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Comparative evaluation of existing and new methods for correcting ocular artifacts in electroencephalographic recordings

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ABSTRACT

EEG signals are often contaminated by ocular artifacts (OAs), in particular when they are recorded for a subject that is, in principle, awake, such as in a study of drowsiness. It is generally desirable to detect and/or correct these OAs before interpreting the EEG signals. We have identified 11 existing methods for dealing with OAs. Their study allowed us to create 16 new methods. We performed a comparative performance evaluation of the resulting 27 distinct methods using a common set of data and a common set of metrics. The data was recorded during a driving task of about two hours in a driving simulator. This led to a ranking of all methods, with five emerging clear winners, comprising two existing methods and three new ones.

1. Introduction

Electroencephalographic (EEG) recordings are often contaminated by signals from other sources. The term "artifact" is used both to qualify the contaminating signals, and to refer to a local deformation of the signal of interest, here the EEG signal. One distinguishes between physiological artifacts and technical artifacts. The most frequent physiological artifacts are due to the activity of the eyes, the heart, and the muscles. The most common physiological artifacts are the ocular artifacts (OAs), due to the movements of the eyeballs and eyelids. Technical artifacts are mostly due to electrode placement problems and body movements. Although we generally record the EEG signals from several electrodes, we often consider one of these signals as a generic exemplar. For conciseness, we also use "EEG" to refer to one or more EEG signals in a recording. All artifacts result in a recorded EEG signal that may be quite different, generally locally, from the true underlying EEG signal reflecting the true brain electrical activity. It is thus critical to do something about OAs.

There are three main ways of dealing with OAs. The first ("prevention") tries to minimize the occurrence of OAs by giving proper instructions to patients. However, some OAs occur in a spontaneous, involuntary way, and are thus unavoidable. The second ("epoch rejection") first detects OAs and then rejects, in totality, any epoch affected by one or more OAs; a typical epoch is 2-s long. This approach has the disadvantage of wasting lots of potentially useful data. The third ("signal correction") modifies the OA-corrupted signal and tries to recover, as best as possible, the true, underlying EEG signal (which will, of course, never be known exactly).

The best approach for cleaning an EEG recording from its OAs is probably to detect (i.e. locate) each successive OA, to select a time interval containing it (with appropriate

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Table 1
Existing methods from the literature, and the tools they use.

Tool families	Tools	Hypotheses	Existing methods										
			1	2	3 .1	3 .2	4 .1	4 .2	5 .1	5 .2	6 (*)	7 (*)	8 (**)
WT	DWT	-											
	SWT	-											
AF	LMS	-											
	RLS	-											
	H^{∞}-TV	-											
ICA	E-INFOMAX	NG											
	FastICA												
	BGSEP	NS											

*Uses stICAra.
**Uses weICAra.

margins on both sides), and to correct the EEG recording only in this interval. This avoids perturbing the signal in time regions where the signal is probably not, or less, corrupted; this also results in savings in computation. This approach thus consists in detection/location followed by correction/cleaning. Most published approaches apply the correction directly to the whole signal (possibly per epoch), i.e. without a preliminary detection. Of course, any correction method can be turned into a detection method by subtracting the corrected signal from the raw signal, and appropriately thresholding the resulting signal. The ideal approach for cleaning long recordings from OAs is probably to apply a fast method to locate each OA, and then a sophisticated method to correct the raw signal within the corresponding interval. This paragraph clearly indicates that one needs various types of methods to detect and/or correct OAs. This paper is precisely devoted to providing and evaluating such methods.

When dealing with OAs, it is useful to also record the electrooculographic (EOG) signals, which allows the observer (and the algorithms) to relate the OAs in the EEG and the corresponding features in the EOG.

Our interest in the handling of OAs arose from the study of drowsiness in subjects actively involved in a task, such as driving. Until they fall asleep, these subjects have their eyes mostly open. Therefore, the EEG signals recorded for studying the evolution of drowsiness are affected by OAs due to eye movements and eye blinks. This should be contrasted with the study of sleep, where subjects have their eyes closed. (However, the eyes and the eyelids can move even when the eyes are closed.)

In this paper, we start by identifying the existing methods for detecting and for correcting OAs in EEG signals, and by decomposing them into their constitutive elements. We continue by creating new methods obtained by recombining and/or complementing these elements in different ways. Finally, we quantify the performance of all existing and new methods on a common set of real-life signals and by using a common set of performance measures. Such a comparative study did not exist for the existing methods.

Section 2 describes the data used. Section 3 describes the existing and new methods for dealing with OAs. Section 4 describes the techniques we designed for evaluating and comparing the performances of all these methods. Section 5 presents the results of the comparative performance evaluation. Section 6 concludes and suggests directions for further work.

2. Description of data

We acquired data at the "Centre d'Etudes des Troubles de l'Eveil et du Sommeil" (CETES) of the University Hospital of Liège in the context of the study of driver drowsiness. We successively placed five subjects in a driving simulator and asked them to drive, for about two hours, at a constant speed of 80 km/h, on a one-way road with no other traffic. A fixed laboratory Embla system recorded the following polysomnographic (PSG) signals, at a sampling rate of 200 Hz: EEG (for electrodes Fz, Cz, Pz, C3, C4, A1, A2), EOG (left and right), and EMG. The PSG signals were oversampled at 500 Hz and partitioned into butting (and thus non-overlapping) epochs. The size (in seconds and/or samples) of each depends upon the method used for dealing with OAs.

3. Methods for dealing with OAs

3.1. Existing methods from the literature

Starting with the reviews of [1] and [2], we identified eight existing "main" methods for dealing with OAs, with