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Epileptic MEG Spikes Detection Using Amplitude Thresholding and Dynamic Time Warping

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ABSTRACT Epilepsy is a brain disorder that may strike at different stages of life. Patients' lives are extremely disturbed by the occurrence of sudden unpredictable epileptic seizures. A possible approach to diagnose epileptic patients is to analyze magnetoencephalography (MEG) signals to extract useful information about subject's brain activities. MEG signals are less distorted than electroencephalogram signals by the intervening tissues between the neural source and the sensor (e.g., skull, scalp, and so on), which results in a better spatial accuracy of the MEG. This paper aims to develop a method to detect epileptic spikes from multi-channel MEG signals in a patient-independent setting. Amplitude thresholding is first employed to localize abnormalities and identify the channels where they exist. Then, dynamic time warping is applied to the identified abnormalities to detect the actual epileptic spikes. The sensitivity and specificity of proposed detection algorithm are 92.45% and 95.81%, respectively. These results indicate that the proposed algorithm can help neurologists to analyze MEG data in an automated manner instead of spending considerable time to detect MEG spikes by visual inspection.

INDEX TERMS Epileptic spikes detection, MEG, dynamic time warping, amplitude thresholding.

I. INTRODUCTION

A. BACKGROUND

Brain disorders are one of the most serious health problems faced by society. Brain related research has gained increasing attention during recent years [1], [2]. A new source of information about brain activities, which can be investigated solely or with the aid of EEG signals, has been created due to the recent advances in MEG technology. The presence of abnormality in the brain signals triggered the interest in the field of MEG when, in 1972, the first MEG measurement of brain signals was conducted with the help of superconducting quantum interference devices (SQUIDs) [3]. The recording of these tiny magnetic fields generated by the brain in a magnetically shielded environment was made possible due to the Josephson's effect which occurs at very low temperatures. Earlier, in 1960, experiments were conducted to record magnetic fields produced by the brain using copper coils wound around ferromagnetic cores [4].

Until 1990, the use of MEG technology was limited because of the small number of sensors used to cover only part of the head. Now, MEG instrumentation with more than 300 channels covering the whole head are available [5]. The advancement in MEG scanners and associated ease of recordings facilitated many new applications and studies [6]–[13]. The MEG technology can acquire information about brain function and epileptic discharges with higher spatial resolution than EEG can do [14], [15]. However, MEG technology has constraints on recording duration and vulnerability to artifacts caused by the subject's movement during seizure [16]. Therefore, it should be emphasized that both modalities (EEG and MEG) are complementing each other.

One of the main differences between MEG and EEG thought to be that MEG is mainly sensitive to tangentially oriented sources and is insensitive to radial sources, whereas EEG can detect sources of all orientations. A radially oriented current source produces no magnetic field outside a spherically symmetric volume conductor. However, since the human head is not exactly spherically symmetric, the radial orientation is not well defined, and an approximately radial source in the brain is not necessarily silent in MEG.

In general, any finite source in the brain will have a range of orientations and it would therefore generate a magnetic field that will be detectable by MEG. Moreover, only very few ($<5\%$) cortical sources are expected to have the orientation of the lowest sensitivity (close to radial) in MEG [17].

B. EEG AND MEG SPIKES

Morphology of spike and sharp waves in EEG signals was analyzed by Gotman [18]. These waves can be used to facilitate diagnosis of epilepsy. For MEG spikes, there is not yet a formal definition [19]. The direct application of criteria developed to define EEG spikes may not always be valid for MEG spikes [20]. However, as compared to EEG spikes, MEG spikes are more clearly distinguishable from the background activity and appear to be sharper [21]. Recent studies reveal that the characteristics of EEG and MEG epileptiform spikes are different. The coincident events of EEG and MEG are statistically different with respect to several morphological features such as duration, sharpness, and shape. One explanation for these differences comes from the fact that the propagation of MEG signals is less distorted by the skull and scalp [22]–[24]. Furthermore, muscle or eye movement artefacts can perplex EEG, particularly at higher frequencies [25], while MEG is less susceptible to these issues [26].

C. MOTIVATION FOR SPIKES DETECTION

Due to recent advances in MEG technology, this utility has now become a clinically significant diagnostic tool in presurgical assessment for both the localization of epileptogenic zone and the forecast of surgical outcomes [27]–[29]. A good representation of the magnetic field distribution over the scalp can be obtained due to the high density of MEG sensors. Because MEG machines are limitedly available around the world, few works have been performed on MEG signals for brain activity analysis. The most common approach for spikes detection from MEG signals is the visual scanning of recordings. This is very laborious and time consuming [30]–[32]. In addition, it is difficult to display and evaluate high number of MEG sensors (more than 300) simultaneously. Furthermore, visual inspection is mainly a subjective method, which can lead to disagreement among different neurologists analyzing the same data [33]. Therefore, automatic detection of epileptic spikes, based on objective criteria, can reduce the drawbacks caused by manual inspection and it would be beneficial for quantitative analysis and clinical diagnosis.

D. PAPER'S CONTRIBUTION

This paper is concerned with the detection problem of interictal epileptic spikes in MEG signals. Several algorithms have been developed in the past for automatic spikes detection; e.g., amplitude thresholding [30], [31], [34], [35], template matching [35]–[38], and signal transformation [39]–[42]. These methods are mainly devoted to EEG signals, possibly due to the lack of public MEG databases enabling testing and evaluation of developed algorithms. Therefore, MEG spikes detection is still an open area for research.

Few MEG spikes detection methods are considered in the literature and, to the best of our knowledge, only two methods are available. The first is developed in [43], where the authors presented a multi-channel MEG spikes localization method. This method uses independent component analysis (ICA) to decompose spike-like and background components into separate spatial topographies and associated time series. Then, a simple thresholding technique is applied to the most spiky independent components for detection purposes. Recently, a patient-independent MEG spikes detection technique based on common spatial patterns (CSP) and linear discriminant analysis (LDA) has also been reported in [44]. Note that both detection algorithms make use of subspace decomposition based techniques for features extraction but they differ in the classification stage. The use of LDA classification in [44] provides a significant performance improvement compared to the simple thresholding used in [43].

In this study, we develop a novel MEG epileptic spikes detection algorithm, which considers the detection of MEG spikes using amplitude thresholding followed by DTW. Amplitude thresholding is used to extract any significant activity of spiky nature in the MEG data. DTW is then applied to all spiky segments of MEG data that passed pre-defined thresholds.

DTW is a distance measure, often employed under the assumption that pre-defined templates are available for similarity computations and matching. In this work, we show how to select the appropriate amplitude thresholds and how to use DTW to detect MEG spikes without a prior knowledge of standard pre-defined MEG spike templates. Note that, unlike EEG spikes, MEG spikes do not have well-defined morphological characteristics.

Performance of the proposed algorithm is evaluated using real data. The results show that it has better performance compared with the previously published work [43], [44]. The MEG data considered here is captured from 30 epileptic patients at the National Neuroscience Institute (NNI), King Fahad Medical City (KFMC), Riyadh, Saudi Arabia. Written informed consent was signed by each participant or responsible adult before they participated in the study. The study was conducted in accordance with the approval of the Institutional Review Board at KFMC (IRB log number: 15-086, 2015). The proposed algorithm is of a potential value for neurologists dealing with MEG data for proper clinical diagnosis.

II. MEG DATA RECORDING AND ANNOTATION

In this work, MEG data was recorded with Elekta Neuromag system (Elekta Neuromag Oy, Helsinki, Finland) in a shielded room due to the nature of the MEG signals, as they are much weaker than normal environmental magnetic noise. MEG sensors were separated into eight non-overlapping sets roughly covering the Left Temporal (LT), Right Temporal (RT), Left Frontal (LF), Right Frontal (RF), Left Parietal (LP), Right Parietal (RP), Left Occipital (LO), and Right Occipital (RO) areas of the head.

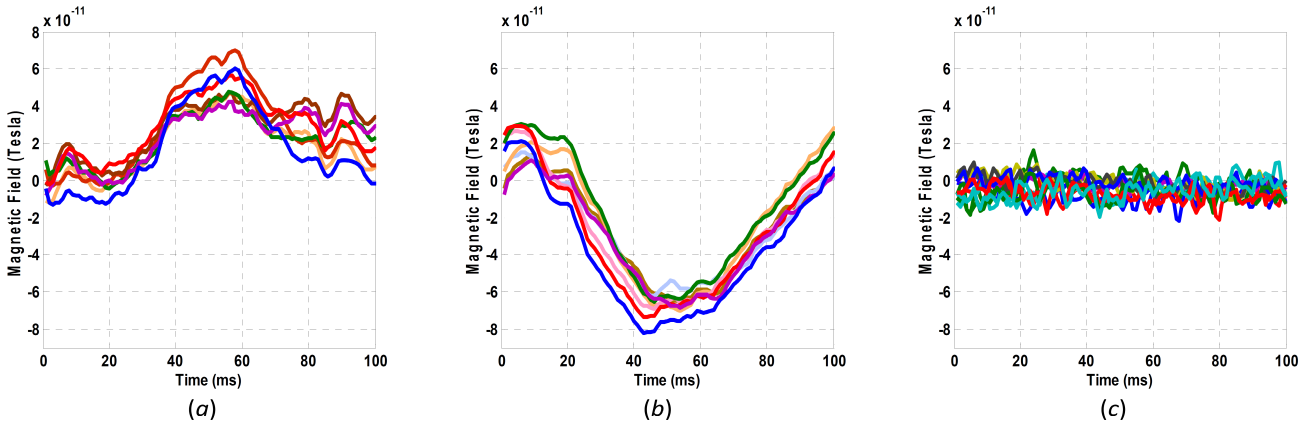

FIGURE 1. Multi-channel 100 ms segment of: (*a*) Epileptic spikes with positive peaks taken from left temporal brain region channels (*b*) Epileptic spikes with negative peaks taken from right frontal brain region channels (c) Spike-free signals taken from left temporal brain region channels.

The MEG signals were pre-processed offline using the temporally-extended signal space separation (tSSS) and movement correction algorithms, implemented in Maxfilter software of Elekta Neuromag system to suppress external and internal interferences, and compensate for subjects head movement during the recording [45], [46]. The MEG data were collected from patients in resting-state supine position at a sampling frequency of 1000 Hz and band-pass of 0.03 to 330 Hz using a 306-channel (102 magnetometers and 204 planar gradiometers) whole-head MEG system (Vectorview; Elekta Neuromag Oy, Helsinki, Finland) at the KFMC MEG Unit. In synchrony with the MEG, 21-channel electroencephalogram (EEG, international 10-20 system), electrooculogram (EOG) and electrocardiogram (ECG) were also recorded.

The MEG signals were then band-pass filtered between 1 and 50 Hz for visual inspection, and examined together with the concurrent 21-channel EEG data by at least one MEG/EEG technician and one neurology consultant, following the standard principles established for clinical EEG. The epileptic spikes were identified in 10 s consecutive windows, based on their morphological and temporal characteristics [19]. The spatial distribution of MEG signals over the sensors was used only to exclude the artifactual events (e.g., when only a single sensor exhibits the spike, etc.). The well-defined epileptic spikes and their durations were then marked from the artifact-free data segments based on the clinical practice guidelines published by the American Clinical Magnetoencephalography Society [47].

Thirty patients with focal epilepsy were selected from the KFMC epilepsy MEG database for this study; see Table 1. The selection of patients was based on the reliability of the spikes found in MEG data and concordant diagnosis: only patients with multiple (>6) clear spikes in MEG data that were concordant with the independent clinical diagnoses were selected. A total of 224 15-minute 26-channel noise-free MEG data records taken from the epileptic patients have been analyzed in the current study. The total number of epileptic spikes marked by the experts in these recordings was 630.

TABLE 1. Sex, Nationality, Ages, and Number of patients whose data belongs to a particular brain region in the MEG database.

Sex	Ages (in years)	Nationality	Brain Regions							
			LT	RT	LF	RF	LP	RP	LO	RO
Male	14 - 43 23.33±9.05	Saudi	5	4	2	3	3	1	3	1
Female		Saudi	3	3	1	0	1	0	0	0

III. MEG SPIKES DETECTION ALGORITHM

The proposed MEG spikes detector makes use of two methods: Amplitude thresholding and DTW. Below, we give brief description for these two methods.

A. AMPLITUDE THRESHOLDING

Amplitude thresholding is a method in which a spike is detected when the signal amplitude exceeds a user defined threshold. A possible approach to determine the thresholds is by analyzing the probability density functions (PDFs) of background and MEG spikes. Note that MEG channels of an epileptic patient may carry spikes with peaks of positive or negative values as shown in Fig. 1(a) and (b). Epileptic spikes of Fig. 1 are taken from channels of left temporal and right frontal brain regions of one epileptic patient. Fig. 1(c) shows spike-free signals taken from the channels of left temporal region of same epileptic patient.

In our analysis, we divide the MEG data into segments of fixed lengths of 100 ms that reasonably approximate the duration of a MEG spike. The lenght is selected based on the analysis of spikes durations, provided by KFMC neurologists. Fig. 2 shows the histogram of spikes durations of all epileptic

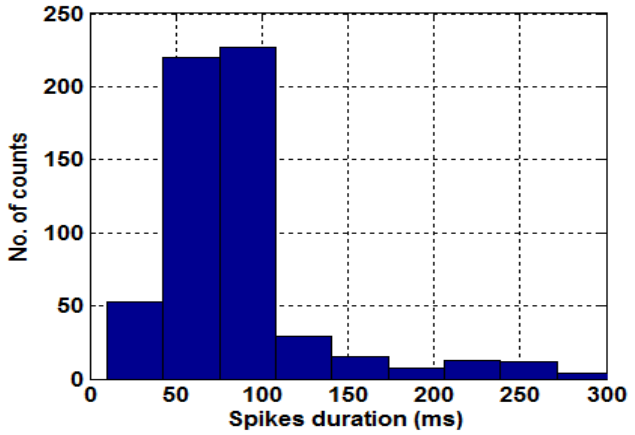

FIGURE 2. Distribution of spikes durations of epileptic patients.

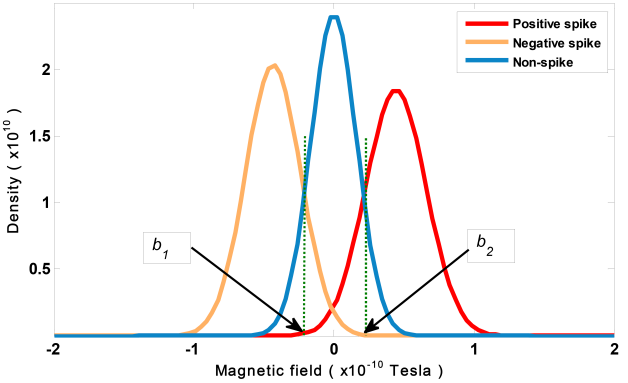

FIGURE 3. PDFs of peaks with positive and negative values and that of background segments.

patients used in this study, from which we can observe that most of the spikes have duration less than 100 ms with the most frequent being between 50-100 ms. Therefore, this justifies our choice of 100 ms data segments.

Let $\boldsymbol{\beta} = [b_1, b_2]$ be the amplitude thresholds. These thresholds are calculated from points of intersections of the two PDFs belonging to the spikes with positive and negative peaks and that of spike-free signals, as shown in Fig. 3. Note that spike-free signals do not refer to signals from normal subjects, but rather to spike-free segments of signals recorded from patients with epilepsy.

Each PDF displayed in Fig. 3 is obtained by fitting the PDF of a normal distribution to the corresponding histogram of MEG data of 10 randomly selected patients. Therefore, if a segment has samples of values greater than b_1 or less than b_2, then it will be considered a MEG spike candidate.

Amplitude thresholding alone does not serve the purpose because it has high false alarms. That is, spikes with different morphological characteristcs and similar amplitudes are indistinguishable. Therefore, DTW is introduced next to identify the actual MEG spikes from the extracted spiky segments that passed the amplitude thresholding. The proposed DTW algorithm is novel in that it does not need standard predefined templates to work.

B. DYNAMIC TIME WARPING

DTW has been used in biomedical applications to classify signals into different categories by comparing the signals with standard templates [48], [49]. Often, templates are extracted from the biomedical signals of interest, like EEG and ECG signals. Because MEG spikes have no definite spike morphology like EEG signals, here, we use DTW in a different manner; it measures the similarities among the channels which already passed amplitude thresholding. If the similarities among the channels are high, then the segment under consideration is declared spike; otherwiswe, it is declared background. In our development, we provide quantitative approach to tell when similarities among channels are considered high.

DTW allows a non-linear mapping of one signal to another by minimizing the distance between two signals. The basis behind DTW is to stretch or compress two given time series so as to make one resembles the other as much as could reasonably be expected [50].

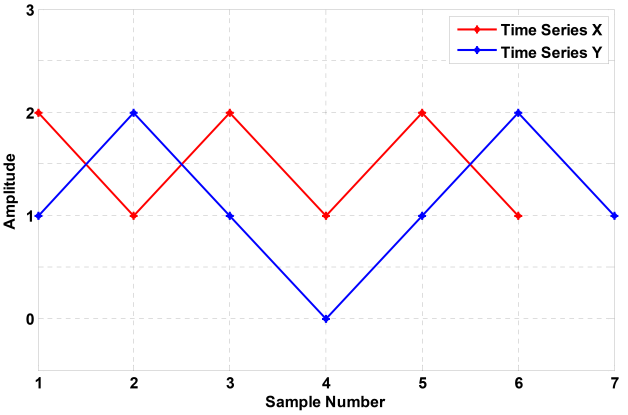

FIGURE 4. Time series X and Y.

Consider two time series sequences $\boldsymbol{X}$ and $\boldsymbol{Y}$ of lengths e and f, respectively, where

$$\boldsymbol{X} = [x_1, x_2, x_3, \ldots, x_g, \ldots, x_e] \quad (1)$$

$$\boldsymbol{Y} = [y_1, y_2, y_3, \ldots, y_h, \ldots, y_f] \quad (2)$$

For illustration purposes, we set $\boldsymbol{X}$ and $\boldsymbol{Y}$ as shown in Fig. 4. Table II(a) gives a distance matrix whose entries are defined as $d(x_g, y_h) = |x_g - y_h|^2$, where x_g and y_h are the g^{th} and h^{th} elements of $\boldsymbol{X}$ and $\boldsymbol{Y}$ sequences, respectively. For computations of DTW, we need to determine the elements $\alpha(g, h)$ of accumulated distance matrix given in Table II(b). Entries of this matrix are computed progressively starting from the upper left corner according to the following relation.

$$\alpha(g, h) = d(x_g, y_h) + min \left\{ \begin{matrix} \alpha(g-1, h-1), \\ \alpha(g-1, h), \alpha(g, h-1) \end{matrix} \right\} \quad (3)$$

$\alpha(g, h)$ is the sum of $d(x_g, y_h)$ and the minimum value of the three adjacent cells belonging to $\alpha(g, h)$.

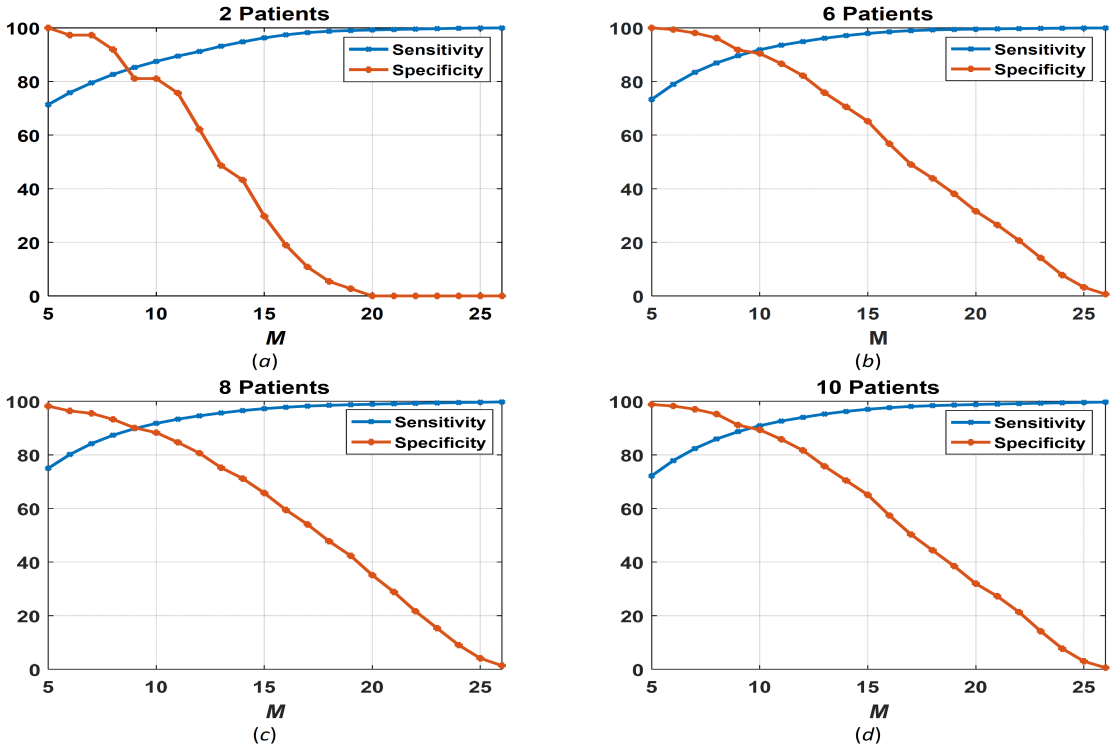

FIGURE 5. (*a-d*) Sensitivity and Specificity of threshold-based spikes detector for MEG data of 2, 6, 8, 10 patients as a function of parameter *M*.

TABLE 2. (*a*) Distance matrix of X and Y. (*b*) Accumulated distance matrix of X and Y.

X \ Y	1	2	1	0	1	2	1
2	1	0	1	4	1	0	1
1	0	1	0	1	0	1	0
2	1	0	1	4	1	0	1
1	0	1	0	1	0	1	0
2	1	0	1	4	1	0	1
1	0	1	0	1	0	1	0

(a)

X \ Y	1	2	1	0	1	2	1
2	1	1	2	6	7	7	8
1	1	2	1	2	2	3	3
2	2	1	2	5	3	2	3
1	2	2	1	2	2	3	2
2	3	2	2	5	3	2	3
1	3	3	2	3	3	3	2

(b)

A warping cost function $DTW(\boldsymbol{X}, \boldsymbol{Y})$ is defined as [51]

$$DTW(\boldsymbol{X}, \boldsymbol{Y}) = min\left\{\sum_{l=1}^{L} m_l\right\} \tag{4}$$

where m_l is the l^{th} element of a warping path. A warping path is a contiguous set of matrix elements that represent a mapping between $\boldsymbol{X}$ and $\boldsymbol{Y}$. The warping path that minimizes the warping cost function $DTW(\boldsymbol{X}, \boldsymbol{Y})$ is retrieved. In Table II(b), this path is highlighted in green color.

The selection of an optimum warping path follows some restrictions. Let (g_l, h_l) be the index of l^{th} element of a warping path. Therefore, [51]

a) The warping path should be monotonically spaced in time. That is,

$$g_{l-1} \leq g_l$$
$$h_{l-1} \leq h_l$$

b) The elements of the warping path should be adjacent to each other. That is,

$$g_l - g_{l-1} \leq 1$$
$$h_l - h_{l-1} \leq 1$$

c) For equal length sequences, the warping path should be as close as possible to the diagonal of accumulated distance matrix, with

$$m_1 = \alpha\,(1, 1)$$
$$m_L = \alpha\,(e, f)$$

The length of the warping path is minimum if it lies along the diagonal of accumulated distance matrix. Closeness of the path to the matrix diagonal corresponds to greater similarity between the two time series.

C. PARAMETERS ESTIMATION

The proposed spike detection algorithm requires estimation of certain parameters from given data sets captured from different patients. For parameters estimation, MEG data sets are divided into d ($d = 1, 2, 3, \ldots$) segments. Each segment, $\boldsymbol{S}^d$, is of size $q \times p$, where $q = 26$ (corresponding to the number of gradiometers of one region of the brain) and $p = 100$ (approximating the number of samples of a MEG spike). For the LO and RO regions, the number of gradiometer sensors is 24. Therefore, we add two zero-value channels to each region in order to facilitate systematic processing of algorithms steps. The processing is performed segment by segment, as follows.

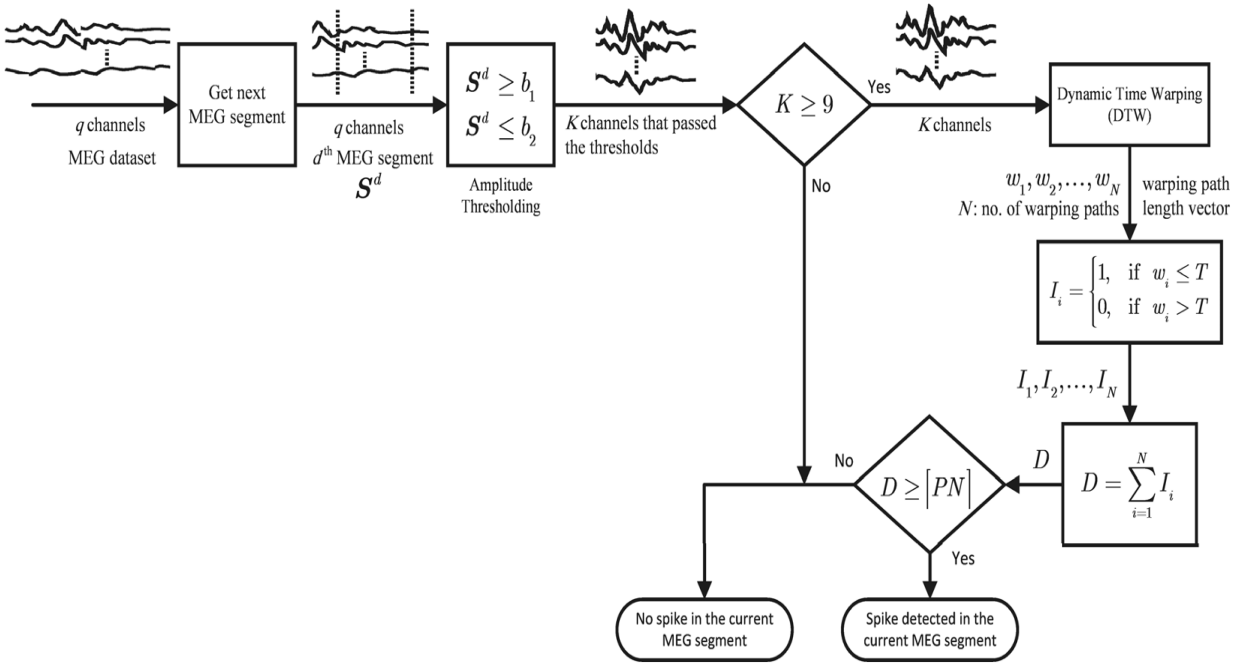

FIGURE 6. MEG spike detection algorithm.

I) We determine the amplitude thresholds $\boldsymbol{\beta} = [b_1, b_2]$, as described in Fig. 3, by computing the PDFs from the given data. We pass each segment of q channels through the amplitude thresholding. Let K be the number of channels whose data passed the thresholds. If $K \geq M$, where $M \leq q$, then we go to the next step of applying the DTW. Otherwise, the current segment is considered as background. Fig. 5 shows the sensitivity and specificity of spikes detector as a function of M, if only the amplitude thresholding is employed and $K \geq M$. The sensitivity is defined as 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, and specificity is the ratio of number of times the classifier makes correct negative decisions (i.e., detects spike-free segments) to the total number of negative decisions it made [52]. The results are displayed when MEG data of 2,6,8 and 10 patients are used in the computations of sensitivity and specificity. It can be inferred from the figures that by increasing M, the sensitivity increases whereas the specificity decreases. The results are almost consistent in that choosing the value of $M = 9$ strikes a good balance between the sensitivity and specificity as far as the amplitude thresholding is concerned. It can also be concluded from Fig. 5 that utilizing more data from different patients does not show significant change with respect to the value of M at which the sensitivity and specificity curves intersect. Therefore, from now on, $M = 9$ or equivalently $K \geq 9$ will be employed. A data set of 10 different patients, each with 15-min recordings, should be sufficient for the estimation phase.

TABLE 3. Estimated parameters for all trials of the spike detection algorithm.

Trial No.	b_1	b_2	T	P
1	2.50e-11	-2.50e-11	160	0.5
2	2.46e-11	-2.46e-11	160	0.55
3	2.52e-11	-2.52e-11	155	0.5
4	2.45e-11	-2.45e-11	160	0.5
5	2.50e-11	-2.50e-11	160	0.55
6	2.45e-11	-2.45e-11	155	0.5
7	2.51e-11	-2.51e-11	160	0.5
8	2.47e-11	-2.47e-11	160	0.55
9	2.50e-11	-2.50e-11	155	0.5
10	2.50e-11	-2.50e-11	160	0.5
Average	2.49e-11	-2.49e-11	158	0.52
Standard Deviation	2.59e-13	2.59e-13	2.41	0.024

II) We apply DTW to a particular segment if the number of channels, which passed the thresholds, is greater than or equal to 9 (i.e. $K \geq 9$). DTW is used to measure the similarity between the channels of MEG segment under consideration. DTW gives the similarity measure, called warping path, between two channels. By comparing each channel with the remaining $K - 1$ channels, a total of $N = C_2^K$ warping paths are calculated. That is,

$$N = C_2^K = \frac{K!}{(K-2)!2!}, \quad K \geq 9 \tag{5}$$

TABLE 4. Performance of the MEG spikes detection algorithm.

Trial No.	Sensitivity			Specificity		
	Proposed MEG spike detector	CSP-LDA [44]	ICA based spike detector [43]	Proposed MEG spike detector	CSP-LDA [44]	ICA based spike detector [43]
1	92.810	86.230	90.075	95.475	89.910	80.654
2	92.256	85.190	89.165	95.310	88.736	81.115
3	91.890	89.745	83.278	96.478	89.154	79.945
4	92.670	84.375	86.926	95.987	90.455	80.178
5	92.110	87.125	87.114	96.145	91.165	82.961
6	91.760	86.865	84.546	95.836	90.805	83.155
7	92.768	85.276	85.167	95.916	89.390	80.678
8	91.829	84.115	86.465	95.109	90.565	79.145
9	92.115	89.655	89.128	95.770	91.645	80.275
10	92.593	85.530	86.455	96.105	92.015	83.865
Aggregated value	**92.455**	**86.145**	**86.915**	**95.813**	**90.384**	**81.197**

Let $\boldsymbol{W}$ be the warping path length vector whose entries are $w_i, i = 1, 2, \ldots, N$. That is, w_i is the length of the i^{th} warping path. The value of w_i varies between 100 and 199 because the duration of a channel of a given segment is 100 ms. The smaller is the value of w_i, the higher is the similarity between two channels of a given segment. Let $I_i = 0$ or 1 such that

$$I_i = 1, \quad if\ w_i \leq T$$
$$I_i = 0, \quad if\ w_i > T$$

where T may take values between 100 and 199 inclusively. Also, let

$$D = \sum_{i=1}^{N} I_i \tag{6}$$

D represents the number of entries of $\boldsymbol{W}$, whose values are less than or equal to T. Therefore, a segment is declared a spike if $D \geq P'\%$ of N. That is,

$$Spike\ if\ :\ D \geq \lceil NP \rceil$$
$$NonSpike\ if\ :\ D < \lceil NP \rceil$$

where $P = P'/100$. The two parameters T and P are unknown and need to be estimated from a given data. First, we compute the sensitivity (Se) and specificity (Sp) of proposed detection algorithm by varying the values of T and P such that

$$100 \leq T \leq 199$$
$$0.1 \leq P \leq 1$$

In our work, the parameter T is changed by step of 5 and parameter P by step of 0.05. The best pair (T, P) satisfying the following conditions are then chosen for the evaluation phase.

a) Both $Se(T, P)$ and $Sp(T, P) \geq 90\%$. This is to ensure high performance.
b) Value of T is as small as possible. This is to ensure high similarities among channels.
c) Value of P is as maximum as possible. This is to ensure the presence of large number of similar channels.

Fig. 6 shows the flow of proposed spikes detection algorithm.

IV. PERFORMANCE EVALUATION

The performance of proposed detection algorithm is evaluated using 30 epileptic patients for 10 trials. In each trial, data of 10 randomly selected epileptic patients is used for estimating the parameters $\boldsymbol{\beta}$, T and P. The data of remaining 20 patients is used for evaluation. Table III shows the estimated parameters for all trials. Table IV shows the corresponding sensitivities and specificities of the proposed algorithm, CSP-LDA algorithm recently developed in [44], and and ICA algorithm of [43]. Note that the value of threshold in [43] is determined, from the training data, at the point where the sensitivity and specificity curves versus threshold intersect. We adopted this method for selecting the threshold in order to conduct fair comparisons with our proposed approach, which does the same in determining the parameter M pertaining to the number of spiky channels.

In reference to Table III, we observe that the standard deviations of estimated parameters are relatively small compared to the average values. Further, the estimated parameters from all trials led to high sensitivities and specificities with low variablities among trials, as shown in Table IV. Therefore, the estimated parameters of any trial (or possibly the average values of all trials) can be used in the spike detection algorithm, described in Fig. 6, in a patient-independent setting. The aggregated sensitivity and specificity, obtained from randomly selected data of 20 epileptic patients for 10 trials,

are 92.45% and 95.81%, respectively. However, the aggregated sensitivity and specificity of CSP-LDA algorithm [44], obtained for the same randomly selected data of 20 epileptic patients for 10 trials, are 86.14% and 90.38%, respectively. That is, the DTW algorithm outperforms the CSP-LDA algorithm in terms of both sensitivity and specificity when the parameters were estimated from data of 10 patients. This conclusion is also true when the DTW algorithm is compared with ICA-based spikes detection algorithm presented in [43]. The aggregated sensitivity and specificity of ICA algorithm obtained using the same data of 20 epileptic patients for the 10 trials are 86.915% and 81.197%, respectively. Note that the superior performance of DTW algorithm over the CSP-LDA and ICA algorithms are intuitively not surprising because the ICA algorithm is based on the assumption that the spikes and coherent background components are statistically independent, and the background noise is negligible. In practice, the above conditions will not be perfectly met. The CSP-LDA, on the other hand, uses all the 26 channels of a particular region of brain for spikes detection. Because spikes may appear only in some channels, inclusion of non-spiky channels in the features extraction stage degrades the algorithm performance. However, the proposed algorithm performs detection by exploiting the temporal characteristics of data to perform template matching in an adaptive (data-dependent) manner. That is, it considers the data segment under processing as the current template and exploits the presence of epileptic spikes in multiple (not necessarily all) channels to perform detection.

V. CONCLUSION

With the recent advances in MEG technology, MEG devices started to gain popularity worldwide in analyzing brain activities. This study proposes an amplitude thresholding and DTW based MEG spikes detection algorithm for the purpose of diagnosing 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 the proposed spikes detection algorithm can achieve 92.45% sensitivity and 95.81% 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.

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