Investigating the 40-Hz Auditory Steady State Response as a Modality for Biometric Verification

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ABSTRACT

Current biometrics, such as fingerprints, can easily be spoofed or circumvented. Biometric based on electroencephalograms (EEG) has emerged in recent years to address this issue; however, current methods suffer from a lack of clearly defined inputs that elicit a known EEG response. In this work, a novel biometric modality – the auditory steady state response (ASSR) – is investigated to determine its inter-subject discriminatory power as a biometric verification tool. ASSR is the brain wave response to a mathematically defined amplitude modulated stimulus presented to the ear, and is normally used in audiometry to evaluate hearing thresholds.

Data was collected from 22 subjects and preprocessed to remove various forms of noise. Ensemble averaging was then performed to extract ASSR cycles for each subject. Three feature sets, derived from discrete wavelet transform coefficients at level 3, were used in this work: approximate and detailed coefficients from levels 2 and 3, approximate coefficients from level 3 (cA3), and the statistics, mean, min, and max of the coefficients. To simulate a biometric system, fourteen subjects were enrolled, four were labelled as intruders, and the remaining four were discarded due to signal quality issues. During classification, an optimal, Gaussian-based binary SVM classifier was generated for each enrolled subject. Verification tests were then performed to determine the system's robustness to imposters and intruders.

A maximum verification accuracy of 98.1%, minimum false acceptance rate (FAR) of 0.177% and minimum false rejection rate (FRR) of 1.77%, was achieved with the cA3 features. Results indicate high potential for ASSR in a practical biometric setting, once permanence, ease of data collection, and revocability traits are further investigated.

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Finally, I would like to thank the subjects that volunteered their time to allow us to record their ASSR data.

CONTENTS

LIST OF ACRONYMS

- ABR – auditory brainstem response
- AEP – auditory evoked potentials
- AR – autoregression, autoregressive
- ASSR – auditory steady state response
- cA3 – approximation coefficient at level 3
- cD2 – detailed coefficient at level 2
- cD3 – detailed coefficient at level 3
- CF – career frequency
- dB HL – decibel hearing level
- EC – eyes closed
- ECG – electrocardiogram
- EEG – electroencephalogram, electroencephalographic
- EER – equal error rate
- EO – eyes opened
- FA – false acceptances
- FAR – false acceptance rate
- FFT – fast fourier transform
- FR – false rejections
- FRR – false rejection rate
- HTER – half total error rate
- LLR – late latency response
- MF – modulation frequency
- MLR – mid latency response
- PPG - phonocardiogram
- SNR – signal to noise ratio
- SVM – support vector machine

- TA – true acceptances
- TR – true rejections

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

1 INTRODUCTION

This thesis report presents an investigation into the use of auditory steady state responses, a type of EEG signal, as a biometric modality for biometric person verification. The structure of this section is as follows: Section 1.1 provides a background to biometric recognition and its general issues. Section 1.2 delves into motivation for the use of EEG for biometric applications, and the motivation for studying ASSR as a biometric modality. The main research goals of the thesis are described in Section 1.3. The structure of this thesis is provided in Section 1.4.

1.1 BACKGROUND TO BIOMETRIC RECOGNITION

Traditionally, secure access control into private and secure systems is accomplished using token-based or knowledge-based identification, such as ID cards or passwords. Both methods use something the user *knows* or *has*; properties that are easily forgotten or stolen [1 - 3]. The main downfall of such systems is that they inherently cannot distinguish between a legitimate user and an attacker. On the other hand, biometrics rely on the unique behavioural or physiological characteristics, known as *biometric modalities*, of the user. Current systems based on physiological characteristics include fingerprint matching, vein pattern recognition, and iris recognition. Systems based on behavioural characteristics include gait, keyboard dynamics, and signature or handwriting patterns [4]. The uniqueness of biometric modalities provides a clear advantage over traditional methods: they are more difficult to forge. Despite this, biometric recognition has several weaknesses. Due to the way modalities are read, intra-subject variability may present false rejection. In addition, several modalities are vulnerable to circumvention and replay attacks. For example, fingerprints are left everywhere – with some work, an attacker can falsify a fingerprint and use it to enter a system. Similarly, an attacker can present a pre-recorded voice to a system based on voice recognition [5]. Finally, in the context of privacy, biometric modalities are not easily revoked; that is, once a biometric is compromised, it cannot be used again [3].

In response to this, a new class of biometrics, called *medical biometrics*, has gained traction in recent years. Medical biometrics are physiological signals traditionally used in clinical settings. Examples include electroencephalograms (ECG) [5], phonocardiograms (PCG) [41], electroencephalograms (EEG) [7, 8, 9, 21, 23], and transient evoked oto-acoustic emissions (TEOAE) [42, 43]. These forms of biometrics are less vulnerable to circumvention, since they inherently contain liveness detection. This thesis focuses on a subset of EEG signals.

It is important to note that a biometric recognition system can run in two modes: identification and verification. Identification (also recognition) seeks to answer the question "*who am I*?" and a match is attempted between the subject and the entire template database. In verification (also authentication), validation is performed by answering the question "*is this person who she says she is?*" and a match is attempted between the subject and a specific template [3]. Figures 1 and 2 show the two steps for a verification system: enrollment and verification.

Figure 1 Enrollment into a Biometric System

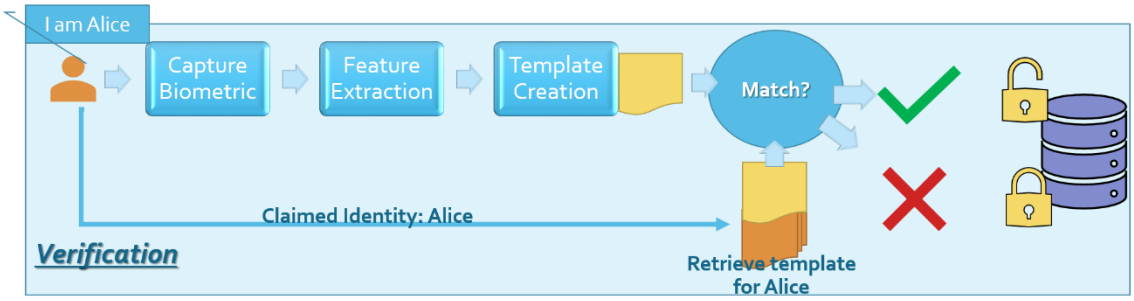


Figure 2 Authentication/Verification into a Biometric System

1.2 EEG BIOMETRICS AND AUDITORY EVOKED POTENTIALS: MOTIVATION

EEG signals represent the electrical activity of the brain in response to general cortical function. They are present and unique for each individual and difficult to spoof [6, 7]. Evoked potentials (EP) is the EEG of the electrical potential recorded when a person is presented with a stimulus. This stimulus can be visual, auditory, or somatosensory. Auditory evoked potentials (AEP) represent the brain's response to auditory stimuli and are used in clinical settings to determine an individual's hearing threshold. A specific type of AEP is the auditory steady state response (ASSR) that is generated in response to an amplitude modulated signal. When determining the efficiency of a signal as a biometric, there are a few factors to consider: universality, uniqueness, permanence, collectability, circumvention, and revocability. These factors and challenges motivate the investigation of ASSR as a biometric modality, an investigation that – to the best of our knowledge – has not yet been performed.

- *Universality:* Ideally, a biometric modality should be present in every individual. ASSR is a subset of EEG signals, which are present in every individual. One advantage of ASSR over general AEPs is that it can be collected from a wider range of audiences – including newborns, young children, and those with hearing loss [15], thus increasing its universality.
- *Uniqueness*: A biometric modality should be unique to an individual. A few works have explored the subject-identification traits within AEP, namely [8, 9, 10]. These works, however, focus on the transient AEP, rather than the ASSR. Works focusing on the ASSR tend to focus on minimizing the inter-subject variability for other classification purposes such as modelling sleep or disease states [11, 12, 13, 14]; however, the variability is still present. Moreover, it is known that the ear shape of an individual is unique: both the outer ear and middle ear act as filters to any auditory stimulus, thus affecting the ASSR. This hints that the ASSR inherently has subject-dependent characteristics that will be further explored in this project.

- *Permanence*: This refers to the stability of a signal over time, required to reliably match a new biometric recording to an earlier recorded template. EEG signals tend to vary based on emotional and physical state. ASSR signals, in particular, appear to be prone to levels of consciousness in a subject [11, 12, 14, 18, 19]. In addition, noise-induced and age-induced hearing loss is common [16] – a factor that would affect ASSR response of an individual over time. Moreover, differences in auditory response has been observed between children and adults, largely due to maturation of the different brain pathways that are involved in auditory processing [17].
- *Collectability*: Clinical methods already exist to stimulate and record EEG signals and ASSR. The downside of ASSR collection is the cumbersome process of placing electrodes on the scalp. Future work could focus on accurately recording ASSR using only one dry electrode.
- *Circumvention*: Due to its liveness and uniqueness characteristics, it is practically impossible to forge another individual's EEG signal.
- *Revocability*: The outcome of an ASSR signal changes depending on the amplitude and modulation frequency of the input stimulus – a level of control not present in [8, 9, 10]. This implies revocability: if an ASSR-based biometric template is compromised, a new one can be collected using a different stimulus.

1.3 RESEARCH GOALS AND SCOPE

With the above factors in mind, this project exploits these subject-specific characteristics to determine if the ASSR of an individual is a viable biometric modality. Of focus is investigating the uniqueness potential of ASSR: **this project aims to determine if ASSR contains discriminatory features that can establish its uniqueness.** Permanence will not be explored in detail, as data would need to be repeatedly collected from a subject over a long period of time – preferably one year or more, with recording sessions every few weeks or months. The time available to record in this project is one month. Another focus of this project is on biometric *verification* rather than *identification*.

At each stage of the project, proven methods from previous works were used to analyze and collect the data, with variations when necessary. In the **collection** phase, data was collected from subjects using the methods in [12]. Multiple sets of data per subject were collected, so that the person-specific approach described in [13] can be used to increase accuracy during classification. During **preprocessing**, the ensemble averaging method described in [9, 14] was used to extract and amplify the ASSR from background EEG signals. During **analysis**, discriminatory features will be extracted, using time-frequency analysis, for input into a classification algorithm. In the **classification** stage, a classifier will be trained on the subject data. In the **verification** stage, untrained ASSR signals from subjects will be presented to the classifier to calculate the accuracy of 1-to-1 matching: that is, will the system successfully match or deny a given ASSR signal against a selected known signal in the database?

If successful 1-to-1 verification using ASSR signals is achieved, ASSR signals can be included in an overall multi-modal biometric security system – the goal of a larger design project [15]. Future extensions within the Biometric Security Research group at the University of Toronto will explore how to design the optimal stimulus that will maximize the inter-subject variability for improved verification results. This allows the stimuli to be controllable, and different stimuli will produce different AEP responses. In this way, the AEP templates are revocable, and various stimuli allow for a multi-modal system.

1.4 REPORT OUTLINE

This report is structured according to the four stages outlined in section 1.3. Section 2 will provide a literature review of previous research in EEG biometric verification. Section 3 provides a detailed description of the experimental framework used in this investigation. Section 4 discusses verification performance results, and future work is outlined in Section 5.

2 BACKGROUND AND PRIOR WORK

This section reviews previous research work that pertains to the current project. Key terms used in verification systems are defined in Section 2.1 Section 2.2 will provide a general overview of current research in EEG biometric verification. Section 2.3 will review the structure of AEP and ASSR signals, and the preprocessing methods used to obtain ASSR data. Finally, previous methods used for feature extraction and subject classification in similar biometric systems will be discussed in sections 2.4 and 2.5.

2.1 PERFORMANCE TERMS

When evaluating the verification performance of biometric systems, the following key metrics are often used:

- *True Acceptances (TA):* The number of correctly accepted users.
- *True Rejections (TR)*: The number of correctly rejected users.
- *False Acceptances (FA):* The number of false acceptances.
- *False Rejections (FR):* The number of false rejections.
- *False acceptance rate (FAR)*: A measure of how likely the system will accept an unauthorized user. Generally,

$$FAR = \frac{FA}{\#\ verification\ attempts}$$

Eq. 1

- *False rejection rate (FRR):* A measure of how likely the system will reject an authorized user. Generally,

$$FRR = \frac{\#\ false\ rejections}{\#\ verification\ attempts}$$

Eq. 2

- *Half Total Error Rate (HTER)***:** The average of FAR and FRR, that is

$$HTER = \frac{FAR + FRR}{2}$$

Eq. 3

- *Equal Error Rate (EER):* The HTER when FAR = FRR.
- Note the following: $\# \, verification \; attempts = FA + FR + TA + TR$

The lower the above values, the better the recognition of a biometric system. For a verification system, higher security prioritizes a low FAR over a low FRR, since the number of imposters allowed into a system should be kept at a minimum.

Other related terms are as follows:

- *Precision rate:* The ratio of all accepted users that are legitimately enrolled users.

$$Precision = \frac{TA}{TA + FA}$$

Eq. 4

- *Recall rate:* The ratio correctly accepted enrolled users over all enrolled users that attempted access to the system.

$$Recall = \frac{TA}{TA + FR}$$

Eq. 5

- *Verification Accuracy:* The percentage of all correct acceptances and rejections from all verification attempts.

2.2 A REVIEW OF EEG BIOMETRIC VERIFICATION

As mentioned earlier, EEG signals describe the electrical activity of the brain. Brain activity is a sum of an individual's behavioural, psychological, and physiological processes. In clinical settings, EEG has been used to diagnose brain disorders such as schizophrenia and epilepsy, and to distinguish between cognitive states [20]. As early as 1980, researchers could show that the EEG is unique to an individual, with Stassen characterizing a person based on their EEG spectral power with 90% confidence [21]. He also found the characterization to be valid for schizophrenic patients, implying that EEG signal identification can be used on individuals with cognitive and brain diseases. Relative to other biometric modalities, EEG is a new area of active research [22]. Thus, despite the advantages mentioned in Section 1, several challenges are still under

investigation before deployment as a real-world system. The challenges include the following: improving the acquisition of data that currently uses electrodes, developing features with higher discriminatory power, and combatting the template ageing effect, where biometric signals change over time [29].

Acquisition of EEG signals can generally be classified in two ways: using medical-grade methods, such as the 10-20 system [9], which provide high signal-to-noise ratio, or cheaper, dry electrode methods which usually have poor signal quality. Several works have focused on improving the acquisition of EEG signals while maintaining medical-grade signal quality; these include solutions such as using headsets containing dry electrodes, or decreasing the number of electrodes needed [23, 24, 25]. This work will not focus on signal recording techniques, as our main objective is to determine the discriminatory potential of ASSR. In this regard, Poulos and his team were one of the first researchers to base a biometric identification system on EEG signals, and explore various EEG components and classification methods – such as EEG spectra – to discriminate between individuals [26, 27, 28]. In one instance, they achieved a correct identification rate of between 80% and 100% [26].

Recognition results vary depending on the type of EEG data collected. The various ways researchers are obtaining EEG data fall into three classes: resting conditions, cognitive processes, and evoked potentials. Resting conditions pertain to data collected when the eyes are either open (EO) or closed (EC). Cognitive processes refer to instances where subjects are required to perform a task – such mathematic calculations. Evoked potentials refer to EEG data collected from the brain's response to visual evoked potentials (VEP) or AEPs. A review of research falling in these three categories is presented below.

2.2.1 Resting Conditions

According to a state-of-the-art review by Campisi and Rocca in [22], resting conditions are by far the most prominent form of EEG data recording. In [30], Rocca et. al. presented a novel method of extracting features using functional brain connectivity – that is, temporal dependence of multiple brain regions that share functional properties. Using

EC and EO resting state conditions, they obtained a 100% identification accuracy on a database of 108 subjects.

In 2016, another work focused on minimizing the features used in the EEG biometric template by projecting the EEG signals unto eigenbrains (EBs) – the "eigenvectors obtained when performing PCA [principal component analysis] on the considered EEG PSD [power spectral density representation]" – and eigentensorbrains (ETB), similar to EBs but using multilinear PCA (MPCA) [31]. EEG signals were recorded in EC and EO resting conditions. In this work, they noted that EO and EC data can be affected by other mental processes ongoing in the brain. Accordingly, they found EC resting conditions to produce cleaner data, while the EO data contained more artifacts due to the subject's eyes wandering, eye blinking, and processing the surrounding visual stimuli. Overall, their ETB system, combined with linear discriminant analysis (LDA), in EC state provided higher classification results.

2.2.2 Cognitive Conditions

In [32], Marcel and Millan used the cognitive tasks of imagining left and right hand movements, in addition to saying a random word beginning with a specified letter. The collected data was used for biometric verification on a database containing 9 subjects. Results showed that authentication was sensitive to the cognitive task, as the left hand movement task had the lowest HTER performance of 6.6%.

Similarly, Yang et. al. explored the sensitivity of biometric recognition to various tasks in [33], over a larger database of 109 subjects. Subjects were given four tasks to perform, and training of the data (template storage) was performed using one set of tasks, then testing or recognition performed using another set of tasks. Performance remained relatively similar between mixed tasks and same-task training. Unlike [32], these results indicate cognitive tasks – under their particular experiment setup – do not influence recognition performance. The authors noted that future biometric systems would benefit from combining multiple cognitive tasks for a subject into one biometric template to improve performance.

2.2.3 Evoked Potentials

Unlike resting and cognitive conditions which do not have expected EEG wave patterns, evoked potentials follow certain wave patterns. In [6], Palaniappan and Mandic developed a biometric system based on VEPs, with a database of 102 subjects. The visual input stimuli were a set of black and white drawings from the picture set in [34]. The distinguishing response of visual stimuli is an EEG P300 signal, depicted in Figure 1. The P300 signal always has a delay between stimulus and response of 250 – 500 ms [36], and has been found to contain inter-subject variability in its power spectrum. Through the use of VEPs, they obtained a maximum identification rate of 98.12%. Several other works have used VEPs, with different input stimuli, to generate a P300 wave and perform biometric recognition [37, 38].

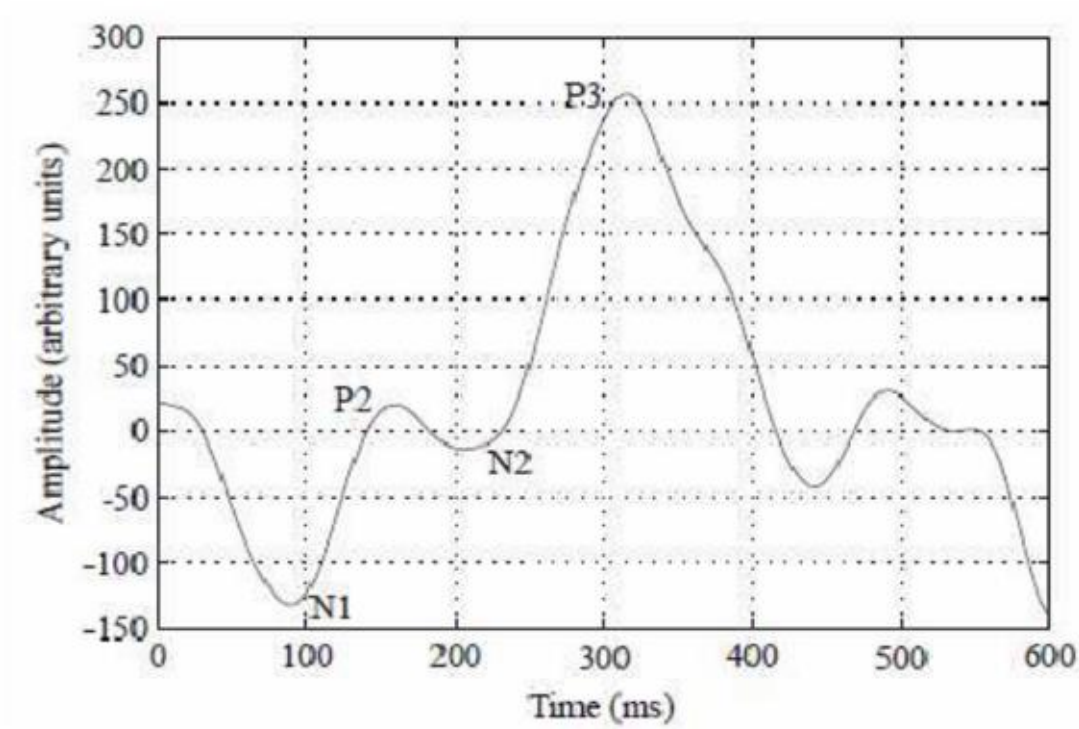


Figure 3: P300 wave, obtained from [35]. The large peak around 300-400ms is characteristic of this wave.

To date, only one work based on AEPs has been investigated: namely, the time-frequency domain analysis performed on a variety of EEG databases by Banos et. al. in [9]. The data was taken from Ullsperger's data set [39], which recorded the AEP response of subjects to English words. Along with the other datasets, Banos et. al. found that

discriminatory components can be found below 40Hz of the frequency distribution of the signals. This solitary work on biometric verification demonstrates an opportunity to further explore the potential of AEP signals as biometric modalities. No work to date has been performed on ASSR as a biometric modality.

2.2.4 Summary

Though the work in [22] had perfect recognition accuracy, the work in [31] brings up an important issue about resting conditions: it is better for the EEG data being acquired to have controllable input that produces predicted output. This can then be distinguished from other brain activity sources. In a real-world biometric system, it cannot be guaranteed that a user will not undergo other mental processes while waiting to be authenticated into the system via EO or EC. Cognitive conditions also have similar issues: mental tasks can be interpreted differently between subjects, and are also subject to other mental processes that may disrupt the data. Moreover, cognitive conditions are heavily prone to template ageing issues – at different points in time, depending on mental state or age, the mental output of a subject corresponding to a specific task can change significantly. This is where AEP and ASSR signals have potential value: similar to VEPs, a controllable, auditory input is used to evoke an EEG waveform that has universal characteristics and can be distinguished from other EEG sources. While VEP has been shown to have potential as a biometric modality, and some minor work has been done on AEP, the ASSR signal may have greater potential as a realistic biometric modality. This is due to the nature of the input: VEP requires visual input that can be interpreted differently amongst subjects, whereas ASSR uses mathematically defined, amplitude modulated signals that have clearly defined parameters – amplitude, repetition rate, and modulation frequency. To elicit a different ASSR response, these three parameters can easily be changed, which implies revocability. Its output is also steady-state, allowing for easier detection of the signal as compared to the transient AEP signal.

2.3 Background on the Auditory Steady State Response

Auditory evoked potentials track the brain's response to a specific auditory stimulus from the basilar membrane in the cochlea to various regions in the cortex. The stimulus is

presented at a low enough rate to allow a transient response to be recorded, before the next tone is presented. Latency of a response is defined as the response time after a stimulus is presented. AEPs follow a typical wave pattern, with low-latency responses occurring within the first 10ms after stimulation, mid-latency responses (MLR) occurring around 10-60ms, and late-latency responses (LLR) occurring after 60ms. Each of these regions of the wave originate from different neural generators of the brain: with the low latency region – also called the auditory brainstem response (ABR) – originating from the auditory brainstem.

AEPs – and particularly the ABR – are used in audiometry tests to determine hearing thresholds and sensitivity in patients. ASSR, a relatively recent audiometry testing method, was developed in response to the lack of frequency specificity in ABR measurements [19]. A modulated tone is presented to the ear, and the neural response is a repeating waveform that is synchronized or "phase-locked" to the stimulus. For example, a stimulus with modulation frequency of 100Hz will result in an ASSR with peaks that repeat at 100HZ. Modulation frequencies below 20Hz generally correspond to activation of neurons responsible for the LLR, 20-60Hz from those responsible for the MLR, and above 60Hz from those responsible for the ABR. In this way, by varying the modulation frequency(MF) of the stimulus, different regions of the brain can be stimulated. The carrier frequency(CF) of the stimulus, typically between 500Hz and 8kHz, also affects auditory response: different portions of the basilar membrane in the cochlea are stimulated in response to the CF [45].

Since the auditory brainstem is not sensitive to subject awareness, ASSR stimuli above 60Hz have been found to be more versatile in patients of all ages and degrees of hearing loss [45]. The 40Hz ASSR, sensitive to subject awareness, is still the most commonly used, for in subjects above 13 years of age, the frequency response of the ASSR shows a more defined frequency response than higher-frequency ASSRs. In addition, it is still present and defined during sleep or unconscious states [11, 12, 47], albeit with lower amplitudes.

2.3.1 Recording and Detecting ASSR

ASSR signals are recorded from the brain using scalp electrodes that measure far-field potentials – that is, potentials from neurons located at a distance from the recording site [48, 49]. Using the 10-20 electrode placement system, shown in Figure 3, the ground electrode is placed on the forehead (Fpz), and the reference electrodes are placed on the two ears [45]. Remaining electrodes can be placed in different locations to observe different EEG potentials.

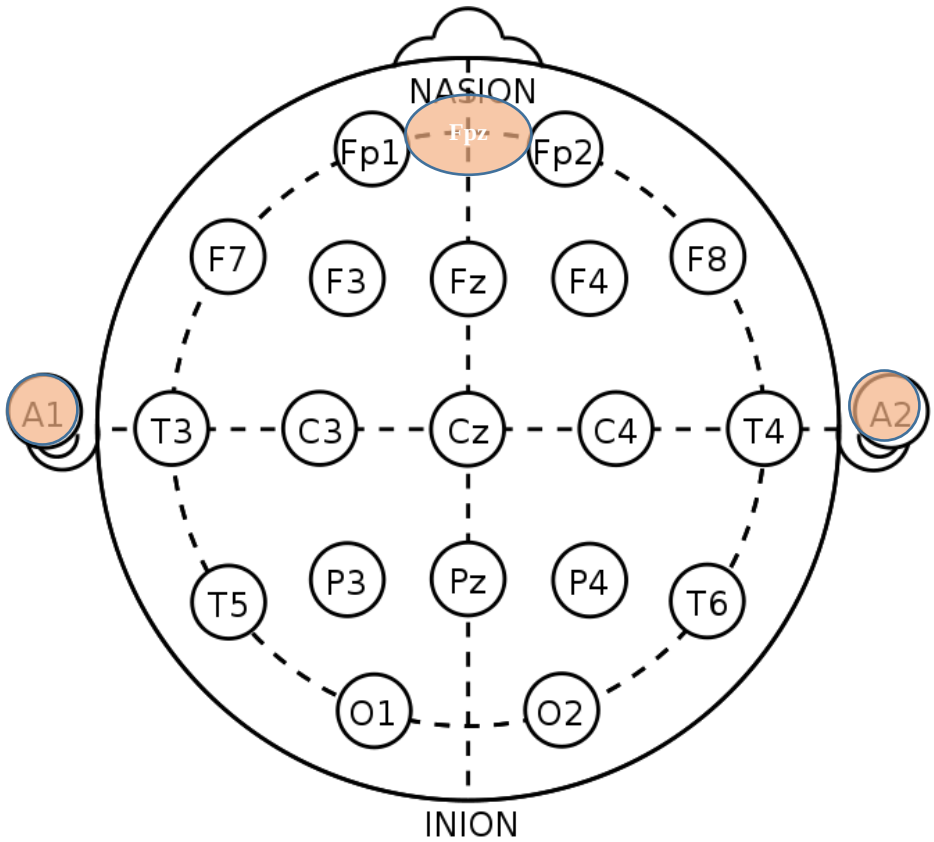


Figure 4 The 10-20 International Placement System for Electrodes. Orange ovals indicate the main sites used for recording ASSR. Image taken and modified from the public domain in [50].

The signals are then amplified, sampled for computer processing, and bandpass filtered between 30-300Hz to prevent aliasing [45, 46]. Note that at this point, the signals from the electrode channels present the entirety of the brain's activity, which is not limited to an auditory response. As such, the ASSR is buried within the overall recorded response,

and non-ASSR data can be treated as noise. Table 1 lists some of the sources contributing to the noise present in EEG.

Table 1 Sources of EEG noise (adapted from [51])

EEG Noise	General Frequency Range (Hz)
ECG	0.5-100
EEG Awake	3-40
EEG Sleep	3-16
Electromyogram (EMG) – from muscle movement	30-500 Hz
Power line noise	60Hz (in Canada)
Radio-frequency noise	Random locations

The recorded, raw EEG signal is then stored in blocks known as epochs. An epoch can be of any length, but generally corresponds to the samples recorded within a cycle of the stimulus. In general, the non-ASSR data contained in the EEG is modelled as white noise, hence averaging over several epochs causes the white, random noise to cancel out, and the ASSR data to be amplified. This is known as ensemble averaging [9, 14, 46]. Once ensemble averaging has been performed to the point where a high SNR ratio is achieved, hearing threshold detection is performed on the FFT of the obtained signal. Two types of tests are generally performed to detect the hearing threshold. Using the amplitude of the frequency component at the MF, F ratio tests can be performed to statistically distinguish whether the component is noise or ASSR. A second method measures the phase coherence variability between the stimulus and ASSR [44, 45]. These two methods underscore the nature of ASSR as a signal: it is characterized by both frequency and time components. This fact is used in this work to determine methods of extracting discriminatory features from the ASSR.

2.4 Feature Extraction in Related Biometric Systems

Feature extraction is the process of identifying the important, discriminatory characteristics of a signal, and in the case of ASSR, compiling them into a biometric template. This template is then later used for verification. No one optimal method of extracting EEG features has yet been identified; different works present incremental

improvements on previous feature extraction methods. Depending on the signal type, various feature extraction methods are appropriate for capturing different types of information, such as those used to capture time-dependent information, frequency information, or both time and frequency information, among others. Though ASSR is theoretically stationary, the process of extracting an estimate of the ASSR from background EEG (cf. Section 3.1.2) will inherently introduce non-stationarity into the signal. As such, this project focuses on wavelet-based features. In the subsequent sections, a popular method of feature extraction – AR – is described followed by a brief explanation of wavelet transformations is provided.

2.4.1 Capturing Frequency or Time-Dependent Information

Frequency-based methods convert a time-series signal into its frequency spectrum using the FFT. This method generally works well for stationary signals. In previous EEG literature, the power spectral density (PSD) and its variations, have normally been used as features [6, 21, 65]. Due to the non-stationary nature of EEG data, Fourier methods tend to discard time localization information. AR and wavelet-based methods, on the other hand, address this issue.

Autoregressive (AR) models are a popular method of feature extraction in EEG biometrics; in a state-of-the-art review by Campisi and La Rocca (2014), 11 out of 16 works used AR or variations of AR parameter estimation for the feature extraction stage of the corresponding biometric system [22]. AR is a type of linear prediction that aims to predict current values of a system based on past values. Thus, as a feature extractor, it can reveal important information on the dependency of present signal values on previous values. In a Kth order system, a signal *x[n]*, is represented as follows:

$$x[n] = c + \sum_{i=1}^{K} a_i x[n-i] + \varepsilon[n]$$

Eq. 6

where c is a constant, ε is white noise, and a_i represents the ith coefficient of the model. Equation (1) can also be expressed as (2):

$$x[n] = c + \sum_{i=1}^{K} a_i B^i x[n] + \varepsilon[n]$$

Eq. 7

where B, a lag operator, operates on *x[n]* to get a previous value of x. Feature extraction based on AR tends to focus on determining the a_i coefficients that best model the data [25], and using different variations of the following: the raw a_i coefficients [52], frequency spectrum of the AR model [53], or the power spectral density of the AR process.

In [52], Paranjape et. al. used AR to examine the characteristics of EO and EC EEG data. Estimation of the best model order was done by generating AR models with orders between 3 and 21. Even at lower orders, they noted that coefficients were clustered per subject, indicating that AR reveals discriminatory information. The work in [52] achieved its highest identification rate of 99% with a model order of 21 using discriminant analysis as a classifier.

In another work, Subasi et. al. used both AR and FFT separately to classify subjects as either healthy or epileptic [53]. Three classifiers were used: logistic regression, feedforward error backpropagation artificial neural networks, and wavelet neural networks. Instead of using the raw AR coefficients as in [52] and other works, the spectrum of the AR model was used as the feature vector. With a model order of 8, the AR spectrum features achieved better classification results with all classifiers than FFT, with a maximum classification accuracy of 93%.

2.4.2 Time-Frequency Based Feature Extraction

In the complete wavelet transform (CWT), a continuous mother wavelet, at a continuous function and scale is used to extract parameters. Features are derived from the wavelet coefficients, defined as:

$$W_x(a,b) = \int_R x(t) * \varphi_{a,b}(t)dt$$

Eq. 8

where the coefficients are W_x, and $\varphi_{a,b}(t)$ is the wavelet function at scale a and shift b [29]. Since the CWT varies the scale continuously, it requires high computational complexity. To reduce this, the discrete wavelet transform (DWT), can be used instead. In DWT, two types of coefficients are created: approximation and detail coefficients. Discrete time samples, x[n], are simultaneously passed through a low pass and high-pass quadrature mirror filters, with impulse responses of g and h, respectively. Samples are downsampled by 2, and the resulting low-pass and high pass output is used for the approximate and detail coefficients, respectively. A level, l, is chosen for decomposition, and the above process is repeated l times for $(2-1)^l$ final coefficients.

Liu used the CWT in [43] for feature extraction of TEOAE data. He noted that in the time domain, time signals between different subjects appeared similar, but once wavelet features were determined at scale 8, the coefficients within the same subject were similar, but varied significantly from other subjects.

In [61], DWT was used to extract features from EEG generated by motor and cognitive tasks. After trying different types of mother wavelets and decomposition levels, the Daubechies 4 wavelet was found to work best. A 96.5% identification accuracy was achieved.

2.5 Verification Methods in Related Biometric Systems

Three types of test can be used to generate the verification performance values described in 2.1: a legal test – where an enrolled subject claims his or her identity, an imposter test – where enrolled subjects claim identities other than their own, and an intruder test – where unenrolled subjects attempt authentication [25]. In this work, all three tests are combined into one to generate performance values.

There are three types of classifiers that can be used to generate models for using biometrics as an authentication tool. In one, the proposed user's template is correlated against the claimed identity's template; if the correlation is above a pre-defined threshold,

the user's claim is accepted [66]. In another method, classifiers are used to generate multiple classes corresponding to each subject, and verification is done by comparing the claimed identity with the identity output by the classifier when given the user's template [62, 64]. This second method is by nature an identification system, with its output modified to appear as a verification system. In a third method, verification is treated as a binary classification problem, and a binary classifier is generated for each subject, with the subject as the positive class, and remaining subjects as the negative class [67]. The last method was chosen in this work, since the high-dimensionality feature space of the ASSR features did not warrant the use of method one.

Previous works on biometric verification have used support vector machines (SVM), detailed in [68], as the classifier of choice [62, 64, 67]. In [64], the performance of SVM and artificial neural networks (ANN), was compared on a multi-modal biometric system suing fingerprints, face recognition, and voice recognition. They found SVM, with a polynomial kernel, to produce better FRR and FAR results than ANN. Generally, SVM algorithms are binary classifiers that learn a decision boundary between two classes. Optimization is performed to either maximize the distance to the decision boundary, or minimize the overall classification error. By default, a linear kernel is used to generate a hyperplane as the decision boundary, but other kernels – such as a polynomial or Gaussian – can be used to map non-linearly separable datasets into linearly separable data. The SVM method is employed in this work.

3 EXPERIMENTAL FRAMEWORK

To determine the viability of the 40Hz ASSR signal as a biometric modality, the experimental framework is modelled after the enrollment and verification phases described in 1.1. Figure 5 outlines the general experimental framework followed in this project.

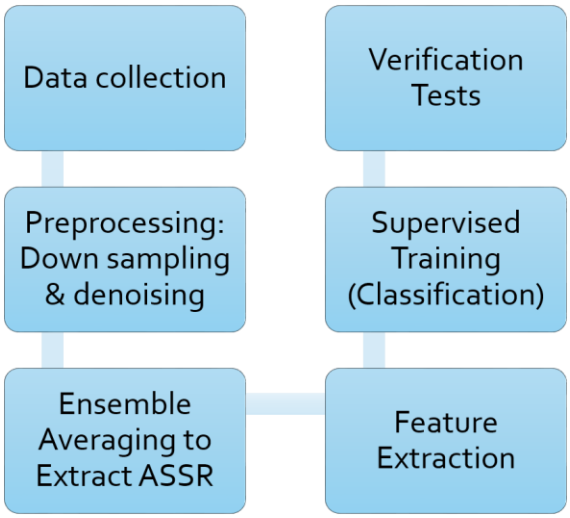


Figure 5 Experimental Framework of this Project

EEG data is first collected, down-sampled for faster computation, and denoised. Once ASSR cycles are obtained using ensemble averaging, the discrete wavelet transform, and variations on the resulting coefficients, are used to extract features to be used as templates. This template creation phase is described in section 3.1.

A random number of subjects are then chosen to be enrolled, while the remaining are identified as imposters. A one-vs-all method is used to generate classifiers for each subject using the Support Vector Machine (SVM) classifier. Different kernels are used to generate performance values, and the classifier achieving the optimal values is selected. This enrollment phase step is described in Section 3.2.

The selected classifier is then run on the dataset a total of 3 times to obtain average verification performance results. Verification performance for different types of features is also explored. This experimental framework for the verification phase is detailed in Section 3.3. Full verification performance results are discussed in section 4.

3.1 TEMPLATE CREATION

To create a biometric template for use in classification, data is first collected, preprocessed, then analyzed for discriminatory features.

3.1.1 Data Collection

Focus was placed on collecting data for the goal of a large ASSR database for use in future investigations. Collection of this data is described in 3.1.1.1. A pre-recorded database is already available from the work of Haghighi et. al. [55, 56] and was used for the preliminary study of ASSR as a viable biometric in this thesis.

3.1.1.1 Data Collection for a General ASSR Database

One goal of this work was to begin the process of creating an ASSR database for use in future uniqueness and permanence studies. Drawbacks in studying biometric systems tend to come from the database: there may not be enough subjects or the recording sessions may not have happened multiple times, among other factors. The goal is to create an ASSR database that contains many subjects – around 100 or more to match works such as [6, 57] – to establish generalizability of any results, and to have multiple recordings that happen over time – to establish repeatability and to determine biometric characteristics such as permanence.

Before recording EEG data from subjects, ethics approval was sought and obtained under protocol ID 33761, from the Office of Research Ethics of the University of Toronto. Call for participation email templates, written consent forms, and general study procedures were also prepared. A session is one hour and broken up into the following steps [40]:

- 15 minutes: The participant arrives at the lab and the experimenter explains the procedure to be performed.
- 15 minutes: The experimenter prepares the subject for data acquisition. A head cap using electrodes placed at the 10-20 international system will be used. Electrode gel is applied to the electrodes of the cap to improve data quality by decreasing skin impedance. The experimenter will then insert an ear tip connected to the Vivosonic Integrity System to begin ASSR stimulation.
- 5min – ASSR data is recorded (1st trial)
- 15 min – break

- 5 min – ASSR data is recorded (2nd trial)
- 5 min – ASSR data is recorded (5th trial)

The subjects will be asked to return multiple times over a year.

The data collection flow used in creating this database is outlined in Figure 6, and the physical layout or the system is highlighted in Figure 7. The stimulus is generated by Vivosonic Inc. Integrity ™ V500 (Vivosonic Inc., Toronto, ON, Canada). It is a wideband chirp signal (700 to 3000 Hz) with center frequency of 2kHz, and modulated by a 40.68Hz sine wave [11]. Without using earmuffs to mute background noise, the stimulus is presented to either ear of a subject separately, using an ER-3A-ABR insert earphone (Etymotic Research) at 60dB HL, a level comfortable enough for most users.

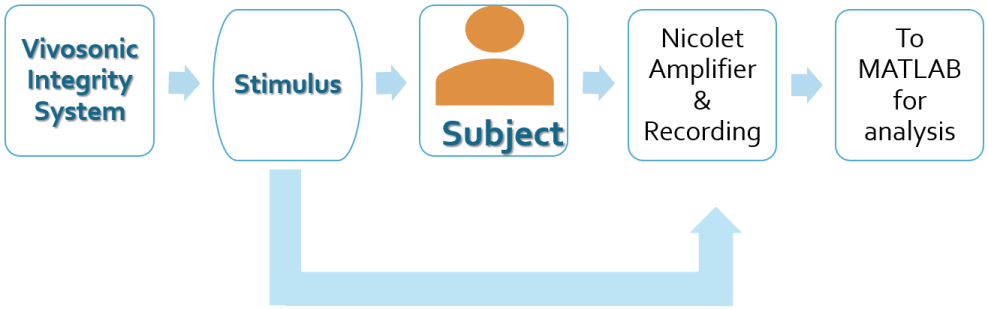
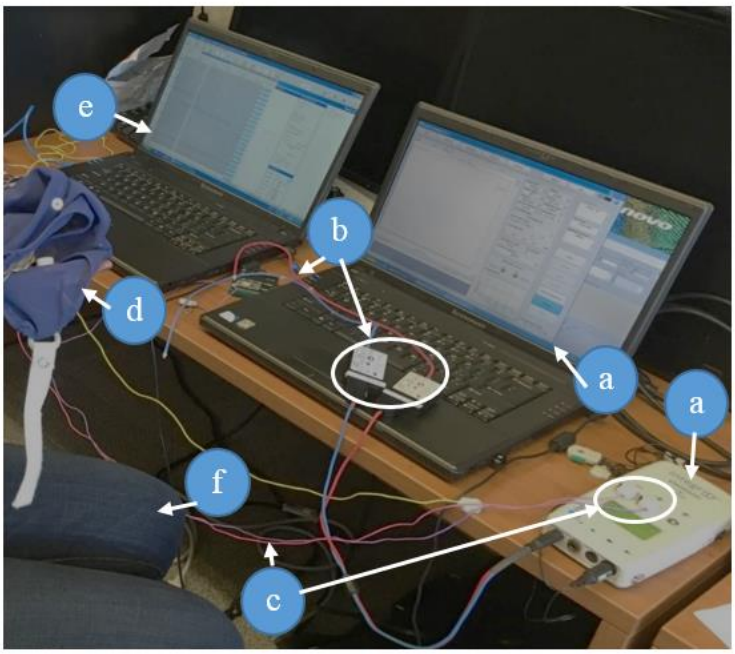


Figure 6 Data Collection Flow

An electrode cap from Bio-Medical Instruments Inc., custom designed for the Biometric Security Lab, is placed on the subject's head to mark the electrode locations from the international 10-20 system. Neuroline 720 surface electrodes are used for the A1 and A2 electrodes on either ear as well as on the forehead. Electrode gel is applied to the electrodes to increase conductivity, and the EEG data is recorded using the Nicolet™ Wireless 32 amplifier system, with a sampling frequency of 12 kHz. The stimulus is also recorded by the amplifier to allow for synchronization when extracting ASSR from the raw EEG later in the experiment workflow (see label c in Figure 7).



a	Vivosonic Integrity™ V500 System
b	ER-3A-ABR insert earphones
c	Stimulus to Amplifier
d	Electrode cap
e	Nicolet™ Wireless 32 Amplifier
f	Subject

Figure 7 Physical Layout for Data Collection

To date, three subjects have been recorded. The database used in the remaining steps of the experimental framework is described in the following section.

3.1.1.2 Pre-recorded ASSR Database

Sahar Haghighi [55, 56] of the Biometric Security Lab generated a database of 22 subjects for use in analyzing the depths of anaesthesia a patient can undergo. A similar setup to section 3.1.1.1 was used to collect this data, except that data was collected in a hospital, before subjects were anaesthetised, and the stimulus was presented binaurally. For my analysis, only the portion of the EEG data corresponding to when a subject was awake is used. The wake portions correspond to recording times between 1 - 25 minutes. Subjects were all over 18 years of age and had no previous history of hearing loss or neurological issues [55, 56].

As highlighted in Figure 8, 11 electrode sites were used to generate the following 8 channels: T3-Fz, T4-Fz, Cz-A1A2, C3-A1A2, C4-A1A2, Fz-A1A2, Oz-Fz, and Nape(Inion)-Fz. The stimulus was on the 9th channel. Mapping of each channel to a channel number if given in Table 2. Data from these 9 channels is passed on to

MATLAB® for preprocessing and ASSR extraction. Each subject had these 8 channels of recorded data, for a total of 176 channels of recorded data, and 22 stimulus channels.

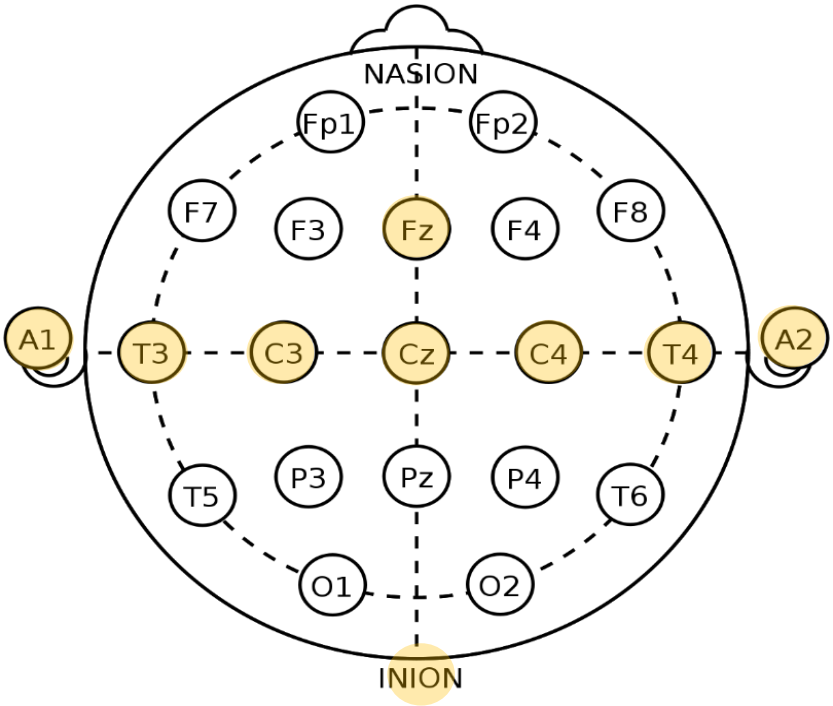


Figure 8 The 11 Electrode sites used in the second database [55, 56].

Table 2 Channel Mapping Used in this Report

Channel #	**Electrode Sites**
1	T3 to Fz
2	T4 to Fz
3	Cz to A1A2
4	C3 to A1A2
5	C4 to A1A2
6	Fz to A1A2
7	Oz to Fz
8	Nape to Fz
9	Stimulus channel

3.1.2 Data Preprocessing and Ensemble Averaging

For faster computation, all recorded data is downsampled from 12000 Hz to 2400Hz. The goal of data preprocessing is to remove noise from the EEG data, as outlined in 2.3.1, and obtain the final ASSR signal. Since the stimulus has a MF of 40.68Hz, the expected ASSR response should have a peak frequency component at 40.68Hz, and a second harmonic near 81Hz. Sections 3.1.2.1 – 3.1.2.7 detail each step taken from raw EEG signal to the final ASSR signal.

3.1.2.1 Bandpass Filtering

Figures 9-12 show the raw EEG signal for a subject on two channels, as well as the corresponding FFT spectrums. Through visual inspection of the frequency spectrums, denoising is needed to remove the large power line peak at 60Hz, and the noise at the lower and higher frequencies. The ASSR peak at 40.68Hz is noticeable in some subjects on some channels (as in Figures 10 and 12), however the second harmonic at around 81Hz is not evident. To remove unwanted frequencies, all data was filtered by a 3rd order, Butterworth filter, designed to pass only frequencies in the range 35-45Hz and 75-85Hz, the expected location range of the ASSR peak and its 2nd harmonic. The corresponding

spectrum after filtering on channels 1 and 4 for subject 103 is shown in Figures 13-14. The peak at 40.68Hz is now clearly defined, and the power line noise is removed.

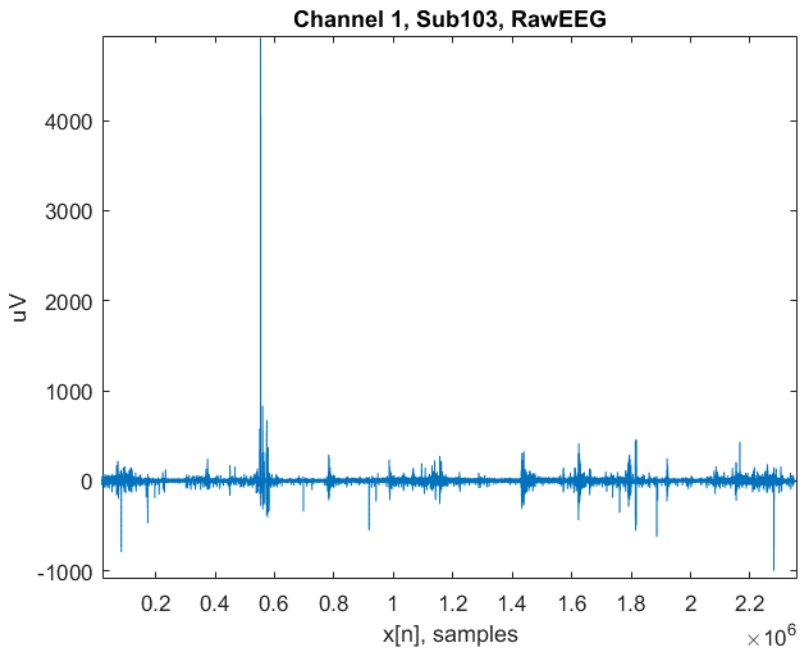


Figure 9 Recorded EEG on Channel 1 for sub103

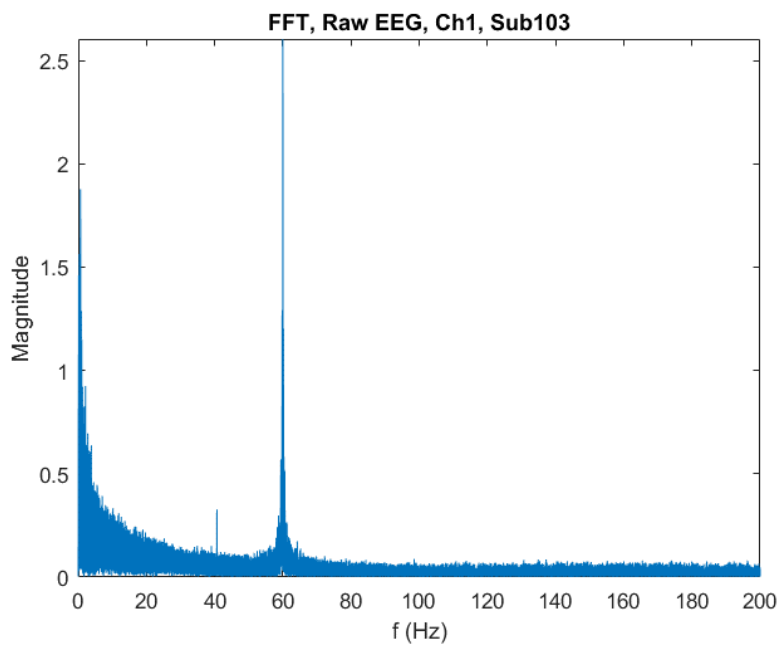


Figure 10 Frequency Spectrum corresponding to EEG on Channel, sub103.

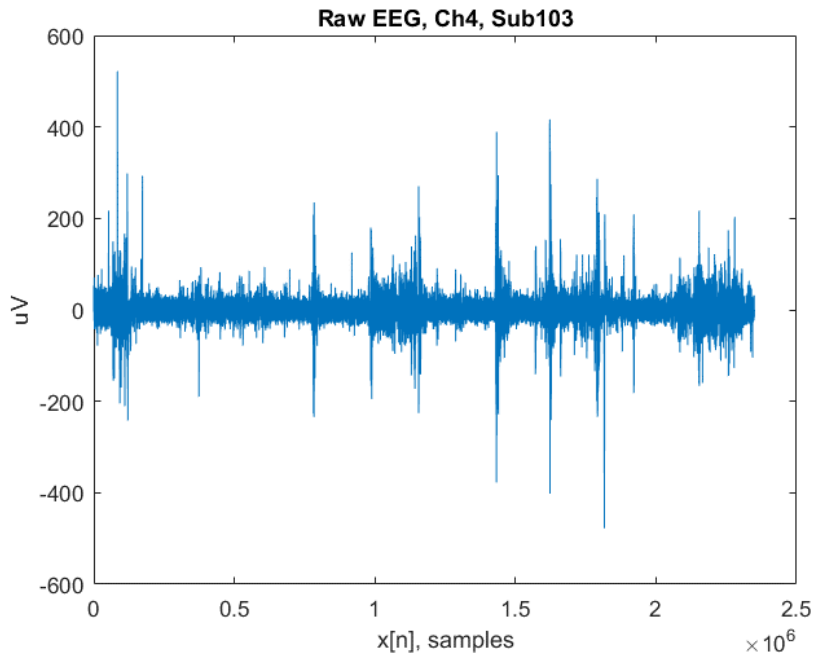


Figure 11 Recorded EEG on Channel 4 for sub103.

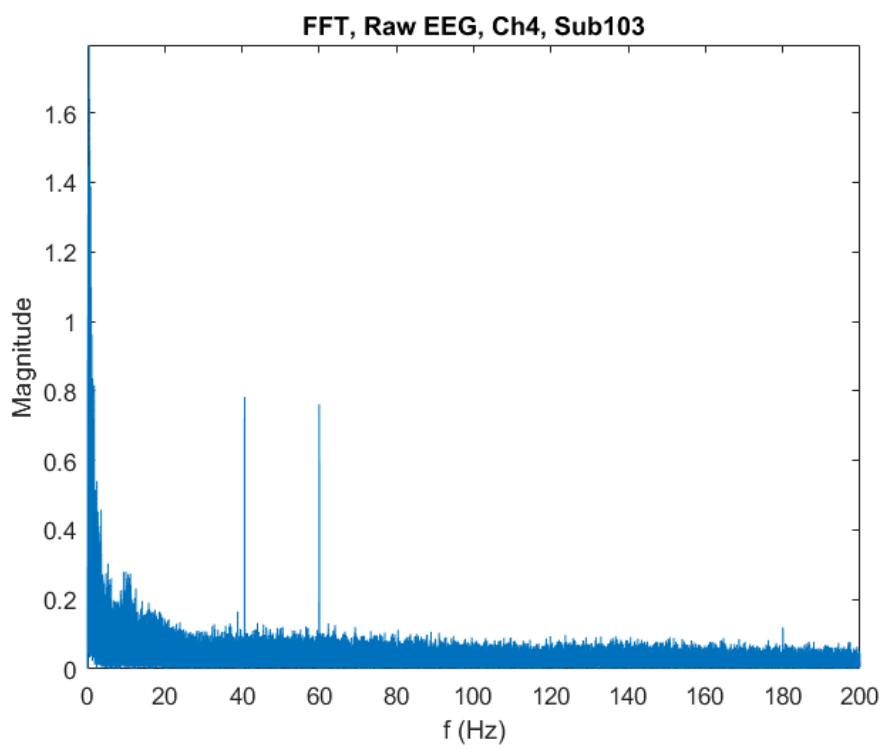


Figure 12 Frequency spectrum, channel 4, sub103.

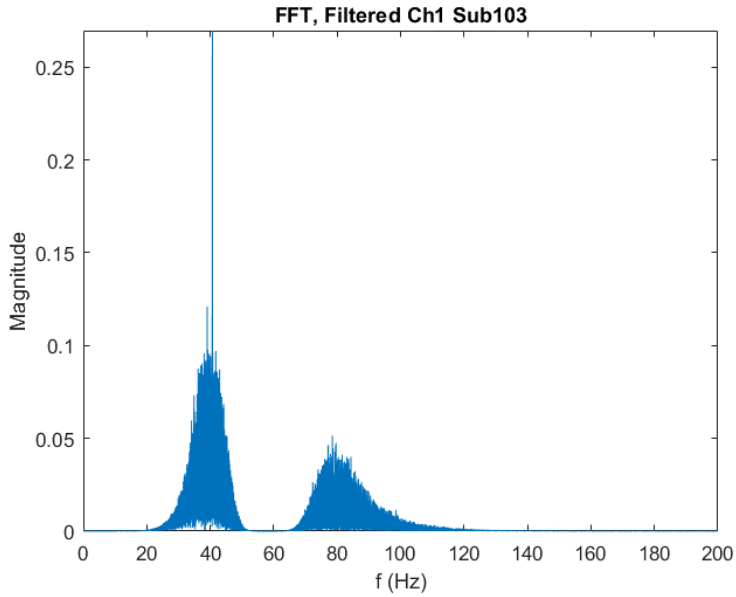


Figure 13 FFT after filtering, sub103, ch1.

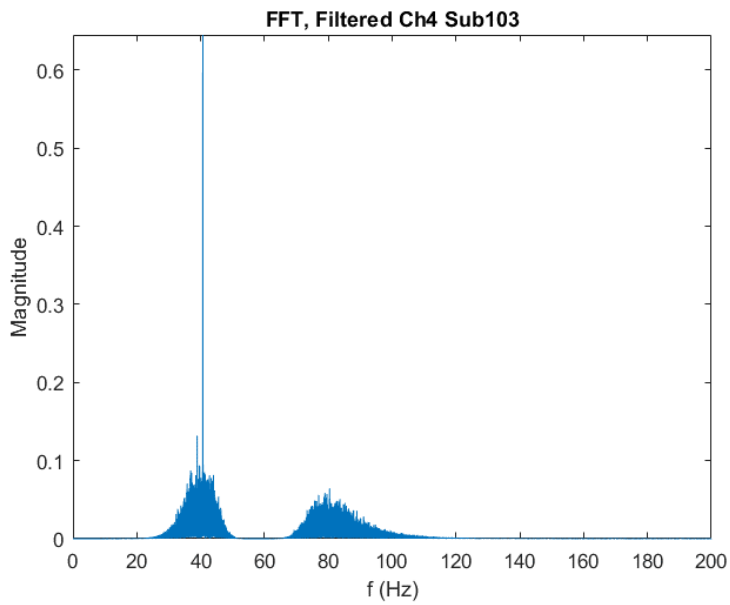


Figure 14 FFT after filtering, sub103, ch1.

3.1.2.2 Determining and Denoising Epochs

An epoch is a section of the EEG signal that corresponds to one cycle of the stimulus. As previously mentioned, the Nicolet amplifier records at a 12000 Hz sampling rate. For a 40.68 Hz stimulus, this corresponds to approximately 295 samples per stimulus cycle.

Once the data is downsampled by a factor of 5 in MATLAB® (to 2400 Hz), there will be 59 samples in an epoch. Before the EEG data was sectioned into epochs, data on each channel was aligned with the stimulus peaks, using the method in [55, 56], to maintain the synchronization property of ASSR with the stimulus. Data on each channel was then extracted into epochs of 59 samples each, with the beginning of each epoch corresponding to either a maximum or minimum peak value in the corresponding stimulus. As a last step, every two epochs were concatenated to form 118-length epochs, due to empirical observations on low frequency resolution with 59 samples.

To further denoise the data, outlier samples, defined as being 3 standard deviations away from the mean value of an epoch, were discarded and replaced with an interpolated value. Finally, the overall mean of all the epochs was computed, and any epoch located 3 standard deviations away from the mean value was discarded.

To ensure the epochs were properly denoised, a visual test was performed. The variance of epochs ranging from one to all the epochs was calculated and graphed for each channel. If the data had been properly denoised, the variance between epochs decreased as epochs were accumulated, indicating a stabilization of EEG noise levels. Figure 15 shows a variance graph on all 8 channels for a subject.

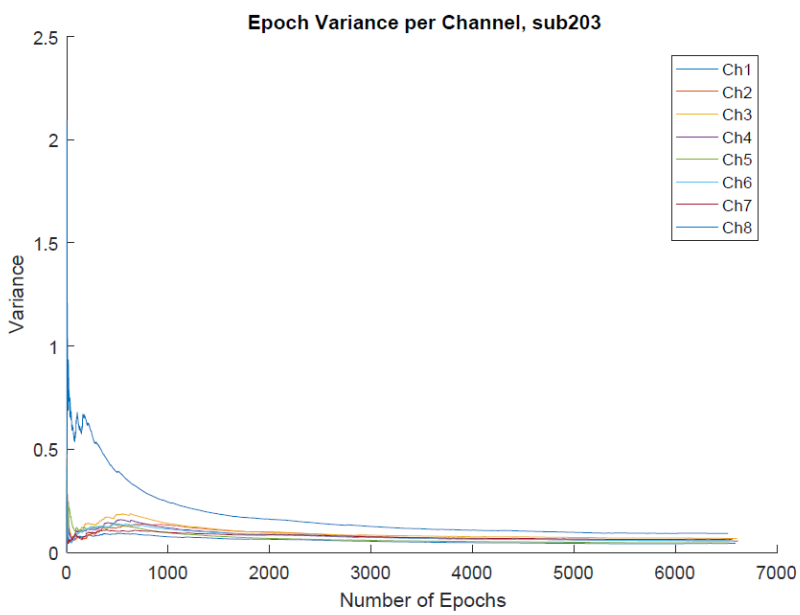


Figure 15 Variance Test on 8 Channels, sub203

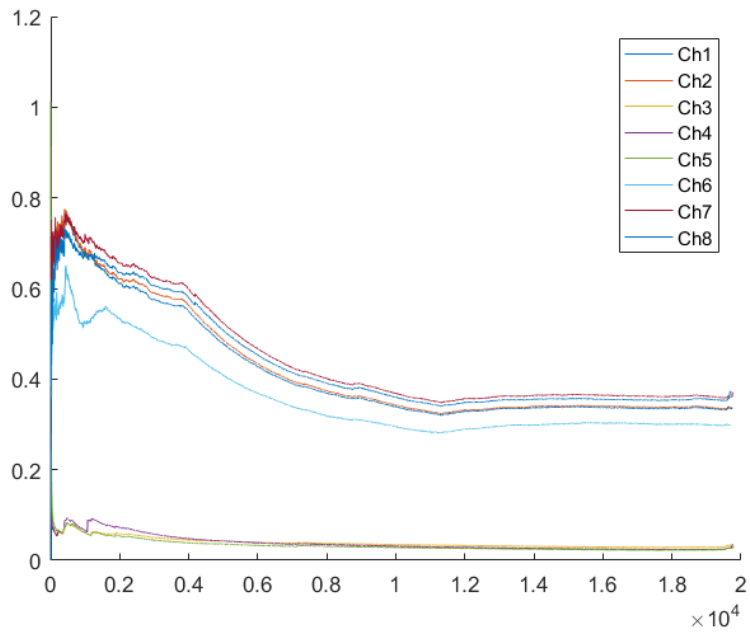


Figure 16 Variance Test for 8 channels, sub122.

3.1.2.3 Extracting ASSR

To estimate the ASSR time signal, ensemble averaging was performed. In previous literature, upwards of a 1000 epochs, known as "sweep length," are averaged to generate an ASSR signal [59, 60]; however, the database used in this study is limited by the wide variety of recording times ranging from 1 – 25 minutes of data. With some subjects having only a few minutes of data, very few epochs are available for averaging. Ensemble averaging is performed assuming the EEG non-ASSR noise has constant variance between epochs. The variance test described in 3.1.2.1 can also be used as a test of this assumption. Figures 15 and 16 show two variance graphs for subject 203 and 122, respectively. For subjection 203, low variance between epochs is obtained after 1000 epochs; however, to use a sweep length of 1000 will generate only 6 ASSR cycles. For subject 122 in Figure 16, low variance is achieved after 10000 cycles, yielding only 2 ASSR cycles. Hence, to increase the number of available ASSR cycles available for later feature extraction, a small sweep length of 300 was used. This value was also used in [47, 55, 56, 58] on the full wake-anaesthesia dataset and produced distinguishable ASSR cycles.

The final ASSR signal can be mathematically represented as

$$x_i[n] = s_i[n] + e_i[n]$$

Eq. 9

where *i* corresponds to the ith sweep of the stimulus, $x_i[n]$ is an estimate of the ASSR on the ith sweep, $s_i[n]$is the true ASSR signal, and *e[n]* is noise or any non-ASSR data, assumed to be of zero mean. Using the same assumptions as [58], where $s_i[n]$ is phase-locked to the stimulus and the noise has constant variance and is uncorrelated between epochs, then the ensemble average is defined as:

$$\overline{x}[n] = \frac{1}{N}\sum_{i=0}^{N-1} x_i[n] = s[n] + \frac{1}{N}\sum_{i=0}^{N-1} e_i[n]$$

Eq. 10

Since $r_i[n]$ is of zero mean and has constant variance between different epochs, the term $\frac{1}{N}\sum_{i=0}^{N-1} e_i[n]$ tends to a small constant value, and $\overline{x}[n]$ provides an estimation to the real ASSR signal $s[n]$.

ASSR cycles for each channel per subject were extracted using the above method. Table 3 shows the number of ASSR cycles extracted for each subject, along with the original recording length. Figures 17-19 show the ASSR cycles in channel 6 for subjects 103, 104, and 203, respectively. Visual investigation showed that subjects with passing variance tests as described in section 3.1.2.2 had low ASSR cycle variance, such as subjects 103 and 203 (cf. Figure 17, 19).

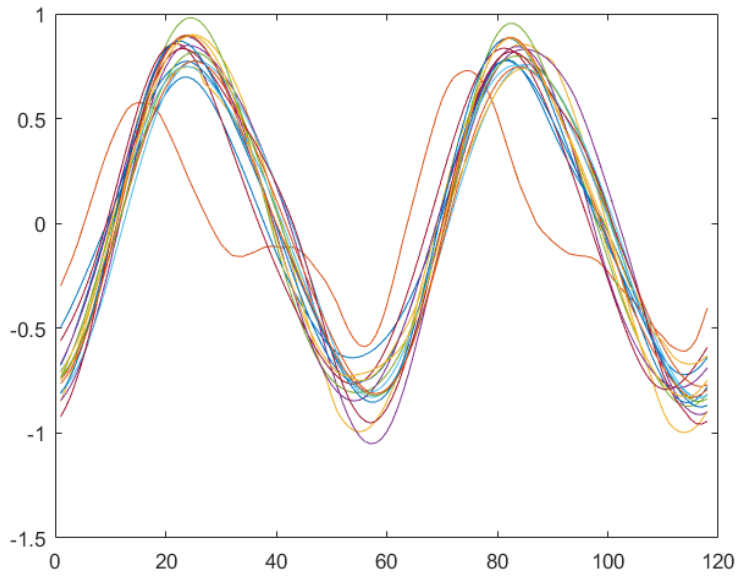


Figure 17 Channel 6, Sub103, ASSR cycles

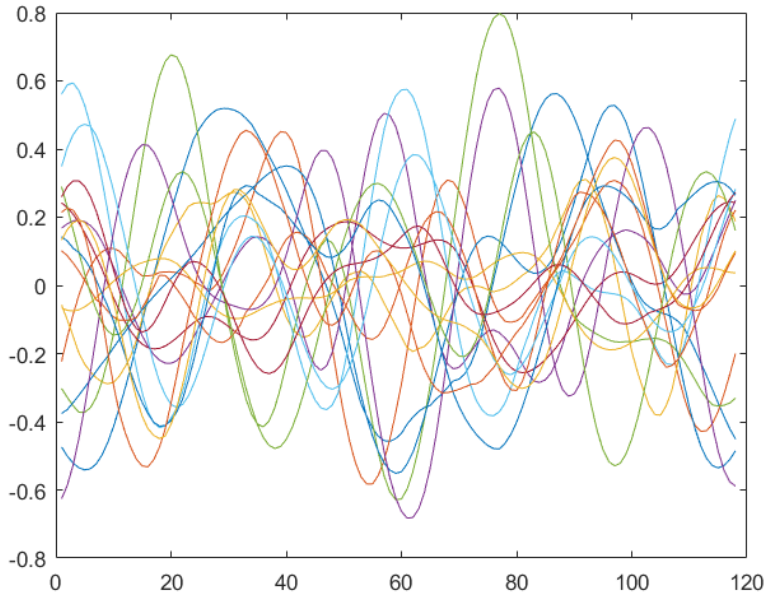


Figure 18 Channel 6, Sub104, ASSR cycles

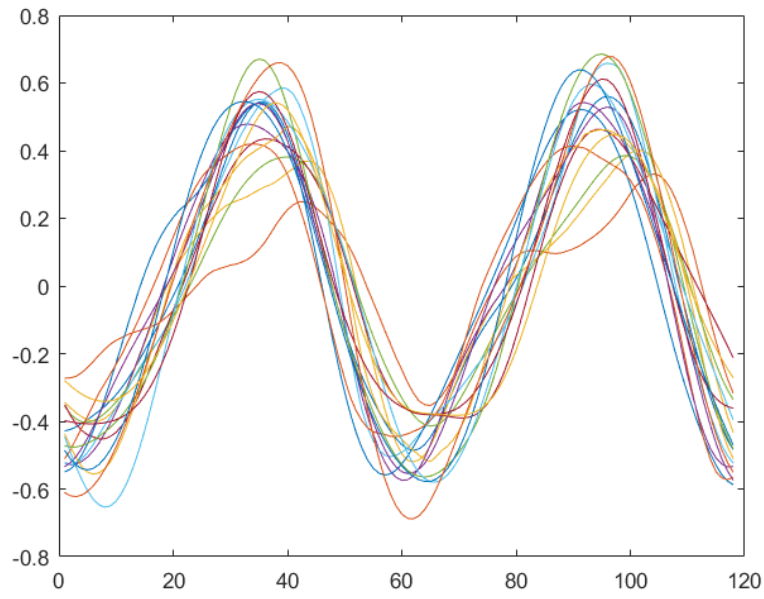


Figure 19 Channel 6, Sub203, ASSR Cycles

3.1.3 Feature Extraction

As introduced in Section 2.4, discrete wavelet transform is a power tool in analyzing time-frequency characteristics of a signal. Based on the methods of [61], a Daubechies 4 wavelet was chosen, and wavelet decomposition was performed on each ASSR cycle at a decomposition level of 3, yielding four sets of coefficients: detailed level 1 (cD1), 2 (cD2), and 3 (cD3) coefficients, and the approximation coefficients for level 3 (cA3). Upon visual analysis of the wavelet coefficients, the detailed coefficients at level 1 were removed, since all were fluctuating around 0. This is due to the random noise in EEG data added at high frequencies (>100Hz), due to the denoising process detailed in 3.1.2.2. Figure 20 shows the frequency spectrum of subject 103 after the outlier removal process. Small frequency components are present in the higher frequency ranges. Figure 21 shows the wavelet decomposition coefficients for subjects 103, 104, and 203, on channel 6. Three sets of features, for three verification systems, were extracted based on these coefficients:

1. All coefficients: The raw wavelet coefficients were used. Coefficients cD3 and cA3 had 20 features, and cD2 had 34 features, for a total of 74 features per ASSR cycle per channel for a subject.

2. One coefficient set: Through visual analysis, it was hypothesized that cA3 contained the most information out of all the coefficient sets, due to its larger amplitudes. Thus, in the second set of features, the 20 values of cA3 were used as features.
3. Statistics of coefficients - standard deviation, mean, max, min: Following Yang and Deravi's method in [61], the standard deviation, mean, max and min of each of the 3 coefficient sets were used as features, for a feature vector length of 12 per ASSR cycle.

The above three types of features were each separately used, for comparison, in the verification system described in the following section. By observing which feature set yields the best verification performance results, further insight into the discriminatory inter-subject characteristics of ASSR can be obtained.

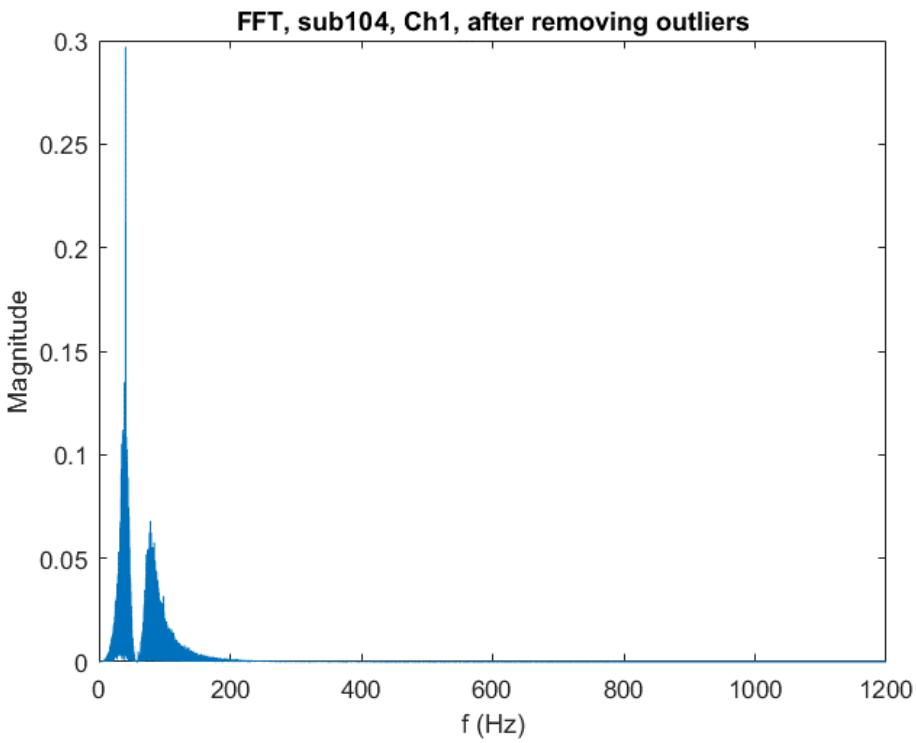


Figure 20 EEG spectrum with noise in higher components

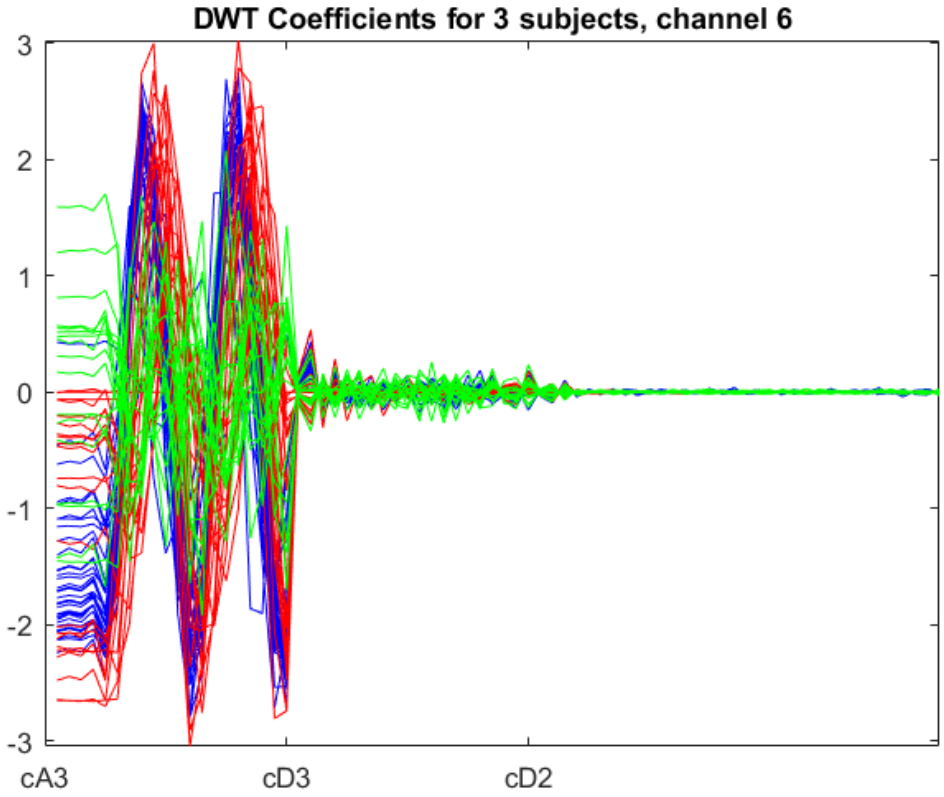


Figure 21 cA3 - Approximating coefficients at level 3, cd3 - detailed coefficients at level 3, cD2 - detailed coefficients at level 2. Red is sub203, blue sub103, green sub104

3.2 SUPERVISED TRAINING – ENROLLMENT AND VERIFICATION SETUP

3.2.1 Choosing a Classifier

SVM (Support Vector Machines), a binary classifier outlined in section 2.5, was the chosen classifier for subject enrollment. Based on the methods of choosing an optimum kernel in [62], four types of kernels were chosen: a linear kernel, a polynomial kernel of order 0.5, a polynomial kernel of order 2, and a Gaussian kernel. The feature set comprising of cA3, cD3, and cD2 was used in choosing the optimal kernel. For each kernel, the following steps were performed:

1. Data was split into 14 “enrolled” subjects and 4 imposters. The remaining four subjects were not included as they had less than 10 feature vectors to use for training or verification.

2. The classifiers were first trained on the dataset. The first 10 feature vectors of each enrolled subject were used for training. Labelling for supervised training was done as follows: the feature vectors of the subject was labelled as the positive class, and the remaining 13 subjects x 10 features were labelled as the negative class.
3. The classifier then used the labeled data for model training. Due to the computation complexity of SVM, the model was run for 30 iterations to determine the best parameters that minimized five-fold cross-validation loss. The *fitcsvm* tool in MATLAB® was used to perform classification, with the box constraint (margin distance) and kernel scale parameters as the basis for optimization.
4. Step 3 was performed for all 14 enrolled subjects, generating a set of 14, individually optimized models. As a biometric system, these 14 models represent a type of template against which users must authenticate.
5. After training, each subject classifier was presented with a maximum of 10 feature vectors from every subject in the system, enrolled and unenrolled. That is, a verification scenario was created where every enrolled subject in the system attempted to authenticate his/herself against every other enrolled subject, including themselves; and every unenrolled subject attempted authentication against every enrolled subject. A total of 2198 verification attempts were made. Performance metrics of FAR, FRR, recall, precision, and verification accuracy were generated from the resulting verification attempts to choose the top two classifiers. Note that the same features were used for verification attempts for each type of kernel-based classifier, to ensure fair comparisons.

Figure 22 shows the structure of the enrollment setup.

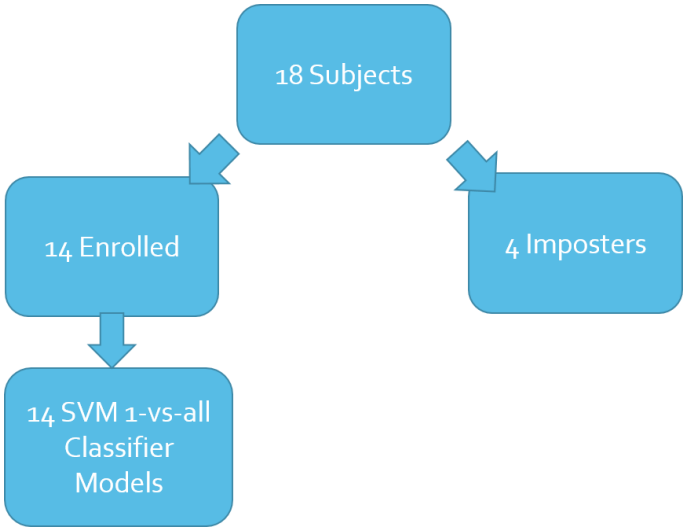


Figure 22 Enrollment setup.

3.2.2 Verification Tests

The winning classifier – a Gaussian Kernel (Section 4.1) – was used in remaining verification tests. The following table outlines the structure of the tests. Verification tests generally followed the same structure as step 5 in 3.1, unless otherwise noted. One feature vector consisted of the concatenation of the features of all 8 channels.

Table 3 Structure of Verification Tests

Feature type	Enrollment	# Trials	Data Used
All coefficients	Already performed in 3.2.1	3	First 2 trials used a maximum of 10 feature vectors per subject. The last trial randomized the number of feature vectors used per subject, and the chosen feature vectors.
One Coefficient Set	Using Gaussian kernels, performed step 4 of 3.2.1 to enroll subjects.	3	Number of features used per subject was randomized, and number of chosen feature vectors was randomized.
Statistics of Coefficients	Using Gaussian kernels, performed step 4 of 3.2.1 to enroll subjects.	3	Similar to the One Coefficient set.

Section 4 presents the performance results of the various classifiers and verification tests.

Table 4 ASSR Cyles and Recording Length for 22 subjects

SubjectID	# ASSR Cycles	Recording Duration (min:sec)
103	39	6:06 (awake)
104	17	6:41 (awake)
106	62	24:34 (awake)
107	31	12:24(awake)
110	20	8:12(awake)
111	43	17:36(awake)
112	3	1:24(awake)
113	10	6:06(awake)
114	12	6:06(awake)
116	50	21:33 (half-way, patient entered anaesthetized)
117	46	19:25(awake)
118	20	8:12(awake)
119	8	3:36(awake)
120	23	9:41(awake)
121	40	16:35(awake)
122	65	27:37 (after 1 min, patient entered anaesthetized)
123	93	39:42 (after 1 min, patient anaesthetized)
124	2	1:05 (awake)
125	10	4:11 (awake)
201	32	13:18 (awake)
202	17	7:07 (awake)
203	21	9:06 (awake)

4 VERIFICATION RESULTS AND DISCUSSION

In this section, the verification performance based on the three feature sets outlined in 3.1.3 are presented and discussed.

4.1 OPTIMAL KERNEL FOR SVM

Table 2 highlights the performance of the four SVM kernels. The Gaussian kernel outperforms the other 3 classifiers on every performance metric, having the lowest FAR and FRR values, as well as the highest verification accuracy. This result is consistent with the optimal kernel types found in [62] and [64]. The Gaussian kernel SVM was used as the classifier type for the remaining verification tests.

Table 5 Performance of 4 SNVM Kernels

Kernel Type / **Performance Metric**	**Linear**	**polynomial, order 0.5**	**Polynomial, order 2**	**Gaussian**
FAR (%)	6.23	0.55	2.18	**0.36**
FRR (%)	2.46	4	2.91	**2.32**
Recall (%)	54.62	26.05	46.22	**57.14**
Precision (%)	32.18	72.09	53.4	**89.47**
F1 Score (%)	40.5	38.27	49.55	**69.74**
vAccuracy (%)	91.31	95.45	94.9	**97.32**
vError (%)	8.91	4.55	5.1	**2.68**

4.2 PERFORMANCE RESULTS

Tale 3 highlights the average performance values of the three different feature types. Table 4 highlights some results of previous works against this work.

Table 6 Performance of the 3 feature sets.

	All Coefficients	**One set**	Coefficient Statistics
FAR (%)	0.250	**0.177**	1.45
FRR (%)	2.25	**1.77**	1.14
Recall (%)	56.9	**62.6**	76.1
Precision (%)	92.2	**94.3**	68.5
vAccuracy (%)	97.5	**98.1**	97.2

vError (%)	2.51	**1.95**	2.8

Table 7 Verification Performance in Previous Works

Previous work	**Modality**	**Classifier**	**FRR**	**FAR**	**Accuracy**
[65]	EEG (cognitive)	FFNN	_	_	97.5
[25]	EEG (EC)	FDA	1	14.3	98.1
[25]	EEG (EC)	FDA	5.5	_	95.1
[25]	EEG (EC)	FDA	11.3	2	87.5
[26]	EEG	_	7.1	13.6	80-100
[64]	Multimodal: face, fingerprint, voice	SVM	1.48	4.52	_
[67]	ECG	SVM	2.46	2.97	_

Overall, the investigation in this work outperformed previous works with regards to FAR and FRR, for all three feature types. The lower FAR values indicate a higher security system that rarely accepts imposters and intruders, while the simultaneously high precision rates for feature sets 1 and 2 indicate that legitimate users are accepted within a reasonable rate. Moreover, compared to other systems, the ASSR system has a lower FRR rate than previous works, indicating that the acceptance rate for legitimate users also outperforms previous methods.

The feature set comprised of just the approximation coefficients outperformed the remaining two feature sets on all performance metrics. Due to the lower number of features (20 per ASSR cycle) than in feature set one, and hence lower computation complexity during classification, this feature set is preferred. Feature set one contains redundant information while feature set three does not contain enough discriminatory information.

The performance results achieved in this preliminary investigation of ASSR indicate that, when combined with wavelet-based feature extraction, the 40 Hz ASSR has unique characteristic per subject that allow for signals from different subjects to be correctly matched or rejected at a high verification rate.

5 CONCLUSIONS AND FUTURE WORK

In this work, EEG data from 22 subjects was preprocessed to remove noise and subsequently analysed to extract 40-Hz ASSR cycles. Discrete wavelet transform was then performed on the ASSR cycles to obtain different types of feature sets: one that used all relevant coefficients ("all coefficients"), another that used only the approximation coefficient ("One set"), and a third that contained only the standard deviation, mean, min, and max of each approximation and detailed coefficient ("Coefficient statistics"). A Gaussian-kernel based SVM binary model was generated and trained on each subject, with the subject as the positive class, and remaining subjects as the negative class. Verification tests were performed using these trained classifiers, to obtain FAR and FRR rates that are on the lower spectrum of previous literature on EEG biometric authentication, as well as high verification accuracies. Hitherto, ASSR-based features have not been used in a biometric setting. Results from this novel investigation indicate ASSR contains discriminatory features that can be used for biometric verification. A variety of factors, however, must be further considered and explored before ASSR is deployed as a practical biometric modality.

For example, no permanence tests were performed in this study. Further investigation is needed to determine whether ASSR templates of the same subject at different times can be correctly matched, and if these templates are sufficiently distinct from those of other subjects. On a related note, the effects of subject consciousness and cognitive state on the discriminatory ability of ASSR-based biometrics should also be studied. In a practical setting, a subject may not always be in a consistent cognitive state – with their eyes closed – when presenting his or her biometric to be captured by the system. The high verification accuracy results in this work, despite three subjects containing features obtained while in an unconscious state (due to anaesthesia), hint that the inter-subject discriminatory power of ASSR may not be affected by consciousness or cognitive state. Moreover, previous literature hints that ASSR above 60Hz, which is less affected by subject state, may have more inter-subject variance [46, 48]. Regardless, different

modulating frequencies should be explored to determine if revocability is possible in the event of a compromised ASSR-based biometric system.

Finally, factors such as recording time, number of electrodes, feature extraction and reduction methods, and classification models need to be addressed to create a practical system with realistic enrollment times, minimum electrodes, and lower computational complexity. This work establishes a precedent on which these factors can be explored to create an improved, practical biometric system.

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