ABNORMAL FEATURE EXTRACTION FROM EEG OF SCHIZOPHRENIA PERSON WITH SWT

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ABSTRACT

The changes in the electrical activity of the human brain are recorded using the method of electroencephalography. Various techniques were used to analyse the impulse signal captured by an electrode placed in the scalp. This paper proposes the newly developed saline EEG electrode, which senses the impulse signal from the brain. It is then subjected to the Stationary wavelet transform (SWT) technique. This technique overcomes the disadvantage of Discrete Wavelet Transform (DWT) by using the same number of samples for analysing throughout the process, thereby giving accurate results. This paper compares the output of both DWT and SWT techniques after the signal captured from the schizophrenia patients and the normal patient.

1. INTRODUCTION

Electroencephalography (EEG) is a recording method to analyse brain activity. EEG is a non-invasive scalp electrode, and it is measured by neurophysiological. The Postsynaptic pyramidal **neuron** brings a summation measurement within a large area (1 to 6 cm2) of the cortical. EEG is one of the excellent temporal resolutions in the millisecond range techniques compared to other FMRI or PET. This study will assist the evaluating the electrical activity of our brain. EEG electrodes are equipped with amplifiers to remove noise and represent the brain's electrical activity. The EEG system comprises wires, electrodes, an amplification circuit, an energy source (Example: battery) and a storage device. The EEG signal was stored in the PC or memory card. The EEG electrode each attached to individual wires to acquire brain activity at different lobes of the brain. Each lobe of the brain has a reference point for EEG signal acquisition. The amplifier in the EEG system protects the maximum data quality with high common-mode rejection and amplifier; the EEG system contains various ranges of electrodes and caps with custom or standard montages accessories. The EEG has different passive, active, wet and dry electrodes**.** The passive electrodes make with silver chloride—these electrodes are placed on the scalp with conductive electrolytic gel. The passive electrode does not include a pre-amplification circuit compared to active electrodes. As an alternative, the connection extended from the conductive material to the equipment for acquiring the EEG signal or amplifying the EEG signal. Compared with passive electrodes, the active electrode has a pre-amplification module. The electrodes enable the signals to be strengthened. It is also possible to reduce the time taken to arrange test subjects to start the EEG recording, in the case of attainment with several channels.

The active electrodes are sensors placed in the housing with high-quality Agcl (sinter) to facilitate the DC acquisition. The integrated active electrode permits the recordings at high transition resistances and reduces the ambient noise. The active electrodes setup improves the signal to noise ratio of EGG signals even in abrasive impedance minimisation and skin sterilisation with alcohol. The active electrodes transition resistance indicates by different colour LEDs. The different EEG types evaluate by the Event-Related Potential Experiment. The Wet electrodes are made of silver/silver chloride material, and it uses the material of electrolytic gel between the skin and the electrode as a conductor. It was very accessible to use active electrodes and stabilised electrodes, and finally, it reduced the conductive gel. Wet electrodes have a very high cost; it depends on the need of the experiment. For the approach of dry electrodes, it is mandatory to carry out the gel application for each electrode.

The gel application can irritate the sensitivity area of electrodes while using the Live cap; it involves the gel application to 64 electrodes for each active channel in the cap. Suppose it should be used for a more extended period. In that case, it should consider that the gel can be dehydrated, and it is necessary for reapplication and interruption of signal monitoring. Furthermore, it takes more time before adequately removing and cleaning the electrodes. Lastly, the sequels of electrodes can leave dry after monitoring. Dry electrodes are made up of a single metal, it acts as a conductor between the electrode and skin, and it is stainless steel. Obtain the higher-level noise of the dry electrodes than wet electrodes. It shows the difference between the values measured by reference value and electrodes. The absence of an electrolytic layer has possible error levels because of the gel applied between the electrode and skin on the wet electrodes. Suppose the electrodes are correctly positioned between the skin and the electrode with firm contact, and a reliable level of spectral EEG can be measured by pre-amplification. The EEG measurement does not seem to add the additional noise of active and passive electrodes. The information is intended to measure. It can significantly influence the decision using between active or passive electrodes. During the measurement, the speed changes in voltage of passive electrodes, which controls the amount of noise in the signal. However, the active electrodes are higher price than passive electrodes. The active electrodes cannot measure the EEG than passive ones accurately.

1.1 EEG and schizophrenia patient:

Sensory gating is a procedure by which extraneous stimuli in the brain filter irrelevant information from all feasible environment stimuli. Sensory gating (SG) is referred a core deficit among patients with schizophrenia. Schizophrenia patients demonstrate all the sensory inundation, excess irrelevant sensory information in the brain, resulting in abnormal information processing, selective attention and cognitive deficits. A stimulus-paired paradigm has analysed the sensory gating in the auditory modality. For two brief, identical stimuli displayed with 400 ms stimulus onset asynchrony.

On the other hand, both stimuli evoke a valuable potential 50 ms post-stimulus (P50), and the second stimulus is generally attenuated of potential amplitude. This circumstance is called P50 suppression because of considered a measure of input inhibitory. The schizophrenia patients responded smaller amplitude to the beginning stimulus than the normal controls, which was a fundamental element to eh deficit in SG. The schizophrenia patients considered the decreased processing to the deficient gating of S1 than of S2. The electroencephalogram incorporates the energetic properties of brain activity; these properties examined by complexity analyses are Shannon entropy, approximate entropy, and Lempel complexity. Schizophrenia patients revealed increased complexity connected with a higher variability or inconsistency analysed by resting state of EEG signal. In addition, it detected a difference in the normal controls between the frontal and temporal regions of schizophrenia patients. The entropy algorithms were beneficial by complexity approaches and evaluated EEG consistency or predictability by robust estimators.

Entropies calculate the advanced probability pattern of time series, and when probability generates a new routine, it will be the complexity of the sequence. The fuzzy structure of entropy indicated a high performance. The complexity of entropy has shown decreased normal controls during the task. Although, schizophrenia patients have displayed a sustainable reduction in task-related changes compared with controls. Specifically, the schizophrenia patients have shown the tones of both target and distracter used spectral entropy by an oddball auditory paradigm. By further analysing the EEG signals raised by the various types of emotions, In Schizophrenia patients, Fz electrodes in the ApEn was considerably coupled with the scores of negative and positive syndrome scales. The normal controls and markedly ill of schizophrenia patients can be sorted by identification of 81.5%. The complex measurement of entropies manifested the dynamic properties of sensitivity to neural brain activity. It provided the main approaches of schizophrenia patients to analyse the mechanisms of abnormal cognition. The schizophrenia patients displayed deficits in the processing of sensory information and sensory gating by using an auditory coupled-stimulus paradigm, which contributed to the symptoms and cognitive deficits of schizophrenia patients. Although, the entropy modulation of mechanisms raises through the auditory coupled-stimulus paradigm in schizophrenia stay unsettled.

1.2 Limitation of EEG signal

The EEG is a primary pre-processing method for EEG analysis by removing disagreeable artifacts. These artifacts are made from eye and muscle movement, the heartbeat or external technical sources. This study involved the removal artifacts, and it is frequently caused by muscle activity neighbouring the head like swallowing or head gesture by high-frequency training. Because muscle activity emerges from the various kinds of muscle groups, these muscles are more complicated to stereotype than eye artifacts. EEG recording is the linear decomposition of EEG signal by reducing the muscle artifacts. The main goal is to isolate the artefacts from neural activity in various components, like the discarded artefacts and cleaners' signals reconstructed from the neural elements. Arrangement techniques to get the independent component analysis. This component resolved the BSS (Blind Source Separation) problem by inflating the independence of the source components. The ICA produces a helpful separation in many instances, but some mingle elements stay from both artefactual and neural origin by containing activity. During the many different BSS/ICA methods are accessible, but several analyses compared the performance of EEG data. In the quantitative evaluation, the EEG signals need to know or assume the actual presence or lack of artifacts by sound basis. It was mainly very arduous for muscle artifacts, which cannot acquire from a single measurement device such as Eye-tracking or EOG (Electrooculogram). Most evidence and contrast studies focus on biological or artefact-free data, and artefactual data are directly mixed at a ratio to evade this problem. Although, the approaches of the limited fact that stimulated data does not fully reflect the characteristics of EEG with muscle contamination. For instance, muscle activity does not occur independently from the interest of neural signals. The validation studies mainly quantified the artifact reduction performance on accurate data focused on eye artifacts. The comparison with basic settings of BSS/ICA algorithms to evaluate the measuring source components, although the sources of ground truth components are unknown. The comparison of 22 different decompositions of BSS algorithms by measuring independence based on mutual information and "Dipolarity" of the elements of resulting sources. The "Dipolarity" indicates the number of components. The scalp maps are well clarified by one parallel dipole source. Such characteristics represent the BSS/ICA algorithms to evoke. The mutual information is based on ICA methods, namely Infomax, the highest near dipolar components.

2. Related works:

The EEG patterns of brain activity and deep learning methods are valuable resources in accomplishing the identification. The prospective title of children expected to improve schizophrenia is the essential tool to support that moderate the risk of progression to clinical psychosis. The proposed automated techniques that can process EEG waveforms to determine children who have an increased risk of schizophrenia are analysed to typically developing children. Analyse abnormal characteristics that remain during cultivating follow-up throughout ~ four years in children with a vulnerability to schizophrenia evaluated the age group of 9 to 12 years—the participants of EEG data captured through the recording with passive auditory oddball paradigm. The author adapted the holistic study to recognise the brain abnormalities, explored traditional machine learning algorithms used by classification methods applied to hand-engineered appearance. The author applied the raw data by end-to-end deep learning techniques method and demonstrated recurrent deep convolution neural network that can perform traditional machine method of learning for the sequence modelling. The author illustrates the model of prominent intuitive information with applicable attributes of a post-stimulus window. The area of credentials system the mental illness supports the disease effects in the pre-prodromal phase of psychosis and developmental evidence. The benefits of deep learning include classifying psychiatric categories and broad neuroscientific research. [1]

The differentiation between schizophrenic patients and bipolar disorder (BD) is crucial because of the substantial overlap between the clinical symptoms and signs. The measurement of EEG that analysed the classifying the schizophrenia patients and bipolar disorder, on the other hand, the EEG evoked by external visual or audio stimuli, has investigated with high signal to noise ratio (SNR). The author analysed that, classifying the schizophrenic patients and bipolar disorder used by external stimuli of EEG. The author used the visual stimulus modulated at a particular frequency to induce SSVEP (steady-state visual evoked potential). In this paper, 16 HZ of photic stimulation displayed two groups of schizophrenia and bipolar patients for 95s when EEG data were recorded. The statistical measurement of SSVEP that narrated in units of SNR was extracted to describe and categorise the variation of two groups of brain activity patterns. The activity pattern of two groups of O1 and Fz has shown a significant reliably variation for SNR mean and Kurtosis. K- the nearest neighbour had contributed the accurate classification of 91.30% by fisher score. The central accuracy for binary classification maintained by the time of analysis has decreased up to 10s using a help of a vector machine classifier and other classifiers of 20 s. the author demonstrates the possible applicability of the preferred SSVEP-based classification access path with relatively short single-trial EEG signals.[2] The healthy adolescents (n = 39) and adolescents with schizophrenia spectrum disorders (n = 39) have done a quantitative analysis of changes in the auto-correlation structure of EEG low segments. The various EEG autocorrelation structure displayed higher patients with the frontage point of most significant trends. It recommended that psychopathology of the schizophrenia spectrum is followed by a mutual assurance of cortical neural networks with predominant localisation in the frontage area of the brain cortex. [3] EEG of cross-correlation used to recognise susceptibility to schizophrenia and adolescents (11 to 14 years old children's). The author finds out the diagnostic characters by using cross-correlation techniques based on the coefficient and functions of Fourier spectrum cross-correlation. The author made it possible to companion the degree of frequency –phase synchronisation in a separate frequency range with the risk of schizophrenia. [4]

Visual appraisal has displayed different kinds of non-specific EEG abnormalities in schizophrenia patients, namely poor alpha rhythm, increased beta activity and disorganised activity correlated to subjects and healthy controls with an alternative mental disorder. The hypo variability of EEG brain activity has demonstrated the decreased alpha power and excess of beta activity of new sophisticated computerised techniques. [5] Detected the autistic spectrum disorder of early childhood aged 5–7 years. To have more noticed right-sided dominant of alpha-rhythm spectral power both in conditions with baseline and on counting or cognitive loading, inclusive with a decreased level of alpha rhythm power. The fast rhythms have increased the spectral energy from the baseline condition on cognitive loading in healthful children. The gamma rhythm of spectral power was more significant than in healthy children with baseline condition. The fast rhythms of spectral power have changed to a lesser extent on cognitive loading than in healthy children. The autism of children has predictors for the transition with both positive and negative symptomatology from autism to schizophrenia by decreased alpha rhythm. The fast rhythm of spectral power has increased in the condition of baseline noticed here in children with autistic spectrum disorder of early childhood is features of schizophrenia with positive symptomatology. In contrast, fast rhythms of decreased reactivity in reaction to cognitive loading noticed here in patients has narrated for adverse symptomatology of schizophrenia. [6] The P300 is considered a psychosis endophenotype of schizophrenia and schizophrenia as a putative risk biomarker.

Although, the P300 amplitude of brain activity does not provide good discrimination of patients during the tasks with schizophrenia from healthy controls. The voluntary action at rest indicates the brain's potential to process the information task effectively; it compensates for the cognitive defects in SEZs. In this analysis, based on the rest shows and p300 task electroencephalogram data sets, the author raised functional networks of EEG and separated the inherent spatial pattern of the network for both brain states. Conclusively, the task networks and the combined SPN features estimate SZs. The paper revealed that the collaborative SPN features achieved the most remarkable accuracy of 90.48%, with a sensitivity of 89.47%and specificity of 91.30%. And these consistencies has implied that rest indicates and the task of P300 EEGs contributed broad information to well categorised SEZs and from HCs. A spatial pattern network is a hopeful tool for the clinical diagnosis of SEZs. [7] Diagnosis of schizophrenia (SZ) is accomplished traditionally via patient's interviews by an experienced psychiatrist. This procedure is time-consuming, subject to error and bias. The study aims to evolve an automatic schizophrenia identification scheme using EEG signals to exterminate the abovementioned problems and support clinicians and researchers. The analysis starts a methodology design by EMD (empirical mode decomposition). This technique for diagnosis perfectly handles the non-stationery behaviour and nonlinear EEG signals of SZ from EEG signals. The EEG signal has decomposed into IMFS (Intrinsic mode functions) by the algorithm of EMD and features of 22 statistical computed from IMFS. Like them, significant features as selected by five features have applied the Kruskal Wallis test. The acquired feature set has been tested on an SG (EEG) data set via various renowned classifiers. Among the reviewed classifiers, the group of bagged trees was executed as the best classifier producing a 93.21% exact classification rate for SZ, with an accuracy of 89.59% for IMF 2. These outcomes have specified that the signal of EEG discriminate patients from HC (healthy control) subjects efficiently and potentially to transpire a tool for the psychiatrist. It was holding the positive diagnosis of SZ. [8]

Recently, the diagnosis of schizophrenia is built exclusive based upon interviews and behaviour monitoring by an expert psychiatrist. EEG is used for various diagnoses, and it does not support the other positive diagnosis of a psychiatrist. The author displayed the EEG recordings as biomarkers of schizophrenia syndrome. The schizophrenia patients candidly seen natural place by the time recorded EEG and examined the EEG average activity locked to the image onset. The author detected meaningful differences between patients and occipital controls area estimated at 500 ms after image onset. These variations instruct a classifier to discriminate the patients from the controls. The 81% sensitivity of the best classifier detected patients found and particularly 59% for the detection of rules by an overall accuracy with 71%. These outcomes specify that the signals of EEG from a free observing paradigm discriminate schizophrenia patients from healthy controls and have the potential to transpire a tool for the psychiatrist. It was holding the positive diagnosis of SZ. [9] The prolonged disorder of the human brain disturbs the image characteristics of an individual by an interruption in process thinking and schizophrenia of speech. It demonstrates many symptoms, namely hallucinations, functional deterioration, disorganised speed, hearing sound, and nonexistent speech. This paper analysed the computerised approach of optimising and classifying schizophrenia from EEG signals. These signals analysed the brain disorders and brain in an in-depth manner of disease. The primary three characteristics extraction techniques are used, namely Partial Least Squares (PLS) Non-linear Regression technique, Expectation Maximisation based Principal Component Analysis (EM-PCA) technique and Isometric Mapping (Isomap) technique. The extracted features are optimised with Flower Pollination algorithm, Eagle strategy using differential evolution algorithm, Backtracking search optimisation algorithm and Group search optimisation algorithm.

The optimised value is grouped with versions of the Adaboost classifier and the Naïve Bayesian Classifier. The specific results displayed that Isomap features optimised with Backtracking search optimisation algorithm for general cases. Classified with Modest Adaboost classifier accuracy of classification obtained of 98.77%. In the case of schizophrenia, optimised by Isomap features with Flower Pollination optimisation algorithm and classified with Real Adaboost classifier, the accuracy of classification obtained of 98.77%. [10] the P3b wave accurately discriminates between the SZ (schizophrenic subjects) and HC (healthy controls) methods. The many machine learning classification accesses optimised the correct classification rate (CCR), the degenerated Youden's index (DYI), and the curve area. Computer-aided diagnosis contains five stages electroencephalography (EEG) pre-processing, seven electrode groupings, feature extraction, discriminant feature selection, and binary classification. Result of this study with optimal combinations of grouping, filtering, feature selection algorithm, and classification machine (either a mean CCR = 93.42%, specificity = 0.9673, sensitivity = 0.8727, DYI = 0.9188, and AUC = 0.9567 (total-15 Hz-J5- MLP), or a mean CCR = 92.23%, specificity = 0.9499, sensitivity = 0.8838, DYI = 0.9162, and AUC = 0.9807) (right hemisphere-35 Hz-J5-SVM), higher than those available to date. The conclusion of this study verified that a lot of restrictive low pass filtering attains higher CCR than the higher frequencies in the P3b wave. Furthermore, the previous hypothesis validates results about the most important region of parietal-temporal combined with memory processing and grants to identify the powerful couples in the diagnosis of SZ, managing within the classification of both left and right hemispheres of Higher CCR and AUC. The implication of diagnosis SZ is made via by psychiatrists, although any decision based on the human has a subjective component. Computer-aided diagnosis brings the human expert along with objective complimentary, which measures to help the diagnosis of SZ. [11]

The proposed identification of children generally to develop schizophrenia is an essential tool to prior support interventions that can alleviate the risk of development to clinical psychosis—the techniques of EEG pattern brain activity and deep learning are valuable resources in completing the identification. The author has proposed the methods of automation can process raw EEG signals to recognise children who have a risk increased of schizophrenia compared to typically developing children and also studied abnormal characteristics that remain follow up over a time of ~ four years children with schizophrenia of vulnerability initially evaluated the aged of 9 to 12 years. The participants captured the recording of a passive auditory oddball paradigm. The author adopted a comprehensive study to identify abnormalities of brain activity by exploring the learning algorithm of the traditional machine by applying and using the categorisation method to hand-engineered characteristics. The performance comparison of these methods with end to end deep learning techniques put into raw data and demonstrated through average cross-validation presentation calculating that repeated deep convolutional neural networks can perform with traditional machine learning for modelling. The salient model information is exemplified with most functional features of the post-stimulus window. The standard identification area system of mental illness assists the growth evidence and effects of the disease in psychosis of the pre prodromal phase. These outcomes strengthen the advantages of deep learning to support psychiatric classification and neuro-scientific research broadly. [12]

The study aims to EEG (electroencephalograms) of schizophrenia patients using power spectral density. The proposal method measured the numerous forces similar to the quantity information contained in frequency components, and this study included 57 schizophrenia and 24 normal subjects. Eyes closed conditions of EEG recordings acquired with under resting, hyperventilation and post hyperventilation. EEG 10s epochs of power have been calculated and used by Welch's methods. The Delta, theta, alpha and beta bands separated from EEG using a limited response band filter and determinate of power. The absolute power of the beta band and alpha bands has a difference between the two groups ($p < 0.001$) during rest. When the brain conditions changed from rest to hyperventilation and posted hyperventilation, the greatest power changes appeared in the alpha and delta bands. This change is heavier for normal subjects compared to the group of schizophrenia. The group of subjects was categorised using a support classifier of a vector machine. It yielded the greatest accuracy of 83.33% with 82% specificity and 87.2% sensitivity the power has used as input. The result proposes that schizophrenia subjects identified by using absolute alpha band power. [13]

3. Methodology

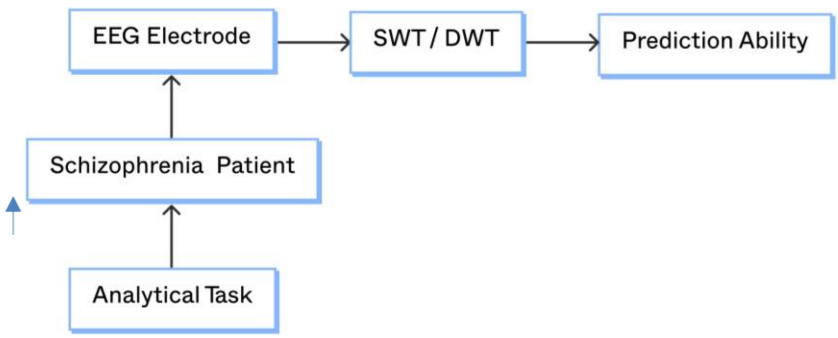


fig 1: Block diagram of the proposed method

3.1 The wavelet transform (WT):

The EEG signal was analysed to detect stationary and non – stationary. It consists of evicting the outermost noise from the signals, constricting the amount of data, and discovering hasty discontinuities. The overview of signal processing is shown in figure 1. Without wavelet transform, it is impossible to decompose a signal within a group of the signal known as wavelets. The Fourier transform has represented the signal of the unlimited duration of sine and cosine functions. The wavelet transform is a short duration of the transient function, which denotes the specific time. The common problem of FT is passing from the time domain to the frequency domain. The information, it happens in time is lost. By noticing the frequency spectrum acquired using the FT is easy to differentiate the signal frequency content being studied even. Hence, it is not feasible to conclude that the components of the signals of the spectrum frequency appear or disappear. The wavelet transform allowed to analyse both time and frequency domains by giving information on the development of the frequency content of the overtime signal. In the case of FT, the wavelet transforms are called a discrete wavelet transform because of discretised and shows an advantage over traditional FT methods. The wavelet transforms decomposes a signal into various scales showing different frequency bands at each scale; the arrangement of WT can be decisive the characteristics time, it can be identified and adequately removed by the components of electrical noise. The short time wavelets grant the information obtained from high-frequency components. The data eradicate the electrical noise after all the electrical noise is expected to display high-frequency fluctuations. Long-term wavelets allowed to excerpt reports from low frequency. Both high and low frequencies have defined a zero frequency and threshold under the disagreeable point of the electric noise.

3.2 Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform (DWT) separates parts of a signal into a set of bilateral orthogonal wavelet basis functions. These functions vary from sinusoidal basis functions in that they are spatially localised - mainly, non-zero over is the single part of the total signal length. Furthermore, a wavelet function is called the Mother wavelets, which are dilated, translated and scaled versions of a standard function. DWT is invertible in Fourier analysis; it can fully recover the original signal from its DWT representation. The DWT is a set of transforms, and it has a different set of wavelet basis functions. The suitable tool of DWT is considered for the rejection of electrical noise by an alternative novel that changes the schedule of attenuation of electrical noise along with benefits of the filters of low pass system. Lock-In amplifier or Fast FT that is only used in the circumstances that electrical noise has a limited overlap of bands, fully different, detached from the signal and noise as used as filtering methods. The DWT is a high number application used for signal coding to serve as a discrete signal in the form of redundant, generally preconditioning for data compression. Haar wavelets and Daubechies wavelets are the most common of DWT. The **Haar wavelet** is a sequence of "square-shaped" by rescaled functions, which form a wavelet basis or family. This wavelet basis is let a target function above an interval be shown in terms of an Orthonormal basis. The **Daubechies wavelets** have used formulated a set of discrete wavelet transforms. The wavelet formulation used the recurrence relations, which gradually bring about finer discrete of an implicit mother wavelet function. The typical properties of Functions of Wavelet are spatially localised; Wavelet functions are translated, dilated and scaled versions of an ordinary mother wavelet; Each set of wavelet functions forms an orthogonal part.

3.3 DWT output: Normal

The several wavelets provide various DWT coefficients to different detection results on the EEG major segment. In this analysis, wavelets families were tested with Daubencies (dB). The data was set to EEG recordings of normal waked subjects with various cognitive questions and examined moderate DWT activity. The data set was recorded during an occurrence within an epileptogenic zone. The level of decomposition is 5: s = a5+d5+d4+d3+d2+d1 denoted as number of occurrence with frequencies. The EEG record is divided into frequencies such as the wavelet occurrence of a5, d5, d4, d3, d2, and d1 using the DWT below. The statistical features used to perform the time-frequency distribution of detected signals include Mean, Maximum, Minimum and Standard deviations of the wavelet occurrence. The statistical characteristics derived from DWT coefficients of the data segment identify seizures using recognition pattern techniques.

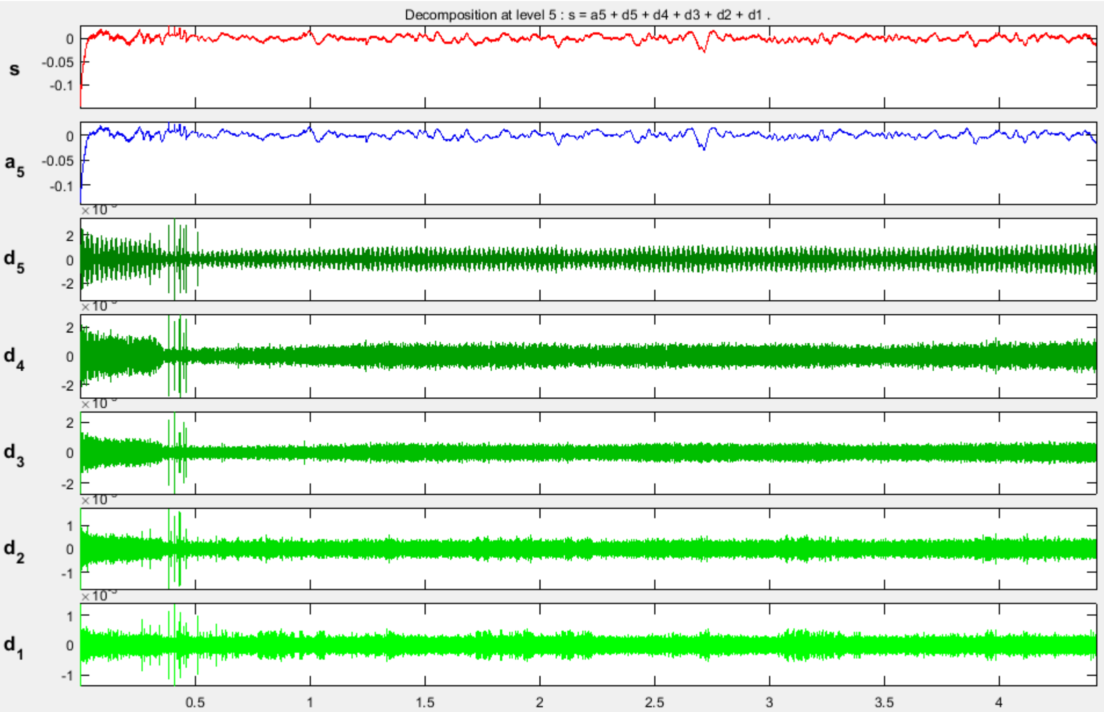


Fig 2. The original signal from a normal person and the coefficients of the captured signal

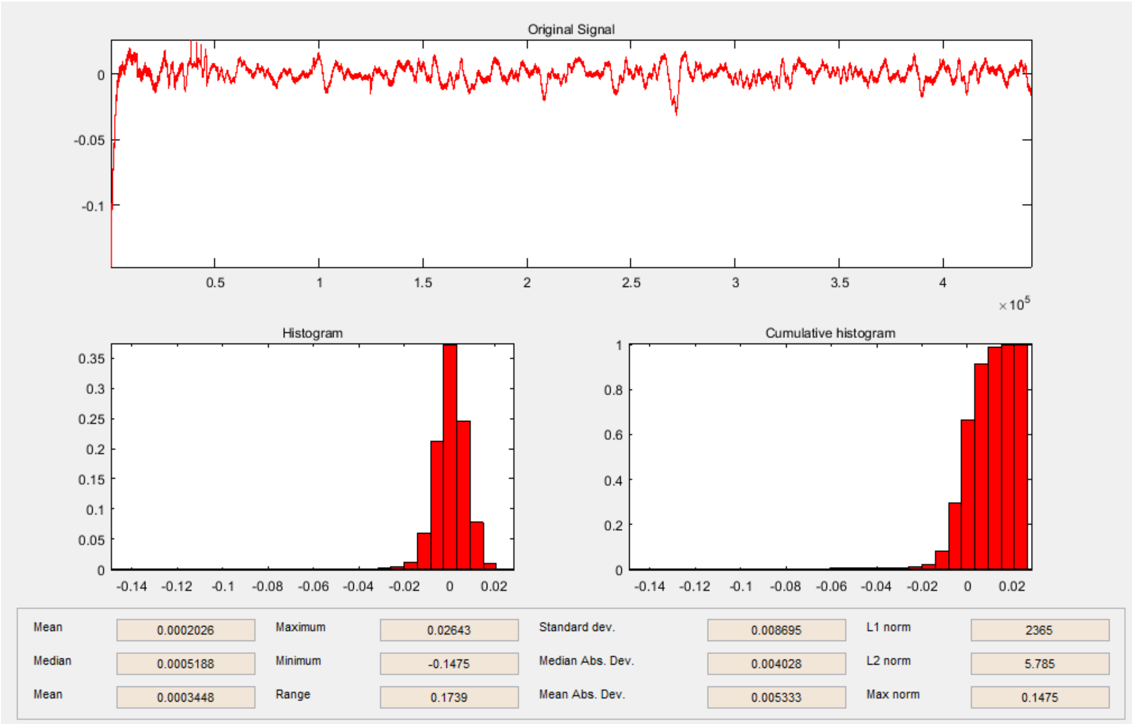


fig 3: Histogram and Cumulative histogram of normal signal

Figure 2 shows the original signal captured from the scalp of a normal person. The captured signal is decomposed into detail and approximation coefficient signals for further analysis. This figure shows the variation of the signal at the 5th decomposition level. Figure 3 shows the Histogram and Cumulative histogram of the captured signal. The frequency distribution at each point of the signal and its cumulative is shown in this figure.4 The normal signal's mean, median, and standard deviation values were displayed above.

Abnormal:

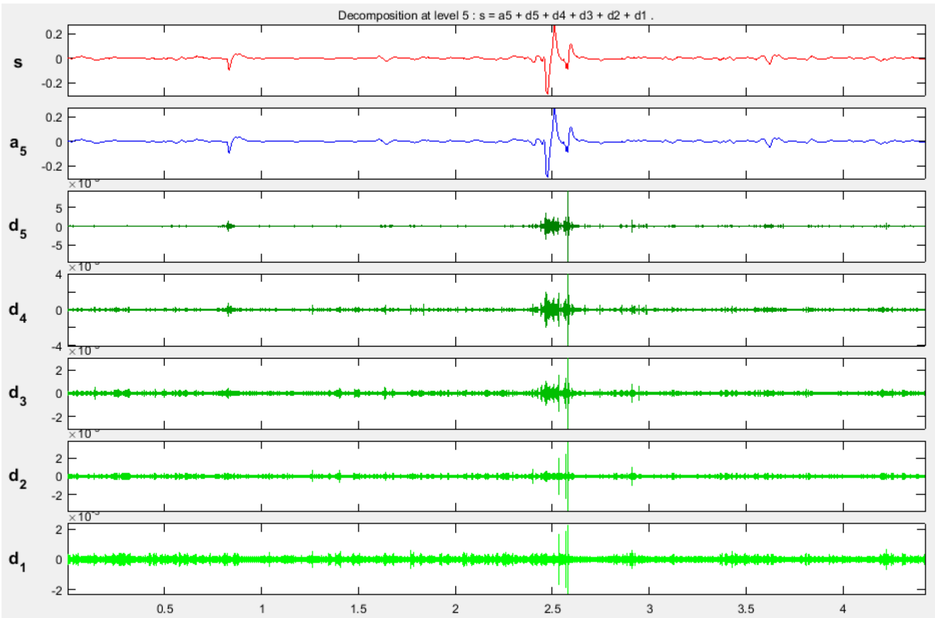


fig 4: Signal from abnormal person and coefficients of the captured signal

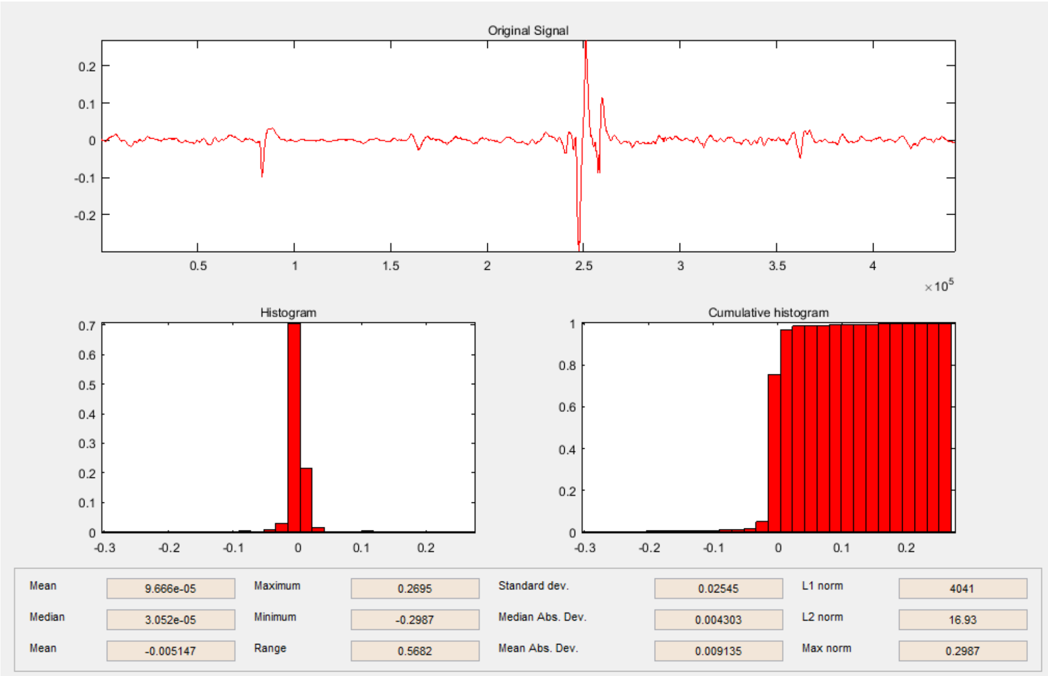


fig 5: Histogram and Cumulative Histogram of abnormal signal

Figure 4 shows the original signal captured from the scalp of an abnormal person. After its decomposition, the detail and approximation coefficients signal of the captured signal is shown above. It can be visible that sudden variation occurred due to its abnormality. Figure 5 shows the frequency distribution of the captured signal. The abnormal signal's mean, median, and standard deviation values were shown above.

Table 1. Comparison of normal and abnormal signal values after DWT analysis.

Signal parameters	Normal	Abnormal
Mean	0.0002026	9.666e-05
Median	0.0005188	3.052e-05
Mean	0.0003448	-0.005147
Maximum	0.02643	0.2695
Minimum	-0.1475	-0.2987
Range	0.1739	0.5882
Standard Dev.	0.000695	0.02545
Median Abs. Dev.	0.004026	0.004303
Mean Abs. Dev.	0.005333	0.009135

L1 norm	2365	4041
L2 norm	5.765	16.93
Maximum norm	0.1475	0.2987

3.4 SWT

The stationary wavelet transform is an algorithm mainly developed to overcome the disadvantage of the discrete wavelet transform. In this SWT, the same number of samples is subjected to the next level of transformation. Some critical applications of SWT are signal denoising, pattern recognition, pathological brain detection. One of the essential applications of SWT is brain signal analysis. In this paper, the saline EEG electrode was used to detect the signals from the brain. It is then subjected to the SWT technique for evaluation. The signal captured is evaluated as follows.

The coefficients of ϵ-decimated DWT will exist in stationary wavelet transform for each value of ϵ. The detail and data at level j in SWT are the shifted versions of DWT coefficients. Let us consider that $D^j(\epsilon)$ be the detail of the jth sequence obtained from ϵ-decimated DWT. Then for each j,

$$\begin{aligned}
\mathcal{S}^{-s_1}\mathcal{D}_0^{J-j}\mathcal{S}^{S}b^j &= \mathcal{D}_0^{J-j}\mathcal{S}^{s_2}b^j = \mathcal{D}_0^{J-j}\mathcal{S}^{s_2}\mathcal{G}^{[J-j-1]}\mathcal{H}^{[J-j-2]}\ldots\mathcal{H}^{[0]}c^J \\
&= \mathcal{D}_0^{J-j}\mathcal{G}^{[J-j-1]}\mathcal{H}^{[J-j-2]}\ldots\mathcal{H}^{[0]}\mathcal{S}^{s_2}c^J \\
&= \mathcal{D}_0\mathcal{G}\mathcal{D}_0^{J-j-1}\mathcal{H}^{[J-j-1]}\ldots\mathcal{H}\mathcal{S}^{s_2}c^J \\
&= \mathcal{D}_0\mathcal{G}\mathcal{D}_0\mathcal{H}\mathcal{D}_0^{J-j-2}\ldots\mathcal{H}\mathcal{S}^{s_2}c^J = \ldots \\
&= \mathcal{D}_0\mathcal{G}(\mathcal{D}_0\mathcal{H})^{J-j-1}\mathcal{S}^{s_2}c^J = d^j,
\end{aligned}$$

The output of SWT depends upon the details obtained from the decimated DWT. When we associate the c^j with the function f for any values of j and k, we can seethat,

$$b_k^j = \int \psi_j(t - 2^{-J}k)f(t)dt$$

We can see that there is no restriction for estimating the integer position. The SWT fills up the gap between the coefficients of decimated DWT.

Results of SWT for normal signal

The brain signal from the normal person using saline EEG electrode is subjected to SWT technique. The results obtained are shown below.

SWT outputs:

Normal

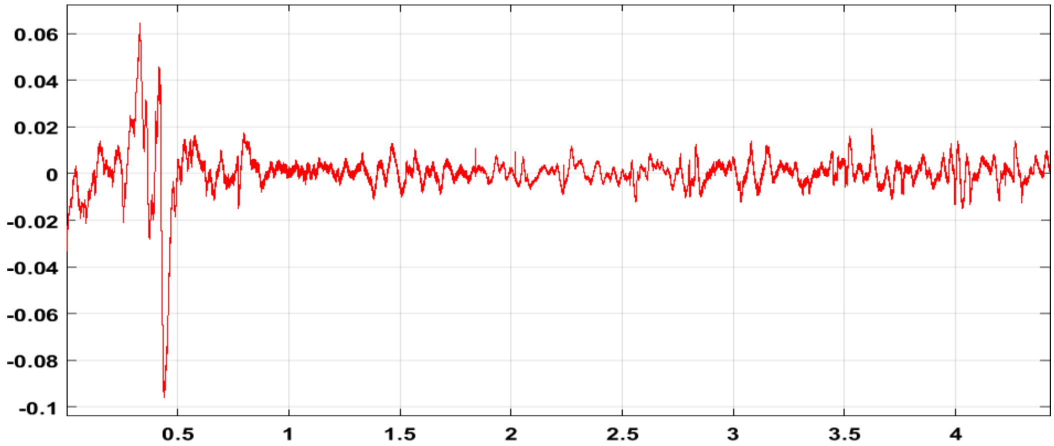


fig 6: Signal from a normal person

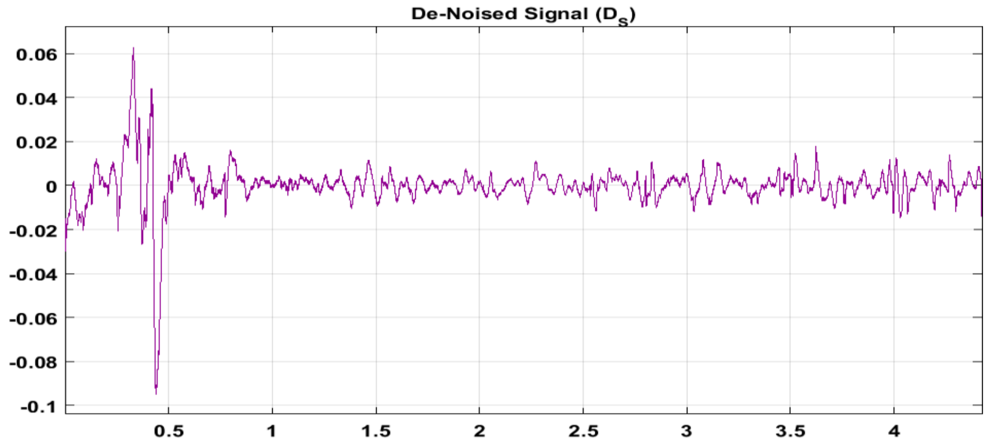


fig 7: De-noised signal

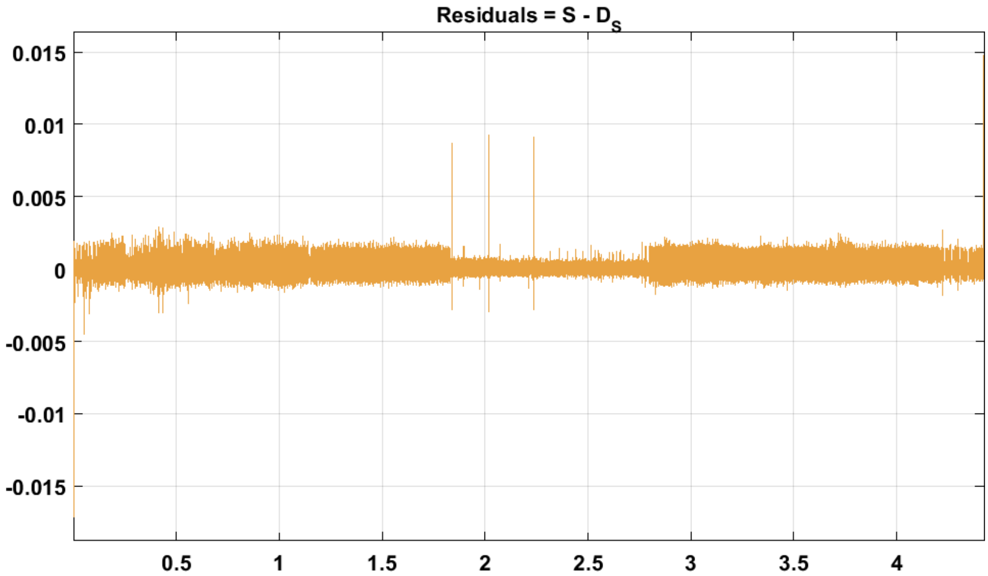


fig 8: Residual signal

Figure 6 and 7 shows the normal signal captured from the scalp of a normal person and the signal after the noises have been removed. Figure 8 shows the residuals, the remaining part of the signal after denoising the original signal.

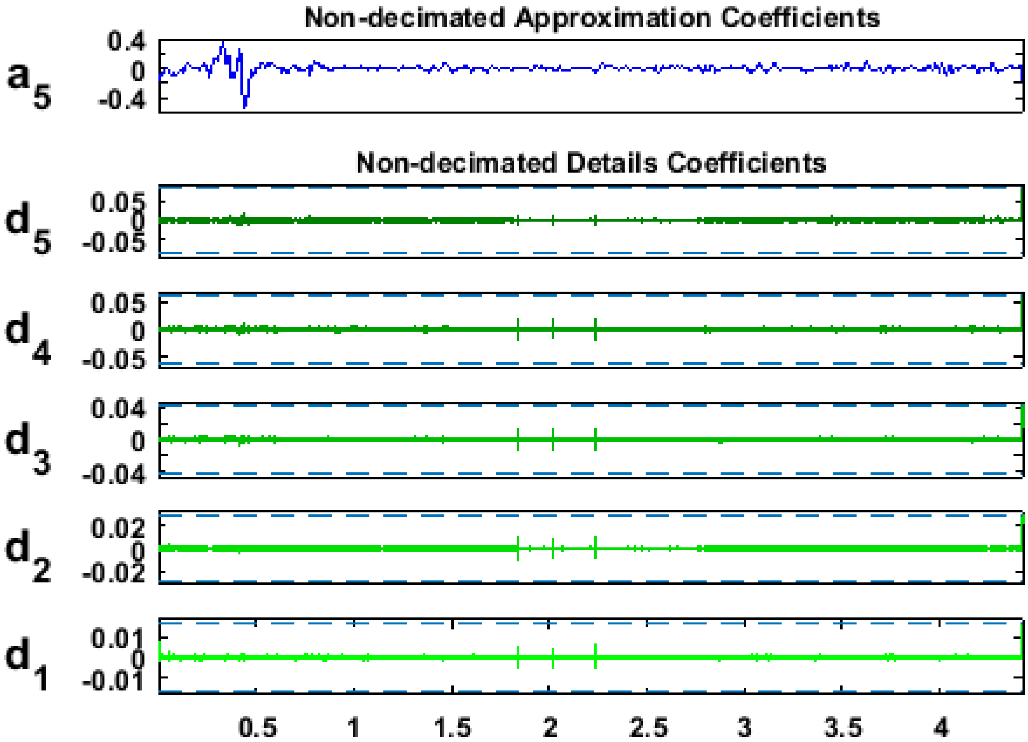


fig 9: Approximation and Details coefficients signal at 5th level of signal decomposition

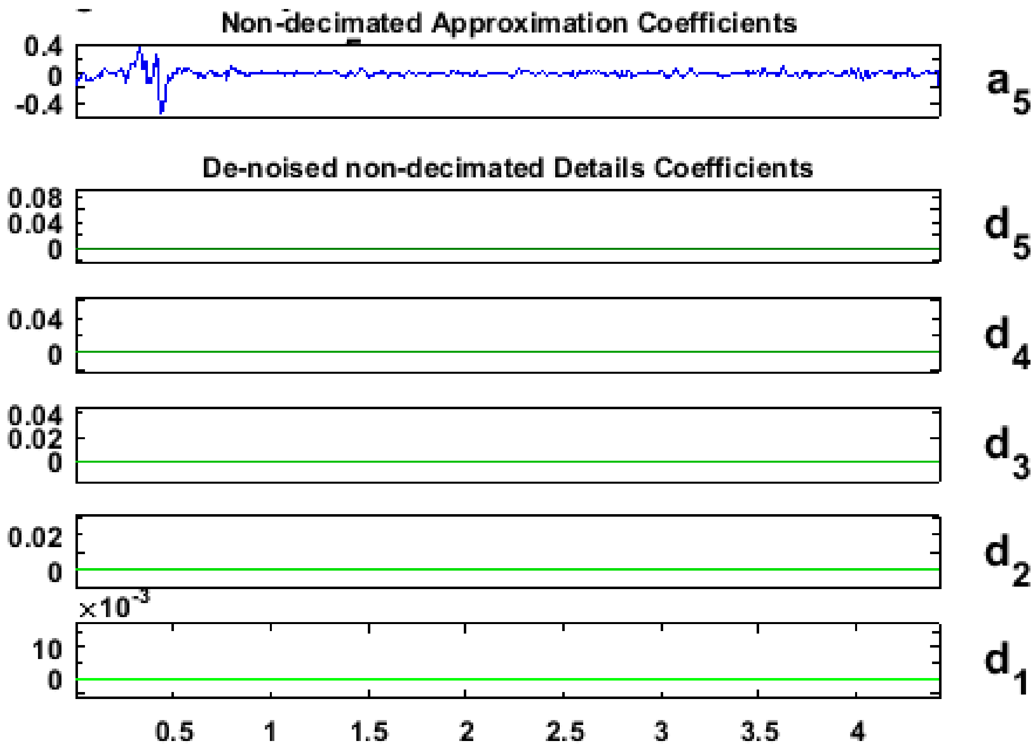


fig 10: De-noised detail coefficient signal at 5th level

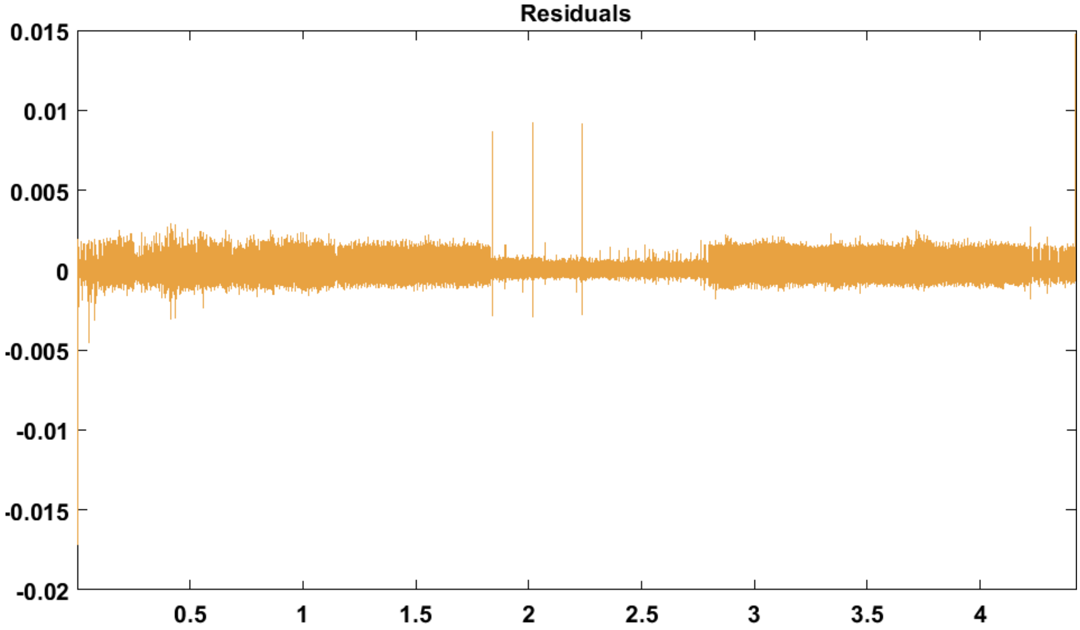
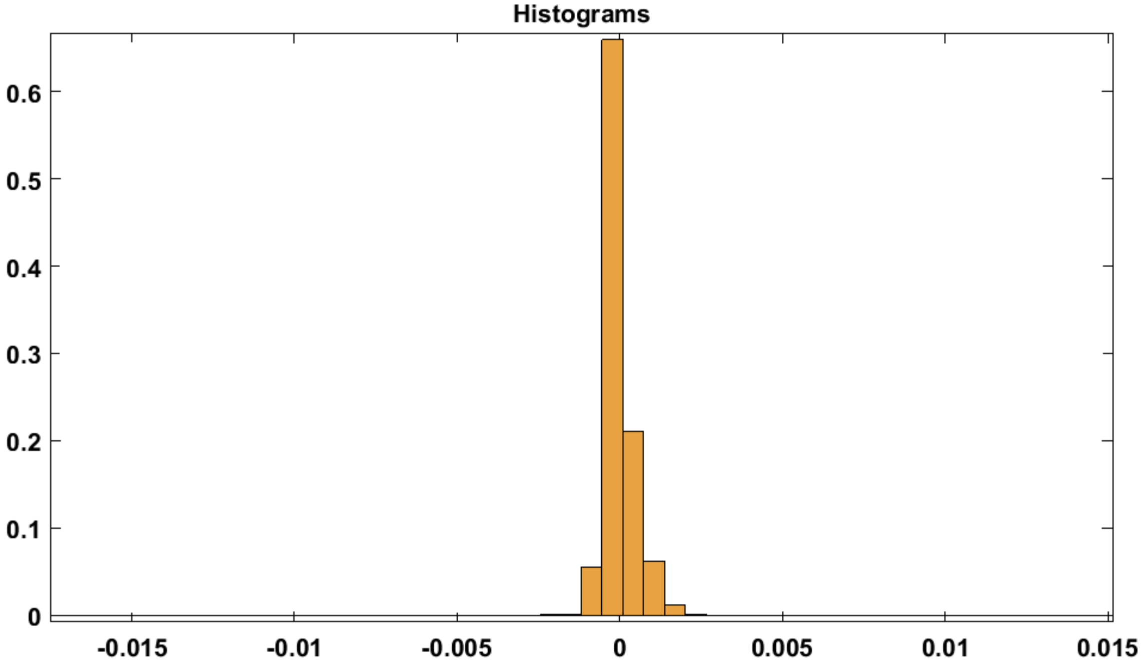
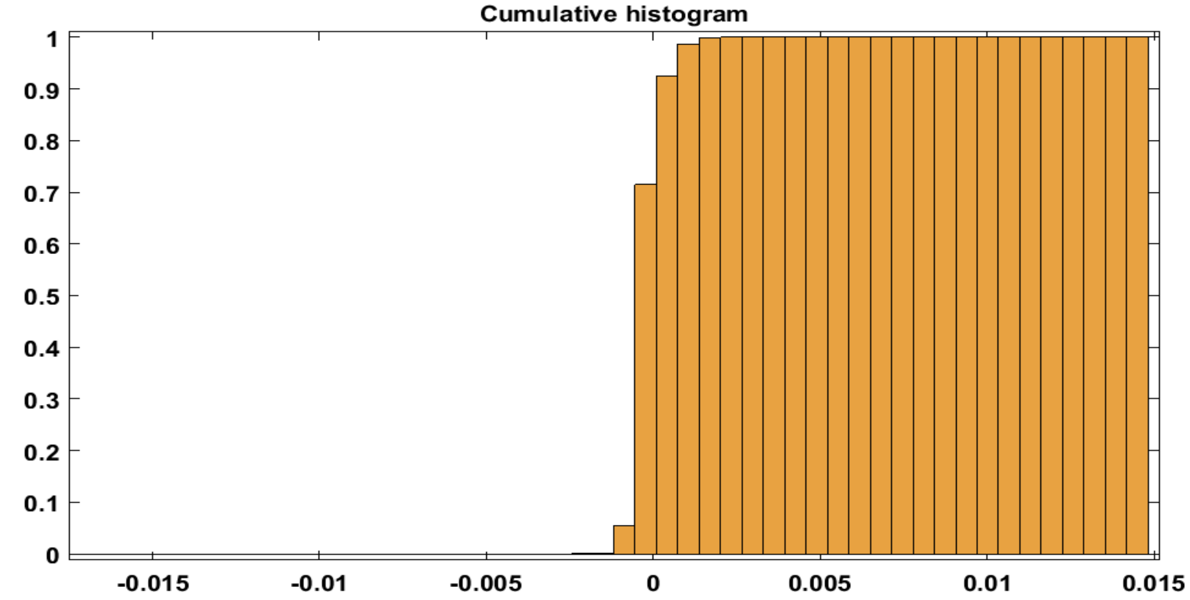


fig 11: Residuals at 5th level

Figures 9 and 10 show the non-decimated approximation and details coefficients signals when the signal has been analysed at the 5th level of decomposition. Figure 11 shows the residuals at this stage.





Mean	0	Maximum	0.01481	Standard dev.	0.0004396	L1 norm	127.8
Median	-4.733e-05	Minimum	-0.01719	Median Abs. Dev.	0.0001754	L2 norm	0.2924
Mean	-0.0002279	Range	0.032	Mean Abs. Dev.	0.0002888	Max norm	0.01719

fig 12: Histogram and Cumulative histogram of normal signal

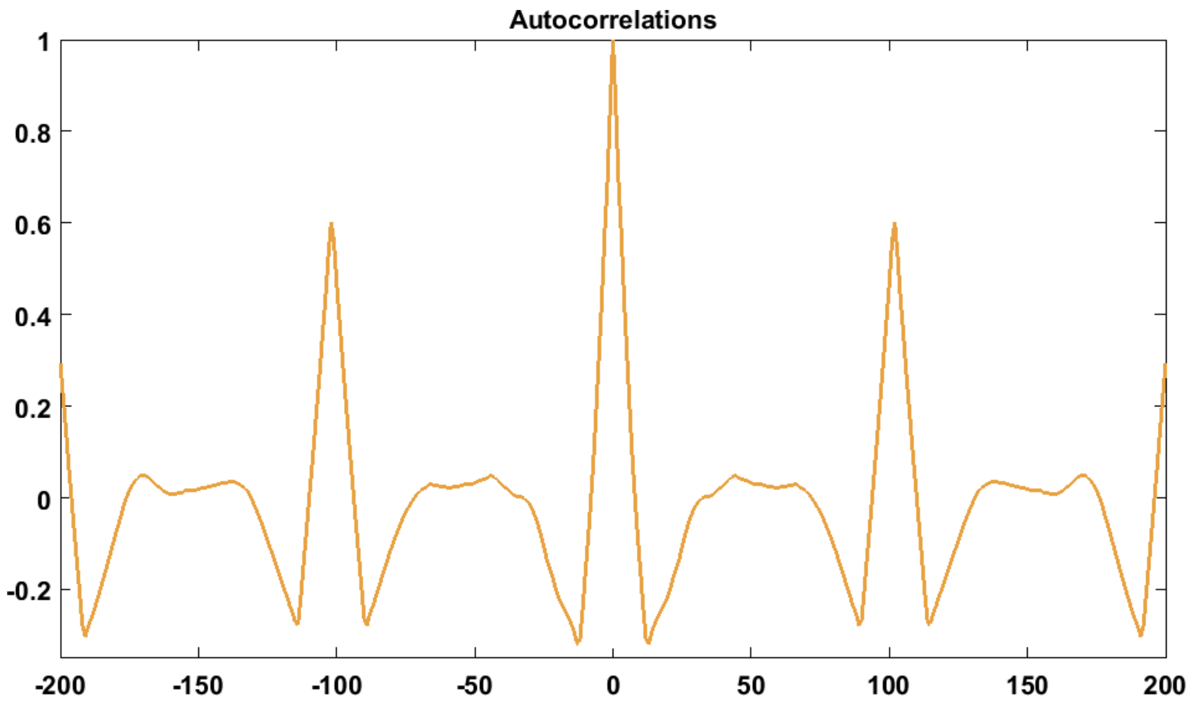


fig 13: Autocorrelation of signal

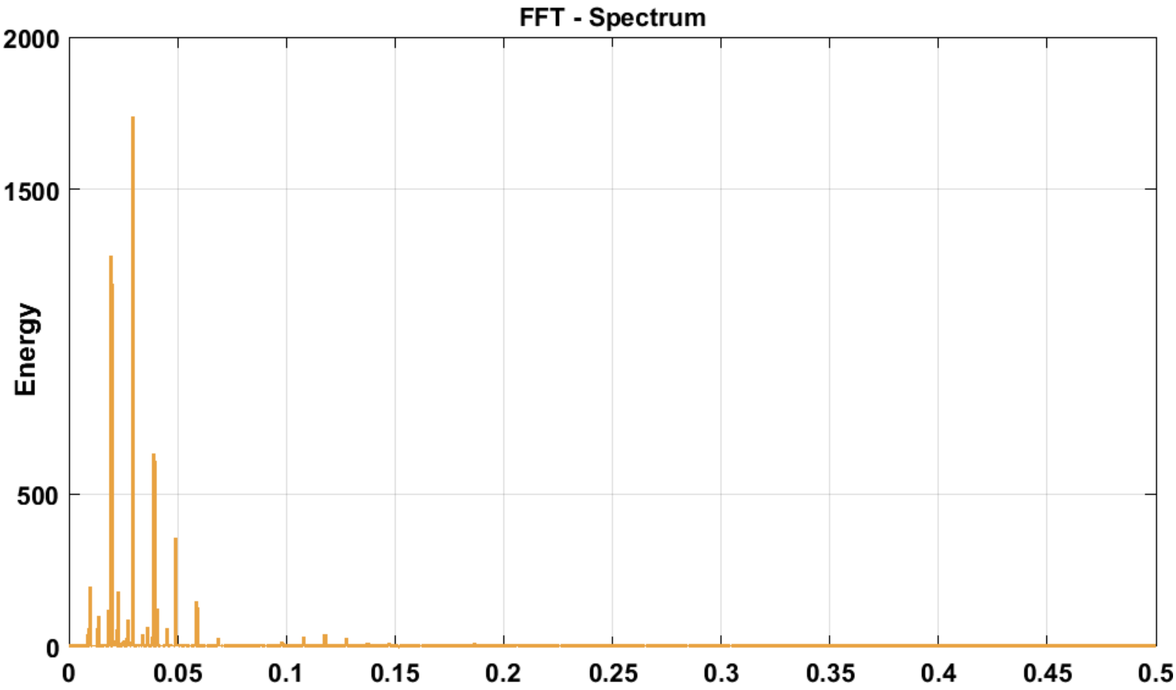


Figure 14. FFT of captured normal signal

Figure 12 and 13 shows the frequency distribution of the captured signal and the autocorrelation of the signal. Figure 14 shows the captured signal's FFT (Fast Fourier Transform). It shows the captured impulse signal in the frequency domain form.

4. Results and Discussion

The impulse signal from the brain of an abnormal person was sensed using a saline EEG electrode, and it is then subjected to the SWT technique. The results obtained are shown below.

Abnormal

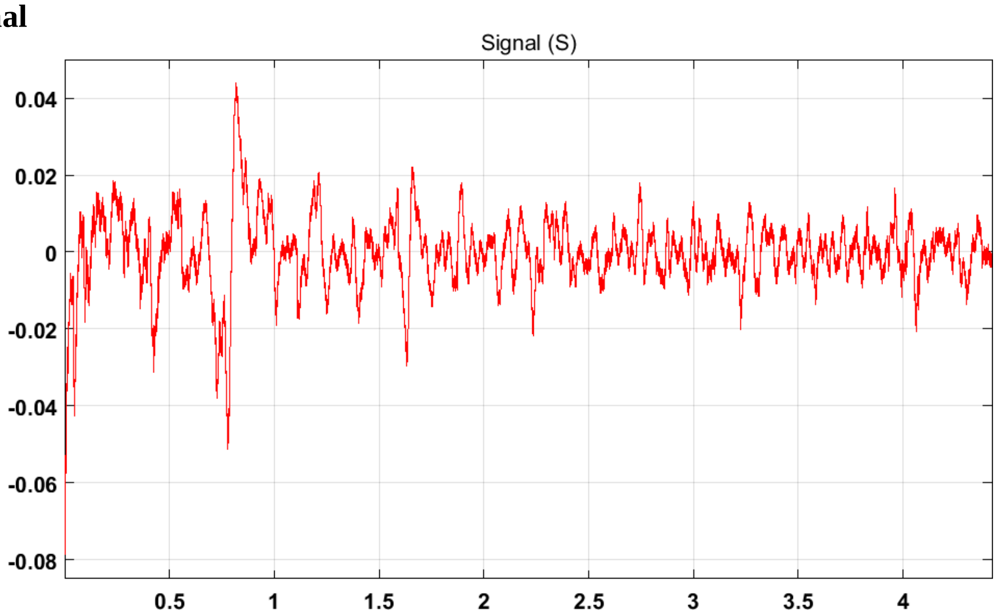


fig 15: Signal from abnormal person

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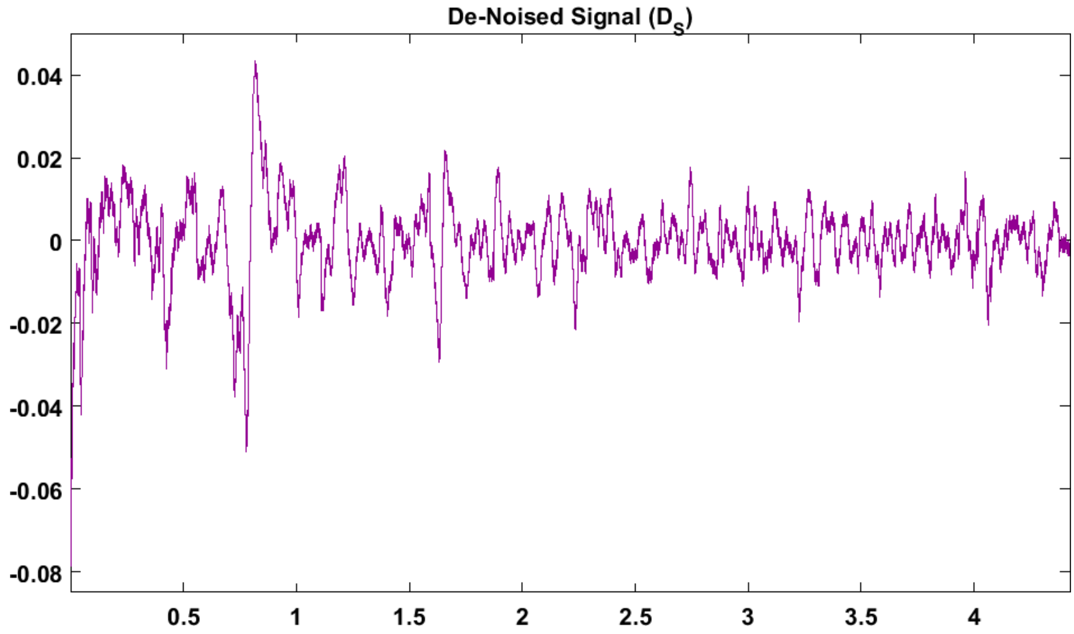


fig 16: De-noised signal

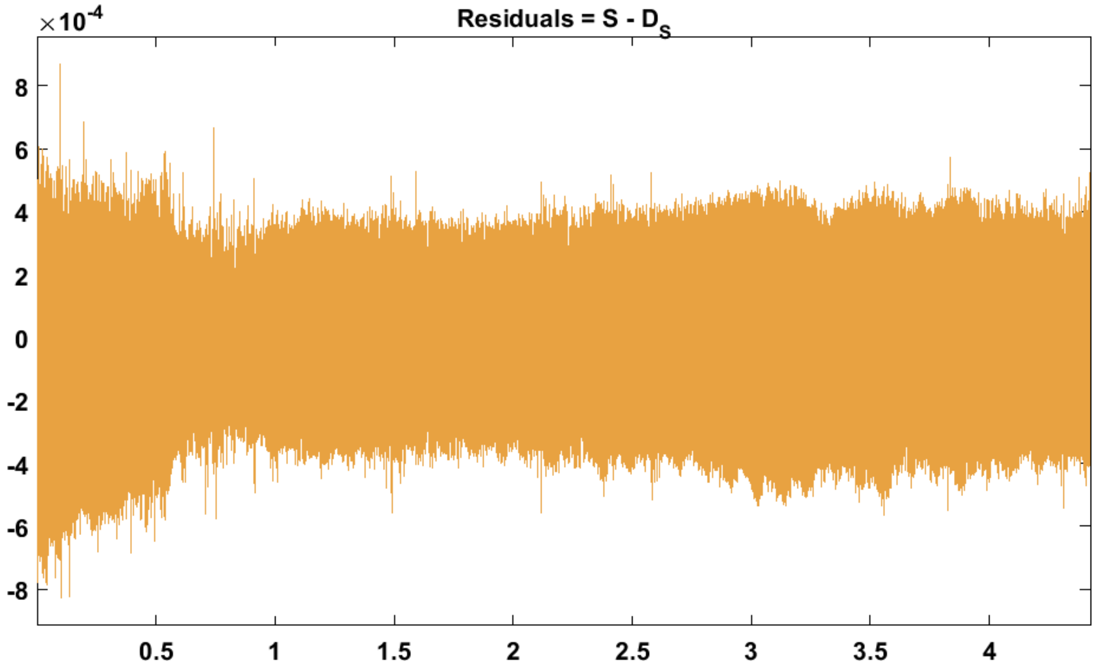


fig 17: Residual signal

Figure 15 and 16 shows the signal captured from the abnormal person and its de-noised signal. Figure 17 shows the residual signal after the original movement has been de-noised.

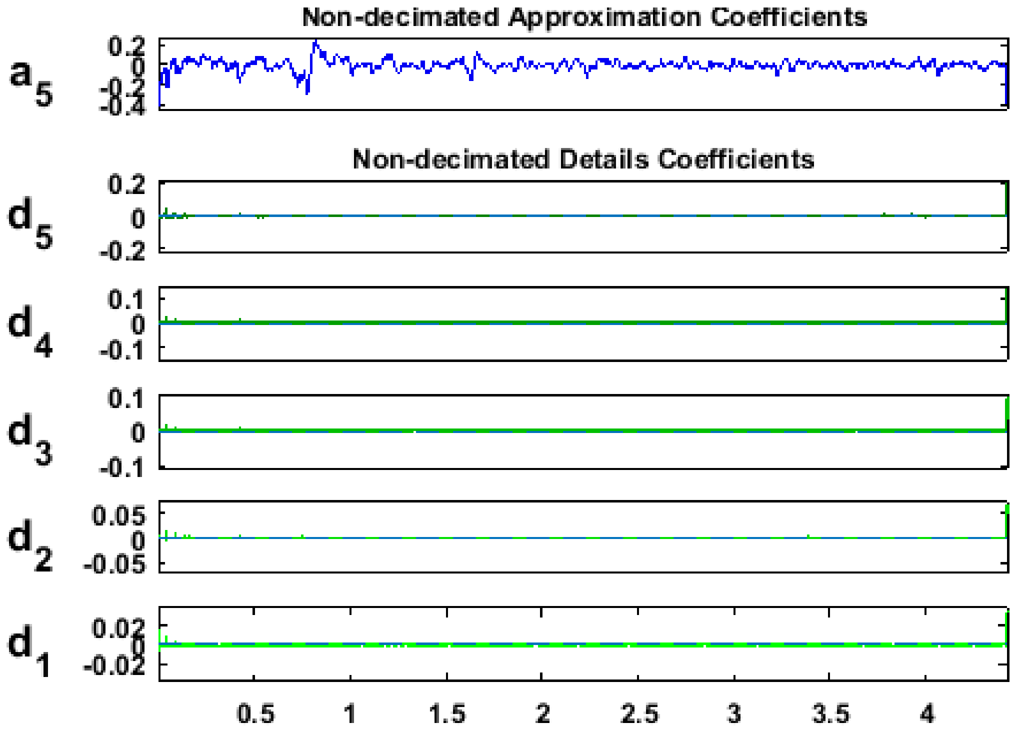


fig 18: Approximation and Details coefficients signal at 5^{th} level of signal decomposition

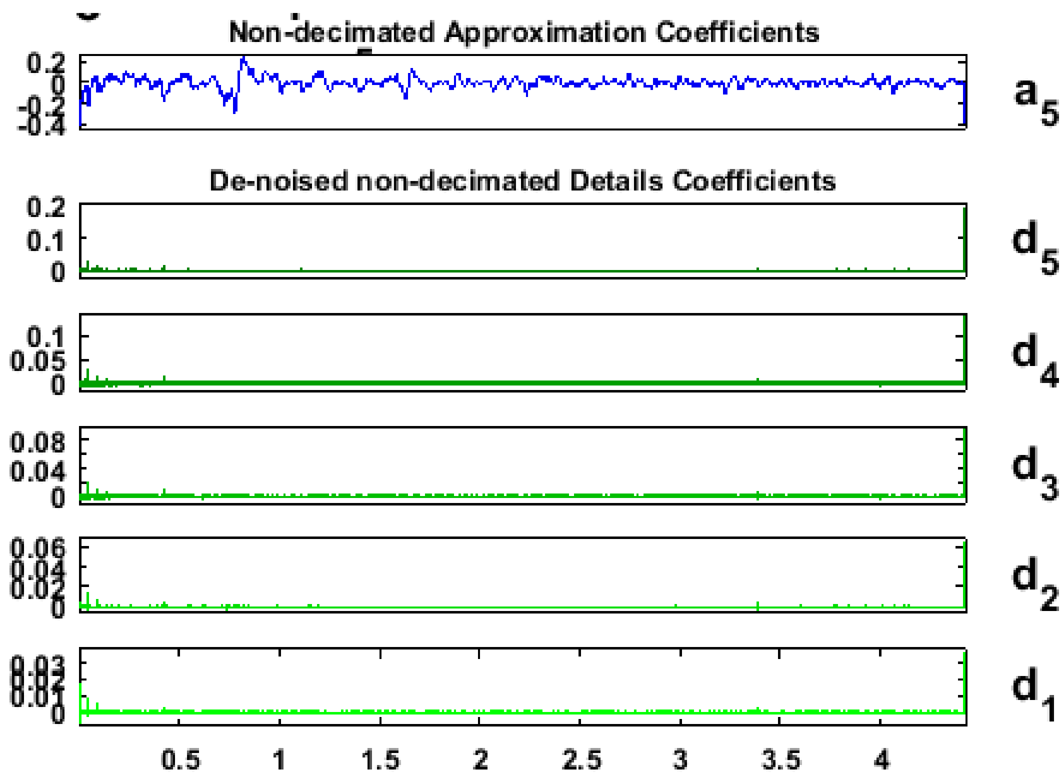


fig 19: De-noised detail coefficient signal at 5^{th} level

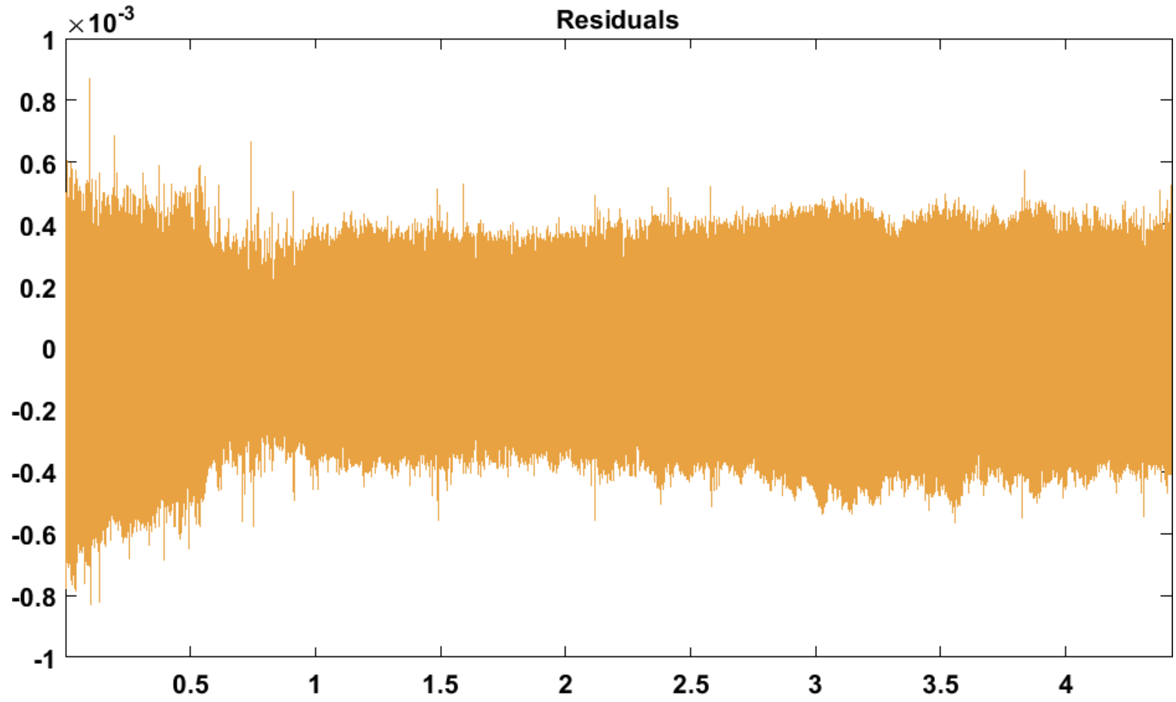
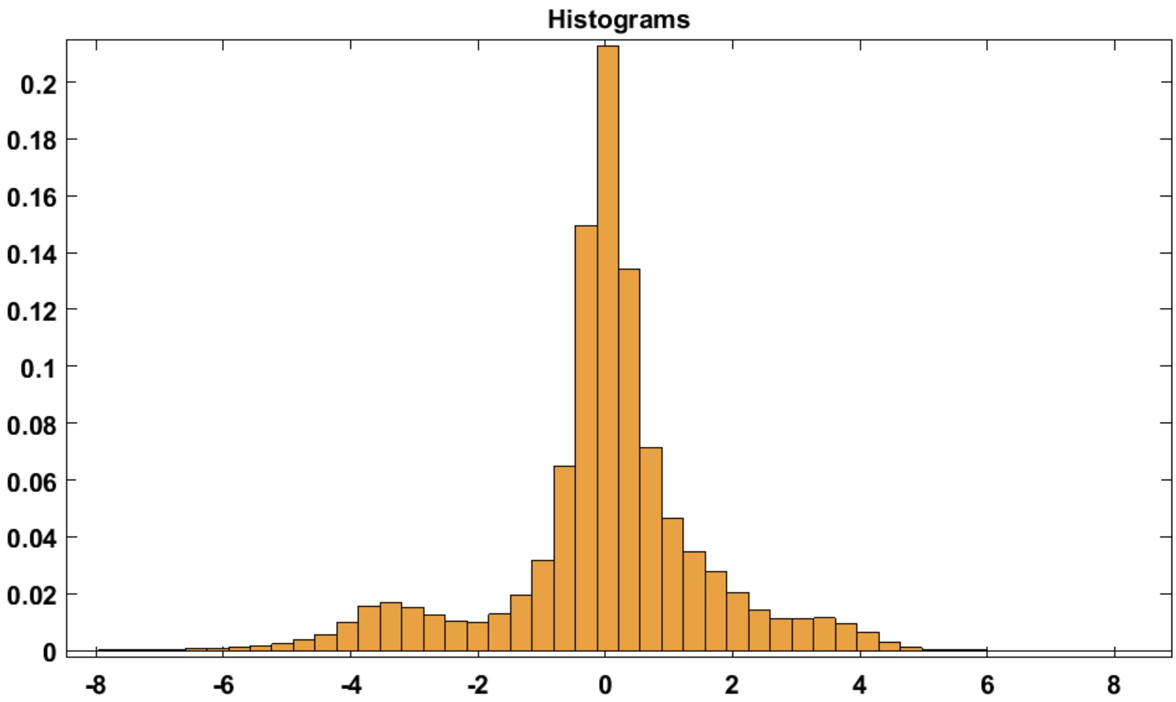


Fig 20. Residual at the 5th level

Figures 18 and 19 show the non-decimated approximation and details coefficient signals when captured at the 5th level of decomposition. Figure 20 shows the residual signal at this 5th level.



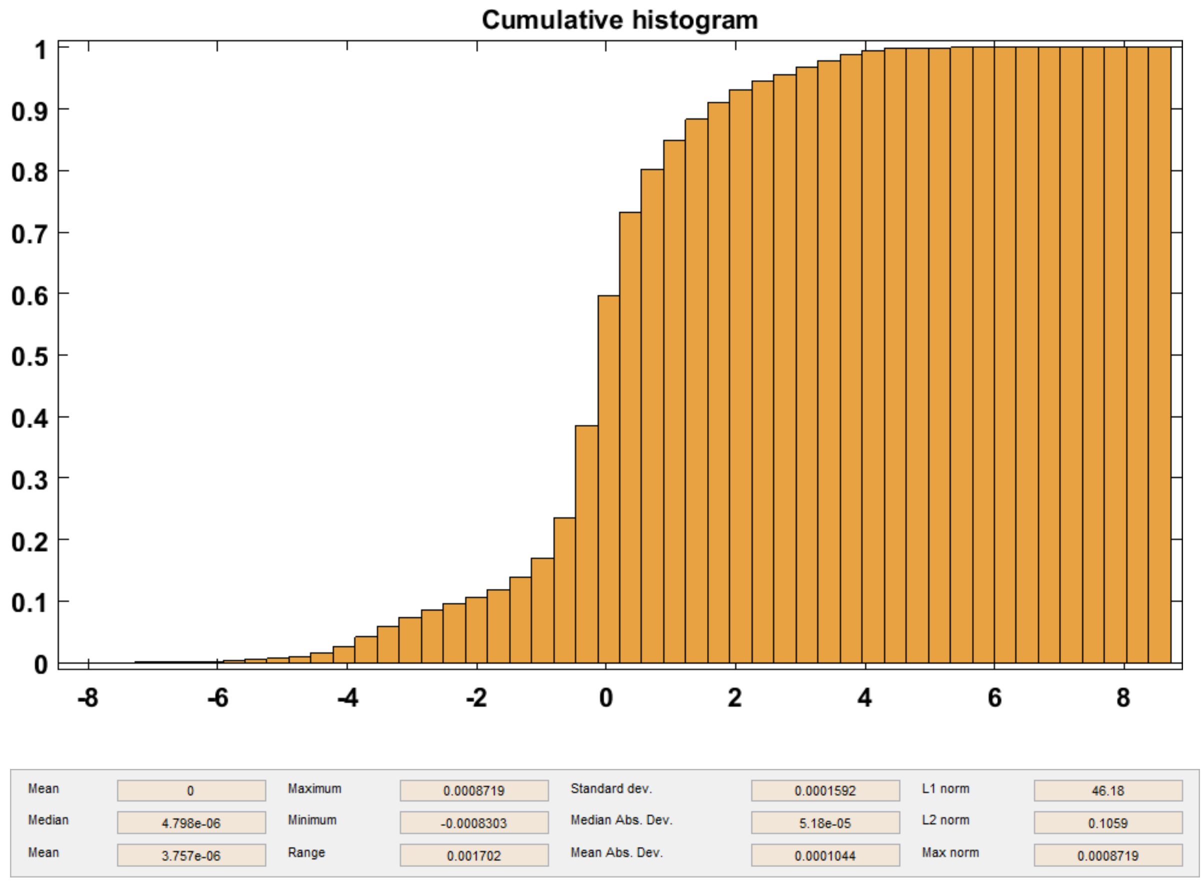


fig 21: Histogram and Cumulative histogram of abnormal signal

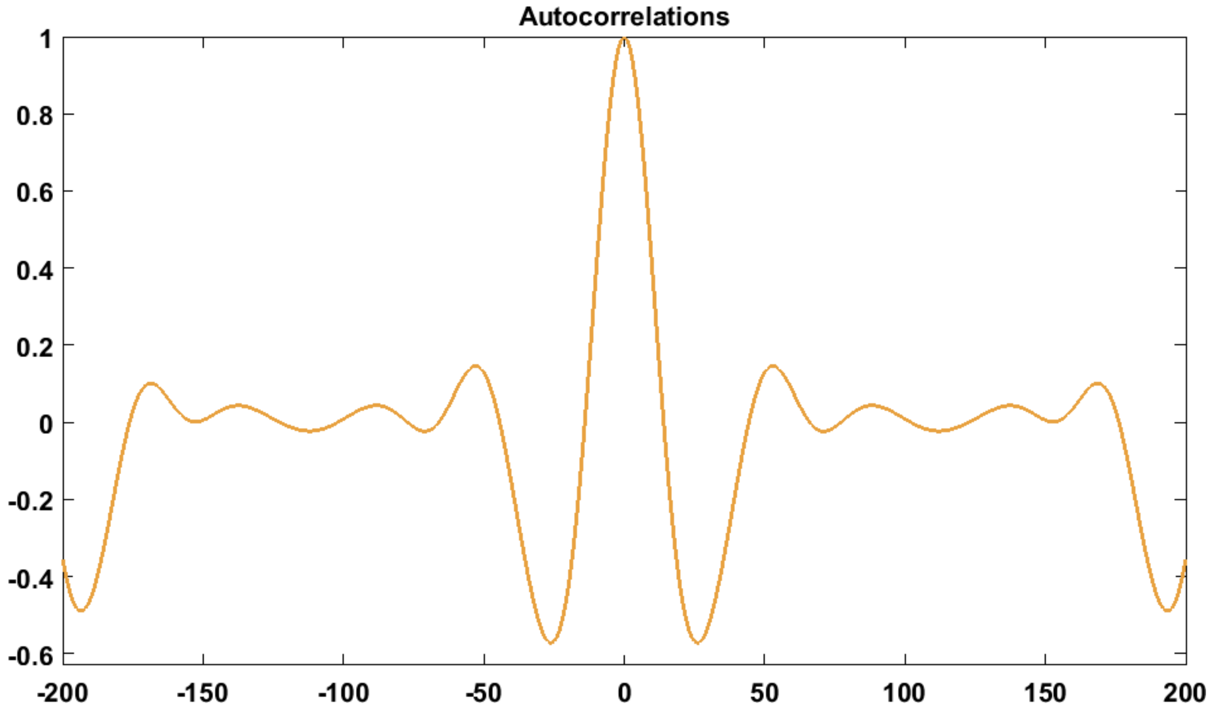


fig 22: Autocorrelation signal

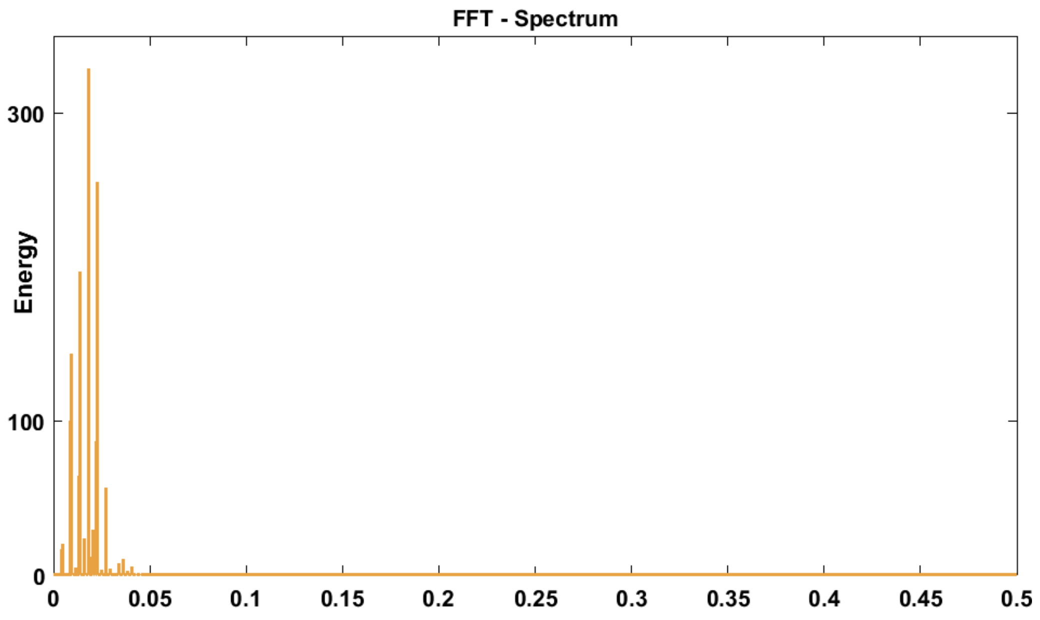


Fig 23. FFT analysis of abnormal signal

Figure 21 shows the histogram and cumulative histogram of captured abnormal signal. Figures 22 and 23 show the autocorrelation and FFT of abnormal movements.

Table 2. Comparison of normal and abnormal signal values after SWT analysis.

Signal parameters	Normal	Abnormal
Mean	0	0
Median	-4.733e-05	4.798e-06
Mean	-0.0002279	3.757e-06
Maximum	0.01481	0.0008719
Minimum	-0.01719	-0.0008303
Range	0.032	0.001702
Standard Dev.	0.0004396	0.0001592
Median Abs. Dev.	0.0001754	5.18e-05
Mean Abs. Dev.	0.0002888	0.0001044
L1 norm	127.8	46.18
L2 norm	0.2924	0.1059
Maximum norm	0.01719	0.0008719

The various parameters such as mean, median, maximum, minimum, standard deviation of both normal signal and the abnormal signal were obtained from the SWT technique as shown above.

Comparison of DWT and SWT:

Figures 2, 9 and 4, 19 show that the changes in approximation and detail coefficient waveforms variation have been delivered. The SWT shows the variation in that waveforms even at a lower level when compared to DWT.

From Figures 3 and 12, we can see that the distribution of frequency level throughout the signal has been clearly shown after SWT analysis compared to DWT analysis.

5. CONCLUSION

In this paper, the saline EEG electrode senses the impulse signals from the brain of schizophrenia and normal patients. Then it was subjected to the SWT technique for further analysation. When compared these results with the DWT technique, the SWT technique produced the more accurate parameters such as mean, median, standard deviation, etc. The variation in the waveforms can be visible even at a lower level in SWT than DWT. From this output received, after the analysis of signals captured by the new saline EEG electrode, we can easily and quickly predict the condition and brain status of schizophrenia patients.

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