Journal of Information Security, 2026, 17(3), 371-391
https://www.scirp.org/journal/jis
ISSN Online: 2153-1242
ISSN Print: 2153-1234

Flexible Analytic Wavelet Transformation Based Brain Signals Extraction and Classification

Shams Al Ajrawi[1,2,3,4], Mahasweta Sarkar[3], Ramesh Rao[4], Sarah Jawad[2], Mohammed Mohammed Raoof[5]

[1]CSML, Alliant International University, San Diego, CA, USA
[2]Department of CSIS, GCCCD, San Diego, CA, USA
[3]Department of Electrical and Computer Engineering, San Diego State University, San Diego, CA, USA
[4]Department of Electrical and Computer Engineering, University of California, San Diego, CA, USA
[5]Independent Researcher, San Diego, CA, USA
Email: shams.alajrawi@alliant.edu, salajrawi2@sdsu.edu, mohammedraoofphd@gmail.com

How to cite this paper: Al Ajrawi, S., Sarkar, M., Rao, R., Jawad, S. and Raoof, M.M. (2026) Flexible Analytic Wavelet Transformation Based Brain Signals Extraction and Classification. *Journal of Information Security*, **17**, 371-391.
https://doi.org/10.4236/jis.2026.173017

Received: May 7, 2026
Accepted: July 27, 2026
Published: July 30, 2026

Abstract

Brain computer interfaces (BCIs) have emerged as communication technologies to re-mobilize individuals with paralysis, neurological diseases, injuries or limb loss. BCI systems detect brain signals and use extraction and classification algorithms to convert the detected signals into useful outputs that can be used to control external devices. Designing and developing BCI systems face several challenges, such as session-to-session transfer, subject-to-subject transfer, non-stationary signals required for adaptivity, idle signals for motionless subjects, and continuous data collection that can be used to expand BCI systems for a broader spectrum of subjects. This paper presents a novel approach to detect and classify the Electrocorticography (ECoG) brain signals. The Flexible Analytic Wavelet Transformation (FAWT) is used to extract entropy features and the Least-squares Support-Vector Machines (LS-SVM) is utilized to classify the activities. ECoG signals are obtained by directly recording from the surface of the cerebral cortex. This provides high-resolution data and stability in signals, in contrast to Electroencephalography (EEG) signals. Three entropy features were extracted from the ECoG signal, which are log energy entropy, SURE entropy, and cross correntropy. Later in this paper, the feature extraction section provides a detailed definition of each feature. Our proposed approach was evaluated by carrying out testbed experiment and by using the dataset I of the public BCI competition III data. A classification accuracy of 95% was achieved during the testbed evaluation. A classification accuracy of 93.02% was achieved using the dataset. Our proposed algorithm was imple-

mented in MATLAB.

Keywords

Brain Computer Interfaces, ECoG Signals, Cross Correntropy, LS-SVM, FAWT, Log Entropy, SURE Entropy

1. Introduction

OVER one million individuals are suffering from being incapacitated due to stroke, cerebrum or spinal string wounds [1]-[4]. Also, many other individuals suffer from related issues in hand motion and dexterity which hinders their daily activities [5]-[8]. Augmentative communication technologies that are based on ECoG signals are important tools to re-mobilize people with motor disabilities. Individuals with paralysis, neurological diseases, injuries or limb loss cannot use the traditional augmentative technologies since they require muscle control [9]. BCI is considered a built-up technology established on the interaction between implantable electrodes, wired or wireless transmission, data decoding algorithms and command signals. ECoG-based BCI systems use extraction and classification algorithms to detect features of brain activities and convert them into useful signals that can be used to control devices [10]. ECoG signals are used with various frequencies to examine the electrical activities of brain functions. Both the proper and diseased functions of the human brain can be detected using these signals.

Implantable electrodes have been developed using Microelectromechanical system (MEMS) [1] [5] [11]. This BCI system aims to bypass the injured spinal cord and build a direct connection between the brain and the associated limb. Many researchers have been working in this field; therefore, different techniques have been proposed to accommodate patients with different disabilities. These techniques have advanced this field and have been critical to the development of BCI systems. However, they have been trained and evaluated using only offline signaling.

This paper proposes a novel technique for using ECoG signals to extract and classify features of brain activities. The FAWT is used to extract entropy features from the ECoG signals [12]-[14], and the LS-SVM with radial basis function (RBF) kernel is used to classify the extracted features. Our proposed algorithm was evaluated using both offline signaling (*i.e.*, dataset) and a testbed experiment that provides real-time data, where speeds may vary. Motor imagery information was collected where the patient envisioned moving either his/her left pinkie finger or his/her tongue. Motor imagery is a mental system in which an individual practices or re-enacts a given activity in his/her mind. It is commonly used as a daily mental exercise for individuals recuperating from neurological injuries. Also, Motor imagery has been investigated in neuroscience research to understand the emotional cerebrum in conjunction with activated neurological pathways before an action is executed [1] [2] [5]. There are several ways for measuring cerebrum activities, such as electroencephalography (EEG), functional magnetic resonance imaging (FMRI), positron emission tomography (PET), magnetoencephalography (MEG), and ECoG. However, the necessity for high precision and accuracy in BCI systems requires the use of ECoG. Using the EEG, information is gathered from outside of the human skull, which leads to a poor signal-to-noise ratio and signal interference. Using ECoG electrodes, which are embedded into the skull, prevents such interference and achieves a better signal-to-noise ratio. Also, it has better specificity for particular brain activities, such as external validity (by allowing the client to move openly), and better motion-to-commotion proportion [3] [4] [6]. This paper also introduces several classification algorithms that were applied to the dataset I of BCI competition III data; these algorithms, however, achieved less classification accuracy as compared to our proposed algorithm.

Several theories have been proposed to classify brain activities [1]-[3] [5] [11], but these studies have almost exclusively focused on just the classification accuracy. Hence, they lack joint classification accuracy and classification time. To design any efficient BCI application, we have to consider the classification time. For example, consider a patient who has a spinal cord injury and is unable to use his hand. To help him, we can design a robotic arm for him. To do so, in the first step, we need to collect his brain activities, classify them and translate them into actions. If the classification accuracy is 100%, but it needs hours to do this simple task, then we cannot consider it as the best solution. If the time is 10 seconds and the accuracy is around 50%, this is also not acceptable. I run my algorithm using software tools, but when we are going to hard-code on VLSI and build the circuit to execute the algorithm, we believe the speed will go up a lot. Because these results are clock time measured on my local machine, which is not a supercomputer.

Motivated by this, in this paper, we proposed an algorithm called FAWT consider both classification accuracy and classification time factors. In order to come up with a novel classification algorithm, we have evaluated all the most commonly used machine learning methods such as ECoGNet, main component analysis (PCA), independent component analysis (ICA), linear discriminant analysis (LDA), Autoregressive (AR) coefficients, moving-average (MA), and shallow convolutional neural networks (ConvNets) [15]-[17]. We will show that we can reach reliable and acceptable results with an accuracy of around 93% as accuracy in less than 5 minutes.

Contribution. In this paper, we propose a novel approach for feature extraction and classification that allows for optimal use with BCI correspondence. We name it *Flexible Analytic Wavelet Transformation* (*FAWT*). The contribution of the paper is summarized below:

- The primary steps consider three features based on their performance in many previous studies, they are:

Correntropy: which can be defined as a generalization of correlation of arbitrary processes. It is also capable to quantify the dependence measures among arbitrary variables.

Sure entropy: which is determined as a common measuring tool for quantifying information-related properties for an accurate representation of a given signal.

Log energy: entropy, which is used to evaluate the degree of complexity of EEG signals.

- Use FAWT to classify the extracted features.
- We give a detailed mathematical analysis for FAWT and explore the adopted Least Square-Support Vector Machine (LS-SVM) with radial basis function (RBF) kernel to classify the extracted features.
- We validate the FAWT on two datasets. First one, real-world BCI signal dataset, which is the real-world BCI signal datasets BCI competition III dataset I. Second one is the experimental setup dataset collected from the Testbed experiment.
- We conclude that the achievements of the FAWT on two datasets confirm that we could reach reliable and acceptable results around 93% as accuracy in less than 5 minutes.

Therefore, we have tested this algorithm against multiple brain activities, BCI competition III dataset III, and the accuracy was around 75%. So we can say this method is suitable for ECoG binary brain activities.

The reminder of this paper is organized as follows. Section II Cybersecurity risks associated with BCI classifications, Section III introduces the related work. Our proposed approach is explained in Section IV. Section V presents the evaluation and results, and the conclusion is given in Section VI.

2. Cybersecurity Risks Associated with BCI Classifications

Typically, in healthcare technology systems, data are stored in database systems, and languages such as Structured Query Language (SQL) are used to communicate with and manage many of these relational database systems. For example, SQL is used to control who can read data, insert/update data, and delete data. Cybersecurity uses these controls to enforce authentication and authorization, but these could raise data security concerns if not handled well in terms of confidentiality, integrity and availability.

This section contains invasive, partially invasive and noninvasive. Their main feature is the spatiotemporal resolution of recording and stimulating neural activity and is related to network security issues. Intrusive systems are mainly used in the medical field. Partially invasive is used in the medical field, with low temporal and spatial resolution. Non-invasive BCI exhibits lower spatial and temporal resolution. From a Cybersecurity perspective, the two most serious risks are temporal and spatial resolution. Invasive systems have the highest risk, followed by partial and non-invasive BCI. For this paper, we considered invasive approach. Compared with asynchronous BCI, the interaction between users of synchronous BCI system and BCI is easier to achieve. The network security risks generated by the BCI series are mainly the communication control between BCI and its users.

Asynchronous BCI has usability problems and risks of malicious stimuli. It has higher confidentiality issues but greater data integrity and availability issues.

Cybersecurity risks depend on the scenarios taken. The first is to use BCI in the field of neuromedicine to establish a communication system with paralyzed patients. The second case is to use BCI as an authentication system. The third category is gaming and entertainment. BCI can simplify development tasks by using common APIs in the video game industry. The highest risks in neuromedicine scenarios are integrity, confidentiality, and security issues, while there are cybersecurity risks in smartphone solutions. In recent years, the brain-computer interface technology has made great progress and rapid development, and the application field is gradually expanding. On the one hand, brain-computer equipment can convert brain signals into machine-recognizable signals to achieve effective control of the machine. On the other hand, it can also receive feedback from the machine to intervene in the brain from the outside. Elon Musk's Neuralink is a company that develops brain-computer interfaces. He showed some research and development results to the public. The company's equipment can be implanted in paralyzed humans to help them control phones or computers. The first big advance is flexible "threads," which are less likely to damage the brain than the materials currently used in brain-machine interfaces.

These threads also create the possibility of transferring a higher volume of data, according to a white paper credited to "Elon Musk Neuralink." The abstract notes that the system could include as many as 3072 electrodes per array distributed across 96 threads. After this, the research of the brain-computer interface was pushed to the public's attention and became a current hot spot.

The use of new materials will allow the brain-computer interface to be approached in a direction that people can fully use. Most current brain-computer implanted devices are sealed in laser-welded titanium housings, so researchers hope to find materials similar to titanium housings, which are lighter, thinner and softer. The team found that silicon dioxide is a very suitable electrode material; it is small and light, and can be perfectly integrated with the brain. And silica is biocompatible, so the material is degradable. This means that trace amounts of silica dissolved into the brain will not cause side effects. At present, they have done tracking experiments on mice and monkeys. The results show that brain-computer equipment can continue to feedback for more than one to two years without side effects. Global Brain Computer Interface (BCI) Market 2020 Research Report provides key analysis on the market status of the Brain Computer Interface (BCI) manufacturers with the best facts and figures, meaning, definition, SWOT analysis, expert opinions and the latest developments across the globe. The Report also calculates the market size, Brain Computer Interface (BCI) Sales, Price, Revenue, Gross Margin and Market Share, cost structure and growth rate. The report considers the revenue generated from the sales of This Report and technologies by various application segments. If you look at the application areas that brain-computer interfaces can affect, whether it is medical, education, or consumption, it will bring a huge market space. In the future, BCI can be applied in many aspects, such as the Internet and video games and the market prospect is very broad.

3. Related Work

Several researchers have investigated the use of brain signals to control external devices. Hence, several algorithms for extracting and classifying the features of brain activities using the support vector machine (SVM), adaptive Gaussian coefficients, and C-SVM have been proposed. However, these algorithms are computationally complicated and lack power [15] [16] [18]. Also, many algorithms were trained and tested using the dataset I of BCI competition III dataset. This dataset was collected by recording each subject performing a consistent task in sessions, one week apart. Two tasks were performed: movement of the left pinkie finger and the tongue. The subject performed motor imagery without feedback, which consisted of two actions: left pinkie finger movement and tongue movement [11].

A typical assignment in BCI is to apply a classifier that was prepared from a past session on a later session without retraining it [4] [6] [7] [18]. To test this assignment, electrical signals are compared for each subject, often presenting unique changes in activity in each trial. This inconsistency can be caused by various reasons, for instance, varying levels of inspiration, excitement, and exhaustion. The recording system cannot be set up in the exact same way between sessions. Therefore, there could be slight differences between electrode position and impedance between the two sessions. The objective of this dataset is to train a classifier on the labeled training data from the first session and apply it to the unlabeled test data from the second session. The execution criteria utilized for assessment were the accuracy of effectively characterizing the test preliminaries. The data set comprises 278 preliminaries performed during the main session (*i.e.*, training data) and 100 preliminaries from the second session (*i.e.*, test data). Electrical cerebrum movement was picked up using an 8 × 8 ECoG platinum electrode grid that was set on the contralateral (right) motor cortex. All recordings were performed with an examining rate of 1000 Hz. The preliminary span was three seconds. To keep away from outwardly evoked possibilities being reflected by the information, the chronicle interval began 0.5 seconds after the visual signal had finished [13]. Data is provided in MATLAB format, containing continuous signals from 64 ECoG channels.

The ECoG-based approaches that are trained and evaluated using the dataset I of BCI competition III dataset are summarized in **Table 1**. As seen in the table, 12 approaches have achieved 81% accuracy or more. The highest accuracy (*i.e.*, 91%) was achieved by approach 1, which utilized the Fisher discriminant analysis to extract features like band-power together with CSSD. This approach applied the linear SVM for classification. It can also be seen from the table that approach 2 has achieved 87% accuracy by applying ICA, AR coefficients, spectral power (0 - 45 HZ), and wavelet coefficients as features along with regularized logistic regression. An accuracy of 86% was achieved by approach 3, which used different techniques for feature extraction. This approach includes selecting channels, applying spectral power on them, finding standard deviation using the Hilbert Transform for time frequency window, along with the Mahalanobis distance, and using logistic regression as the classification method. The remaining approaches have utilized other extraction and classification techniques; the accuracy they achieved was between 22% and 79%.

Table 1. Related work [11].

Approach	Classification Method	Features	Accuracy
1	linear SVM	CSSD, Combination of Bandpower, Fisher Discriminant Analysis	91%
2	Regularized Logistic Regression	ICA, spectral power (0 - 45 Hz), combination of AR coefficients, wavelet coefficients	87%
3	Logistic Regression	Spectral Power of Selected Channels and Offset	86%
4	Mahalanobis Distance Between classes	Selected 7 Channels and Standard deviation of Hilbert-Huang Transform for time-frequency windows (5 Hz × 0.2 S)	86%
5	Non classical Algorithms Models	Selected 7 Channels	86%
6	LDA	CWT, correlation between trials, Bandpass (2.5 Hz to 25 Hz), CSP	86%
7	LDA	AR coeffients and band power (10 - 12 Hz and 16 - 24 Hz) from 10 channels	84%
8	LDA	CSP, Bandpass (5 - 30 Hz), CWT with Coefficients Corr. to 4 - 24 Hz, 12 Channels, Weighting of Coefficients by T-Test	84%
9	semi-supervised learning (self training) based on a quadratic classifier	CSP feature and the coefficients of AR mode	83%
10	via cluster mean	bandpass (8 - 12 Hz), Gaussian Mixture Model for channel selection and clustering	82%
11	SVM	correlation and covariance matrix coefficients	81%
12	leave-one-out cross-validation on the whole training set	AR coefficents and bandpower (7 - 10, 10 - 12, 16 - 24 Hz), 11 channels chosen	81%
13	ensemble of neural networks and fisher discriminant functions	bandpower	79%
14	Robust Discriminant Analysis	phase, PSD, and Empirical Mode Decomposition	79%
15	FDA	band power of 4 channels, selected by Fisher ratio, multi-variate AR coefficients	69%
16	Bayesian classifier and SVM	bandpass (0.5 - 45 Hz), statistical and parametric models, various transforming functions	67%
17	sparse model from ’finite prediction error’	bandpass (8 - 40 Hz), AR coefficients and “coupled fits”	66%
18	SVM	channel reduction via feature subset selection, correlation coefficients of all trials	65%
19	probabilistic classification	Cross-spectrum in alpha frequency range	65%
20	discriminative biorthogonal bases	discriminative biorthogonal bases	59%
21	linear model with Tikhonov regularization	downsampling, subset of 30 channels	58%
22	AttributeClustering Network via Nearest Neighbors	time-frequency coefficients chosen by Rayleigh Coefficients	54%

Continued

23	neural network (single layer FF) with ELM training	AR coefficients for overlapping windows	50%
24	SVM	2 CSP components, AR coeffients	48%
25	1-nearest neighbor AR coefficients	cross-correlation between test and training trials	44%
26	Nearest neighbor, SVM	AR coefficients	22%

The performance of BCI systems depends on many factors. These include, but are not limited to the kind of signal used to measure brain activities, the response time of the external device, and the accuracy of the features extraction and classification algorithms. Current BCI systems have two main disadvantages. First, they quickly exhaust the patient by requiring continued movement/imagery for a few seconds. This is because neural signals related with non-continued movement/imagery diminish rapidly, and a more extended example of information is required for characterization. Second, after the neural signals are received, the external device requires a delay for perceiving and transmitting a response, particularly when the function is complex. This causes a delay period between the patient's activities and the BCI reaction, diminishing the ease of use and comfort of BCI systems.

To address these issues, we proposed an accurate ECoGbased features extraction and classification technique that measures the cerebrum activities post imagery and pre-movement. This allows for the extraction of preliminary neural data from a solitary, non-supported movement/imagery, and can diminish the delay time between the patient's activities and the reaction time of the BCI system [7], [8] [19] [20]. Our proposed technique achieved high accuracy by applying the FAWT for features extraction, and LS-SVM for features classification. The technique was evaluated using both a testbed experiment and the dataset I of BCI competition III dataset. The evaluation results proved the validity of our proposed approach and the importance of applying the FAWT for features extractions and the LS-SVM as a classification tool.

4. Our Proposed Approach

Our proposed approach for extracting and classifying the features of brain activities is depicted in **Figure 1**. As shown in the figure, sub-sampling and frequency filtering are applied to process the dataset I of BCI competition III, which includes samples of ECoG signals. Then, the FAWT is used to extract three entropy features (*i.e.* cross correntropy, log energy entropy, and SURE entropy). After the three features are extracted, the LS-SVM is used for classifying the extracted features. The following sections explain the steps of our proposed approach in detail.

Algorithm 1 FAWT

Requirements: BCI III Dataset 1

1) initialization.

2) Sub-sampled the ECoG signals using 250 Hz frequency.

3) Apply a frequency band between 8 - 30 Hz.

4) Extract specific features as (Correntropy, Log energy entropy, and SURE entropy).

5) Apply features classification using LS-SVM method.

6) receive classified activities.

a) *Signal Sub-Sampling*

In order to reduce the memory overhead and the processing time, we have subsampled the ECoG signals using 250 Hz frequency. This is below the Nyquist rate, which is the minimum rate that must be used to sample a bandwidth signal in order to sustain all of its information [21].

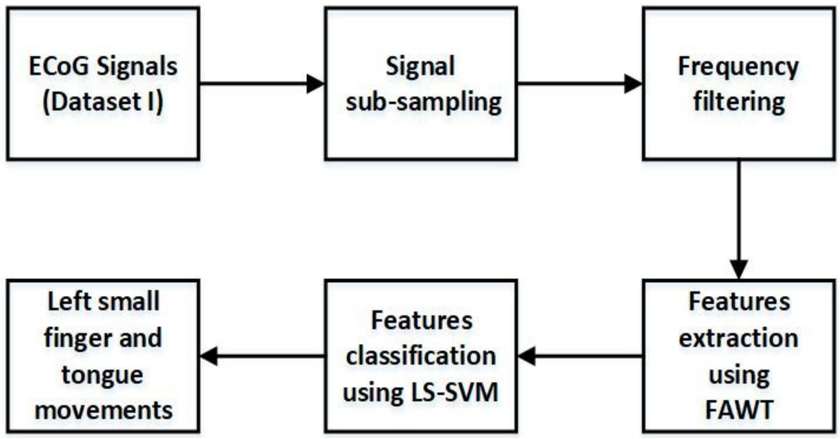

Figure 1. Our proposed extraction and classification approach.

b) *Frequency Filtering*

The frequency band used in this work is between 8 and 30 Hz. This band was chosen as 8 Hz is the frequency where the unclear direct current level of some individual channels could be eliminated and 30 Hz is the frequency that could pick up maximum power.

c) *Features Extraction*

The FAWT was used for ECoG signals decomposition. Dataset I was collected using 64 channels; it contains a total of 3000 samples. We applied the FAWT with J levels, where we had the approximate and detailed signal at each level [22]-[24]. These J + 1 level's details were brought back to the time domain separately, leading to J + 2 signals for each channel, where each channel corresponded to different details. For each of the corresponding J + 2 levels, we computed correlation and wavelet entropy features [17] [23]. Above correlations and entropy were concatenated for all levels, leading to a 2016 × (J + 2) × 3 length feature vector for each channel.

The FAWT utilizes the Hilbert transform pairs of atoms and provides flexibility in order to control the redundancy, quality factor (QF), and dilation factor. It also helps in analyzing signals with easily adjustable parameters, which are: up sampling factor for low pass channel (s), down sampling factor for low pass channel (t), up sampling factor for high pass channel (u), down sampling factor for high pass channel (v), and parameters that controls the QF (β). By applying the iterative filter bank structure, we obtained J^{th} level of FAWT. At each level, two channels are obtained from the decomposition. One channel corresponds to low pass filters and the other channel corresponds to high pass filters. The frequency response of low pass filter is expressed as:

$$f(w)=\begin{cases}(st)^{\frac{1}{2}} & |w|<|w_p| \\ (st)^{\frac{1}{2}}\theta\left(\dfrac{w-w_p}{w_s-w_p}\right) & w_p\le w\le w_s \\ (st)^{\frac{1}{2}}\theta\left(\dfrac{\pi-(w-w_p)}{w_s-w_p}\right) & -w_s\le w\le -w_p \\ 0 & |w|\ge|w_s|\end{cases} \tag{1}$$

While, the frequency response of high pass filter is expressed as:

$$R(w)=\begin{cases}(2uv)^{\frac{1}{2}}\theta\left(\dfrac{\pi-(w-w_0)}{w_1-w_0}\right) & w_0\le w<w_1 \\ (2uv)^{\frac{1}{2}} & w_1\le w\le w_2 \\ (2uv)^{\frac{1}{2}}\theta\left(\dfrac{\pi-(w-w_2)}{w_3-w_2}\right) & w_2\le w\le -w_3 \\ 0 & w\in[0,w_0)\cup(w_3,2\pi)\end{cases} \tag{2}$$

For proper signal reconstruction, the following two conditions must be satisfied:

$$\theta\left|(\pi-w)\right|^2+\theta(w)^2=1 \tag{3}$$

$$1-\frac{s}{t}\le\beta\le\frac{u}{v} \tag{4}$$

The parameters of FAWT are deduced based on the above conditions, where $s = 2$, $J = 16$, $u = 1$, $t = 4$, and $v = 2$. Based on these values, the values of Q_F and β were 4 and 0.4, respectively. The Q_F was calculated using the following equation:

$$Q_F=\frac{2-\beta}{\beta} \tag{5}$$

We were able to produce the reconstructed ECoG signal and its 15 sub-band signals. The 16 signals are depicted in **Figure 2**. As shown in the figure, signals a - o are the subband signals. While signal p is the reconstructed signal. Our feature extraction algorithm was implemented in MATLAB [25]. Entropy MATLAB functions were used to extract entropy features from the reconstructed signal (*i.e.*, signal p), the extracted features are as follows [22] [26] [27]:

- Cross correntropy: It is a generalized correlation of arbitrary processes that determines the similarity between two random variables [24] [28] [29]. With the help of cross correntropy, information can be captured from higher order moments. The cross correntropy was calculated as follows:

$$V_{N,\sigma}(x,y)=\frac{1}{N}\sum_{i=1}^{N}K_{\sigma}(X_i-Y_i) \tag{6}$$

where X and Y are the two random variables with N data samples, denoted by $(X_i,Y_i)_{i=1}^{N}$.

- Log energy entropy: To evaluate the degree of complexity in ECoG signals, the computation of log energy entropy is performed [30]. It is expressed in the following equation:

$$E_{LogEn}=\sum_{i=1}^{N}\log(a_{2i}) \tag{7}$$

where N denotes to the length of the signal, and x_i represents the i^{th} sample of the signal. To compute the log energy entropy, sub-band signals from "X" and "Y" channels of bivariate ECoG signals have been used [19] [31].

- SURE entropy: The SURE energy is based on SURE [32], which is an accurate representation of a signal; it is the common measuring tool to quantify the properties that are related to the information. It can be expressed as:

$$E_{SEn}=N-\#\{i \text{ such that } |x_i|\le\varepsilon\}+\sum_{i}\min(x_i^2,\varepsilon^2) \tag{8}$$

where ε is a positive threshold value, x_i is the i^{th} sample of the signal, and X_i is sample observation.

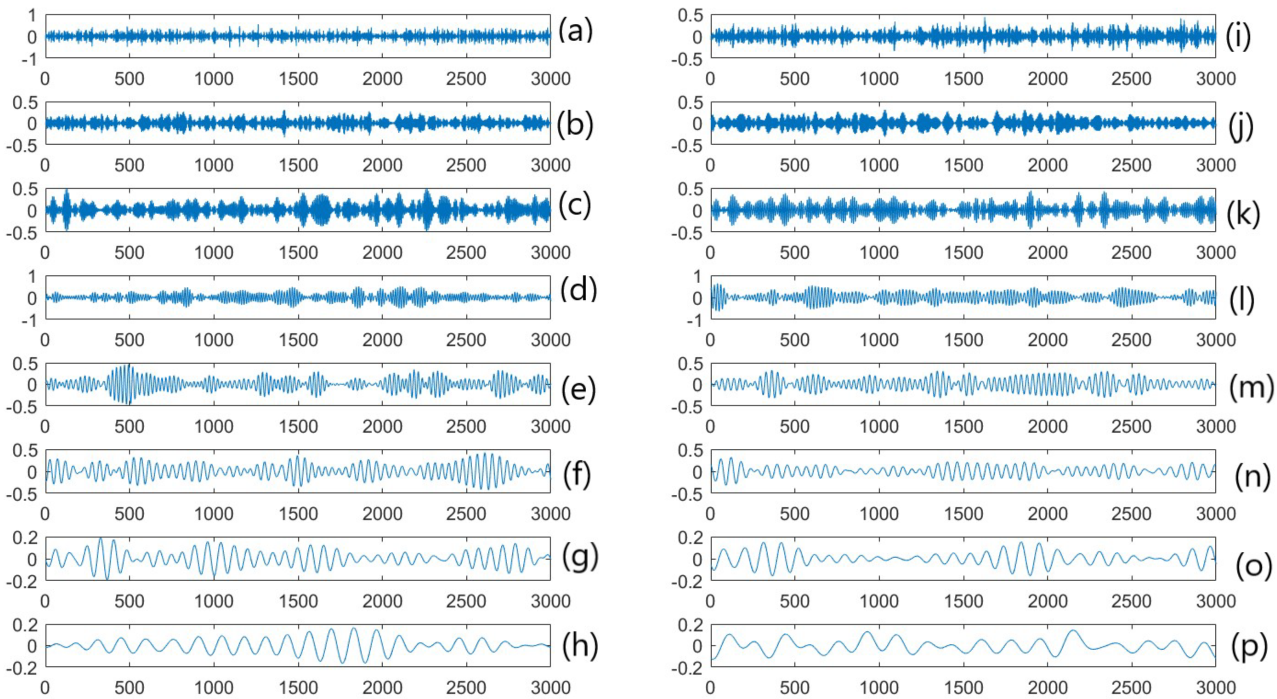

Figure 2. The 15 sub-band signals (a - o), and the reconstructed ECoG signal (p).

d) *Features Classification*

Support vector machines have been widely used for pattern recognition [31].

To discriminate the dissimilar sets of patterns, this approach maps the data into a higher dimensional input space, which allows for a hyper-plane to be constructed. SVM classifier has the fewest square formulation known as LS-SVM classifier. We have applied the LS-SVM to classify the brain activities. The discrimination function for the two class classification problem can be expressed as:

$$u(x) = \text{sign}\left[\sum_{i=1}^{N} \alpha_i u_i \phi(x, x_i) + b\right] \quad (9)$$

Here x_i, u_i, b, α_i, and $\phi(x, x_i)$, show the i^{th} output vector and i^{th} input vector, bias, Lagrange multiplier and mapping function, respectively.

Different kernel functions can be used with LS-SVM (e.g., RBF and polynomial). The RBF kernel function is used in this paper. The RBF non-linearly maps examples into a larger-dimensional space. It manages the status when there are nonlinear relations between the labels of class and the attributes. After extracting the features in the previous step, we implemented an LS-SVM classifier with an RBF kernel. For model selection, the LS-SVM hyperparameters, namely the regularization parameter γ and the RBF kernel bandwidth σ, were optimized on the training data using 5-fold cross-validation. A grid-search procedure was performed over candidate (γ, σ) pairs, and the optimal pair was selected as the one that minimized the average cross-validation misclassification error. Using the extracted cross correntropy, log-energy entropy, and SURE entropy features together with the optimized RBF kernel, we obtained approximately 7% misclassification error on the validation set.

5. Evaluation and Results

Our proposed approach was evaluated by using both the dataset I of BCI competition III, and by carrying out a testbed experiment. The following sections elaborate the evaluation of our proposed system.

1) *Dataset Based Evaluation*

The aim of this study is to develop an accurate algorithm for extracting and classifying brain activities. Three entropy features were extracted from the ECoG signals. The FAWT was used to extract the features, and the LS-SVM with RBF kernel was used to classify the extracted features.

During the BCI experiment, a subject had to perform imagined movements of either the left small finger or the tongue. The time series of the electrical brain activity was picked up during these trials using an 8 × 8 ECoG platinum electrode grid. All recordings were performed with a sampling rate of 1000 Hz. Every trial was recorded for 3 seconds duration.

The objective of this data set is to train a classifier on the labeled training data from the first session and apply it to the unlabeled test data from the second session. Training data and test data were recorded from the same subject and with the same task, but on two different days, with about 1 week in between.

The objective of this investigation was to demonstrate the practicality of utilizing movement/imagery prediction for BCI systems, and to determine whether

Electrocorticography (ECoG) neural activity would be best for controlling the device to perform a given task. The data set can be summarized as follows:

- Imagined movements of either the left small finger or the tongue.
- 8 × 8 ECoG platinum electrode grid used to collect the data.
- Sampling rate is 1000 Hz.
- Training matrix (3D) is (64 × 247 × 3000).
- Testing matrix (3D) is (64 × 100 × 3000).

The performance of our classifier was evaluated using the dataset I of BCI competition III data. Our classifier achieved 93.02% classification accuracy. This is considered a significant improvement compared to the approaches that are explained in **Table 1**. The evaluation results of classifying the left pinkie finger and tongue movements using our proposed classifier are explained in **Figure 3**. As shown in the figure, using the correntropy, a classification accuracy of 90.29% was achieved. A classification accuracy of 89.57% was achieved using the log entropy. Using the SURE entropy, the classification accuracy was 90.7%. Using the three entropy features achieved a classification accuracy of 93.02%.

The dataset I consists of 100 test preliminaries and our maximum accuracy throughout all trials (1000 times) was 93%. when we selected 70% of the available test data for each ensemble and used 5 ensembles, the highest accuracy on average is determined. Throughout each of our repeated experiments, 5 models were trained and tested, receiving 100 samples per trial. It is reasonable to expect that each example might get correctly classified in at least one of the 1000 trials. We found that trials 13, 16, 53, 56, 58 were not classified correctly at any point. Sample 97 was classified correctly only once in over 1500+ repetitions. Potential sources of error include erroneous samples from divergence in subject motor imagery (imagined moving the tongue instead of the finger, or vice versa). When these samples were removed, we obtained 99.35% classification accuracy with 5 fold cross validation on the training data for model selection and validation.

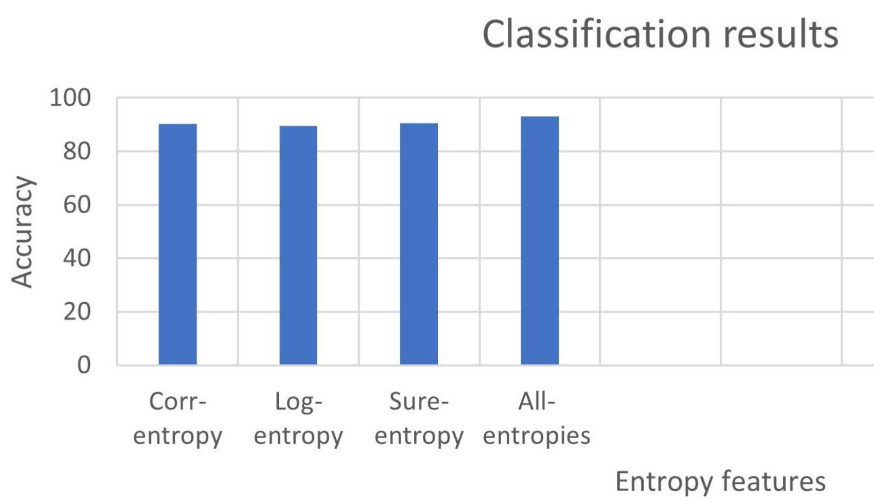

Figure 3. Classification results.

2) *Discussion*

In this study, we are aiming to develop a fast and efficient algorithm for extracting and classifying brain activities. In this part, we are evaluating all the proposed algorithms based on accuracy and time classification. Table 2 shows FAWT has a competitive accuracy, but it is slow, so it is not suitable for the lifetime brain data.

Table 2. Evaluation of proposed algorithms.

Algorithm	Accuracy
L1LR	56%
L2LR	55%
SVM	58%
ECoGNet	65%
L1LR + AR	85%
L2LR + AR	86%
SVM + AR	85.6%
LDA + AR	81.4%
L1LR + MA	91%
L2LR + MA	86%
SVM + MA	82.6%
LDA + MA	79.4%
FAWT	92.99%

3) *Testbed Based Evaluation*

This section introduces the evaluation of our proposed approach using a test experiment. In order to evaluate our proposed extraction and classification approach, we replicated the brain environment in the lab. We used a chemical solution that duplicates the dielectric tissue [33] [34].

Nowadays, low-power implantable wireless sensors are widely used in the healthcare domain for continuously monitoring certain body parts (e.g., brain), and sending data to external receivers or processing units (e.g., smart phone, PDA, etc.) for immediate response to any health related problem [35]-[38]. We have modified the brain environment proposed in [33] [34] by using a pre-passive wireless identification and sensing Platform (WISP), which is battery-free and uses power transfer mechanism to excite its circuitry. WISP is powered by a RFID reader which emits RF signal continuously in UHF range (908 - 928 MHz). It adheres to the requirements of the stage of experimentation, which is low computation, sensing of power and communication. It is an open and transparent source and is not dependent on any alternative sources of energy. It gets connected to the network and sends RF signals to tags consisting of data and for generating power. We have used R420 model of Impinj's reader [39]-[46].

Experimental Setup: We have used glycerine whose dielectric properties in ultra high frequency (UHF) band resembles closely to tissue fluid at room temperature, and salt water (Sodium chloride (NaCl)) solution resembles blood which is the medium through which UHF RFID signals traverse [33] [34] [47]. A plastic beaker with the specifications 44.95 cm × 32.7 cm × 19 cm has been used. The beaker being strongly resistant to radio frequencies waves, mimics the human skull. In order to create the virtual environment of the brain we have used Ziploc bags with glycerine in it and have added salt-water to the beaker. This imitates the surrounding of cerebellum with blood. We use salt-water as its dielectric properties resemble the human blood. For our experiment, we have used a single wireless sensor (WISP) to transmit the collected signals to a receiver located outside the brain on the scalp.

Table 3. Network parameters for one sensor.

D	RSS	SNR	CC
4 Cm	−15.918 dBm	18.232	2.93E+06
3 Cm	−15.23 dBm	19.012	3.23E+06
2 Cm	−14.718 dBm	20.125	3.43E+06
1 Cm	−13.418 dBm	21.45	3.52E+06
0 Cm	−10.918 dBm	25.203	4.34E+06

Figure 4 shows the brain environment where the WISP is placed in a Ziploc bag and placed over the solution of glycerine and salt-water barely touching it. RFID antenna is placed below the beaker which would replicate the real world scenario where RFID antenna would be outside the brain and WISP would be implanted inside the brain surrounded by blood and tissue fluid. As shown in **Figure 5**, the RFID reader is connected to the controller (*i.e.* laptop) through an Ethernet cable, and cable from RFID antenna is connected to the Impinj RFID reader. WISP contains a microcontroller that needs to be programmed to read the RF signal from the reader. This is done by connecting the WISP to the laptop through a USBFET debugger and coding it through Code Composer Studio IDE [48].

WISP operates at UHF range and the reader used is compatible with WISP, it reads the Electronic Product Code (EPC) sent by WISP and store it in log files to be processed by our extraction and classification algorithm. The transmit power from the Reader to the WISP is varied from 25 dBm to 30 dBm. WISP is forced duty cycled, RF power device, and burns around 2 mW of power when operating. As per the FCC regulations, frequency hopping can be used to make the system more reliable. Therefore, it is being used in RFID systems to increase reliability and to avoid collision when multiple tags operate simultaneously (e.g., Bluetooth). The UHF band here is divided into 50 channels. EPC codes sent by the WISP to the reader at various channels and it keeps hoping in the frequency domain after it sends an EPC. We collected data from single sensor at different implant depths and we have considered the data from single transmitters at 2 centimeter as ECoG signals.

Table 3 shows the received signal strength (RSS), the signal-to-noise ratio (SNR), and the channel capacity (CC) at different implant depths (D). At 0 cm, we can consider the data as EEG signal, at 1, 2, 3, and 4 cm, we consider it as ECoG signals.

We built wireless network based on the experiment setup to mimic the brain environment using NS2 simulator. Because the dataset I was collected from 64 channels, we have fed the data that we collected from the testbed 64 times using NS2 simulator by building a small network that consists of single transmitter and single receiver in order to classify the received and not received signals as two classes. For our network, we used the WISP with specific parameters explained in Table 4. We have run our proposed extraction and classification algorithm and the accuracy to classify two classes (*i.e.*, left pinkie finger and tongue) is 95%.

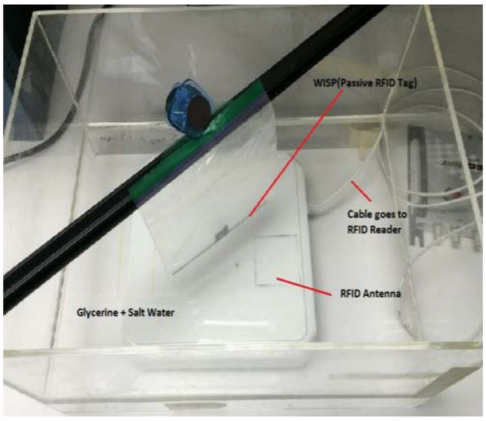

Figure 4. The mimicked brain environment.

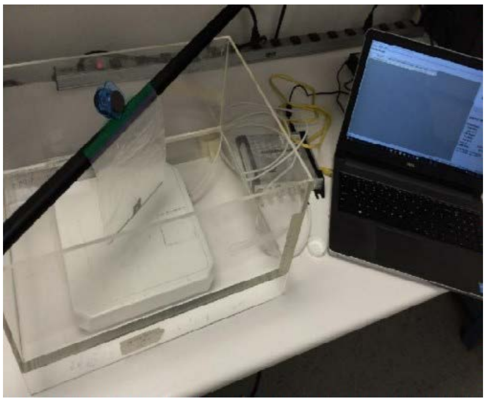

Figure 5. Complete lab setup.

As our study concludes, the testbed results demonstrate the feasibility of the proposed approach under controlled conditions, suggesting its potential for reliable real-world deployment. However, translation to in-vivo settings may introduce variability due to biological noise, environmental interference, and physiological constraints, which could affect performance [49]. Generally, In-vivo settings refer to experiments or measurements conducted inside a living organism (such as a human or animal) [50] [51].

Table 4. Network simulation parameters.

Frequency of operation	914 MHZ
Channel Bandwidth	250 KHZ
Receiver Sensitivity	−84 dBm
Data Rate	2 Mbps
T_X and R_X power	0.175 mW
Number of tags	1 × 1

6. Conclusion

Developing BCI systems is vital to help individuals with motor disabilities. BCI systems detect brain activities using signal extraction and classification algorithms, and convert them into useful commands that can be used to control external devices. Designing and developing BCI systems requires accurate extraction and classification algorithms to detect brain activities in a timely manner. In this paper, we presented an accurate ECoG signal extraction and classification approach. The FAWT was used to extract three entropy features (*i.e.*, log energy entropy, SURE entropy, and cross correntropy), and the LS-SVM was utilized to classify the extracted features. Testbed experiment and the dataset I of the BCI competition III were used to evaluate our proposed approach. The evaluation result has proved the validity of our proposed approach. Our LS-SVM classifier has achieved 93.02% and 95% classification accuracy using the dataset I of BCI competition III and the testbed experiment, respectively. Our future work includes investigating other features, developing a data mining technique to classify the ECoG signals, and implementing other feature extraction techniques. The feature visualization has been left for future work. Future work concerns the data distribution and the analysis of particular mechanisms using advanced feature extraction software tools. The paper has mainly focused on the accuracy and the feature extraction speed.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Bablani, A., Edla, D.R., Tripathi, D. and Cheruku, R. (2019) Survey on Brain-Computer Interface: An Emerging Computational Intelligence Paradigm. *ACM Computing Surveys*, **52**, 1-32. https://doi.org/10.1145/3297713

[2] Lebedev, M.A. and Nicolelis, M.A.L. (2006) Brain-Machine Interfaces: Past, Present and Future. *Trends in Neurosciences*, **29**, 536-546. https://doi.org/10.1016/j.tins.2006.07.004

[3] Wolpaw, J.R., Birbaumer, N., Heetderks, W.J., McFarland, D.J., Peckham, P.H.,

Schalk, G., *et al.* (2000) Brain-Computer Interface Technology: A Review of the First International Meeting. *IEEE Transactions on Rehabilitation Engineering*, **8**, 164-173. https://doi.org/10.1109/tre.2000.847807

[4] Hochberg, L.R., Serruya, M.D., Friehs, G.M., Mukand, J.A., Saleh, M., Caplan, A.H., *et al.* (2006) Neuronal Ensemble Control of Prosthetic Devices by a Human with Tetraplegia. *Nature*, **442**, 164-171. https://doi.org/10.1038/nature04970

[5] Mittal, A., Zisserman, A. and Torr, P. (2011) Hand Detection Using Multiple Proposals. In: Hoey, J., McKenna, S. and Trucco, E., Eds., *Proceedings of the British Machine Vision Conference* 2011, BMVA Press, 75.1-75.11. https://doi.org/10.5244/c.25.75

[6] Alomari, M.H., Samaha, A. and Al Kamha, K. (2013) Automated Classification of L/R Hand Movement EEG Signals Using Advanced Feature Extraction and Machine Learning. *International Journal of Advanced Computer Science and Applications*, **4**, 207-212. https://doi.org/10.14569/ijacsa.2013.040628

[7] Costa, E.J.X. and Cabral, E.F. (2000) EEG-Based Discrimination between Imagination of Left and Right Hand Movements Using Adaptive Gaussian Representation. *Medical Engineering & Physics*, **22**, 345-348. https://doi.org/10.1016/s1350-4533(00)00051-5

[8] Quandt, F., Reichert, C., Hinrichs, H., Heinze, H.J., Knight, R.T. and Rieger, J.W. (2012) Single Trial Discrimination of Individual Finger Movements on One Hand: A Combined MEG and EEG Study. *NeuroImage*, **59**, 3316-3324. https://doi.org/10.1016/j.neuroimage.2011.11.053

[9] Schalk, G., Wolpaw, J.R., McFarland, D.J. and Pfurtscheller, G. (2000) EEG-Based Communication: Presence of an Error Potential. *Clinical Neurophysiology*, **111**, 2138-2144. https://doi.org/10.1016/s1388-2457(00)00457-0

[10] Yeager, D.J., Sample, A.P. and Smith, J.R. (2017) WISP: A Passively Powered UHF RFID Tag with Sensing and Computation. In: Ahson, S.A. and Ilyas, M., Eds., *RFID Handbook*, CRC Press, 261-276. https://doi.org/10.1201/9781420055009-14

[11] Blankertz, B., Muller, K.-R., Krusienski, D.J., Schalk, G., Wolpaw, J.R., Schlogl, A., *et al.* (2006) The BCI Competition III: Validating Alternative Approaches to Actual BCI Problems. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **14**, 153-159. https://doi.org/10.1109/tnsre.2006.875642

[12] Donoho, D.L. and Johnstone, I.M. (1995) Adapting to Unknown Smoothness via Wavelet Shrinkage. *Journal of the American Statistical Association*, **90**, 1200-1224. https://doi.org/10.1080/01621459.1995.10476626

[13] Han, J., Dong, F. and Xu, Y.Y. (2009) Entropy Feature Extraction on Flow Pattern of Gas/Liquid Two-Phase Flow Based on Cross-Section Measurement. *Journal of Physics: Conference Series*, **147**, Article ID: 012041. https://doi.org/10.1088/1742-6596/147/1/012041

[14] Hyndman, R.J. and Athanasopoulos, G. (2018) Forecasting: Principles and Practice. OTexts.

[15] Wang, F., Kim, K., Wen, S., Zhang, Y. and Wu, C. (2012) EEG Based Automatic Left-Right Hand Movement Classification. 2012 24*th Chinese Control and Decision Conference* (*CCDC*), Taiyuan, 23-25 May 2012, 1469-1472. https://doi.org/10.1109/ccdc.2012.6244236

[16] Li, W., Duan, F., Sheng, S., Xu, C., Liu, R., Zhang, Z., *et al.* (2018) A Human-Vehicle Collaborative Simulated Driving System Based on Hybrid Brain-Computer Interfaces and Computer Vision. *IEEE Transactions on Cognitive and Developmental Systems*, **10**, 810-822. https://doi.org/10.1109/tcds.2017.2766258

[17] Hammon, P.S. and de Sa, V.R. (2007) Preprocessing and Meta-Classification for Brain-Computer Interfaces. *IEEE Transactions on Biomedical Engineering*, **54**, 518-525. https://doi.org/10.1109/tbme.2006.888833

[18] Schloegl, A., Neuper, C. and Pfurtscheller, G. (1997) Subject Specific EEG Patterns during Motor Imaginary [sic.: For Imaginary Read Imagery]. *Proceedings of the* 19*th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. "*Magnificent Milestones and Emerging Opportunities in Medical Engineering*", Vol. 4, 1530-1532. https://doi.org/10.1109/iembs.1997.757001

[19] Wei, Q. and Wei, T. (2008) Channel Selection by Genetic Algorithms for Classifying Single-Trial ECoG during Motor Imagery. 2008 30*th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Vancouver, 20-24 August 2008, 624-627. https://doi.org/10.1109/iembs.2008.4649230

[20] Lal, T.N., Hinterberger, T., Widman, G., Schroder, M., *et al*. (2005) Methods towards Invasive Human Brain Computer Interfaces. *Advances in Neural Information Processing Systems* 18 [*Neural Information Processing Systems*], *NIPS* 2005, Vancouver, 5-8 December 2005, 737-744.

[21] Geerts, Y., Steyaert, M. and Sansen, W.M. (2006) Design of Multi-Bit Deltasigma A/D Converters. Vol. 686, Springer Science & Business Media.

[22] Donoho, D.L. (1994) On Minimum Entropy Segmentation. In: Chui, C.K., Montefusco, L. and Puccio, L., Eds., *Wavelets*: *Theory*, *Algorithms*, *and Applications*, Elsevier, 233-269. https://doi.org/10.1016/b978-0-08-052084-1.50017-x

[23] Bayram, I. (2013) An Analytic Wavelet Transform with a Flexible Time-Frequency Covering. *IEEE Transactions on Signal Processing*, **61**, 1131-1142. https://doi.org/10.1109/tsp.2012.2232655

[24] Liu, W., Pokharel, P.P. and Principe, J.C. (2007) Correntropy: Properties and Applications in Non-Gaussian Signal Processing. *IEEE Transactions on Signal Processing*, **55**, 5286-5298. https://doi.org/10.1109/tsp.2007.896065

[25] Moore, H. (2017) MATLAB for Engineers. Pearson.

[26] Andrzejak, R.G., Schindler, K. and Rummel, C. (2012) Nonrandomness, Nonlinear Dependence, and Nonstationarity of Electroencephalographic Recordings from Epilepsy Patients. *Physical Review E*, **86**, Article ID: 046206. https://doi.org/10.1103/physreve.86.046206

[27] Das, A.B. and Bhuiyan, M.I.H. (2016) Discrimination and Classification of Focal and Non-Focal EEG Signals Using Entropy-Based Features in the EMD-DWT Domain. *Biomedical Signal Processing and Control*, **29**, 11-21. https://doi.org/10.1016/j.bspc.2016.05.004

[28] Kumar, M., Pachori, R.B. and Acharya, U.R. (2017) Characterization of Coronary Artery Disease Using Flexible Analytic Wavelet Transform Applied on ECG Signals. *Biomedical Signal Processing and Control*, **31**, 301-308. https://doi.org/10.1016/j.bspc.2016.08.018

[29] Kumar, M., Pachori, R.B. and Acharya, U.R. (2017) Use of Accumulated Entropies for Automated Detection of Congestive Heart Failure in Flexible Analytic Wavelet Transform Framework Based on Short-Term HRV Signals. *Entropy*, **19**, Article No. 92. https://doi.org/10.3390/e19030092

[30] Kumar, M., Pachori, R.B. and Rajendra Acharya, U. (2016) An Efficient Automated Technique for CAD Diagnosis Using Flexible Analytic Wavelet Transform and Entropy Features Extracted from HRV Signals. *Expert Systems with Applications*, **63**, 165-172. https://doi.org/10.1016/j.eswa.2016.06.038

[31] Liu, C., Zhao, H.-B., Li, C.-S. and Wang, H. (2010) Classification of ECoG Motor

Imagery Tasks Based on CSP and SVM. 2010 3*rd International Conference on Biomedical Engineering and Informatics*, Vol. 2, 804-807. https://doi.org/10.1109/bmei.2010.5639943

[32] Avci, D. (2009) An Expert System for Speaker Identification Using Adaptive Wavelet Sure Entropy. *Expert Systems with Applications*, **36**, 6295-6300. https://doi.org/10.1016/j.eswa.2008.07.012

[33] Al Ajrawi, S., Sarkar, M., Rao, R. and Mihovska, A. (2017) Investigating Feasibility of Multiple UHF Passive RFID Transmitters Using Backscatter Modulation Scheme in BCI Applications. *International Symposium on Performance Evaluation of Computer and Telecommunication Systems* (*SPECTS*), Seattle, 9-12 July 2017, 143-148.

[34] Al Ajrawi, S., Bialek, H., Sarkar, M., Rao, R. and Ahmed, S.H. (2018) Bi-Directional Channel Modeling for Implantable UHF-RFID Transceivers in Brain-Computer Interface Applications. *Future Generation Computer Systems*, **88**, 683-692. https://doi.org/10.1016/j.future.2018.03.036

[35] Cleveland Jr., R.F. and Ulcek, J.L. (1999) Questions and Answers about Biological Effects and Potential Hazards of Radiofrequency Electromagnetic Fields. OET Bulletin 56, 4th Edition, Office of Engineering and Technology, Federal Communications Commission, Washington DC.

[36] Mark, M., Bjorninen, T., Chen, Y.D., Venkatraman, S., Ukkonen, L., Sydanheimo, L., *et al.* (2010) Wireless Channel Characterization for mm-Size Neural Implants. 2010 *Annual International Conference of the IEEE Engineering in Medicine and Biology*, 31 August-4 September 2010, 1565-1568. https://doi.org/10.1109/iembs.2010.5626695

[37] Roundy, S., Wright, P.K. and Rabaey, J.M. (2004) Energy Scavenging for Wireless Sensor Networks: With Special Focus on Vibrations. Kluwer Academic Publishers, 45-47.

[38] Sweet, J.A., Hdeib, A.M., Sloan, A. and Miller, J.P. (2013) Depths and Grids in Brain Tumors: Implantation Strategies, Techniques, and Complications. *Epilepsia*, **54**, 66-71. https://doi.org/10.1111/epi.12447

[39] Talla, V. and Smith, J.R. (2013) Hybrid Analog-Digital Backscatter: A New Approach for Battery-Free Sensing. 2013 *IEEE International Conference on RFID* (*RFID*), Johor Bahru, 4-5 September 2013, 74-81. https://doi.org/10.1109/rfid.2013.6548138

[40] Burdet, L.A. (2004) RFID Multiple Access Methods. ETH Zurich.

[41] Finkenzeller, K. (2010) RFID Handbook: Fundamentals and Applications in Contactless Smart Cards, Radio Frequency Identification and Near-Field Communication. Wiley. https://doi.org/10.1002/9780470665121

[42] Yeager, D.J., Powledge, P.S., Prasad, R., Wetherall, D. and Smith, J.R. (2008) Wirelessly-Charged UHF Tags for Sensor Data Collection. 2008 *IEEE International Conference on RFID*, Las Vegas, 16-17 April 2008, 320-327. https://doi.org/10.1109/rfid.2008.4519381

[43] Buettner, M., Prasad, R., Philipose, M. and Wetherall, D. (2009) Recognizing Daily Activities with RFID-Based Sensors. *Proceedings of the* 11*th International Conference on Ubiquitous Computing*, Orlando, 30 September-3 October 2009, 51-60. https://doi.org/10.1145/1620545.1620553

[44] Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G. and Vaughan, T.M. (2002) Brain-Computer Interfaces for Communication and Control. *Clinical Neurophysiology*, **113**, 767-791. https://doi.org/10.1016/s1388-2457(02)00057-3

[45] Fort, A., Desset, C., De Doncker, P., Wambacq, P. and Van Biesen, L. (2006) An Ultra-Wideband Body Area Propagation Channel Model—From Statistics to Imple-

mentation. *IEEE Transactions on Microwave Theory and Techniques*, **54**, 1820-1826. https://doi.org/10.1109/tmtt.2006.872066

[46] Koski, K., Björninen, T., Sydänheimo, L., Ukkonen, L. and Rahmat-Samii, Y. (2014) A New Approach and Analysis of Modeling the Human Body in RFID-Enabled Body-Centric Wireless Systems. *International Journal of Antennas and Propagation*, **2014**, Article ID: 368090. https://doi.org/10.1155/2014/368090

[47] Marciani, M.G., Stefanini, F., Stefani, N., Maschio, M.C.E., Gigli, G.L., Roncacci, S., *et al*. (1992) Lateralization of the Epileptogenic Focus by Computerized EEG Study and Neuropsychological Evaluation. *International Journal of Neuroscience*, **66**, 53-60. https://doi.org/10.3109/00207459208999789

[48] T Instruments (2005) Code composer studio ide getting started guide. User's Guide. https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=%5B48%5D%09T.+Instruments%2C+%E2%80%9CCode+composer+studio+ide+getting+started+guide%2C%E2%80%9D+User%E2%80%99s+Guide%2C+2005.&btnG=

[49] Wu, L.C., Nangia, V., Bui, K., Hammoor, B., Kurt, M., Hernandez, F., *et al*. (2015) *In Vivo* Evaluation of Wearable Head Impact Sensors. *Annals of Biomedical Engineering*, **44**, 1234-1245. https://doi.org/10.1007/s10439-015-1423-3

[50] Saeidnia, S., Manayi, A. and Abdollahi, M. (2015) From *in Vitro* to *in Vivo*: Methods and Applications in Biomedical Research. *Journal of Pharmacy & Bioallied Sciences*, **7**, 125-129.

[51] Raoof, M.M., Aldaghmi, N. and Aljuaid, H. (2025) IoT Security in Healthcare: A Recent Trend and Predictive Study of SQL Injection Attacks. *The Journal of Engineering*, **2025**, e70103. https://doi.org/10.1049/tje2.70103