Automatic Detection and Classification of Artifacts in Single-Channel EEG

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***Abstract*— Ambulatory EEG monitoring can provide medical doctors important diagnostic information, without hospitalizing the patient. These recordings are however more exposed to noise and artifacts compared to clinically recorded EEG. An automatic artifact detection and classification algorithm for single-channel EEG is proposed to help identifying these artifacts. Features are extracted from the EEG signal and wavelet subbands. Subsequently a selection algorithm is applied in order to identify the best discriminating features. A non-linear support vector machine is used to discriminate among different artifact classes using the selected features.**

Single-channel (Fp1-F7) EEG recordings are obtained from experiments with 12 healthy subjects performing artifact inducing movements. The dataset was used to construct and validate the model. Both subject-specific and generic implementation, are investigated.

The detection algorithm yield an average sensitivity and specificity above 95% for both the subject-specific and generic models. The classification algorithm show a mean accuracy of 78 and 64% for the subject-specific and generic model, respectively. The classification model was additionally validated on a reference dataset with similar results.

I. INTRODUCTION

Electroencephalography (EEG) is a biological signal reflecting the electrical activity of the brain. The signal is acquired by placement of electrodes on the scalp, which benefits from being non-invasive, cheap and provides a high temporal resolution. This makes it an important tool in disease diagnosis and brain research [1]. Due to the very low amplitude of EEG in the range of μV, it is easily contaminated by noise and artifacts. In the following, noise is defined as signals originating from non-physiological sources while artifacts are defined as signals originating from internal or external sources other than the cerebral cortex.

The most common artifacts occurring in the EEG are eye and muscle activity artifacts [1].

The eye forms an electrical dipole, which changes when the eye moves. This potential change causes a serious distortion to the electrical field generated by the brain due to the fact that the potential arising from eye-movements and blinks are in the mV range. The eye-movement and eye blink artifacts occur very frequently in the EEG, especially in the frontal regions [2].

The activation of different muscle groups close to the head, can cause serious distortion to the EEG signal. Tension of the neck or movement of the eye brows can cause significant electromyographic (EMG) artifacts. Muscular artifacts typically show in the EEG as high amplitude and high-frequency activity [3].

In ambulatory settings, body-movement artifacts have also been reported to be of particular concern [4].

The presence of artifacts can severely distort the characteristics of the EEG signal, which can lead to significant loss of reliability of algorithms performing automatic analysis on EEG signals.

While advances in signal acquisition, data storage and communication has made it possible to move EEG data collection from the clinic into the home environment of the patient, the magnitude and frequency of artifacts occurring in the EEG significantly increases when the data collection is moved out of the clinic. This creates a crucial need for effective artifact detection algorithms [4].

For some applications only a single frontal channel is necessary for monitoring purposes [5]. Recording EEG with only a single channel makes it critically important to develop a method for the effective detection of different types of artifacts. Assessment of EEG quality with an artifact classification algorithm can help in determining whether the signal can be used for further processing even though an artifact is present or must be discarded because of too high artifact-contamination.

II. MATERIALS AND METHODS

A. EEG Data Collection

Continuous EEG was recorded at 128 Hz using a single channel ActiWave recording device (CamNtech, Ltd., Cambridge, United Kingdom). Electrodes were positioned according to the international $10-20$ system with the reference placed at Fp1 and the recording electrode at F7. The ActiWave recording device was secured with tape on the left chest of the subject, and wires were drawn from the specified recording locations to behind the ears in order to minimize discomfort.

Recordings were obtained from 12 healthy subjects (10 male) with a mean age of 30 (± 12.7) years while conducting artifact inducing movements.

A reference dataset was provided by the authors of [6]. The dataset consists of multi-channel EEG recordings from 7 subjects performing artifact inducing movements. In total, 160 epochs of 0.5 seconds duration were obtained from each subject. 8 classes were present in the data: jaw clench

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(JC), jaw movement (JM), eye blinks (EB), eye movement to the left (EL), eye movement up (EU), eye brows movement (ME), head rotation (RH) and an artifact-free class (None). The channel Fp1-F7 was used for analysis.

B. Experimental Protocol

Subjects performed a series of artifact inducing facial and head movements in order to obtain a dataset with different types of artifacts present. Prior to the recording, the subject reviewed the protocol describing the movements in order to make sure the subject understood the task. The subject was told to strictly follow the protocol and was instructed not to talk during the time of the recording. The following movements were performed: Jaw clench (JC), eye blinks (EB), eye movements from side to side (EM), rotate head (RH), move eye brows (ME) and casual jumping on the spot (Jump). The experiment (except the jumping) was performed sitting down in front of a computer. Between each type of movement the subject was instructed to relax with eyes open for 1 minute and subsequently relax with eyes closed for 1 minute. This was used as an artifact-free class (None). Each of the artifact-inducing movements were performed for 30 seconds.

A program written in MATLAB (v. R2013a, Mathworks Inc., Natic, MA, USA) was developed to control the timing and execution of the protocol. A clear sound was played each time the subject should perform a new task, while the computer screen always displayed which type of movement should be performed at the given time.

C. Pre-processing

In order to remove power-line interference, a notch filter with a cut-off frequency at 50 Hz was applied before further processing. All processing and analysis of the recorded signals were conducted in MATLAB.

From the recorded EEG, epochs of 1 second duration with an overlap of 50% were extracted for further analysis.

Some delay in the reaction of the subject, from the sound is heard to the subject performs the new intended task, is expected. This could potentially result in a significant error in the automatic labelling procedure. A manual inspection of all epochs was performed in order to validate the scoring. Another reason for the need of a manual inspection, is that eye-blink artifacts naturally occur when the subject has open eyes .

D. Feature Extraction

A wide range of features were previously proposed for classifying artifacts in EEG signals. Autoregressive (AR) coefficients have shown good discriminative power of distinguishing among different artifact types [6]. The use of higher order statistics and features derived from wavelet subbands have also shown reasonable performance [7]. These feature extraction methods have typically been applied to multi-channel EEG.

We chose to extract features which previously demonstrated good discriminative power between artifact classes. The idea was then to apply a selection algorithm in order to identify the best discriminating features for a single-channel application. The complete list of extracted features is found in Table I.

TABLE I

LIST OF FEATURES EXTRACTED FROM THE EEG SIGNAL, $x(n)$ AND THE WAVELET DETAIL BANDS, $d_1 - d_7$.

Feature	Number of Features
Energy of $x(n)$	1
Energy of d_{1-7}	7
Line length of $x(n)$	1
Line length of d_{1-7}	7
Zero crossings of $x(n)$	1
Avg. magnitude of $x(n)$	1
Avg. magnitude of d_{1-7}	7
Kurtosis of $x(n)$	1
Kurtosis of d_{1-7}	7
Renyi's entropy of $x(n)$	1
Renyi's entropy of d_{1-7}	7
AR coeffs ($P = 1$) of $x(n)$	1
AR coeffs ($P = 2$) of $x(n)$	2
AR coeffs ($P = 3$) of $x(n)$	3
Reflection coeffs from AR models	6
AR coeffs ($P = 2$) of ACF of $x(n)$	2
Mean of $x(n)$	1
Std of $x(n)$	1
Variance of $x(n)$	1
Range of $x(n)$	1
Max amplitude of $x(n)$	1
RMS of $x(n)$	1
Max gradient of $x(n)$	1
Skewness of $x(n)$	1
Mean of $x(n)'$	1
Std of $x(n)'$	1
Kurtosis of $x(n)'$	1
Total # of features	66

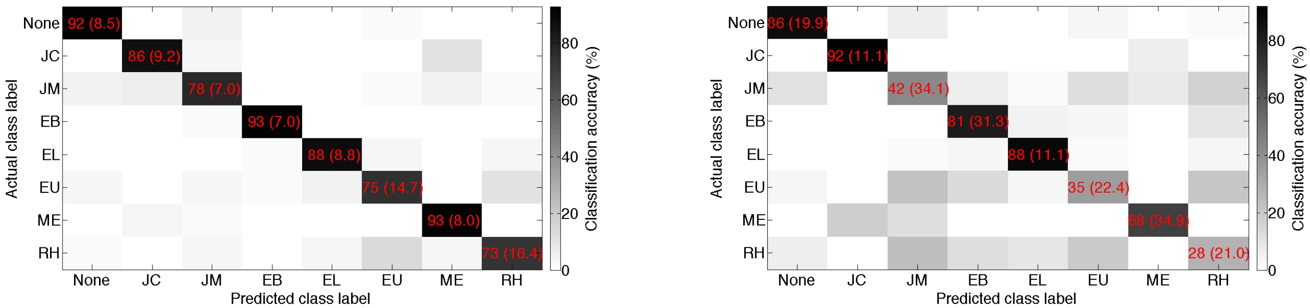
E. Feature Selection

A sequential forward selection algorithm was used to identify an optimal feature subset from the original feature vector. A relatively small amount of features are desired for this application in order to avoid over-fitting and reduce the complexity of the classifier. The forward selection procedure was chosen because of its reported ability to fast and effectively find a good subset [8]. A wrapper approach with the test accuracy from a support vector machine (SVM) was used as evaluation criterion in order to select the best features. The selection procedure was stopped when 10 features had been selected and the subset yielding the highest classification accuracy was chosen for further analysis.

F. Classification

A SVM was used to make predictions on unseen observations. SVM is a popular supervised binary classification technique where the model learns an optimal decision boundary from training data and then applies this learned decision boundary to a test set in order to classify new unseen datapoints.

SVM exploits the use of kernels to explicitly map the input data into a higher dimensional space where a linear decision boundary provide good separation between classes. Support



(a) Classification within-subject over all subjects.

(b) Classification with the Leave-One-Out generic model.

Fig. 1. Confusion matrix for classification on the reference dataset. The red numbers indicate the average classification accuracy of each artifact-type over all iterations of the cross-validation procedure . (a) results of the patient-specific model which yields an average accuracy over all subjects off $85(4.9)\%$. (b) results from the generic model which have a mean accuracy off $65(12.7)\%$ over the 7 iterations.

vectors are identified in the training data as observations from two different classes, which lies in a similar range. The support vectors are used to construct margins which best separate the classes. An optimal decision boundary is then found by maximizing the distance between margins between two classes [9].

The model is in its nature a binary classifier. In order to build a multi-class model some modifications are made. A common approach in building a multi-class SVM is to build $N(N-1)/2$ binary classifiers, with N being the number of classes. Each classifier is then trained on data from two classes, producing individual classifiers for all combinations of the classes and majority voting is used to make final predictions.

The multi-class SVM was implemented with the *LIBSVM* package [10]. A non-linear radial basis function was used as kernel, which previously has shown to provide good performance in classifying different artifact types [6]. A fine grid-search was performed in order to find the optimal values of the parameters C and γ, which controls the trade-off between the penalty variable and the margin and controls the width of the kernel, respectively.

The subject-specific model was validated by a 5 times repeated 4-fold cross-validation. The test set was completely held out of the feature selection and SVM training procedure. Between each of the 5 repetitions, data were shuffled in order to generate new folds between different iterations. The performance of the model was computed as the mean over all iterations. The generic model was validated by Leave-One-Out (LOO) cross-validation [11].

III. Results

The classification accuracy is calculated as the number of correctly classified epochs divided by the total number of epochs. The results are presented as the mean classification accuracy over all iterations of the cross-validation procedure.

A. Reference Dataset

The classification model was applied to the reference dataset which benefits from an aligned class distribution with 20 epochs per class for all 7 subjects. The results are summarized in Figure 1a and 1b for the subject-specific and generic model, respectively. The model shows an average classification accuracy of 85% and 65% for the subject-specific and generic approach, respectively. It is evident that the generic model produces a more noisy results, where the grouping of the classes are not as distinct as in the subject-specific model. In general, the artifact classes being responsible for the largest error are jaw movements, head rotations and eye up movements.

B. ActiWave Database

The dataset recorded for this project suffers from a more skewed class distribution, why initially the detection algorithm was applied and subsequently the detected artifacts were classified using the classification model. The detection results are presented in Figure 3 and the classification results are presented in Figure 2a and 2b.

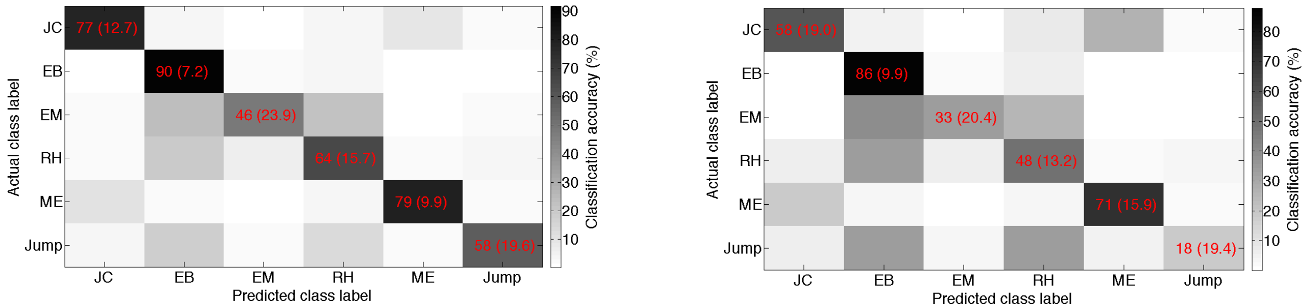
For the subject-specific model, the detection of artifacts resulted in an average sensitivity, specificity and positive predictive value of 96, 97 and 94%.

The subsequent classification of the detected features shows an average classification accuracy of 78 and 64% for the subject-specific and generic model, respectively. It is evident that the jump class is very hard to classify, where the accuracy of classifying this artifact class in the generic model almost equals random guessing.

IV. Discussion

The best discriminating features showed to be Renyi's entropy calculated from wavelet sub bands, $d_1 - d_5$. Amplitude range and coefficients from low order AR models also showed good discriminative properties in both models [12]. Head rotation, jaw movements and eye up artifacts are observed to be the hardest artifacts to classify on the reference dataset. The two former classes activates muscles relatively far away from the recorded EEG channel. This can explain why the single-channel algorithm has difficulties in detecting these types of artifacts.

The jaw clench, jaw movement and eye brow movements are observed to group together, creating a general muscle



(a) Classification within-subject over all subjects.

(b) Classification with the Leave-One-Out generic model.

Fig. 2. Confusion matrix for artifact classification on the ActiWave dataset. The red numbers indicate the average classification accuracy of each artifact-type over all iterations of the cross-validation procedure. (a) results of the patient-specific model which yields an average classification accuracy over all subjects off $78(5.0)\%$. (b) results from the generic model which have a mean classification accuracy off $64(8.2)\%$.

artifact group. All three artifact types produces significant muscle activity clearly evident as high frequency activity in the EEG.
The generic results show the same tendencies to a wider extend. The large standard deviation in the results indicate that classification of different artifacts is "easier" in some subjects than others.

The artifact detection results showed good performance on the ActiWave dataset. Figure 3 shows similar performance across all subjects with a sensitivity and specificity above 95%.
The classification model on the ActiWave dataset shows similar grouping tendencies as observed on the reference dataset. The jaw clench and eye brow movements are seen to group together, creating a muscle artifact group. The eye artifacts are seen to group together with head rotations. Using only a single frontal channel, the muscle activity caused by head rotations, are not expected to be captured by the frontal electrode. The head rotation usually causes an eye movement artifact most pronounced in the frontal regions, explaining why the head rotations groups with the eye artifacts.

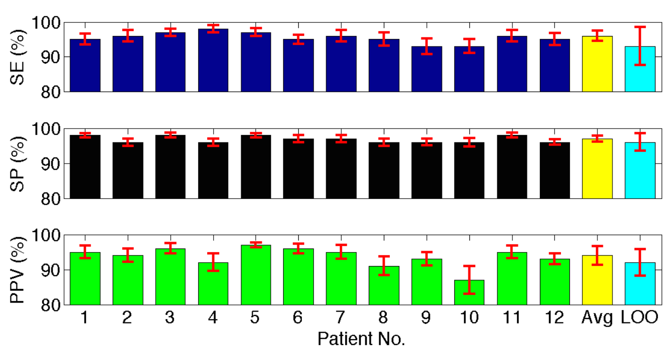


Fig. 3. Artifact detection results on the ActiWave dataset. SE, SP and PPV respectively denotes the mean sensitivity, specificity and positive predictive value over 5 iterations of 4-fold cross-validation for each subject and the generic model indicated by LOO. "Avg" denotes the mean over all subjects. The red lines indicate the standard deviation.

The results indicate that single-channel artifact detection is feasible in both a subject-specific and generic setting. The classification procedure is sensitive to similar characteristics in artifact types, but indicate that concatenating the artifacts into more general groups such as muscle, eye and movement artifacts, could lead to an increase in performance and the possibility of obtaining a more reliable model.

A. Future Work

The performance of the detection and classification model should be evaluated on a large clinical dataset containing seizure activity, in order to asses the opportunities in applying the model as a pre-processing step for a seizure detection algorithm. The generic classification model should be further developed in order to obtain reliable performance.

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