hz can cover exactly two cycles of an artifact with 1.5 Hz, having a really high correlation both in its beginning and end, and a really low correlation in the exact middle of the correlation.

Once the matrix combination process is done, it is time to normalize and convert the matrix into an array, much like the one in Figure 5.5. This plot shows that the areas with higher correlation periods can in fact be separated from the rest of the signal based only on its values. This poses the next big problem of this algorithm, that is: how to separate artifactual detections from normal brain activity periods? Given that the answer focused on the definition of an optimal threshold that best performs this separation, one must consider the thresholds in Table 5.1. These ranges take into account the thresholds for each subject from each different artifact, and it is easily seen that for the first four algorithms the thresholds are always within a certain range, which is a good thing because there is always a certain amount of variability associated with each different subject, which can influence the threshold value, but in these cases that does not pose as a major problem and all values are relatively close to each other, within the same artifact. For the last two algorithms, the ECG and EMG ones, the same does not occur. Unfortunately, the threshold ranges for these two algorithms are broader than the rest, and that might pose as a challenge when the algorithm is not on a training or testing phase but already in daily use. For that matter, this is a weak spot for the overall algorithm given that the user still does not have a short scope of values to choose from. With that in mind, future steps on this algorithm must be considered: given that these two artifacts are, from the seven proposed, the most commonly found artifacts in the literature for infant and adult EEG, comparison with other detection methods must be set in place and test which approaches are best on the detection of its respective artifacts. Statistical analysis on these thresholds - in order to find the best optimal value - was not performed due to the fact that there are only five values per artifact, and that did not consist on a population large enough to perform tests. The fact that this algorithm is still in a preliminary phase can also constitute an argument as to why this kind of analysis was not performed on this data.

Assuming that all best thresholds are now found for every subject on this training/testing set, the separation between non-artifact and artifact is performed in the normalized array and we obtain a plot like Figure 5.7. In this plot it is possible to see that within the artifactual periods there are a lot of small detections, due to the fact that the array from the correlation matrix had a very irregular shape and in the periods with high values, one can find differences of values up to 0.2. This means that if the threshold is e.g., 0.54, an array in an artifactual periods that always has values between 0.5 and 0.6 will have a lot of shorter detections and not a single, consistent detection. With this problem in mind, a function was created – joint_peaks – that allows for the joining of detection peaks that are too close apart, turning the result from Figure 5.7 into Figure 5.8, and the time that separates the
smaller detections can be chosen by the user as well. In concordance to this problem, sometimes random detections also arise from the methods described before, even in portions of signal where there are no artifacts whatsoever. These random detections are spurious in the detection arrays and do not translate any artifactual presence at all, being the result of random brain activity in the EEG that could maybe resemble the artifact in question for a short period of time. With this in mind, a different function was created – end_peaks – that eliminates detections that are shorter than a certain duration that is also selected by the user. If one considers that most artifacts occur for periods longer than 5-10 seconds, it becomes useful to eliminate detections that last less than this amount of time. This function allows for the fine-tuning of the algorithm’s results and for a better understanding of where the real artifacts are in the data.

With regards to the other algorithms’ results from Figure 5.9 up to Figure 5.20 it is possible to see six different samples of raw EEG from six different subjects containing the other types of artifacts mentioned before. Just as the example detailed in the previous chapters, the green and red bars aid the visual identification of the artifacts in the raw data, marked by an experienced doctor. When the artifacts’ amplitudes are very low (around 10 to 20 μV) it is possible to see that the overall variation of the EEG’s amplitude is still present and the artifact is only an addition to the signal, like in the cases of the HFO, ECG and EMG. For the cases of the PED-Like and Zeta artifacts, it’s as though the artifact is superimposing itself on any brain activity that could be present and the artifact is all that the user can see in the acquisition, much like in the Sinus (LF) case.

For the case of the PED-Like artifact, the detections can be found exactly within the artifactual period, as it is also the case for the Zeta and for the HFO artifacts. For the ECG and EMG artifact, the detection of the artifacts lasts a bit longer than the artifact itself, but as one can see in the raw EEG plots, the EEG signal does not return to a smoother shape right after the artifact, so this irregular shape – even though not being considered artifact – is passing the algorithm’s criteria for artifact and therefore it’s being classified as such. Focusing on these two examples, the user must take one thing into account: the manual markings of the artifacts in the raw EEG were performed by only one experienced doctor and there was no opportunity for other classifications by different observers. This means that there was no possibility for inter-observer reliability calculations or any sort of analysis such as this, in order to make sure that the golden standard considered here if in fact agreed upon by more than one member of the clinical staff. With this in mind, the algorithm only has one measure to consider as the real truth between artifactual and non-artifactual data and the results are therefore prone to be different should more classifiers be included in the project.

For the Movement artifact, the signal considered in the example belonged to a subject with 40 gestational weeks of age, and therefore the maximal and minimal values for a normal EEG are considered to be in the range of ±100 μV. This way, the algorithm takes the age value and associates it with an agreed upon value for both limits in the EEG signal. The algorithm then considers the raw signal and every time the signal if over (or under) these values, an artifact is detected. The advantage of this specific algorithm is that it does not need a golden standard to
compare it’s results because the method is very binary: the EEG signal is either within the normal values or not. The only dependence of this algorithm is the subject’s age, a characteristic that the clinical staff can always access whenever they need to, and that can even be found in the BrainZ file when opened.

The small delay in the detection of the artifacts when comparing them to the actual beginning of the artifact in the raw EEG is not yet considered an obstacle to the algorithm because this project focuses on a first approach for the algorithm, and also due to the fact that when the clinical staff uses the algorithm, a visual check of the results is still recommended given that there are still features to be optimized in the algorithm. Considering this, it suffices that the algorithm identifies the artifacts where they are present, but it’s not yet essential that the detections have a perfect match with the beginning and end of the artifact in the raw signal, given that for now this is a detection tool and as long as the algorithm alerts for the presence of an artifact in the acquisition, the user can check the results in the end and determine with more accuracy the exact start and finish of the artifacts.

Considering now the assembling methods that were set in place, it is easy to understand the need for a second approach, given that Table 5.2 elucidates that when all algorithms run at the same time, the results are sub-optimal. When observing this table, one can see that in the first attempt to build the overall algorithm - with all algorithms running – some algorithms could never really detect their own artifacts because other methods were superimposing themselves and overshadowing the results. It is clear that the method for the HFO was able to detect more than it should, as it is visible that this algorithm had the highest percentage of detections for all artifacts, except for Zeta waves and EMG activity. Alongside with this, even if the other algorithms had high detection percentages but a bit smaller than the ones from the HFO, the results didn’t matter because the right algorithm would not be the chosen one. Taking the case of the Sinus (LF) artifact: when running all algorithms on an EEG signal with this artifact, the detection percentage might even be the correct one, but the HFO method was detecting more artifacts that could not even be so, in reality. The reason some artifacts have a checkmark on two different algorithms is because for all five subjects from each artifact, some methods had different percentages: in the case of the five subjects with PED-Like artifacts, two subjects had the ECG method as the one with highest detection percentages and the other three had the HFO one with the highest detections. Even though the HFO and the EMG artifacts were correctly identified by the corresponding algorithms, this approach was not developed any further because the other artifacts were being erroneously recognized and the overall algorithm could not be trusted with its final results.

This method was clearly not the best one and further consideration was taken into this part of the project. After a careful analysis on the problem at hand, the second approach was decided with the clinical staff: given that the user always overviews the raw signal before analysing it and can know beforehand what type of artifact he/she is looking for, the overall detection algorithm will ask the user for two different inputs before running any detection methods: the subject’s age and what type of artifact is to be detected. This solution comes with two main
advantages: the first one is that the computational time of the detection algorithm is cut short because instead of running seven different algorithms, only one is running. The second one is that this gives the user freedom to select the goal of the detection, being able to identify more accurately and with more confidence the artifact in question, especially when considering the one EEG acquisition usually only has one type of artifact, out of the seven described. This second and chosen approach on the detection algorithm does not need further training or testing because the results are in every way like the ones from the separate algorithms presented in the plots before.

In any case, the results for every algorithm and every subject must be scrutinized, in order to demonstrate the efficacy of the overall detection algorithm. For that, one must take into consideration Table 5.3. In this table it is possible to see all the results for the three evaluation criteria considered: True Positives (TP), False Positives (FP) and False Negatives (FN). True Negatives were not considered due to the fact that these criteria would take most of the signal, i.e., this criteria would just indicate when the algorithm purposely does not detect anything and the main focus of this analysis is the opposite: when the algorithm in fact detects something, and how correct those detections are. This way, one can see the values for all three criteria, for every algorithm and for every subject.

From a more careful analysis on the table, one can see that the TP rate is always the one with the highest values, which translates as a good outcome of the detection algorithm because that means that the methods are preforming as they should and that most artifacts are being properly identified. In fact, out of all the 23 subjects for all algorithms, 6 had TP values below 90%, proving the algorithm's efficacy in detecting artifacts. Following this rate is the FP values, which demonstrates lower values, but still higher than desired. Even though some artifacts have low values for this criterion, one of the weak spots of the detection algorithm is the False Positives it originates, meaning that the algorithm is detecting more artifacts than actually exist in the data. This can be due to two different reasons: first, it can happen because of the doctor’s classification and the need of more than one golden standard, because what one doctor sees as artifact might be brain activity for another, and vice-versa. The second reason is due to the threshold selection. With a higher threshold, more time points would be below the threshold and therefore not classified as artifact; this would mean that the detections that are correctly identified would be either shorter in duration or not existing at all – this proves that the threshold selection is a topic that should be focused on in future work and that can still be optimized. Once the thresholds are improved and its ranges are narrowed, the FP rate will certainly reach lower values.

When considering the FN rate, as one would desire, this is the lowest rate out of all three. This is a very optimistic feature from the detection algorithm, for it proves that the methods are not letting artifacts undetected, as this criterion evaluates the artifacts that are present in the data but were not identified by the algorithm. The fact that for some subjects (in different artifacts) this rate is 0.0% is a truly positive discussion point, because it means that the algorithm is not missing any artifacts in the raw signal. Following the discussion from the previous paragraph where threshold selection needs to be improved, if the threshold is
lowered than one must take into account that the FP rate will be lower (and therefore, better) but this FN rate might increase, so optimization of the thresholds must be performed very carefully and in discussion with the clinical staff, as their preferences must be always put first.

At this point, it is important to clarify one thing about these criteria: a true positive classification does not necessarily imply that the algorithm’s detection and the manual marking match perfectly. As it was noticed before, these two are not always in perfect synch, so a true positive is classified as a detection from the algorithm that is within the green and the red bar in the manual markings, independently on which one starts or ends first. As long as the algorithm identifies an artifact where an artifact is indeed present, that is enough to consider as a rightful detection, because at this stage of the project one must always rely on the user’s final assessment in confirming the algorithm’s results.
7 Conclusion

The acquisitions of newborns’ brain activity that are performed in the environment of the NICU in several hospitals are very often filled with different types of artifacts that may mask the true EEG signal that should be acquired. This may lead to misinterpretations of the EEG and therefore to erroneous conclusions when it comes to diagnostic and/or therapeutic procedures.

Given the wide variety of different artifacts that can be found, the methods previously developed by other groups usually focus on a particular artifact, due to its predominance in a specific set of data or to the specific needs of a certain study. The project at hands here is, to the best of the author’s knowledge up to date, the first approach on the simultaneous detection of seven (Sinus LF and HF, PED-Like, Zeta, EMG, ECG and Movement/Electrode displacement) different artifacts that were previously identified by the clinical staff.

The algorithm developed focused on each artifact’s specific features and tried to identify those features in EEG data with several sets of data, intermixed with artifactual and non-artifactual periods of time.

When considering the methods described and its results, the overall conclusion is that the algorithm is indeed detecting the artifacts and, therefore, serves the purpose it was developed for.

There are clear - yet minor - discrepancies when comparing the manual annotations and the results from the algorithm, but that does not present as an obstacle, given that the algorithm is in a stage where it still relies on the user’s final assessment.

There is still work to be done in this project, which is developed in the chapter Future Work, but the project described here already comprises a first approach on the detection of artifacts in neonatal EEG, contributing to a better understanding of the brain’s true activity and hopefully, to a more efficient and advantageous tool in signal processing in neurosciences, a field with so much that is already known, and yet so much to be discovered.
8 Future Work

As mentioned before, this project reports a first approach on an algorithm that aims at detecting seven different types of artifacts that can be frequently found in neonatal EEG acquisitions. As any first step at achieving something, there is always room for improvement, especially when the matter concerns diagnostic-related decisions.

With this in mind, there are aspects in this algorithm that can benefit from optimization. The main limitation of this project is the small amount of data that was used to train and test the individual smaller algorithms. Unfortunately, due to the time-consuming task of manually annotating the artifacts in the data, it was only possible to obtain five different subjects for each type of artifact (excepting the EMG artifact, which only had three subjects). Another limitation that undermines this is the fact that all acquisitions were used as training and testing data, meaning that the way the algorithm was built might be the result of overfitting the methods into the specific set of data that was available. Considering this liability, the first step on optimizing the algorithm must be to consider more data for every type of artifact and divide it into two distinct sets: one for training and another one for testing, assuring the better quality of the methods developed. This will not only improve the methods overall, but more data available can also be translated into a better certainty as to what is the best threshold for each artifact, thus reducing the ranges presented in Table 5.1 and allowing for statistical analysis to be set in place and therefore providing with more certainty a single value for each different artifact, regardless of the subject.

Once the final detection algorithm is optimized and the clinical staff agrees with its outcomes, implementation in SignalBase can be set in motion. This requires a set of programming skills that include MATLAB (where the algorithm was developed) and Embarcadero Delphi, the language in which SignalBase was developed. This implementation will allow for the synchronization of the EEG signals with other types of acquisitions (e.g. NIRS, ECG) and the possible identification of other artifacts that are not EEG-specific, but can be found in other physiological parameters.

When it comes to implementation, one must also mention the bedside software that is currently used in the NICU monitors – BrainZ – which performs real-time seizure detection. One of the downsides of this software is that its seizure detection algorithm relies too much on rhythmicity – a feature that is inherent to artifacts as well – so misclassifications of seizures that are indeed artifacts can also occur from time to time. Once the algorithm is already finished, its implementation on BrainZ is also something to consider, hopefully improving the true classification of seizures and reducing the administration of anticonvulsant drugs to treat what is, in fact, an artifact.

The final optimization point is not fully related to this algorithm, but an improvement in the overall signal analysis tool: artifact detection is the first step in artifact identification, of course, but that does not change the quality of the signal, because the erroneous information is still there. With that in mind, artifact
removal should also be a topic to discuss and to set in motion in the future. This might be a difficult task due to the fact that the acquisitions in the NICU from the WKZ rely on 2 channels only, but there is always room for improvement of the signal quality and for the optimization of the tools that are within our reach.
9 References


10 Appendices

The current section comprises the appendices referring to the project that was developed.

The first sub-sections include diagrams of the individual algorithms for the artifacts developed, which took a big part in the development of the initial logic and method behind each algorithm, whilst also easing the interpretation of the overall process.

Following the diagrams, the original MATLAB code written throughout this project is also included in this section, in order to demonstrate the computational logic within each method.

**APPENDIX I** – Diagram referring to the algorithms for the Sinus, PED-Like and Zeta Waves artifacts;

**APPENDIX II** – Diagram referring to the algorithm for the HFO artifact;

**APPENDIX III** – Diagram referring to the algorithm for the EMG and ECG artifacts;

**APPENDIX IV** – Diagram referring to the algorithm for the Movement/Electrode Displacement artifact;

**APPENDIX V** – Body of the overall detection algorithm;

**APPENDIX VI** – Auxiliary function for the Sinus Wave artifact’s detection algorithm;

**APPENDIX VII** – Auxiliary function for the PED-Like Wave artifact’s detection algorithm;

**APPENDIX VIII** – Auxiliary function for the Zeta Wave artifact’s detection algorithm;

**APPENDIX IX** – Auxiliary function for the HFO artifact’s detection algorithm;

**APPENDIX X** – Auxiliary function for the ECG artifact’s detection algorithm;

**APPENDIX XI** – Auxiliary function for the EMG artifact’s detection algorithm;

**APPENDIX XII** – Auxiliary function for the Movement/Electrode Displacement artifact’s detection algorithm;

**APPENDIX XIII** – Auxiliary function;

**APPENDIX XIV** – Auxiliary function;

**APPENDIX XV** – Use Cases;
manual marking of artefacts

beginning of the algorithm

Creating a surrogate signal

Correlation between signal and surrogate

Result: correlation matrix

combination of the matrices from every surrogate

maximal values for each time point

normalised and combined correlation values
The best threshold is the one with the highest Sensitivity and Specificity in the ROC Curve.
The periods of signal with HFO artifacts have a lower amplitude in the aEEG because of the smaller differences in amplitude during this artifact.

\[
(1 - \text{aEEG}) = \text{artifactual periods with higher values}
\]

Selection of the best threshold

End of the algorithm
manual marking of artefacts

Beginning of the algorithm

distance between two consecutive points

higher muscle activity
higher distance between consecutive points (d)

d becomes a function of distance between points

Averaging the d function with a window of:
7 seconds for EMG artifacts
5 seconds for ECG artifacts

selection of the best threshold

end of the algorithm
APPENDIX IV
because when there’s movement of the infant or the electrodes, the values in the EEG signal are much higher than normal or NaN (not a number)

acquisitions above this threshold or equal to NaN are considered artifact
APPENDIX V
clear all
close all

% LOAD SIGNAL
signal = load('filename.mat');
fs = 64; % Hz
L = length(signal);
T = 1/fs;
t = (0:L-1)*T; % time array

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% THRESHOLDS FOR EACH ARTIFACT
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
thresh_muscle = 0.3;
thresh_ecg = 0.52;
thresh_hfo = 0.94;
thresh_zeta = 0.76;
thresh_pedlike = 0.75;
thresh_wave = 0.49;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

artif = input('Which artifact do you want to detect? (wave, pedlike, zeta, hfo, muscle, ecg, movement) ', 's');
switch artif
    case 'wave'
        col = 'g';
        [artifact_1, time] = semi_full_wave(signal, thresh_wave);
    case 'pedlike'
        col = 'g';
        [artifact_1, time] = semi_full_pedlike(signal, thresh_pedlike);
    case 'zeta'
        col = 'g';
        [artifact_1, time] = semi_full_zeta(signal, thresh_zeta);
    case 'hfo'
        col = 'g';
        [artifact_1, time] = semi_full_hfo(signal, thresh_hfo);
    case 'muscle'
        col = 'g';
        [artifact_1, time] = semi_full_muscle(signal, thresh_muscle);
    case 'ecg'
        col = 'g';
        [artifact_1, time] = semi_full_ecg(signal, thresh_ecg);
    case 'movement'
        ga = input('Insert the gestational age (in weeks): ');
        [artifact_1, time] = semi_full_movement(signal, ga)
end

if exist('time') == 0 % if there are no detections
     sprintf('There are no artifacts!')
else
    if isempty(find(time~=0)) == 0
        all_time = time;
        figure(2)
        plot(t, signal)
        for g = 1:length(all_time)
            line([(all_time(g,1) all_time(g,1))],[-200 200], 'Color', char(col), 'LineWidth', 3)
            line([(all_time(g,2) all_time(g,2))],[-100 100], 'Color', 'r')
        end
    else
        figure(2)
        plot(t, signal)
end
APPENDIX VI
function [ artifact_1, time ] = semi_full_wave( signal, thresh )

fs = 64; % Hz
L = length(signal);
T = 1/fs;
e = 1; h = 1;
cycle = 1;
w = fs*60*10;
tot_cycle = round(L/w);

definitions:
fs = 64; % Hz
L = length(signal);
T = 1/fs;
e = 1; h = 1;
cycle = 1;
w = fs*60*10;
tot_cycle = round(L/w);

for a = 1:w:L
    if L-a < wind
        sig = signal(a:L);
    else
        sig = signal(a:a+wind-1);
    end
    % if length(sig) < 60*fs
    % break
    % end
    w = 5; % Time window
    t_small = t(1:fs*w)';
    step = 10;
    m = 1;
    freq = 0.02:0.02:3;
    sin1_matrix = zeros(length(freq), length(t_small));
    cos1_matrix = zeros(length(freq), length(t_small));
    for i = 1:length(freq)
        sin1_matrix(i,:) = sin(2*pi*t_small.*freq(i));
        cos1_matrix(i,:) = cos(2*pi*t_small.*freq(i));
    end
    for s = 1:length(freq)
        surrogate_sin1 = sin1_matrix(s,:);
        surrogate_cos1 = cos1_matrix(s,:);
        n = 1;
        for i = 1:step:
            new_wave = sig(i:(i+fs*w)-1);
            coef_1_sin1(m,n) = diag(corrcoef(new_wave, surrogate_sin1),1);
            coef_1_cos1(m,n) = diag(corrcoef(new_wave, surrogate_cos1),1);
            n = n+1;
        end
        m = m+1;
    end
    d = 10;
    lixo = zeros(d, size(coef_1_sin1,2)+d);
    coef_wave_1 = zeros(size(coef_1_sin1,1), size(coef_1_sin1,2)+d);
    for r = 1:size(coef_1_sin1, 1)
        for dt = 1:d
            for c = 1(size(coef_1_sin1,2)+(2*dt))
                if (1<=c) && (c<=dt)
                    lixo(dt,c) = 2.*(coef_1_cos1(r,c).^2);
                end
                if (size(coef_1_sin1,2)+1 <= c) && (c <= (size(coef_1_sin1,2)+dt))
                    lixo(dt,c) = 2.*(coef_1_sin1(r,c-dt).^2);
                end
                if (dt+1<=c) && (c <= size(coef_1_sin1,2))
                    lixo(dt,c) = (abs(coef_1_sin1(r,c-dt)) + abs(coef_1_cos1(r,c))).^2;
                end
            end
        end
    end
    index = find(max(mean(lixo,2)));
    coef_wave_1(r,:) = abs(lixo(index,:));
end
coef_wave = max(coef_wave_1)./max(max(coef_wave_1));

% WAVE
for k = 1:length(coef_wave)
    if coef_wave(k) >= thresh
        artifact_wave_1(k) = 1;
    else
        artifact_wave_1(k) = 0;
    end
end
q = 1;
for p = 1:length(artifact_wave_1)
    artifact_wave(q+9) = artifact_wave_1(p);
    q = q + 10;
artifact_2 = joint_peaks(artifact_wave,fs,10);
artifact = end_peaks(artifact_2, fs, 2);

if artifact(1) == 1
    time(e,1) = t(1 + (cycle-1)*length(sig));
    e = e + 1;
end

for c = 2:length(artifact)
    if artifact(c-1) == 0 && artifact(c) == 1
        time(e,1) = t(c + (cycle-1)*length(sig));
        e = e + 1;
    end
end

for c = 1:length(artifact)-1
    if artifact(c) == 1 && artifact(c+1) == 0
        time(h,2) = t(c + (cycle-1)*length(sig));
        h = h + 1;
    end
end

if artifact(end) == 1
    time(h,2) = t(cycle*length(sig));
    h = h + 1;
end

if cycle == 1
    artifact_1 = artifact;
else
    artifact_1 = [artifact_1 artifact];
end

cycle = cycle + 1;

end
function [ artifact, time ] = semi_full_pedlike( signal, thresh )
fs = 64; % Hz
L = length(signal);
T = 1/fs;
t = (0:L-1)*T;
e = 1; h = 1;
cycle = 1;
wind = fs*60*5;
tot_cycle = round(L/wind);
for a = 1:winding
    if L-a < wind
        sig = signal(a:L);
    else
        sig = signal(a:a+wind-1);
    end
    load('pedlike_surr_1.mat')
    pedlike_surrogate1 = pedlike_surr_1(25:280);
    clear pedlike_surr_1
    load('pedlike_surr_2.mat')
    pedlike_surrogate2 = pedlike_surr_2(75:330);
    clear pedlike_surr_2
    load('pedlike_surr_3.mat')
    pedlike_surrogate3 = pedlike_surr_3(2:end);
    clear pedlike_surr_3
    load('pedlike_surr_4.mat')
    pedlike_surrogate4 = pedlike_surrogate_4;
    clear pedlike_surrogate_4
    w = length(pedlike_surrogate1);
    step = 2:13;
    surrogate1 = NaN(length(step), L);
    for i = step
        k = 1;
        for j = 2:1:w
            surrogate1(1,i-1, k) = (pedlike_surrogate1(j-1) + pedlike_surrogate1(j))/2;
            surrogate1(1,i, k) = (pedlike_surrogate1(j-1) + pedlike_surrogate1(j))/2;
            surrogate1(4,i-1, k) = (pedlike_surrogate4(j-1) + pedlike_surrogate4(j))/2;
            k = k + 1;
        end
    end
    clear surrogate5
    k = 1;
    for j = 1:3:w-2
        surrogate5(1,1,k) = pedlike_surrogate1(j); 
        surrogate5_1(1,k+1) = pedlike_surrogate1(j)*0.5 + pedlike_surrogate1(j+1)*0.5;
        surrogate5_2(1,k+1) = pedlike_surrogate2(j); 
        surrogate5_2(1,k+2) = pedlike_surrogate2(j)*0.5 + pedlike_surrogate2(j+1)*0.5;
        surrogate5_3(1,k) = pedlike_surrogate3(j); 
        surrogate5_3(1,k+1) = pedlike_surrogate3(j)*0.5 + pedlike_surrogate3(j+1)*0.5;
        surrogate5_4(1,k) = pedlike_surrogate4(j); 
        surrogate5_4(1,k+1) = pedlike_surrogate4(j)*0.5 + pedlike_surrogate4(j+1)*0.5;
        k = k + 2;
    end
    clear surrogate6
    k = 1;
    for j = 1:6:w-5
        surrogate6_1(1,k) = pedlike_surrogate1(j); 
        surrogate6_1(1,k+1) = pedlike_surrogate1(j)*0.8 + pedlike_surrogate1(j+1)*0.2;
        surrogate6_1(1,k+2) = pedlike_surrogate1(j)*0.6 + pedlike_surrogate1(j+1)*0.4;
        surrogate6_1(1,k+3) = pedlike_surrogate1(j)*0.4 + pedlike_surrogate1(j+1)*0.6;
        surrogate6_1(1,k+4) = pedlike_surrogate1(j)*0.2 + pedlike_surrogate1(j+1)*0.8;
        surrogate6_2(1,k) = pedlike_surrogate2(j); 
        surrogate6_2(1,k+1) = pedlike_surrogate2(j)*0.8 + pedlike_surrogate2(j+1)*0.2;
        surrogate6_2(1,k+2) = pedlike_surrogate2(j)*0.6 + pedlike_surrogate2(j+1)*0.4;
        surrogate6_2(1,k+3) = pedlike_surrogate2(j)*0.4 + pedlike_surrogate2(j+1)*0.6;
        surrogate6_2(1,k+4) = pedlike_surrogate2(j)*0.2 + pedlike_surrogate2(j+1)*0.8;
        surrogate6_3(1,k) = pedlike_surrogate3(j); 
        surrogate6_3(1,k+1) = pedlike_surrogate3(j)*0.8 + pedlike_surrogate3(j+1)*0.2;
        surrogate6_3(1,k+2) = pedlike_surrogate3(j)*0.6 + pedlike_surrogate3(j+1)*0.4;
        surrogate6_3(1,k+3) = pedlike_surrogate3(j)*0.4 + pedlike_surrogate3(j+1)*0.6;
        surrogate6_3(1,k+4) = pedlike_surrogate3(j)*0.2 + pedlike_surrogate3(j+1)*0.8;
        surrogate6_4(1,k) = pedlike_surrogate4(j); 
        surrogate6_4(1,k+1) = pedlike_surrogate4(j)*0.8 + pedlike_surrogate4(j+1)*0.2;
        surrogate6_4(1,k+2) = pedlike_surrogate4(j)*0.6 + pedlike_surrogate4(j+1)*0.4;
        surrogate6_4(1,k+3) = pedlike_surrogate4(j)*0.4 + pedlike_surrogate4(j+1)*0.6;
        surrogate6_4(1,k+4) = pedlike_surrogate4(j)*0.2 + pedlike_surrogate4(j+1)*0.8;
k = k + 5;
end
k = 1;
for j = 1:1:w-1
surrogate2_1(1,k) = pedlike_surrogate1(j);
surrogate2_1(1,k+1) = (pedlike_surrogate1(j) + pedlike_surrogate1(j+1))/2;
surrogate2_2(1,k) = pedlike_surrogate2(j);
surrogate2_2(1,k+1) = (pedlike_surrogate2(j) + pedlike_surrogate2(j+1))/2;
surrogate2_3(1,k) = pedlike_surrogate3(j);
surrogate2_3(1,k+1) = (pedlike_surrogate3(j) + pedlike_surrogate3(j+1))/2;
surrogate2_4(1,k+1) = (pedlike_surrogate4(j) + pedlike_surrogate4(j+1))/2;
end
k = k + 2;
end
k = 1;
for j = 1:3:w-3
surrogate3_1(1,k) = pedlike_surrogate1(j);
surrogate3_1(1,k+1) = pedlike_surrogate1(j)*0.4 + pedlike_surrogate1(j+1)*0.6;
surrogate3_1(1,k+2) = pedlike_surrogate1(j+1)*0.6 + pedlike_surrogate1(j+2)*0.4;
surrogate3_1(1,k+3) = pedlike_surrogate1(j+2)*0.4 + pedlike_surrogate1(j+3)*0.6;
surrogate3_2(1,k) = pedlike_surrogate2(j);
surrogate3_2(1,k+1) = pedlike_surrogate2(j)*0.4 + pedlike_surrogate2(j+1)*0.6;
surrogate3_2(1,k+2) = pedlike_surrogate2(j+1)*0.6 + pedlike_surrogate2(j+2)*0.4;
surrogate3_2(1,k+3) = pedlike_surrogate2(j+2)*0.4 + pedlike_surrogate2(j+3)*0.6;
surrogate3_3(1,k) = pedlike_surrogate3(j);
surrogate3_3(1,k+1) = pedlike_surrogate3(j)*0.4 + pedlike_surrogate3(j+1)*0.6;
surrogate3_3(1,k+2) = pedlike_surrogate3(j+1)*0.6 + pedlike_surrogate3(j+2)*0.4;
surrogate3_3(1,k+3) = pedlike_surrogate3(j+2)*0.4 + pedlike_surrogate3(j+3)*0.6;
surrogate3_4(1,k) = pedlike_surrogate4(j);
surrogate3_4(1,k+1) = pedlike_surrogate4(j)*0.4 + pedlike_surrogate4(j+1)*0.6;
surrogate3_4(1,k+2) = pedlike_surrogate4(j+1)*0.6 + pedlike_surrogate4(j+2)*0.4;
surrogate3_4(1,k+3) = pedlike_surrogate4(j+2)*0.4 + pedlike_surrogate4(j+3)*0.6;
surrogate_1{1} = surrogate2_1(1,~isnan(surrogate2_1(1,:)));
surrogate_1{2} = surrogate3_1(1,~isnan(surrogate3_1(1,:)));
surrogate_1{3} = surrogate4_1(1,~isnan(surrogate4_1(1,:)));
surrogate_1{4} = pedlike_surrogate1;
surrogate_1{5} = surrogate6_1(1,~isnan(surrogate6_1(1,:)));
surrogate_2{1} = surrogate2_2(1,~isnan(surrogate2_2(1,:)));
surrogate_2{2} = surrogate3_2(1,~isnan(surrogate3_2(1,:)));
surrogate_2{3} = surrogate4_2(1,~isnan(surrogate4_2(1,:)));
surrogate_2{4} = pedlike_surrogate2;
surrogate_2{5} = surrogate6_2(1,~isnan(surrogate6_2(1,:)));
surrogate_3{1} = surrogate2_3(1,~isnan(surrogate2_3(1,:)));
surrogate_3{2} = surrogate3_3(1,~isnan(surrogate3_3(1,:)));
surrogate_3{3} = surrogate4_3(1,~isnan(surrogate4_3(1,:)));
surrogate_3{4} = pedlike_surrogate3;
surrogate_3{5} = surrogate6_3(1,~isnan(surrogate6_3(1,:)));
surrogate_4{1} = surrogate2_4(1,~isnan(surrogate2_4(1,:)));
surrogate_4{2} = surrogate3_4(1,~isnan(surrogate3_4(1,:)));
surrogate_4{3} = surrogate4_4(1,~isnan(surrogate4_4(1,:)));
surrogate_4{4} = pedlike_surrogate4;
surrogate_4{5} = surrogate6_4(1,~isnan(surrogate6_4(1,:)));
end
step = 5;
m = 1;
for i = 1:length(sig)
    if sig(i) > 50 || sig(i) < -50
        sig(i) = 0;
    end
end
end
for j = 1:length(surrogate_1) % number of surrogates
n = 1;
for i = 1:step:(length(sig)-length(surrogate_1{j}))
    new_wave = sig((i:(i+length(surrogate_1{j}))-1));
    coef_pedlike_1(m,n) = diag(corrcoef(new_wave, surrogate_1{j}),1);
    coef_pedlike_2(m,n) = diag(corrcoef(new_wave, surrogate_2{j}),1);
    coef_pedlike_3(m,n) = diag(corrcoef(new_wave, surrogate_3{j}),1);
    coef_pedlike_4(m,n) = diag(corrcoef(new_wave, surrogate_4{j}),1);
    n = n + 1;
end
m = m + 1;
l1 = length(find(coef_pedlike_1>0.8));
l2 = length(find(coef_pedlike_2>0.8));
l3 = length(find(coef_pedlike_3>0.8));
l4 = length(find(coef_pedlike_4>0.8));
lcof_max = [l1 l2 l3 l4];
if max(coef_max) == l1
    coef_pedlike = abs(coef_pedlike_1)*2 + abs(coef_pedlike_2).^2
    + abs(coef_pedlike_3).^2 + abs(coef_pedlike_4).^2;
elseif max(coef_max) == l2
    coef_pedlike = abs(coef_pedlike_1).^2 + abs(coef_pedlike_2)*2
    + abs(coef_pedlike_3).^2 + abs(coef_pedlike_4).^2;
elseif max(coef_max) == l3
    coef_pedlike = abs(coef_pedlike_1).^2 + abs(coef_pedlike_2).^2
    + abs(coef_pedlike_3)*2 + abs(coef_pedlike_4).^2;
else
    coef_pedlike = abs(coef_pedlike_1).^2 + abs(coef_pedlike_2).^2
    + abs(coef_pedlike_3).^2 + abs(coef_pedlike_4)*2;
end
coef_pedlike = max(coef_pedlike1)./max(max(coef_pedlike1));
% PEDLIKE
clear artifact_pedlike
for k = 1:length(coef_pedlike)
    if coef_pedlike(k) >= thresh
        artifact_pedlike_1(k) = 1;
    else
        artifact_pedlike_1(k) = 0;
    end
end
q = 1;
for p = 1:length(artifact_pedlike_1)
    artifact_pedlike(q:q+4) = artifact_pedlike_1(p);
    q = q + 5;
end

artifact_1 = joint_peaks(artifact_pedlike,fs,10);
artifact = end_peaks(artifact_1, fs, 2);
if artifact(1) == 1
    time(e,1) = t(1 + (cycle-1)*length(sig));
    e = e + 1;
end
for c = 2:length(artifact)
    if artifact(c-1) == 0 && artifact(c) == 1
        time(e,1) = t(c + (cycle-1)*length(sig));
        e = e + 1;
    end
end
for c = 1:length(artifact)-1
    if artifact(c) == 1 && artifact(c+1) == 0
        time(h,2) = t(c + (cycle-1)*length(sig));
        h = h + 1;
    end
end
if artifact(end) == 1
    time(h,2) = t(cycle*length(sig));
    h = h + 1;
end
if cycle == 1
    artifact_1 = artifact;
else
    artifact_1 = [artifact_1 artifact];
end
cycle = cycle + 1;
end
end
function [ artifact, time ] = semi_full_zeta( signal, thresh )

fs = 64; % Hz
L = length(signal);
T = 1/fs;
t = (0:L-1)*T;
e = 1; h = 1;
cycle = 1;
wind = fs*60*5;
tot_cycle = round(L/wind);

for a = 1:wind:L
    if L-a < wind
        sig = signal(a:L);
    else
        sig = signal(a:a+wind-1);
    end
    if length(sig) < 60*fs
        break
    end
    load('zeta_surrogate2.mat')
    load('zeta_surrogate3.mat')
    load('zeta_surrogate4.mat')
    load('zeta_surrogate5.mat')
    w = 2;
    for i = 1:length(sig)-fs
        if sig(i) > 65 || sig(i) < -65
            sig(i) = 0;
        end
    end
    clear blu1 blu2 blu3 blu4
    n = 1;
    blu1 = zeros(1, length(sig)-w*fs);
    blu2 = blu1;
    blu3 = blu2;
    blu4 = blu3;
    z1 = zeta_surrogate2(1:2*fs);
    z2 = zeta_surrogate3(1:2*fs);
    z3 = zeta_surrogate4(1:2*fs);
    z4 = zeta_surrogate5(1:2*fs);
    for j = 1:length(sig)-w*fs
        piece = sig(j:w*fs-1);
        blu1(:,j:w*fs-1) = diag(corrcoef(piece, z1),1);
        blu2(:,j:w*fs-1) = diag(corrcoef(piece, z2),1);
        blu3(:,j:w*fs-1) = diag(corrcoef(piece, z3),1);
        blu4(:,j:w*fs-1) = diag(corrcoef(piece, z4),1);
    end
    blu = abs(blu1) + abs(blu2) + abs(blu3) + abs(blu4);
    coef_zeta = blu/max(blu);
    clear artifact_zeta
    for k = 1:length(coef_zeta)
        if coef_zeta(k) >= thresh
            artifact_zeta(k) = 1;
        else
            artifact_zeta(k) = 0;
        end
    end
    artifact_l = joint_peaks(artifact_zeta,fs,2);
    artifact = end_peaks(artifact_l, fs, 2);
    if m < 0.2
        artifact = zeros(length(artifact), 1);
    end
    if artifact(1) == 1
        time(e,1) = t(1 + (cycle-1)*length(sig));
        e = e + 1;
    end
    for c = 2:length(artifact)
        if artifact(c-1) == 0 & & artifact(c) == 1
            time(e,1) = t(c + (cycle-1)*length(sig));
            e = e + 1;
        end
    end
for c = 1:length(artifact)-1
    if artifact(c) == 1 && artifact(c+1) == 0
        time(h,2) = t(c + (cycle-1)*length(sig));
        h = h + 1;
    end
end

if artifact(end) == 1
    time(h,2) = t(cycle*length(sig));
    h = h + 1;
end

if cycle == 1
    artifact_1 = artifact;
else
    artifact_1 = [artifact_1 artifact];
end

cycle = cycle + 1;
end
end
function [ artifact_1, time ] = semi_full_hfo( signal, thresh )

fs = 64; % Hz
L = length(signal);
T = 1/fs;
t = (0:L-1)*T;
e = 1; h = 1;
cycle = 1;
winding = fs*60*2;
tot_cycle = round(L/winding);

for a = 1:winding:
    if L-a < winding
        sig = signal(a:L);
    else
        sig = signal(a:a+winding-1);
    end
    % if length(sig) < 60*fs
    % break
    clear aeg
    d = fs;
j = 1;
    for i = 1:length(sig)-d
        aeg(j) = max(sig(i:i+d)) - min(sig(i:i+d));
j = j+1;
    end
    for i = 1:d
        aeg(j-1+i) = aeg(j-1);
    end
    coef_hfo = 1-aeg/max(aeg);
    clear artifact_hfo
    for k = 1:length(coef_hfo)
        if coef_hfo(k) >= thresh
            artifact_hfo(k) = 1;
        else
            artifact_hfo(k) = 0;
        end
    end
    artifact_1 = joint_peaks(artifact_hfo,fs,2);
    artifact = end_peaks(artifact_1, fs, 2);
    if artifact(1) == 1
        time(e,1) = t(1 + (cycle-1)*length(sig));
e = e + 1;
    end
    for c = 2:length(artifact)
        if artifact(c-1) == 0 && artifact(c) == 1
            time(e,1) = t(c + (cycle-1)*length(sig));
e = e + 1;
        end
    end
    for c = 1:length(artifact)-1
        if artifact(c) == 1 && artifact(c+1) == 0
            time(h,2) = t(c + (cycle-1)*length(sig));
h = h + 1;
        end
    end
    if artifact(end) == 1
        time(h,2) = t(cycle*length(sig));
h = h + 1;
    end
    if cycle == 1
        artifact_1 = artifact;
    else
        artifact_1 = [artifact_1 artifact];
    end
    cycle = cycle + 1;
end
end
function [ artifact_1, time ] = semi_full_ecg( signal, thresh )

fs = 64; % Hz
L = length(signal);
T = 1/fs;
t = (0:L-1)*T;
e = 1; h = 1;
cycle = 1;
w = fs*60*1;
tot_cycle = round(L/w);

for a = 1:w:L
    if L-a < w
        sig = signal(a:L);
    else
        sig = signal(a:a+w-1);
    end
    if length(sig) < 60*fs
        break
    end
    clear p_dist p_dist1
    p = 1;
    for i = 1:length(sig)-p
        p_dist(i) = sqrt((sig(i+p)-sig(i)).^2 + (1/fs).^2);
    end
    q = 350;
    for j = 1:q:(length(p_dist)-(q-1))
        p_dist1(1,j:j+(q-1)) = mean(p_dist(1,j:j+(q-1)));
    end
    coef_ecg = 1-(p_dist1/max(p_dist1));
    clear artifact_ecg
    for k = 1:length(coef_ecg)
        if coef_ecg(k) >= thresh
            artifact_ecg(k) = 1;
        else
            artifact_ecg(k) = 0;
        end
    end
    artifact_1 = joint_peaks(artifact_ecg,fs,2);
    artifact = end_peaks(artifact_1, fs, 2);
    if artifact(1) == 1
        time(e,1) = t(1 + (cycle-1)*length(sig));
        e = e + 1;
    end
    for c = 2:length(artifact)
        if artifact(c-1) == 0 && artifact(c) == 1
            time(e,1) = t(c + (cycle-1)*length(sig));
            e = e + 1;
        end
    end
    for c = 1:length(artifact)-1
        if artifact(c) == 1 && artifact(c+1) == 0
            time(h,2) = t(c + (cycle-1)*length(sig));
            h = h + 1;
        end
    end
    if artifact(end) == 1
        time(h,2) = t(cycle*length(sig));
        h = h + 1;
    end
    if cycle == 1
        artifact_1 = artifact;
    else
        artifact_1 = [artifact_1 artifact];
    end
    cycle = cycle + 1;
end
end
APPENDIX XI
function [ artifact, time ] = semi_full_muscle( signal, thresh )

fs = 64; % Hz
L = length(signal);
T = 1/fs;
t = (0:L-1)*T;
e = 1; h = 1;
cycle = 1;
wind = fs*60*20;
tot_cycle = round(L/wind);

for a = 1:wind:L
    if L-a < wind
        sig = signal(a:L);
    else
        sig = signal(a:a+wind-1);
    end
    if length(sig) < 60*fs
        break
    end
    for i = 1:length(sig)-fs
        if sig(i) > 200 || sig(i) < -200
            if i >= fs/2
                sig(i-fs/2:i+fs/2) = 0;
            else
                sig(1:i+fs/2) = 0;
            end
        end
    end
    clear p_dist coef p_dist1
    p = 1;
    for i = 1:length(sig)-p
        p_dist(i) = sqrt((sig(i+p)-sig(i)).^2 + (1/fs).^2);
    end
    q = 450;
    for j = 1:q:(length(p_dist)-q-1)
        p_dist1(j:j+(q-1)) = mean(p_dist(j:j+(q-1)));
    end
    coef_muscle = p_dist1./max(p_dist1);
    clear artifact muscle
    for k = 1:length(coef_muscle)
        if (coef_muscle(k) >= thresh)
            artifact_muscle(k) = 1;
        else
            artifact_muscle(k) = 0;
        end
    end
    artifact_1 = joint_peaks(artifact_muscle,fs,2);
    artifact = end_peaks(artifact_1, fs, 2);
    if artifact(1) == 1
        time(e,1) = t(1 + (cycle-1)*length(sig));
e = e + 1;
    end
    for c = 2:length(artifact)
        if artifact(c-1) == 0 && artifact(c) == 1
            time(e,1) = t(c + (cycle-1)*length(sig));
e = e + 1;
        end
    end
    for c = 1:length(artifact)-1
        if artifact(c) == 1 && artifact(c+1) == 0
            time(h,2) = t(c + (cycle-1)*length(sig));
h = h + 1;
        end
    end
    if artifact(end) == 1
        time(h,2) = t(cycle*length(sig));
h = h + 1;
    end
    if cycle == 1
        artifact_1 = artifact;
    else
        artifact_1 = [artifact_1 artifact];
    end
end
end

cycle = cycle + 1;

end

end
function [ artifact, time ] = semi_full_movement( signal, ga )

fs = 64; % Hz
L = length(signal);
T = 1/fs;
t = (0:L-1)*T;
e = 1; h = 1;
cycle = 1;
w = 1/wind;
tot_cycle = round(L/w);

for a = 1:w:L
    if L-a < wind
        sig = signal(a:L);
    else
        sig = signal(a:a+wind-1);
    end
    if length(sig) < 60*fs
        break
    end
    if ga <= 23
        disp('Error. The minimal age is 24 GA.
    elseif (24 < ga) && (ga < 29)
        m = 300;
    elseif (30 < ga) && (ga < 34)
        m = 200;
    elseif (35 < ga) && (ga < 41)
        m = 100;
    elseif ga >= 42
        m = 50;
    end
    alert_1 = zeros(1,length(sig));
    for i = 1:length(sig)
        if sig(i) > m || sig(i) < -m || isnan(sig(i)) == 1
            alert_1(i) = 1;
        else
            alert_1(i) = 0;
        end
    end
    if sum(alert_1) > fs/2
        alert = joint_peaks(alert_1,fs,20);
    end
    X = 10;
    coef_mov = zeros(length(alert), 1);
    for i = 1:length(alert)-X*fs
        if alert(i:i+X*fs) == 1
            artifact(i:i+X*fs) = 1;
        end
    end
    if m < 0.2
        artifact = zeros(length(artifact), 1);
    end
    if artifact(1) == 1
        time(e,1) = t(1 + (cycle-1)*length(sig));
        e = e + 1;
    end
    for c = 2:length(artifact)
        if artifact(c-1) == 0 && artifact(c) == 1
            time(e,1) = t(c + (cycle-1)*length(sig));
            e = e + 1;
        end
    end
    for c = 1:length(artifact)-1
        if artifact(c) == 1 && artifact(c+1) == 0
            time(h,2) = t(c + (cycle-1)*length(sig));
            h = h + 1;
        end
    end
    if artifact(end) == 1
        time(h,2) = t(cycle*length(sig));
        h = h + 1;
    end
    cycle = cycle + 1;
end
end
APPENDIX XIII
function [out1] = joint_peaks(x1,fs,dur)
% This function merges peaks too close to each other and considers the whole
% interval as artifactual
% if the distance is shorter than 'dur' (in seconds) this function
% merges them and considers one larger detection
% x1 - signal to process
% fs - sampling frequency
% dur - time length (in seconds) between detections to merge

der = x1(2:end)-x1(1:end-1);
start = find(der>0);
stop = find(der<0);
out1 = x1;
if x1(1) == 1
    start = [1 start];
end
if isempty(find(der==1)) == 1
    out1 = x1;
else
    for i = 1:length(start)-1
        if abs(start(i+1)-stop(i)) < dur*fs
            out1(stop(i):start(i+1)) = 1;
        end
    end
end
end
function [out2] = end_peaks(x2,fs,dur)
% This function eliminates peaks too short to be considered artifacts
% if the peaks are shorter than 'dur' (in seconds) this function
% ignores them and turns those into zeros
% x2 - signal to process
% fs - sampling frequency
% dur - time length (in seconds) to eliminate

der = x2(2:end)-x2(1:end-1);
start = find(der>0);
stop = find(der<0);
out2 = x2;

if x2(1) == 1
    start = [1 start];
end

if isempty(find(der==1)) == 1
    out2 = x2;
else
    for i = 1:length(start)-1
        if abs(stop(i)-start(i)) < dur*fs
            out2(start(i):stop(i)) = 0;
        end
    end
end
Use Cases

From the methods explained in the present dissertation, it is clear that the algorithm still needs some input from the user, like subjects’ gestational age or what type of artifact to look for. With that in mind, and to specify how the user can interact with the algorithm, it becomes important to develop the concept of Use Cases.

This appendix focuses on a number of Use Cases to describe the desired functionality of the Artifact Detection Algorithm. In each Use Case, it is described an interaction between the user and the algorithm, i.e., how a user achieves a certain goal within the algorithm. In addition to that, it is also described which users are qualified for each different Use Case.

Definitions

. Artifact Detection Algorithm: algorithm developed in this project, described throughout this report, that aims at the detection of artifacts in electroencephalographic data from neonates;

. User: medical and technical staff that has access to the algorithm and has the possibility to use it.

The following table describes the different levels a user can have, as well as the different functions that correspond to each level and its users.

<table>
<thead>
<tr>
<th>User Level</th>
<th>Rights within the algorithm</th>
<th>Users</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Select artifact detection</td>
<td>Untrained medical students</td>
</tr>
<tr>
<td>2</td>
<td>Select artifact detection and accept</td>
<td>Experienced medical students and medical staff</td>
</tr>
<tr>
<td>3</td>
<td>Select artifact detection and modify</td>
<td>Technical staff (physicists and engineers)</td>
</tr>
<tr>
<td>4</td>
<td>Select artifact detection, accept and modify</td>
<td>Algorithm developer</td>
</tr>
</tbody>
</table>
**Use Case 1 – Select artifact detection**

- **Goal** – To run the algorithm on EEG data;
- **Users** – Levels 1 to 4;
- **Description** – This level allows all users to run the algorithm and from there get as a result a plot of the data with the beginning of the artifactual periods marked with a green bar and the end of the same periods with a red bar;
- **Risk** – If there are errors in the data this use case is not enough to correct them.

**Use Case 2 – Accept**

- **Goal** – To see the results of the algorithm and assess if they are correct (given that the algorithm is still in a preliminary phase of development and is not yet built in any clinical software);
- **Users** – Levels 1 and 4;
- **Description** – Trained medical staff can recognize artifacts in data due to their extensive experience with neonatal EEG, as well as the developer of the algorithm due to extensive study and research on the matter. This Case is only accessible to these two users due to the fact that the results from the algorithm ultimately need to be accepted by experienced users, given that the algorithm is still in a premature phase of development;
- **Risk** – Acceptance of the results is always prone to discrepancies between definitions of artifacts, as well as subjectivity in the assessment of the results.

**Use Case 3 – Modify**

- **Goal** – To alter the structure of the algorithm in case there’s an error in the algorithm’s functioning;
- **Users** – Levels 3 and 4;
- **Description** – In case the algorithm needs optimization, these users are the ones with the skills and knowledge to do so;
- **Risk** – none found.