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Epileptic MEG Spikes Detection Using Common Spatial Patterns and Linear Discriminant Analysis

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ABSTRACT Epilepsy is a brain disorder, where patients' lives are extremely disturbed by the occurrence of sudden unpredictable seizures. This paper develops patient-independent signal processing techniques based on common spatial patterns and linear discriminant analysis to detect epileptic activities (spikes) from multi-channel brain signal recordings. In contrast to current existing studies which heavily rely on the analysis of electroencephalogram (EEG) data for the detection of epileptic activities, this research work considers magnetoencephalography (MEG) recordings for the detection of epileptic spikes. This requires careful development since unlike EEG spikes, MEG spikes do not have well-defined morphological characteristics. Due to the recent advances in MEG technology, it became possible to consider MEG signals to detect and analyze epileptic activities, but efforts to develop signal processing tools in this area are still in its outset, as compared with those devoted to EEG signal processing.

INDEX TERMS Epileptic spikes detection, MEG, common spatial patterns, linear discriminant analysis.

I. INTRODUCTION

Epilepsy is a neurological disorder which is rampant in 1% of the world population, and this disorder is classified as the second most serious neurological disease known to humanity, after stroke [1]. The brain activities hold great promise for monitoring and analyzing neurological disorders. Studies of epilepsy often rely on the EEG signals in order to analyse the behaviour of the brain activities during seizures. However, EEG signals are strongly degraded due to absorption of the head tissues. The advances in MEG technology have created a new source of information for brain activities which can be investigated solely or with the aid of EEG signals. On the contrary to EEG signals, MEG signals are less noisy and not attenuated by the brain tissues [2].

MEG is a neurophysiological examination procedure that uses a superconducting quantum interference device (SQUID) for measuring brain signals. Spikes and sharp waves in MEG signals can be used to facilitate diagnosis of epilepsy. MEG spikes are more clearly distinguishable as compared to EEG spikes, from background activity and appear to be sharper [3]. The MEG signals are of multi-channel nature. Few works have been performed on MEG signals for brain activity analysis, due to the limited number of MEG machines available around the world, due to their high cost.

The most common approach for detecting spikes from brain signals is by visual scanning of recordings. Locating the epileptic spikes in MEG recordings manually is very laborious and time consuming [4]–[6]. Note that the high density of MEG sensors provides a good representation of the magnetic field distribution over the scalp. However, the high number of MEG sensors (~300) makes visual inspection time-consuming, as it is impossible to display and evaluate so many channels simultaneously. Furthermore, visual inspection is mainly a subjective method, which can lead to disagreement among different neurologists analyzing the same data [7]. Therefore, in order to overcome the drawbacks caused by manual inspections, automatic detection of epileptic spikes, based on objective criteria, would be beneficial for quantitative analysis and clinical diagnosis.

There are many algorithms to detect epileptic spikes from EEG data, but the objective of this paper is to develop spikes detector for MEG data. The proposed algorithm consists of features extractor followed by classifier, carefully selected to take into account the inherent characteristics of MEG signals. Specifically, this study shows that

1) The common spatial patterns (CSP) can effectively be used to capture discriminating features from MEG spikes which, unlike EEG signals, do not have well-defined morphological characteristics.
2) The CSP features, derived from actual MEG data, reasonably follow normal distribution. Therefore, linear discriminant analysis (LDA) can be used for classification; LDA is well-suited for applications where features are normally distributed [8].

CSP algorithm obtains spatial filters that can be used for the discrimination between two classes of signals. The obtained filters must guarantee maximization of the variance of one class of signals, while minimizing that of the other class [9]. LDA, on the other hand, is a simple, mathematically robust classification method which searches for a linear combination of predictors that best separates different classes.

In this study, the MEG data is captured from 20 epileptic patients at the National Neuroscience Institute (NNI), King Fahad Medical City (KFMC), Riyadh, Saudi Arabia. The proposed spikes detection algorithm achieves 91.03% sensitivity and 94.21% specificity; therefore, it is is a valuable tool for neurologists dealing with MEG data for proper clinical diagnosis.

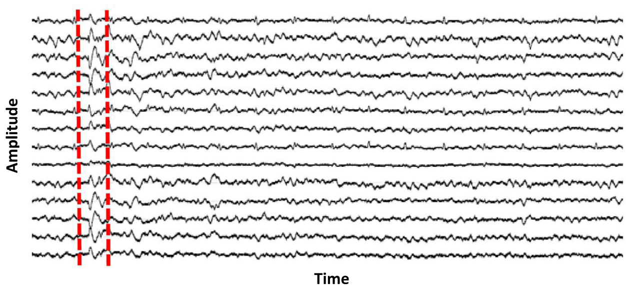


FIGURE 1. MEG recordings of an epileptic patient.

II. SPIKE DETECTION METHODS

Fig.1 shows MEG recordings from left temporal brain region of an epileptic patient. The areas between the dotted red lines in Fig. 1 are the spiky regions of MEG data. Note that MEG spikes are usually shorter in duration and have a steeper ascending slope as compared to EEG spikes. MEG signals also have a higher signal-to-noise ratio (SNR) for more superficial sources than that of EEG, which indicates MEG is more suitable for accurate localization of neocortical epileptiform sources [10], [11]. Consequently, interictal MEG is increasingly used in epilepsy pre-surgical evaluation. MEG localization of interictal spike zone has shown excellent agreement with intracranial video-EEG [12], [13]. Therefore, MEG signals typically provide interictal and intraictal but rarely ictal information. The commonly used methods for the detection of spikes are described next. These methods have been widely studied for spikes detection in EEG recordings. However, they can serve here to pave the road and provide the necessary background for the development of MEG spikes detection algorithms.

A. AMPLITUDE THRESHOLDING

It is the simplest method for detection of spikes. A spike is detected when the signal amplitude exceeds a user-defined threshold. Spikes with different morphologies and similar amplitudes are not distinguishable by this method. The performance of this method is sensitive to the selected threshold and degrades rapidly due to many sources of noise [4], [5], [14], [15].

B. TEMPLATE MATCHING

Template matching, which is often used in image processing, is another method to detect spikes. In this method, the waveform with a typical spike shape is first selected as a template. Second, this template is used to locate possible close matches in the signal and, finally, detected matches of templates are marked as spikes [14], [15].

C. SIGNAL TRANSFORMATIONS

The third approach uses signal transformations such as nonlinear energy operator (NEO or NLEO). It calculates the energy content of the signal. NEO enhances the signal where a spike is located and suppresses the other parts of the signal. DWT (discrete wavelet transforms), FD (Fractal dimension), Kalman Filter (KF), Singular Spectrum Analysis (SSA) and Empirical Mode Decomposition (EMD) also transform the signals so that useful features can be extracted for classification [6], [16]–[20].

III. MEG SPIKES DETECTION ALGORITHM

The proposed MEG spikes detector makes use of two algorithms: the CSP algorithm for features extraction and LDA for classification. Below, we give brief description for these two algorithms.

A. THE CSP ALGORITHM

The main idea of CSP algorithm is to obtain spatial filters that can be used for the discrimination between two classes of signals; in our case spikes and non-spikes signals. The obtained filters must guarantee maximization of the variance of one class of signals, while minimizing that of the other class [20], [21].

Let $\boldsymbol{D}_i = \left\{\boldsymbol{d}_i^1, \boldsymbol{d}_i^2, \boldsymbol{d}_i^3, \ldots, \boldsymbol{d}_i^n, \ldots, \boldsymbol{d}_i^{N_i}\right\}$ be the data sets of class i, $i = 1, 2$. Each data set $\boldsymbol{d}_i^n$ is of size $q \times p$ and N_i is the total number of data sets of class i. The parameter q denotes the number of MEG channels and p denotes the number of samples per channel. The output of CSP filters for class i, $\boldsymbol{S}_i^n$, is a matrix of size $q \times p$, which is given by

$$\boldsymbol{S}_i^n = \boldsymbol{\omega}^T \boldsymbol{d}_i^n \tag{1}$$

The spatial filters $\boldsymbol{\omega}$ are obtained by extremizing the following $J(\boldsymbol{\omega})$ function [9],

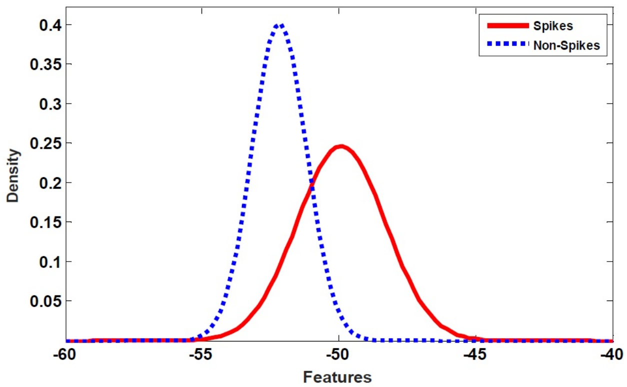
$$J(\boldsymbol{\omega}) = \boldsymbol{\omega}^T \boldsymbol{C}_1 \boldsymbol{\omega} \tag{2}$$

subject to the constraint $\omega^T C_2 \omega = I$, where T denotes transpose and C_i is given as follows.

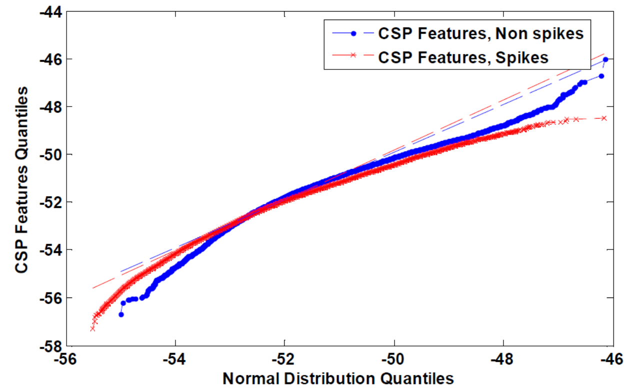
$$C_i = \frac{1}{N_i} \sum_{n=1}^{N_i} \left(d_i^n\right) \left(d_i^n\right)^T \tag{3}$$

C_1 and C_2 are $q \times q$ spatial covariance matrices of class 1 (spikes signals) and class 2 (non-spikes signals). This optimization problem can be solved by extremizing Eq. 2 using the method of Lagrange multipliers, the spatial filters ω are then the eigenvectors of $P = C_2^{-1} C_1$ [9]. Let $x_i^{n,k}$ be the k^{th} element of $q \times 1$ feature vector x_i^n, and $s_i^{n,k}$ be the k^{th} row of matrix S_i^n. Therefore, the element $x_i^{n,k}$ is calculated as follows.

$$x_i^{n,k} = log \left(\frac{var\left(s_i^{n,k}\right)}{\sum_{k=1}^{q} \left(var\left(s_i^{n,k}\right)\right)} \right) \tag{4}$$



(a)



(b)

FIGURE 2. (a) Pdfs of CSP features extracted from spike and non-spike data segments. (b) *qq*-plot of CSP features.

Fig. 2(a) shows the pdfs of all CSP features conbined together in vector $V_i = \{x_i^{n,1}, x_i^{n,2}, \ldots, x_i^{n,k}, \ldots, x_i^{n,q}\}_{n=1}^{N_i}$. The CSP features are obtained from 48 spike and non-spike data segments of real MEG data. Fig. 2(b) shows the quantile-quantile *qq*-plot of CSP features. This figure compares the features of class 1(class 2) on the vertical axis to normal data, having the same mean and variance of class 1(class 2), on the horizontal axis. The approximate linearity of quantile points suggests that both classes are closely follow the normal distribution. Next, we introduce the LDA which is known to be a good choice for the binary classification of normally distributed data [8].

B. LINEAR DISCRIMINANT ANALYSIS

We use LDA to classify MEG data into two classes; signals with spikes and signals without spikes. Classification is often performed through a learning process in which a training set is used to provide observations (features) with known labelling of their classes.

LDA is a simple, mathematically robust classification method based on selecting the class having the highest posteriori probability. In LDA, the data is assumed to follow a normal distribution. In principle, LDA searches for a linear combination of predictors that best separates different classes. For a two-class problem, LDA maximizes the Fisher criterion defined as [22],

$$J\left(\beta\right) = \frac{\beta^T X_B \beta}{\beta^T X_W \beta} \tag{5}$$

where $\beta = \left[\beta_1, \beta_2, \beta_3, \ldots, \beta_q\right]^T$ is a $q \times 1$ discriminant vector, X_B is the between classes scatter matrix, and X_W is the within classes scatter matrix. Let μ_i be a $q \times 1$ mean vector of class i. That is,

$$\mu_i = \frac{1}{N_i} \sum_{n=1}^{N_i} x_i^n \tag{6}$$

The scatter for each class is defined as

$$X_i = \sum_{n=1}^{N_i} \left(x_i^n - \mu_i\right) \left(x_i^n - \mu_i\right)^T \tag{7}$$

Therefore, the definitions of scatter matrices are as follows.

$$X_B = \left(\mu_1 - \mu_2\right)\left(\mu_1 - \mu_2\right)^T \tag{8}$$
$$X_W = X_1 + X_2 \tag{9}$$

Therefore, the unknown weighting coefficients β of linear model can be shown to have the form [22],

$$\beta = X_W^{-1} \left(\mu_1 - \mu_2\right) \tag{10}$$

The weighting coefficients vector β is the normal to the discriminant hyperplane. The features to be discriminated are projected onto β. That is,

$$y^n = \beta^T x_i^n \tag{11}$$

Because projections of features from both classes exhibit approximately the same distributions, as shown in Fig. 2(a), therefore, the threshold c, against which y^n is compared, can be set as follows.

$$c = \frac{1}{2}\boldsymbol{\beta}^T(\boldsymbol{\mu}_1 + \boldsymbol{\mu}_2) \tag{12}$$

C. TRAINING AND TESTING

The proposed detection algorithm has two stages; training phase and testing phase, as shown in Fig. 3.

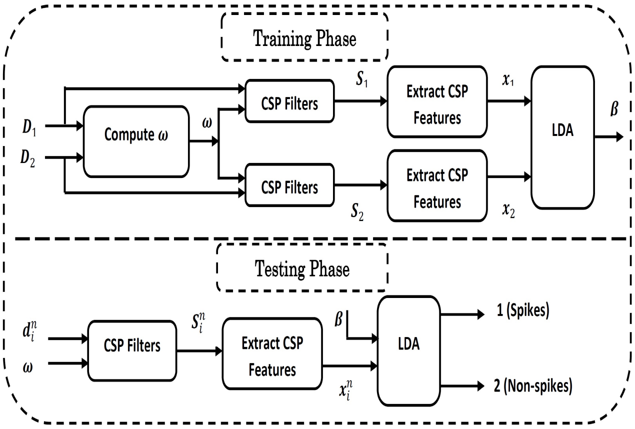


FIGURE 3. **MEG spikes detection methodology. S_i, x_i are the filtered outputs and feature vectors from all data sets, respectively.**

In the training phase, MEG data sets $\boldsymbol{D}_i$ are first used to determine the CSP filters, $\boldsymbol{\omega}$. Each data set $\boldsymbol{d}_i^n$ is of size $q \times p$. where $q = 26$ (corresponding to the number of sensors of one region of the brain as will be described in Section 4) and $p = 100$ (approximating the duration of a MEG spike). The MEG data sets are then filtered by $\boldsymbol{\omega}$. Features are extracted from the filtered MEG data sets according to Eq. 4, and then used to determine LDA weighting coefficients $\boldsymbol{\beta}$ for the purpose of classification.

In the testing phase, MEG data set $\boldsymbol{d}_i^n$ is filtered by $\boldsymbol{\omega}$, which is determined during the training phase. Features are extracted from data set, and then applied to the LDA, with the previously determined parameters for classification.

Leave-one-out cross-validation (LOOCV) method is used to evaluate the performance of the classifier. In one round of this method, N data segments are partitioned into two sets: $N-1$ data segments for training and one data segment for testing. N rounds of cross-validation method are performed by changing each time the data segment under test. In our work, a data segment is of length 15 minutes, where at least 10 spikes exist. The performance of proposed spikes detection algorithm is then evaluated by taking the average of all N validation results.

IV. MEG DATA RECORDING AND ANNOTATION

MEG data was recorded in a shielded room at NNI-KFMC with an Elekta Neuromag system. The MEG signals are much weaker than normal environmental magnetic noise. The shielded room blocks the majority of environmental magnetic fields so that the magnetic fields generated by the brain can be detected. Elekta Neuromag head system (helmet) contains 102 magnetometer and 204 gradiometer sensors. These sensors are further categorized according to the different brain regions.

Clinically, brain is divided into eight regions; left temporal, right temporal, left frontal, right frontal, left parietal, right parietal, left occipital, and right occipital. Each element of the Elekta Neuromag system comprised of three sensors, one magnetometer and two gradiometers.

Magnetic brain activity was recorded at a sampling frequency of 1 kHz. MEG data was filtered by tSSS (Spatiotemporal signal space separation) method [23]. The data were then off-line band-pass filtered 1–50 Hz for visual inspection.

A total of 49 MEG data segments, each of 15 minutes duration and 26 channels, were taken from 20 epileptic patients. These segments are analyzed by expert neurologists from NNI, KFMC, Riyadh. The neurologists marked the MEG spikes locations, in different brain regions, by visual inspection. The total number of spikes in these recordings is 391.

TABLE 1. **MEG spikes of an epileptic patient, annotated by KFMC neurologists.**

#	Time (Peak) (in Seconds)	Spike Duration (Start - End) (in Seconds)	Lobe of Interest
1	171.114	171.068_171.125	Right Frontal
2	253.492	253.476_253.547	Right Frontal
3	291.559	291.545_291.596	Right Frontal

As mentioned earlier, there are 306 sensors to cover the whole head. These sensors are further marked according to the brain regions. Table 1 shows the annotation of three MEG spikes of an epileptic patient, marked by KFMC neurologists. Specifically, for each spike, the table provides information about the location of its peak, its duration, and in which region of head it is located.

V. RESULTS AND DISCUSSION

Sensitivity and specificity are the two most widely used metrics for the performance evaluation of binary classification problems. Sensitivity is a performance metric representing the ratio of number of times the classifier makes correct positive decisions (i.e., detects spikes) to the total number of positive decisions it made. Specificity, on the other hand, is the ratio of number of times the classifier makes correct negative decisions (i.e., detects spikes-free segments) to the total number of negative decisions it made [24].

In this study, sensitivity and specificity of the classifier are calculated by LOOCV procedure. We use the spike and non-spike data sets from 48 data segments for training and leave the spike and non-spike data sets of the remaining data segment for testing. We repeat this process by changing each time the data segment under test, following the LOOCV methodology.

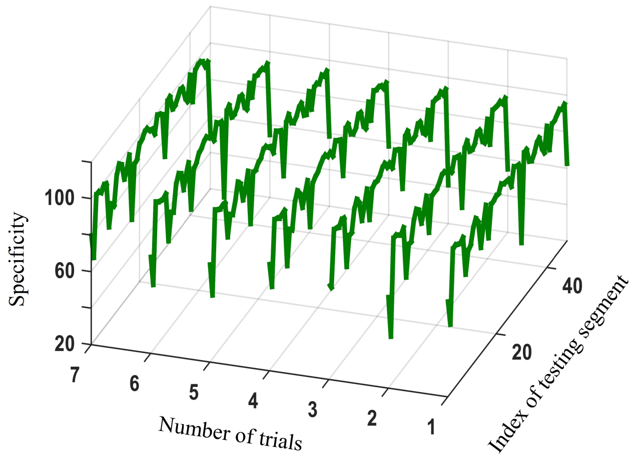


FIGURE 4. Specificity of each testing segment for all trials of LOOCV method.

TABLE 2. Performance of the MEG spikes detection algorithm.

Trial No.	Sensitivity	Specificity
1	90.258	94.199
2	90.769	93.875
3	91.560	94.281
4	90.491	94.415
5	90.514	94.562
6	90.304	94.250
7	92.327	93.889
Average	91.032	94.210

To study the effect of selecting spike-free data sets on the performance of proposed algorithm, we compute the specificity 7 times for each data segment under test by randomly selecting the spike-free data sets during the training phase. Fig. 4 shows the specificity computed for the 49 data segments when the spike-free data sets get changed 7 times during the training phase. It can be seen that specificity patterns are almost the same for all trials. That is, random selection of the non-spike data sets during the training phase does not affect the performance of the classifier. The overall performance of the classifier is shown in Table 2. The average sensitivity and specificity obtained from data segments of 20 patients and 7 trials, each of which is trained with different non-spike data sets, are 91.03% and 94.21%, respectively.

VI. CONCLUSION

With the recent advances in MEG technology, MEG devices started to gain popularity worldwide in analyzing brain activities. This study proposes a CSP-LDA based MEG spikes detection algorithm for epileptic subjects. We have demonstrated using real data that the proposed detection algorithm can achieve high sensitivity and specificity in a patient-independent data setting. In particular, the work here shows that a CSP-LDA based spikes detection algorithm can achieve 91.03% sensitivity and 94.21% specificity when applied to MEG data. The developed MEG spikes detection algorithm has the potential to help neurologists to analyze MEG data in a timely manner instead of spending considerable time to detect MEG spikes by visual inspection.

REFERENCES

[1] J. Engel, *Seizures and Epilepsy*, vol. 83. Oxford, U.K.: Oxford Univ. Press, 2013.

[2] J.-M. Schoffelen and J. Gross, ''Source connectivity analysis with MEG and EEG,'' *Human Brain Mapping*, vol. 30, no. 6, pp. 1857–1865, 2009.

[3] P. Ossenblok, J. C. De Munck, A. Colon, W. Drolsbach, and P. Boon, ''Magnetoencephalography is more successful for screening and localizing frontal lobe epilepsy than electroencephalography,'' *Epilepsia*, vol. 48, no. 11, pp. 2139–2149, 2007.

[4] S. B. Wilson and R. Emerson, ''Spike detection: A review and comparison of algorithms,'' *Clin. Neurophysiol.*, vol. 113, no. 12, pp. 1873–1881, 2002.

[5] J. J. Halford, ''Computerized epileptiform transient detection in the scalp electroencephalogram: Obstacles to progress and the example of computerized ECG interpretation,'' *Clin. Neurophysiol.*, vol. 120, no. 11, pp. 1909–1915, 2009.

[6] N. Acır, İ. Öztura, M. Kuntalp, B. Baklan, and C. Güzeliş, ''Automatic detection of epileptiform events in EEG by a three-stage procedure based on artificial neural networks,'' *IEEE Trans. Biomed. Eng.*, vol. 52, no. 1, pp. 30–40, Jan. 2005.

[7] A. S. Gevins and A. Rémond, *Methods of Analysis of Brain Electrical and Magnetic Signals*, vol. 1. Amsterdam, The Netherlands: Elsevier, 1987.

[8] M. Spiliopoulou, L. Schmidt-Thieme, and R. Janning, *Data Analysis, Machine Learning and Knowledge Discovery*. Switzerland: Springer, 2014.

[9] F. Lotte and C. Guan, ''Regularizing common spatial patterns to improve BCI designs: Unified theory and new algorithms,'' *IEEE Trans. Biomed. Eng.*, vol. 58, no. 2, pp. 355–362, Feb. 2011.

[10] A. Hillebrand and G. R. Barnes, ''A quantitative assessment of the sensitivity of whole-head MEG to activity in the adult human cortex,'' *NeuroImage*, vol. 16, no. 3, pp. 638–650, 2002.

[11] D. M. Goldenholz *et al.*, ''Mapping the signal-to-noise-ratios of cortical sources in magnetoencephalography and electroencephalography,'' *Human Brain Mapping*, vol. 30, no. 4, pp. 1077–1086, 2009.

[12] R. C. Knowlton and J. Shih, ''Magnetoencephalography in epilepsy,'' *Epilepsia*, vol. 45, no. s4, pp. 61–71, 2004.

[13] R. C. Knowlton, ''Can magnetoencephalography aid epilepsy surgery?'' *Epilepsy Currents*, vol. 8, no. 1, pp. 1–5, 2008.

[14] S. Kim and J. McNames, ''Automatic spike detection based on adaptive template matching for extracellular neural recordings,'' *J. Neurosci. Methods*, vol. 165, no. 2, pp. 165–174, 2007.

[15] Z. Ji *et al.*, ''An automatic spike detection system based on elimination of false positives using the large-area context in the scalp EEG,'' *IEEE Trans. Biomed. Eng.*, vol. 58, no. 9, pp. 2478–2488, Sep. 2011.

[16] A. Tzallas, P. S. Karvelis, C. D. Katsis, D. I. Fotiadis, S. Giannopoulos, and S. Konitsiotis, ''A method for classification of transient events in EEG recordings: Application to epilepsy diagnosis,'' *Methods Inf. Med.*, vol. 45, no. 6, pp. 610–621, 2006.

[17] İ. Güler and E. D. Übeyli, ''Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients,'' *J. Neurosci. Methods*, vol. 148, no. 2, pp. 113–121, 2005.

[18] K. P. Indiradevi, E. Elias, P. Sathidevi, S. D. Nayak, and K. Radhakrishnan, ''A multi-level wavelet approach for automatic detection of epileptic spikes in the electroencephalogram,'' *Comput. Biol. Med.*, vol. 38, no. 7, pp. 805–816, 2008.

[19] T. P. Exarchos, A. T. Tzallas, D. I. Fotiadis, S. Konitsiotis, and S. Giannopoulos, ''EEG transient event detection and classification using association rules,'' *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, no. 3, pp. 451–457, Jul. 2006.

[20] M. Adjouadi *et al.*, ''A new mathematical approach based on orthogonal operators for the detection of interictal spikes in epileptogenic data,'' *Biomed. Sci. Instrum.*, vol. 40, pp. 175–180, Dec. 2003.

[21] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, ''Optimal spatial filtering of single trial EEG during imagined hand movement,'' *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 8, no. 4, pp. 441–446, Dec. 2000.

[22] M. Welling, ‘‘Fisher linear discriminant analysis,’’ Ph.D. dissertation, Dept. Comput. Sci., Univ. Toronto, Toronto, ON, Canada, 2005.

[23] S. Taulu and J. Simola, ‘‘Spatiotemporal signal space separation method for rejecting nearby interference in MEG measurements,’’ *Phys. Med. Biol.*, vol. 51, no. 7, p. 1759, 2006.

[24] M. I. Khalid, S. A. Aldosari, S. A. Alshebeili, T. Alotaiby, M. H. Al-Hameed, and L. Jad, ‘‘MEG data classification for healthy and epileptic subjects using linear discriminant analysis,’’ in *Proc. IEEE Int. Symp. Signal Process. Inf. Technol. (ISSPIT)*, Dec. 2015, pp. 360–363.

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