A Comparison of Automatic EEG Blink Removal Techniques*

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***Abstract*—Comparativa de métodos de eliminación de blinks (VME + DWT VS. Correlation + EMD + CCA VS. Propia)**

***Index Terms*—EEG, blink, artifact detection, artifact removal**

I. Introduction

An electroencephalogram (EEG) is a method for measuring and analyzing the electrical activity in the brain. The non-invasive procedure, which consists of placing electrodes on the scalp, has been widely used for years because it allows measurements of the brain regions of interest to be taken easily.

However, the EEG signals are usually contaminated by other electrical signals originated from a variety of sources, which can make it difficult to analyse the the real brain activity. These signals, called artifacts, can come from non-physiological or physiological sources:

1) The former proceed from the experimental environment, e.g. the lightning of the room, nearby noise or vibrations, or even the electrical connections of the measuring device.
2) The latter proceed from the subjects themselves. These artifacts can be caused by the heart rate (cardiac or pulse artifacts), any muscle contraction (myogenic artifacts) or any eye movement (ocular artifacts).

In the field of study of cognitive diseases, having clean-up techniques that ensure the removal of these artifacts while preserving as much brain information as possible in real time could be crucial. The non-physiological artifacts can be easily reduced by ensuring that the EEG recording sessions are made under appropriate environment conditions as well as myogenic artifacts if the subject is in a comfortable position and without any movement. Cardiac artifacts only occur if the sensor is pressed on a blood vessel, but they can be filtered. The most common artifact is the ocular one: even if the ocular movements can be restricted, the blinks are and unavoidable.

Although the blink artifact detection and removal is a subject that has been discussed for years and for which many different methods have been developed, new alternatives are still being proposed. The last year, many papers about different ocular artifact removal procedures were published.

As can be seen below, all of the methods apply the same kind of algorithms, but differ in the way they are combined. Among these algorithms, the decomposition ones are the most commonly used because they allow to limit the data to be modified or removed and preserve as much useful brain information as possible. For example:

1) Those applying a source decomposition belong to the Blind Source Separation (BSS) group. The most important algorithm is the Independent Component Analysis, which decomposes the signal into independent sources. Another one is the Canonical Correlation Analysis (CCA), which extracts the uncorrelated sources.
2) Those applying a level spectral decomposition of some kind. On the one hand, the Empirical Mode Decomposition (EMD) extracts a set of components called Intrinsic Mode Functions (IMFs) through upper and lower envelopes. On the other hand, the Discrete Wavelet Transform (DWT) applies pairs of symmetric high-pass and low-pass filters.

Apart from that, other techniques to be mentioned use some sort of Machine Learning algorithms in order to detect automatically the presence of an artifact by classification.

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Some of the studies, [1]–[4], try to eliminate all the ocular artifacts in general, i.e. eye movements and blinks: the first one applies a combination of CCA and NAPCT, a variant of Principal Component Analysis (PCA), both of them being BSS algorithms. The second one uses a Wiener Filter, an adaptive filter. The third one applies a combination of SCICA, an ICA variant, and Ensemble-Empirical Mode Decomposition (EEMD), an EMD variant. The latter one uses another combination of ICA too, this time with DWT.

Others focus only on blink artifacts. The BSS techniques are used in [5], where two of them are combined (PCA+ICA); [6] uses a combination of CCA and a faster variation of EMD; and [7] applies ICA to decompose into the sources and a classification algorithm to detect if any of them is contaminated by an artifact.

In [8] a combination of ICA, two Support Vector Machines (SVM) and one Autoencoder is proposed, making a total of three Machine Learning algorithms; and in [9], the same authors proposed another combination, this time with DWT and SVM.

There are other algorithms that decomposes the signal into spectral Mode Functions as the EMD, like Multivariate Variational Mode Decomposition [10] or Variational Mode Extraction (VME) [11], both of them are variations of the Variational Mode Decomposition (VMD) algorithm.

This paper proposes an automatic blink detection and removal technique and compare it with two of the above methods: those proposed in [11] and [6]. All of them apply different algorithms to perform the detection and the removal of the blinks contained in the EEG signal, so the aim of this study is to compare the detection and elimination performance of this recently proposed techniques. For this purpose, a blink dataset of EEG recording sessions of healthy subjects has been created to allow the comparison of these methods with real blinks.

The structure of this work is as follows. Firstly, the next section (II) explains in detail the different techniques for the automatic identification and removal of blink artifacts to be compared and mentioned in the previous paragraph. Section III describes the conditions under which the dataset used was recorded and the implementation of each of the algorithms, while Section IV presents the results of each experiment, followed by a discussion on the obtained results. Finally, the conclusions are drawn.

II. Blink detection and removal techniques

The first study to be compared, developed by [11], presents a technique where the blink detection phase is performed by the Variational Mode Extraction (VME) algorithm and the removal phase is carried out by applying the Discret Wavelet Transform (DWT). Both algorithms perform a frequency decomposition of the signal:

- The VME algorithm receive an input signal and extract the component of a certain frequency band, called Band Limited Intrinsic Mode Function (BLIMF). It is determined by two parameters: the value of the center frequency (ω_c) and the compactness coefficient (α), which regularizes the bandwidth around (ω_c).
- The DWT algorithm decomposes the input signal in frequency components by applying pairs of symmetrical low-pass and high-pass filters consecutively until a certain level is reached. In each level, the component of high frequency is preserved while the next filter pair is applied to the low frequency component.

Secondly, the study presented by [6] applies an unsupervised correlation-based blink detection method that uses a blink template created from the EEG signal itself through a variant of the Empirical Mode Decomposition (EMD) algorithm and then employs the Canonical Correlation Analysis (CCA) to remove the blink component within the signal.

- The EMD algorithm receive an input signal and extract the components, called Intrinsic Mode Functions (IMFs), using the upper and lower envelopes of the signal until a certain level is reached. Because of this, each new level represents activity of the original signal of lower frequency than the following one.
- The CCA algorithm is a Blind Source Separation (BSS) technique that decomposes the input signal into its uncorrelated sources. All the BSS algorithms work under the assumption that the original signal is formed by the linear combination of these sources.

The third method was proposed in a previous paper, [12], and employs a dynamic threshold technique for the detection of the blink artifacts and a combination of CCA and Ensembled-EMD (EEMD) for the removal stage.

- The Dynamic Threshold technique is based on the method proposed by [13]: a normal template is created with non-artifactual contamination EEG windows and a distance metric is used to compute all the distances between all the templates in order to calculate a normal threshold value. Then, the maximun distance between the template windows and a raw EEG window are used to determine if the raw window is contaminated or not.
- The combined method CCA+EEMD method is the one proposed by [14]: firstly, CCA algorithm is applied to an EEG window to decompose it in its uncorrelated sources; then, the blink component is detected and EEMD is used to decompose it in its IMFs; finally, the blink IMFs are detected and removed. This procedure allows to remove the blink contamination and preserving as much brain information as possible.

All these algorithms will be explained in the subsections below separating them into Detection and Removal Techniques.

A. Blink Detection Techniques

1) Using VME and Peak Detection: VME is a variant of the VMD (Variational Mode Decomposition) algorithm: this technique receive an input signal and extract all possible components, the BLIMFs, each one centered around a frequency value.

Unlike VMD, the VME algorithm decomposes the original signal into the desired mode $u(n)$ centered around a certain frequency value ω_d and the residual signal $r(n)$. In order to extract only the desired frequency component, this method has to minimize:

- The bandwidth around the center frequency:

$$J_1 = \left\| \partial_n \left[\left(\delta(n) + \frac{j}{n\pi} \right) * u(n) \right] e^{-j\omega_d n} \right\|_2^2 \quad (1)$$

where $\delta(n)$ is the Dirac distribution and $\left[\left(\delta(n) + \frac{j}{n\pi}\right) * u(n)\right]$ is the Hilbert transform.

- The spectral overlap of the component and the residue. The following filter must be applied to extract the component of the desired frequency band:

$$\beta(\omega) = \frac{1}{\alpha(\omega - \omega_d)^2} \quad (2)$$

where (α) is the compactness coefficient which regularizes the bandwidth. The minimization of the overlapping can be solved by the following penalty equation:

$$J_2 = \|\beta(n) * r(n)\|_2^2 \quad (3)$$

where $\beta(n)$ is the impulse response of the filter β_ω

Finally, the desired mode can be extracted by minimizing the criterion:

$$\min_{\omega_d, u(n), r(n)} \{\alpha J1 + J2\} \quad (4)$$

subject to the sum of the desired mode extracted and the residual must reconstruct the original signal.

The VME detection process applied by [11] is explained below:

Given a window taken from the blink-contaminated EEG signal (X_i), firstly it is checked for any blink artifact using the VME algorithm: on the one hand, since the approximate frequency range of the eye blinks is 0.5Hz - 7.5Hz, the center frequency ω_c is fixed to 3Hz; on the other hand, higher values of the coefficient α ensure that the extracted mode corresponds to the selected ω_c value, but smaller α values allow to extract the blink components in its frequency band despite the overlap with the brain activity, so α is finally set to 3000. VME is applied to the window X_i with these parameters and the desired mode $m(t)$ is calculated.

The Universal Threshold is calculated for each mode $m(t)$ of each window X_i as follows:

$$\theta = \frac{median(|m(t)|)}{0.6745} * \sqrt{2 * Log(N)} \quad (5)$$

where N is the number of samples of the mode signal.

The local maxima samples of $m(t)$ are located and those that are higher than the threshold θ are classified as a blink artifact peak. These peak samples are searched for in the original window X_i and smaller windows of 500 ms centered in them are extracted. The onset of these windows is f_s / 8 samples pre-peak and the offset is $3f_s$ / 8 samples post-peak, where f_s is the sample rate of the signal. The blink window created starts 125 ms before the peak and ends 375 ms after it. Only blink intervals extracted this way are processed in the removal stage: if there is no sample higher than the threshold in the initial window X_i, it is preserved.

2) Correlation-based Detection: EMD is a decomposition algorithm that receives a single input signal X_i and extracts a certain number of components called IMFs. In each level of decomposition, one IMF is calculated from the previous signal by following these steps:

1) Compute the upper and lower envelopes (ue, le) of the signal by a Cubic Spline Interpolation passing through local maxima and minima.
2) The possible IMF h_a is the difference between the initial signal and the average of the two envelopes.

$$a = \frac{ue + le}{2} \rightarrow h_a = X_i - a \quad (6)$$

Check the following conditions:

a) The number of extrema must be the same as the number of zero crossings or differ by one.
b) The mean value of the two envelopes must be zero at all samples.

3) If h_a hold these criteria, it is an actual IMF. Otherwise, it is used as the new initial signal and the first two steps are repeated until an IMF is obtained.
4) Generate the residue as the difference between the initial signal and the IMF. It is used as the new initial signal and all the steps are repeated until the desired decomposition level is reached.

$$r_a = X_i - h_a \quad (7)$$

Another criterion to check whether h_a is an actual IMF is to calculate its standard derivation and check if it is in the range $[0.2, 0.3]$.

The original signal can be reconstructed by the sum of all the IMFs and the last residue.

A variant of the EMD algorithm, called Fast-EMD, is applied in [6]. It uses the Akima Spline Interpolation algorithm to calculate the upper and lower envelopes of the signal in the EMD process instead of the Cubic Spline, which is the most commonly used in the basic EMD algorithm, because Akima is quicker and requires lower computational cost. The correlation with Fast-EMD process applied by them is explained below:

From the original EEG signal, the channels Fp1 and Fp2, which correspond to the electrodes nearest to the left and the right eye respectively, are extracted and the correlation between them are calculated in 500 samples[1] windows. This is because the correlation coefficient between the channels Fp1 and Fp2 increase when a blink occurs: the blink-free segments generate a correlation lower than 0.7 while the blink-contaminated ones generate a correlation higher than 0.9.

If a window produces a correlation coefficient between channels Fp1 and Fp2 higher than 0.85, there is blink contamination. Due to the amplitude of a blink is greater than the EEG signal, a threshold based on the displacement of the amplitude in Fp1 channel is used: the displacement calculates the absolute difference between the signal and its mean, as expressed in Eq.8. If blink artifacts have higher amplitude, they will produce higher displacement. Then, the threshold is calculated with Eq.9 only for this particular window, i.e., every window with blink contamination will have their own displacement distribution and threshold value.

$$disp(t) = |X_{Fp1}(t) - \mu| \tag{8}$$

where μ is the mean of the channel Fp1 EEG window.

$$threshold = \mu_{disp} + 2 * \sigma_{disp} \tag{9}$$

where μ_{disp} and σ_{disp} are the mean and the standard derivation of the displacement of the window.

The first sample of the current window exceeding the threshold is located because it is considered the starting point of the blink, and a blink window is created around it: the onset of the window is set 100 samples[1] pre-start and the offset is set 1 second post-start.

Once all the blink windows are extracted from all the starting points detected in the current 500-samples[1] window, move on to the next one.

In order to create the blink template, each new blink window extracted is compared with all the previous one through the correlation between them until one pair has a correlation coefficient higher than 0.8. Then, the Fast-EMD variant is applied to these two blink segments.

The EMD algorithm performs the decomposition of the two blink windows up to level 5. Each level represents the activity of a lower frequency than the following ones, so the brain oscillations will be retained in the first IMFs while the next ones represents the blink contamination. Thus, the two blink signals are reconstructed from their respectively third IMF onwards. Finally, the blink template is created as the mean of the two blink signals.

In the detection phase, a sliding window of the same size as the template is used throughout the raw EEG signal. The correlation between the EEG window and the blink template is computed and the window is classified as contaminated if this coefficient is higher than 0.5.

3) Threshold-based Detection: The threshold detection process applied in a previous paper, [12], and based in the method proposed by [13] is explained below:

Firstly, a template of EEG windows with normal activity, i.e. without blink artifact contamination, is created.

Given an EEG window (X_i), its 0-50 Hz PSD (p) is computed. Then it is compared using the Bhattacharyya Distance with the PSD (q) from each of the available templates. The distance is computed using Eq. 10 and 11, where $p(k)$ and $q(k)$ are the kth sample of the p and q window of K size and s^{BD} is the similarity value, which inverse d_{BD} is the distance value. Therefore, we compare the current EEG window to each of those included in the template set.

$$s^{BD} = -ln(\sum_{k=1}^{K}(\sqrt{p(k) * q(k)})) \tag{10}$$

$$d_{BD} = \frac{1}{s^{BD}} \tag{11}$$

Once the threshold values are obtained, the current EEG window is compared with each of the normal windows of the template computing the distance between them. The highest distance is extracted: this value represents the lowest similarity between the EEG window and the signals considered normal (no blink artifact presence).

However, determining thresholds represents a challenge itself as they suffer variability from one participant to other and also the amount of signal might vary for the same participant along the test. To minimize these drawbacks, this paper proposes to use the Empirical Rule -a.k.a. 68–95–99.7 rule- to determine whether a point represents an outlier.

Let μ and σ be the mean and the standard derivation of the distances between all the normal template signals. These values are calculated once at the beginning and are constant throughout the process.

In this study, whenever the maximum distance among the current EEG window and a normal template holds the condition in Eq. 12, the window is labelled as contaminated with a blink artifact. In Eq. 12, μ and σ are the mean and the standard derivation of the distances between normal templates, respectively, while $d_{max}(X_i)$ is the highest distance between the current EEG window X_i and a normal template.

$$d_{max}(X_i) - \mu > 3 * \sigma \tag{12}$$

B. Methods for Blink Removal

1) DWT-based Blink Removal: DWT is a decomposition algorithm that receives a single input signal and extracts its components by sequentially dividing the continuous spectrum: each component corresponds to a different frequency band.

In each level of decomposition, the initial signal is passed through two symmetric filters: a low-pass filter and a high-pass filter at a certain frequency value. The former one extracts the low frequency component, called the approximation component, which will be the new initial signal in the next level until the desired decomposition level is reached; and the latter one extracts the high frequency component, called the detail component. Each component can be represented by a approximation or a detail component respectively.

These filters are designed according to the discrete variant of the mother wavelet function chosen.

The application of the DWT algorithm for blink removal proposed by [11] is explained below:

Given a blink window, it is processed by applying the DWT algorithm: Daubechies-4 (*db4*) is chosen as the mother wavelet function because its morphology is very similar to the

[1]The number of samples chosen for the window sizes depends on the sampling rate. Their study was carried out using a sampling rate of 256Hz.

blink one. In terms of the level of decomposition, a skewness-value method is applied: as said before, blink artifact affects low frequencies ranges, so the skewness of the approximation component is calculated in each level of decomposition and compared with the previous one. High absolute values of skewness indicates blink presence in the component due to its larger amplitude than the EEG. If the difference between two consecutive skewness values are greater than a threshold, the maximum level of decomposition has been reached.

To conclude, the approximation component of the last level is removed and the clean EEG window is reconstructed from all the detail components.

2) CCA Blink Removal: CCA algorithm belongs to the group of BSS techniques, which assume that these signals are formed by the linear combination of their sources:

$$X = A * S \rightarrow A = W^{-1} \rightarrow S = W * X \tag{13}$$

where X is the measured signals, S is the sources and A and W are the mixing matrix and its inverse, the unmixing matrix, respectively.

All BSS methods try to estimate the unmixing matrix and, therefore, the sources that compose the measured signals, in different ways.

Thus, CCA is a decomposition algorithm that receives a set of n input signals and extracts their uncorrelated sources with the autocorrelated values maximized.

The removal process based on the CCA algorithm proposed by [6] is very simple and it is applied as follows: the algorithm is executed to the blink window and the first component computed, which usually corresponds to the artifact, are removed. Then, the EEG window is reconstructed from the remaining components.

3) Combined CCA-EEMD Blink Removal: Since EMD suffers with mixing and aliasing problems despite performing well, another variant is presented: EEMD is more noise-robust than the basic EMD algorithm. This method adds white noises of different amplitudes to the original signal in a way that each noise signal is applied individually creating different noisy variations of the original. Then, noisy IMFs are extracted from each noisy variation until the chosen level of decomposition is reached. Finally, each i^{th} real IMF of the original signal is calculated as the average of all the i^{ths} noisy IMFs.

The combined CCA+EEMD removal technique used in the previous paper [12] and presented in [14] is explained below:

CCA is applied to separate the uncorrelated source signals and ordered according to their kurtosis value. The artifact component is identified as the source with the highest kurtosis. Then, EEMD is applied only to that component to compute its IMFs and the blink components are identified again by the same method: IMFs are sorted by kurtosis value. The higher ones corresponded to artifacts components. These artifact signals are removed and the rest of the IMFs are preserved to rebuild the CCA component and then all the sources are combined again to reconstruct the EEG signal, now clean and free of artifacts. The algorithm is outlined as follows:

If a blink is detected in the current window:

1) CCA algorithm is applied to the current window, extracting the uncorrelated sources and sorting them by their kurtosis value. The highest kurtosis corresponds to the blink component.
2) EEMD algorithm is applied to that component, computing the IMFs and sorting them using the kurtosis value. The blink data contamination corresponds to components with high kurtosis.
3) Dismiss the IMFs from the blink -i.e., the two IMFs with the highest kurtosis- and reconstruct the component using the remaining IMFS.
4) Reconstruct the free-from-blink EEG window from the components.

III. Materials and Methods

This section describes the recording of dataset used and the experiments carried out.

A. Data Set Description

The EEG dataset used in this paper was collected specifically for this study, but it will be useful for future projects. These EEG signals were recorded with the Ultracortex Mark IV helmet manufactured by OpenBCI, which has 16 electrodes that can be controlled by their combined Cyton-Daisy Board.

As shown in Fig.1, the 16 channels that have been used to create this dataset are placed following the 10-20 international standardization: Fp1, Fp2, F3, F4, F7, F8, T7, T8, C3, C4, P3, P4, P7, P8, O1 and O2. The channels A1 and A2 are used as the reference of all EEG electrodes.

The EEG signals were collected from 13 healthy participants. Each participants had 2 recording sessions. Each session consisted of a 5-minutes continuous recording. The subject

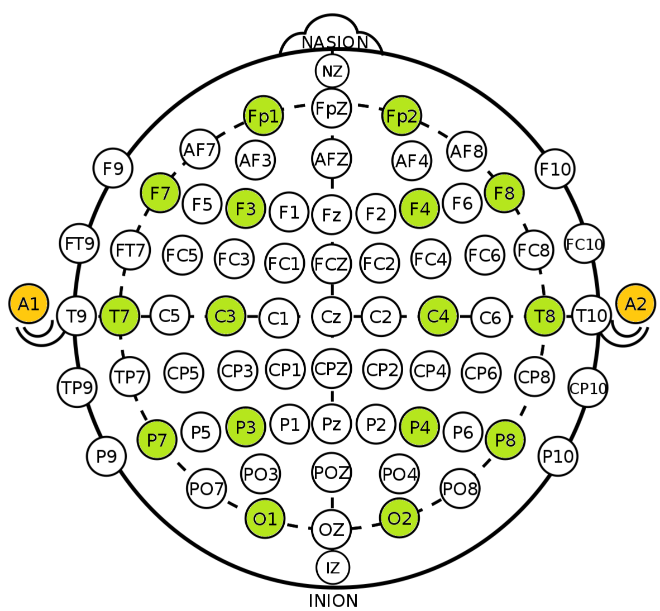

Fig. 1. Position of the 16 channels using the 10-20 system.

was seated comfortably in front of a screen. In the first 5 seconds, the subject had to blink quickly to set a mark of the start of the trial in the EEG. Then, the subject had to keep their eyes open and blink naturally for 30 seconds, followed by another 30 seconds with their eyes closed. These two phases were repeated 5 times in total. The screen showed a presentation indicating the current phase and beeped at each phase change. In addition to the EEG recording, the subject's face was also recorded throughout the session in order to be able to see the eye blinks.

All the EEG signals were recorded at a sampling rate of 125Hz and were filtered using a Notch filter with a 50Hz null frequency and a Band-Pass filter with with 1Hz to 50Hz cut off frequencies using the OpenBCI GUI application.

For this study, 10 open-eyed segments were extracted from all the dataset and the windows were manually labeled as clean or blink for the evaluation of each of the algorithms. Each segment is 3750 samples length ($30 seconds * 125 Hz$).

B. Experimentation Design

The experimentation is split in two stages: the former compares the three techniques for blink detection, while the latter focuses on the comparison of the three techniques for blink removal. The removal algorithms are applied after using the best performing detection method.

1) Experiment I: Comparison of Blink Detection Algorithms: The aim of the first experiment is to compare the three different blink detection techniques described in Section II: VME, Correlation-based and Dynamic Threshold.

- The VME algorithm was implemented in MATLAB [2]. A few small changes were added to the code to make it more generic. Since a 2-seconds sliding-window with no overlapping was applied to the EEG signals, a first manual labelling was performed to all the signals following these conditions. This algorithm requires no initial training, so it can be applied online.
- The Correlation-based one was implemented in Python. It requires an initial pass over the signal in order to extract the blink template, so two passes are considered for each subject: the first one through a previous test signal to extract the subject's pattern and the second one through the actual EEG recording for online detection.
- The Dynamic Threshold algorithm was implemented in Python. For each of the 10 target EEG segments, a normal template of blink-free windows is created by extracting these windows from all the other 9 EEG segments, i.e., each EEG signal is being compared with the normal activity of all the other signals, which means that each subject signal has its own normal template and, therefore, its own dynamic threshold value created from signals from other subjects. Since a 1-second sliding-window with 50% overlapping was applied to the EEG signals, another manual labelling was performed following these new conditions. Due to a certain template is created before running the algorithm on the corresponding subject signal and its threshold value is constant, it only needs to be calculated once, and the detection can be performed online. Tabla de media+varianza+umbral de cada plantilla

[2]The MATLAB code is available on GitHub with repository name: VMEDWT-Eyeblink-Elimination

The detection performance of all methods is being compared by three statistics: Accuracy, Sensitivity and Specifity. These values are calculated for each algorithm and each one of the 10 target EEG signals. The Mean, the Median and the Standard Derivation of each statistic are also calculated.

2) Experiment II: Comparison of Blink Removal Algorithms: The aim of this experiment is to compare the three different blink removal techniques described in Section **??**

IV. Results and Discussion

A. Comparison of detection methods

B. Comparison of removal techniques

Comparativa de metodos de removal

V. Conclusions

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	VME			Correlation			Dynamic Threshold		
Fold	Acc	Sens	Spec	Acc	Sens	Spec	Acc	Sens	Spec
1	0.9333	1.0000	0.9000	0.9600	1.0000	0.9592	0.7458	1.0000	0.6939
2	0.8667	0.8000	0.9000	0.9057	1.0000	0.9029	0.6779	1.0000	0.5957
3	0.5333	0.7143	0.3750	0.9114	1.0000	0.9086	0.5254	1.0000	0.3636
4	0.8667	0.8571	0.8750	0.8486	1.0000	0.8452	0.4068	1.0000	0.1463
5	0.7333	0.5000	1.0000	0.9543	1.0000	0.9525	0.4407	1.0000	0.1750
6	0.7333	0.5000	1.0000	0.9429	1.0000	0.9399	0.9153	0.8235	0.9524
7	0.5333	0.3333	0.8333	0.9629	1.0000	0.9614	0.8305	0.5909	0.9730
8	0.6667	0.4444	1.0000	0.9514	1.0000	0.9500	0.8644	0.6111	0.9756
9	0.8667	0.7778	1.0000	0.9971	1.0000	0.9971	0.9492	0.8421	1.0000
10	0.8000	0.6250	1.0000	0.9229	1.0000	0.9208	0.9153	0.7222	1.0000
Mn	0.7533	0.6552	0.8883	0.9357	1.0000	0.9338	0.7271	0.8590	0.6876
Mdn	0.7667	0.6697	0.9500	0.9471	1.0000	0.9449	0.7882	0.9210	0.8232
StD	0.1407	0.2098	0.1913	0.0408	0.0000	0.0417	0.2049	0.1677	0.3494

TABLE I

RESULTS OF CROSS-VALIDATION USING VME (LEFT), CORRELATION (CENTER) AND DYNAMIC THRESHOLDING (RIGHT) AS THE DETECTION TECHNIQUE. MN = MEAN. MDN = MEDIAN. STD = STANDARD DEVIATION.

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