SeizureNet: A Deep Convolutional Neural Network for Accurate Seizure Type Classification and Seizure Detection

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1 Introduction

Epilepsy is a neurological disorder which affects almost 1% of the world’s population. Epilepsy causes sudden and unforeseen seizures which can result in suffocation, critical injury, or even death of the patient. One third of the epileptic patients do not have appropriate medical treatments available. For the remaining two thirds of the patients, the treatment options vary due to the fact that seizure semiology is different for every epileptic patient. An important technique to diagnose epilepsy is through visual inspection of electroencephalography (EEG) recordings by physicians to analyse activities of the brain for any abnormalities. This task is time-consuming, inefficient, and subject to inter-observer variability. With the advancements in IoT-based data collection, machine learning based automated systems have been developed. They promote standardization in seizure analysis by reducing inter-observer variability, and allow better management of the disease through more efficient and reliable patient monitoring. A typical automated system performs feature extraction from the EEG data followed by classification using a machine learning model. In this process feature extraction is the most crucial step as the extracted features capture meaningful characteristics of neural patterns from the EEG data and enable the classifier to discriminate the data into normal and abnormal neural behaviours. Furthermore, seizure semiology varies not only across different epilepsy patients but also for the same individual over time. Therefore, it is highly desirable to learn robust features from the EEG data which can generalize among different neural semiologies (e.g., among different patients).

In literature, automatic seizure detection and seizure prediction from EEG have received considerable research focus because of their importance for better understanding of epilepsy and more efficient management of the disease. For instance, [Fan and Chou, 2018] proposed the use of spectral graphs to extract spatial-temporal patterns for seizure detection. The work of [Zandi et al., 2010] proposed wavelet-transform based features to automatically distinguish between seizure and non-seizure states of the brain. The work of [Vidyaratne et al., 2016] proposed Cellular Neural Networks and Bidirectional Recurrent Neural Networks to extract temporal features for seizure analysis. The work of [Golmohammadi et al., 2017] proposed an LSTM based approach for seizure detection using the TUH EEG Corpus dataset. The work of [Hussein et al., 2018] also explored seizure detection using an LSTM based model on the EEG dataset provided by the University of Bonn. Recently, deep learning based methods [Långkvist et al., 2014; Jia et al., 2014; Thodoroff et al., 2016; Vidyaratne et al., 2016; Golmohammadi et al., 2017] have shown to outperform classical methods for learning more discriminative features from the EEG data compared to the hand crafted features. In a typical deep learning based approach, time-frequency based spectrogram representations are used for training the machine learning algorithms. These engineered representations describe the non-stationary nature of the EEG patterns and exhibit more rich information than the raw EEG signals. In this context, methods such as [Pramod et al., 2014; Turner et al., 2014] used deep belief networks applied on multi-channel EEG data for seizure detection. Other meth-
ods such as [Johansen et al., 2016; Antoniades et al., 2016; Supratak et al., 2014; Li et al., 2016] used autoencoders to automatically learn features from raw EEG data for seizure detection. The methods of [Yan et al., 2016; Lin et al., 2016] used a combination of sparse auto-encoders for feature learning and an SVM-based classifier for EEG signal classification. Methods such as [Boubchir et al., 2014a; Boubchir et al., 2014b] proposed several other hand-crafted representations (based on the mean, variance, skewness, and kurtosis of histogram spectrogram intensities) for SVM based seizure classification.

Most of the above studies apply machine learning for seizure detection or seizure prediction from the EEG data. However, an automated seizure analysis system should not be restricted to these tasks only. It should also have the capability to discriminate between different types of seizures as they are detected. This is because automatic epileptic seizure type logging has the potential to improve long-term patient care, enabling timely drug adjustments and remote monitoring in clinical trials. In [Roy et al., 2019], the authors attempted the seizure type classification task by conducting a search space exploration of various standard machine learning algorithms and pre-processing techniques. In this paper, we improve on the results reported in [Roy et al., 2019] by presenting a deep learning framework which uses an efficient dense sampling technique and convolutions with dense connections to learn highly robust features for seizure type classification from limited training data which is a common limitation in health informatics. Moreover, we present a novel visual representation of the raw time-series EEG data which combines frequency transformation of the EEG signals and their divergence information into a 3D data structure which can be used to learn highly discriminative feature representations for seizure type classification compared to hand-crafted features. Furthermore, we show that the proposed algorithm is adaptable beyond the seizure type classification task and can also produce superior performance in the seizure detection task. In summary, the main contributions of this paper are as follows:

1. We present a deep learning framework termed SeizureNet, which uses convolutional layers with dense connections and learns features from the EEG data at different spatial and temporal resolutions. Experiments show that the proposed model learns highly robust features for cross-patient seizure type classification and seizure detection without suffering from over-fitting using limited training data.

2. We present a feature representation termed Divergence-encoded Spectrograms (DivSpec) which transforms time-series EEG data into a 3D data structure that encodes information about EEG frequency transform and its divergence in the two dimensional image space.

3. We evaluate our framework on the TUH EEG Seizure Corpus [Shah et al., 2018] and present benchmark results for seizure type classification and seizure detection in cross-patient scenarios.

2 Proposed Framework

Fig. 1 shows the overall architecture of the proposed framework. It consists of two main modules. i) Divergence-encoded Spectrogram generation which transforms the time-series EEG data into a 3D structure for training a CNN model, and ii) Dense feature learning, which generates the proposed divergence-encoded spectrograms at different frequency and temporal resolutions of the EEG spectrum for seizure classification. In the following, we describe in detail the individual modules of the proposed framework.

2.1 Divergence-encoded Spectrograms

Our EEG-visual representation termed “Divergence-encoded Spectrogram” (DivSpec) consists of three 2-dimensional feature maps concatenated into an RGB-like data structure. To generate DivSpec, we first extract EEG segments by sliding a fixed-length window through the time-series EEG signals. Fig 2-A shows a sample EEG segment extracted from the EEG data with 20 channels. Next, we apply a Fast Fourier Transform (FFT) to each EEG segment to generate its time-frequency representation. Specifically, given an EEG segment \( E(c, t) \) from a channel \( c \) parameterized by time \( t \), the FFT of the segment can be computed as:

\[
FFT(c) = \int_{\infty}^{-\infty} E(c, t)e^{-2\pi it}dt
\] (1)

We compute the FFT on all 20 channels and reshape the data into a \( S \in \mathbb{R}^{p \times 20} \) dimensional map, where \( p \) denotes the number of data points contained in the EEG segment. Our second feature map encodes the divergence information of the EEG data in the time-frequency domain. It is computed by taking partial derivatives of the feature map \( S \) along \( x \) and \( y \) dimensions in the 2D image space. Mathematically, \( D(S) \) can be written as:

\[
D = \frac{\partial S_x}{\partial x} + \frac{\partial S_y}{\partial y}
\] (2)

The divergence representation \( D \) can be interpreted as \textit{Laplacian} of the electric potentials measured by EEG exhibiting a local measure of the sources and sinks of the electric field. Our third feature map \( I \) is a transformation of \( D \), where each feature value in \( D \) is replaced by the average of the values of its 8 nearest neighbours in the 2D image space. Finally, we concatenate the three feature maps \( S \), \( D \), and \( I \) into an RGB-like data structure (\( D_s \)) which is normalized to 0 to 255 range, and resized to \( 224 \times 224 \times 3 \)-dimensions. It can be written as:

\[
D_s = [\|S\|, \|D\|, \|I\|],
\] (3)

where, \( \| \cdot \| \) denotes normalization of the feature map. Our divergence-encoded spectrogram has two main benefits. **First**, the divergence information acts as a spatial filter and reduces spatial noise arising from low frequency artefacts such as eye-blinks. **Second**, the raw time-frequency signals \( S \) and their corresponding divergence information \( D \) provide complimentary information for learning discriminative features using deep learning.
2.2 Dense Feature Sampling

While deep neural networks are well suited for feature learning, deep architectures require sufficient amount of training data to effectively learn to differentiate patterns of the target classes. When confronted with limited training data which is a common issue in health informatics, deep architectures suffer from poor convergence or over-fitting. To overcome these challenges, we present a dense sampling method which extracts the proposed divergence-encoded spectrograms at different frequency and temporal resolutions of the EEG data spectrum to learn highly robust features for seizure type classification. Fig. 2-B shows an overview of the proposed dense sampling. Specifically, during the training process, the proposed sampling method generates feature representations \( \{D_s\} \) using sampling frequency \( f \in \mathcal{F} \) Hz, window length \( w \in \mathcal{W} \) seconds, and overlap percentage of \( o \in \mathcal{O} \), given by:

\[
\{D_s(f, w, o)\}, \forall f \in \mathcal{F}, \forall w \in \mathcal{W}, \forall o \in \mathcal{O},
\]

where, \( \mathcal{F} = \{12, 24, 48, 64, 96\} \) Hz, \( \mathcal{W} = \{1, 2, 4, 8, 16\} \) seconds, and \( \mathcal{O} = \{25, 50, 75\} \). By generating feature representations \( D_s \) at different frequency and spatial levels, the proposed sampling effectively captures neocortical dynamics of the brain which exhibits different characteristics at different areas of the brain as recorded by EEG. This increases variation in the training data and enables the deep learning model to learn rich and highly discriminative features for seizure type classification.

2.3 The proposed CNN model (SeizureNet)

Our model architecture consists of two sub-networks. The first sub-network is a deep convolutional network (DCN) which uses multiple convolutional layers interconnected through fuse connections and produces abstract-level feature representations from the divergence-encoded spectrogram data. The second sub-network is a classification network which uses the dense features produced by the DCN model and learns probabilistic distributions of the input data with respect to the target seizure classes. The basic building block of the DCN model is a Dense Block which is composed of multiple bottleneck convolutions interconnected through dense connections [Huang et al., 2017]. Specifically, the DCN model starts with a \( 7 \times 7 \) convolution followed by Batch Normalization (BN), a Rectified Linear Unit (ReLU), and a \( 3 \times 3 \) average pooling operation. Next, there are four dense blocks, where each dense block consists of \( N_l \) number of layers termed Dense Layers which share information from all the preceding layers connected to the current layer through fuse connections. Fig. 1-C shows the structure of a dense block with \( N_l = 6 \) dense layers. Each dense layer consists of \( 1 \times 1 \) and \( 3 \times 3 \) convolutions followed by Batch Normalization (BN), Rectified Linear Units (ReLU), and a dropout block. The output of the \( l^{th} \) dense layer (\( X_l \)) in a dense block can be written as:

\[
X_l = [X_0, \ldots, X_{l-1}],
\]

where \( \cdots \) represents concatenation of the features produced by the layers 0, \ldots, \( l - 1 \). Our classification sub-network is
composed of a global pooling layer, a fully connected layer, and a Softmax layer. The DCN model produces $Y_{dense} \in \mathbb{R}^{k \times 1664 \times 7 \times 7}$—dimensional feature maps which are squeezed to $k \times 1664$—dimensions through a global averaging operation, and then fed to a fully connected layer $f_{c} \in \mathbb{R}^{K}$. Mathematically, the output of the fully connected layer ($Y_{fc}$) and the softmax layer can be written as:

$$Y_{fc} = Y_{dense} \ast W_{fc} + B_{fc},$$

$$Y_{softmax} = \text{Softmax}(Y_{fc})$$

where, $W_{fc}$ and $B_{fc}$ represent weights and bias matrices, respectively. We use an objective function based on Cross Entropy Loss defined as:

$$L_{x,j} = -\sum_{j=1}^{N_{o}} Y_{x,j} \log(p_{x,j}),$$

where $Y_{x,j}$ is a binary indicator if class label $j$ is the correct classification for observation $x$, and $p$ is the predicted probability of observation $x$ of class $j$.

2.4 Training and Implementation

We train the convolutional and the fully connected subnetworks from scratch using the loss function in Eq. 8. The weights were initialized from zero-mean Gaussian distributions, standard deviations were set to 0.01, and biases were set to 0. We trained the sub-networks for 200 epochs with a learning rate of 0.01 (which was divided by 10 at 50% and 75% of the total number of epochs), and a parameter decay of 0.0005 (on the weights and biases). Our implementation is based on the auto-gradient computation framework of the Torch library [Paszke et al., 2017]. Training was performed by ADAM optimizer with a batch size of 50.

3 Experiments

3.1 Dataset

We used the recently released TUH EEG Seizure Corpus [Shah et al., 2018] (v1.4.0) which includes information about the time of occurrence and type of each seizure. The dataset contains 2012 seizures thereby making it the world’s largest publicly available dataset for seizure type classification. Table 1 shows the distribution of seizures in terms of different seizure types. For baseline methods, We compare the performance obtained by our architecture with the results reported in [Roy et al., 2019] which used kNearest Neighbors (kNN), SGD classifier, XGBoost, AdaBoost, and Convolutional Neural Networks (CNNs) for seizure type classification. We adopted a 5-fold cross-validation approach, where for each fold, the seizures for each type were proportionally divided into the training and the test sets.

3.2 Results

Seizure Type Classification

Table 2 shows seizure type classification results on the TUH EEG Seizure Corpus of our model compared with the baseline methods. From the table we see that the classification performance of the traditional machine learning algorithms is affected by the data sampling frequency. This is mainly due to the fact that the EEG recordings exhibit different characteristics of neural activities of the brain at different frequency bands. The proposed dense feature learning captures information from different frequency and spatial resolutions during training, and enables the CNN model to learn features which are more robust compared to the features learnt at individual frequency bands or spatial locations. This results in improved performance in the average f1 scores as shown in Table 2. For instance, our model outperforms the compared
Table 1: A short description and total count of different types of seizures in the TUH EEG Seizure Corpus.

| Seizure type | Description | Count |
|--------------|-------------|-------|
| 1. Focal Non-Specific Seizure (FN) | Focal seizures which cannot be specified further by type | 992 |
| 2. Generalized Non-Specific Seizure (GN) | Generalized seizures which cannot be further classified into one of the groups below | 415 |
| 3. Simple Partial Seizure (SP) | Partial seizures during consciousness; Type specified by clinical signs only | 44 |
| 4. Complex Partial Seizure (CP) | Partial Seizures during unconsciousness; Type specified by clinical signs only | 342 |
| 5. Absence Seizure (AB) | Absence Discharges observed on EEG; patient loses consciousness for few seconds (Petit Mal) | 99 |
| 6. Tonic Seizure (TN) | Stiffening of body during seizure (EEG effects disappears) | 67 |
| 7. Tonic Clonic Seizure (TC) | At first stiffening and then jerking of body (Grand Mal) | 50 |

Figure 3: Confusion matrices for seizure type classification on the TUH EEG Seizure Corpus for the proposed SeizureNet (A, B) and a DenseNet model without using the proposed dense feature sampling (C, D) at different frequency levels.

Table 2: 5-fold cross validation results in terms of average weighted f1 scores on the TUH EEG Seizure Corpus for cross-patient seizure type classification.

| Methods | Sampling frequency |
|---------|--------------------|
|        | 24 Hz | 48 Hz | 96 Hz |
| [Roy et al., 2019] kNN | 0.884 | 0.882 | 0.883 |
| [Roy et al., 2019] SGD | 0.649 | 0.669 | 0.724 |
| [Roy et al., 2019] XGBoost | 0.782 | 0.751 | 0.773 |
| [Roy et al., 2019] Adaboost | 0.509 | 0.503 | 0.531 |
| [Roy et al., 2019] CNN | 0.723 | 0.720 | 0.703 |
| SeizureNet (this work) | **0.900** | **0.896** | **0.909** |

Table 3: Seizure detection results in terms of average weighted f1 scores on the TUH EEG Seizure Corpus.

| Methods | Sampling frequency |
|---------|--------------------|
|        | 24 Hz | 48 Hz | 64 Hz |
| SGD | 0.8041 | 0.7424 | 0.7923 |
| XGBoost | 0.8411 | 0.8419 | 0.8432 |
| SeizureNet (this work) | **0.8801** | **0.8650** | **0.8736** |

Methods with an improvement of 2 points in the average f1 score compared to the best performing kNN for seizure type classification. Fig. 3 shows a comparison of the confusion matrices of the proposed SeizureNet and a CNN model without using the proposed dense feature learning at different frequency levels. From the comparison we see that the confusions decrease for almost all the seizure classes at the different frequency bands using the proposed SeizureNet compared to the baseline CNN model. Fig. 4 shows the TSNE visualization of the features learnt by the proposed SeizureNet and the features learnt by an off-the-shelf CNN model without using the proposed dense feature sampling. The comparison shows that the features learnt by the proposed SeizureNet are better separated in the feature space (as shown in Fig. 4 top-row) compared to the features learnt by a CNN model without using the proposed dense feature sampling (as shown in Fig. 4 bottom-row).

Seizure Detection
Here we evaluate the performance of the proposed framework for the seizure detection task in a cross-patient approach, where the objective is to classify the input data into two classes (a seizure class and a non-seizure class). Table 3 shows the average f1 scores of the proposed model and the baseline methods on the TUH EEG Seizure Corpus. From Table 3 we see that the proposed model outperforms the baseline models. We attribute this improvement mainly to the proposed multi-spectral feature learning, where combining divergence-encoded spectrogram data from different frequency and temporal resolutions enables the model to learn more discriminative features in distinguishing seizure
Figure 4: TSNE visualization of the features learnt by the proposed SeizureNet using the proposed Divergence-encoded spectrograms (top row), and features learnt by a CNN without using the proposed dense feature learning (bottom row) at different frequency levels. The comparison shows that the features learnt by the proposed SeizureNet are better separated in the high-dimensional feature space compared to the features learnt by an off-the-shelf CNN model without using the proposed dense feature learning.

and non-seizure samples compared to the baseline methods.

3.3 Conclusion and Future Work

This paper presents a deep learning based framework for EEG-based automatic seizure type classification and seizure detection in cross-patient scenarios. The greatest challenge in a cross-patient approach is to learn robust features from limited training data which can effectively generalize to patient data that was not used during the training phase. To achieve this, we present a deep CNN architecture with densely connected convolutional layers and a dense feature learning strategy to utilize information from different frequency and temporal resolutions of the EEG data spectrum. Experiments show that the proposed dense feature learning enables a deep CNN architecture to learn highly discriminative features for seizure type classification without suffering from over-fitting. We also present a 3D visual representation of time-series EEG data which encodes frequency transforms and their corresponding divergence information and use these representations for CNN based feature learning. Experiments show that the proposed divergence-encoded spectrogram representation of the EEG data improves seizure classification and seizure detection performance compared to the traditional features. To our best knowledge, this study is the first to implement a deep CNN model for seizure type classification in a cross-patient approach, thereby laying a benchmark for new work exploring deep learning enabled seizure type classification. In future, we plan to investigate memory efficient CNN architectures which can be used in wearable devices for real-world applications.

References

[Antoniades et al., 2016] Andreas Antoniades, Loukianos Spyrou, Clive Cheong Took, and Saeid Sanei. Deep learning for epileptic intracranial eeg data. In Machine Learning for Signal Processing (MLSP), 2016 IEEE 26th International Workshop on, pages 1–6. IEEE, 2016.

[Boubchir et al., 2014a] Larbi Boubchir, Somaya Al-Maadeed, and Ahmed Bouridane. Haralick feature extraction from time-frequency images for epileptic seizure detection and classification of eeg data. In Micro-
electronics (ICM), 2014 26th International Conference on, pages 32–35. IEEE, 2014.

[Boubchir et al., 2014b] Larbi Boubchir, Somaya Al-Maadeed, and Ahmed Bouridane. On the use of time-frequency features for detecting and classifying epileptic seizure activities in non-stationary eeg signals. In Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on, pages 5889–5893. IEEE, 2014.

[Fan and Chou, 2018] Miaolin Fan and Chun-An Chou. Detecting abnormal pattern of epileptic seizures via temporal synchronization of eeg signals. IEEE Transactions on Biomedical Engineering, 2018.

[Golmohammadi et al., 2017] Meysam Golmohammadi, Saeedeh Ziyabari, Vinit Shah, Eva Von Weltin, Christopher Campbell, Iyad Obeid, and Joseph Picone. Gated recurrent networks for seizure detection. In Signal Processing in Medicine and Biology Symposium (SPMB), 2017 IEEE, pages 1–5. IEEE, 2017.

[Huang et al., 2017] Gao Huang, Zhuang Liu, Kilian Q Weinberger, and Laurens van der Maaten. Densely connected convolutional networks. CVPR, 2017.

[Hussein et al., 2018] Ramy Hussein, Hamid Palangi, Rabab Ward, and Z Jane Wang. Epileptic seizure detection: A deep learning approach. arXiv preprint arXiv:1803.09848, 2018.

[Jia et al., 2014] Xiaowei Jia, Kang Li, Xiaoyi Li, and Aidong Zhang. A novel semi-supervised deep learning framework for affective state recognition on eeg signals. In Bioinformatics and Bioengineering (BIBE), 2014 IEEE International Conference on, pages 30–37. IEEE, 2014.

[Johansen et al., 2016] Alexander Rosenberg Johansen, Jing Jia, Tomasz Maszczyk, Justin Dauwels, Sydney S Cash, and M Brandon Westover. Epileptiform spike detection via convolutional neural networks. In Acoustics, Speech and Signal Processing (ICASSP), 2016 IEEE International Conference on, pages 754–758. IEEE, 2016.

[Längkvist et al., 2014] Martin Längkvist, Lars Karlsson, and Amy Louifi. A review of unsupervised feature learning and deep learning for time-series modeling. Pattern Recognition Letters, 42:11–24, 2014.

[Li et al., 2016] Dazi Li, Guifang Wang, Tianheng Song, and Qibing Jin. Improving convolutional neural network using accelerated proximal gradient method for epilepsy diagnosis. In Control (CONTROL), 2016 UKACC 11th International Conference on, pages 1–6. IEEE, 2016.

[Lin et al., 2016] Qin Lin, Shu-qun Ye, Xiu-mei Huang, Si-you Li, Mei-zhen Zhang, Yun Xue, and Wen-Sheng Chen. Classification of epileptic eeg signals with stacked sparse autoencoder based on deep learning. In International Conference on Intelligent Computing, pages 802–810. Springer, 2016.

[Paszke et al., 2017] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. Automatic differentiation in pytorch. 2017.

[Pramod et al., 2014] Siddharth Pramod, Adam Page, Tinoosh Mohsenin, and Tim Oates. Detecting epileptic seizures from eeg data using neural networks. arXiv preprint arXiv:1412.6502, 2014.

[Roy et al., 2019] Subhrajit Roy, Umar Asif, Jianbin Tang, and Stefan Harrer. Machine learning for seizure type classification: Setting the benchmark. arXiv preprint arXiv:1902.01012, 2019.

[Shah et al., 2018] Vinit Shah, Eva Von Weltin, Silvia Lopez de Diego, James Riley McHugh, Lillian Veloso, Meysam Golmohammadi, Iyad Obeid, and Joseph Picone. The temple university hospital seizure detection corpus. Frontiers in Neuroinformatics, 12:83, 2018.

[Supratak et al., 2014] Akara Supratak, Ling Li, and Yike Guo. Feature extraction with stacked autoencoders for epileptic seizure detection. In Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE, pages 4184–4187. IEEE, 2014.

[Thodoroff et al., 2016] Pierre Thodoroff, Joelle Pineau, and Andrew Lim. Learning robust features using deep learning for automatic seizure detection. In Machine learning for healthcare conference, pages 178–190, 2016.

[Turner et al., 2014] JT Turner, Adam Page, Tinoosh Mohsenin, and Tim Oates. Deep belief networks used on high resolution multichannel electroencephalography data for seizure detection. In 2014 AAAI Spring Symposium Series, 2014.

[Vidyaratne et al., 2016] L Vidyaratne, A Glandon, Mahbubul Alam, and Khan M Iftekharuddin. Deep recurrent neural network for seizure detection. In 2016 International Joint Conference on Neural Networks (IJCNN), pages 1202–1207. IEEE, 2016.

[Yan et al., 2016] Bo Yan, Yong Wang, Yuheng Li, Yei Jiang Gong, Lu Guan, and Sheng Yu. An eeg signal classification method based on sparse auto-encoders and support vector machine. In Communications in China (ICCC), 2016 IEEE/CIC International Conference on, pages 1–6. IEEE, 2016.

[Zandi et al., 2014] Ali Shahidi Zandi, Manouchehr Javidi, Guy A Dumont, and Reza Tafreshi. Automated real-time epileptic seizure detection in scalp eeg recordings using an algorithm based on wavelet packet transform. IEEE Transactions on Biomedical Engineering, 57(7):1639–1651, 2010.