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One-class classification of temporal EEG patterns for K-complex extraction*

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***Abstract*— The purpose of this study was to detect one of the constituent brain waveforms in electroencephalography (EEG), the K-complex (KC). The role and significance of the KC include its engagement in information processing, sleep protection, and memory consolidation [1]. The method applies a two-step methodology in which first all the candidate KC waves are extracted based on fundamental morphological features imitating visual criteria. Subsequently each candidate wave is classified as KC or outlier according to its similarity to a set of different patterns (clusters) of annotated KCs. The different clusters are constructed by applying graph partitioning on the training set based on spectral clustering and exhibit temporal similarities in both signal and frequency content. The method was applied in whole-night sleep activity recorded using multiple EEG electrodes. Cross-validation was performed against visual scoring of singular generalized KCs during all sleep cycles and showed high sensitivity in KC detection.**

I. Introduction

EEG has been widely used as a diagnostic tool in sleep studies since it provides the means for analysis of sleep macrostructure which includes the identification of the different sleep stages (referred to as sleep scoring [2]) and microstructure which refers to the identification of the conspicuous and quite repeated individual brain waves and rhythms. One of these waveforms is the K-complex (KC), which was first described by Loomis et al. [3]. KCs have been suggested to protect sleep and also to provide gating functions in idiopathic generalized epilepsies or sleep disorders [1]. They happen mainly during the non-rapid eye movements (NREM) sleep stage and are one of the hallmarks of sleep stage 2 [2]. They are also considered precursors of delta waves and their frequency of appearance in EEG is one of the key features for sleep scoring. Due to the extreme size of all night sleep EEG, visual recognition of KCs is almost prohibitive in a routine setting, thus the necessity of an automatic detection method becomes apparent.

Apart from labor-intensive, visual marking is also highly scorer dependent mainly due to high intra- and inter-subject variability of KC characteristics and variation in human perception. KCs have been defined by standardized scoring rules [2][4] based on the visual appearance of the signal. The American Association of Sleep Medicine (AASM) gives the following definition: "a K complex is a well delineated negative sharp wave immediately followed by a positive component standing out from the background EEG with total duration ≥0.5 sec. It is usually maximal in amplitude over the frontal regions" [4]. Due to the close similarity of KCs and other waves, such as delta waves, and the high variation of KC appearance (large range of amplitudes and durations), the development of a reliable detection method is not easy.

Several pattern analysis algorithms have been reported in the literature for automated extraction of KCs. A continuous density hidden Markov model was used in [5] to model the background EEG and the phases of the KC, while in [6] the EEG wave patterns were modeled as the sum of two sinusoidal curves with piece-wise linear amplitude. Hjorth parameters activity and complexity and fuzzy decision making were used to create a single channel detector [7]. Also joint linear filtering in time and time-frequency domains was introduced in [8] for classification of KCs and delta waves. All these methods have been applied for classification of isolated waveforms, such as segments of KCs or non-KCs, delta waves and background, and have not been assessed for detection of KCs in whole night EEG.

Devuyst et al. [9] proposed a KC detection algorithm based on features reflecting visual criteria of scoring and the use of likelihood thresholds. The likelihood thresholds were determined by the distribution of the features as calculated from a training set of KCs. Although the results of the method are promising (details are provided in the discussion section), detection methods that apply thresholding of features with experimentally defined thresholds on the dataset used for testing, may have poor performance when applied on different datasets derived from multiple subjects or institutes due to lack of cross-validation and overfitting. Erdamar et al. [10] suggested a detection method based on Teager Energy Operator and wavelet decomposition. The detection algorithm achieved high sensitivity with low false positive (FP) rate but was tested only on NREM stage 2 epochs from a single subject. Likewise, Saccomandi et al. [11] proposed a two-step algorithm based on multiple channels for the detection of transient events such as KCs, delta waves and cycling alternating patterns in sleep stage 2 and 3 occurring in the descending branch of the 2nd sleep

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cycle. Both methods don't report results from sleep stage 4, where usually the most FPs appear due to their similarity with the delta waves.

In this paper we propose a two-step KC detection methodology, which first identifies all possible candidates according to pre-defined expert-based rules using multi-channel information and then reduces false detections by applying a machine-learning algorithm. The novelty of the method mainly relies on the second step which (i) exploits both the time-varying signal and the spectral content of it, (ii) applies a novel outlier detection methodology based on graph partitioning by spectral clustering, and (iii) uses time-frequency (TF) representations that describe the spatiotemporal KC characteristics via their time-varying spectral content. Although time and frequency representations have independently been used for KC detection, TF representations have mainly been used in non-automated (visual) methods [12] and rarely in KC classification [8], but have not been sufficiently explored in automated KC detection.

II. METHOD

The aim of the method was to automatically detect spontaneously occurring KCs imitating the practice followed by expert scorers without however requiring sleep stage information. In this study, the visual scorer selected KCs from NREM stage 2 and 3 that are singular (without another KC or slow wave activity immediately preceding or following) and generalized (distinguishable in the EEG across all the midline electrodes). The proposed method includes 2 steps. In the first step, all the candidate KC waves are extracted based on empirical rules and thresholding. Fundamental features are used for the description of KC morphology, such as peak to peak amplitude of the wave. In the second step the candidates are reduced by evaluating their similarity to a set of training segments (labeled KCs) regarding both signal and frequency content. The components of the method are explained with more details next.

A. Preprocessing

The raw EEG recordings were first resampled at a sampling frequency of 200 Hz to reduce dimensionality and then low-pass filtered to remove high frequency noise. We used a Dolph-Chebyshev window (with a filter order of 100) and a cut-off frequency at 5Hz to include the frequency range of KCs. Subsequently baseline correction was performed. Specifically, EEG signals are undergoing slow shifts over time during the recording, such that the zero level (DC component) might differ considerably across channels. The DC component was extracted by calculating the mean signal in overlapping segments and then smoothing this stepwise constant DC component by using a moving average filter (Fig. 1). The smoothed DC component was afterwards subtracted from the original signal (resulting in the blue bold trace in Fig. 1, bottom).

B. First step: Knowledge-based detection

In the first step, for each one of the selected channels (usually a subset of the available channels) all the large local minima are detected and considered as candidate K-complexes. The peaks should have at least a minimum absolute peak height and be at least separated by a distance threshold; thus smaller peaks that may occur in close proximity to a large local peak are ignored. The center of each candidate KC is defined as the location of the local minimum. The idea is to limit the number of the candidates by imposing some knowledge-based rules specific to the K-complex morphology and possible noise. The features used in this process are the following:

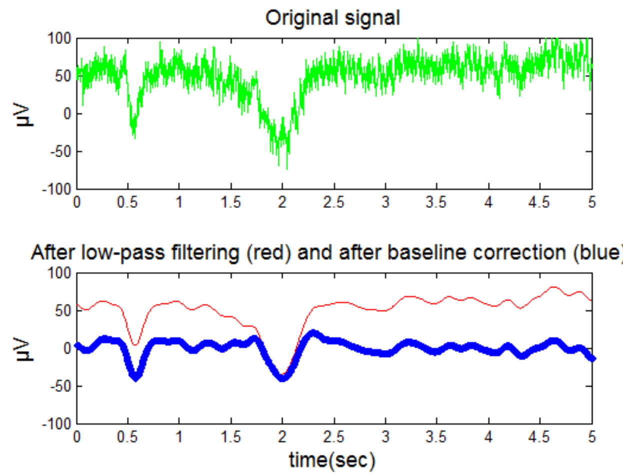

Figure 1. Preprocessing of an EEG channel. A KC appears at 2 sec.

- peak to peak amplitude, both as independent value and relative to background neighborhood
- ratio of standard deviation of waveform versus standard deviation of background
- duration of the negative sharp wave
- ratio of power of high frequencies versus total power of the waveform (high ratio might indicate that muscle noise is contaminating the data).

The thresholds for these features are first set to the values defined by the expert scorer and then slightly relaxed to account for signal changes due to preprocessing and also ensure that as few KCs as possible are missed in this step (with the burden of many FPs). The candidates are detected in each channel independently and subsequently combined into a single set by checking for temporal coincidences across channels.

The above rules however failed to differentiate well between KCs and delta waves. Delta waves are similar to KCs and occur mainly in Slow Wave Sleep (SWS). Their characteristic is the fact that they occur repeatedly compared to the single appearances of KCs. Since the method does not rely on sleep staging (while visual rating does), it is important to reject candidates in SWS. We follow a simplified procedure based on the assumption that the frequency of appearance of waves resembling KCs is higher in SWS than during the rest of the sleep. If the frequency of appearance exceeds a threshold, it is assumed that the epoch belongs to sleep stage 4 and thus all candidates in the epoch are rejected. The threshold has been selected as an appropriate percentile of frequency of KC appearance in whole night sleep recordings.

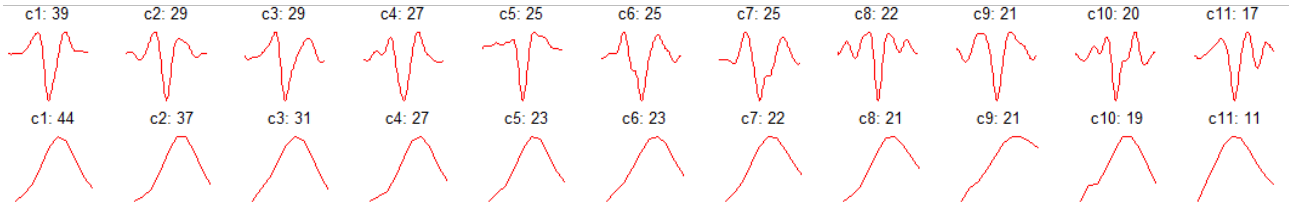

Figure 2. KC training patterns calculated by spectral clustering (N_c=11). The amplitude and power of signal over time are averaged over all samples per cluster and illustrated in 1st and 2nd row, respectively.The titles show the number of samples per cluster.

C. Second step: False positive reduction by outlier detection

In the second step, an outlier detection scheme is applied to reduce the number of false detections. Each KC segment is represented by two temporal patterns: (i) the amplitude change over time (signal representation) and (ii) the frequency content over time, which is calculated as the power spectral density (TF representation) integrated in the range 0.5-5Hz. Thus one time series is produced for each representation $x^t \in \mathbb{R}^{d_t}$ and $x^f \in \mathbb{R}^{d_f}$, where d_t and d_f is the dimensionality, i.e. number of time points. We extracted KC segments of 2sec duration (± 1sec around the peak of the negative phase). At 200Hz sampling frequency (as in our experiments) the dimensionality of the signal corresponds to $d_t = 400$ time points, while the power spectral density has been calculated at $d_f = 40$ time points. Both vectors x^t and x^f are downsampled by a factor of 4 to reduce dimensionality and z-score normalized. Then, each vector is assigned a pseudo-probability value of being a KC depending on its similarity with manually marked KC segments, as described next. The classification algorithm includes a training and a testing phase.

Training phase: Since different patterns of KC morphology exist, the distribution of the training vectors in space is not expected to be around a unique center and neither have a known shape (that for example could be modeled by a Gaussian distribution). We only assume that enough examples exist from each pattern of KC morphology and that these examples lie closer to each other in space than examples from different patterns. In order to detect these patterns, we apply a graph partitioning technique known as spectral clustering [13] to partition the training set into a set of clusters. Spectral clustering divides graph nodes into groups so that connectivity is maximized between nodes in the same cluster and the connectivity is minimized between nodes in different clusters. Connectivity is measured by some affinity (similarity) measure. We define as affinity measure between sample *i* and *j*, the quantity

$$A_{ij} = e^{-\frac{D_{ij}^2}{2\sigma^2}}, \tag{1}$$

where D_{ij} is the distance of sample i and j and σ some normalization constant. We use the Euclidean distance as distance measure and the dimensionality of the samples (d_t or d_f) for σ. Each of the resulting clusters includes examples of a pattern of KC morphology regarding the amplitude change or power of signal over time. These patterns, extracted from the provided dataset are illustrated in Fig. 2 by averaging over all samples per cluster. For each training cluster $c = 1, .., N_c$, where N_c is the number of clusters, the cumulative histogram of all pairwise affinities is calculated, $p_c(A_i)$, as a probability measure of a sample i with affinity value A_i to be an inlier of the distribution. The higher p_c, the smaller the significance (p-value) and thus the possibility of the sample to be an outlier (FP).

Testing phase: For each test vector i we calculate its distance D_{ic} of to each training cluster c as the distance to the closest sample in cluster c and calculate the affinity A_{ic} according to (1). The probability of the sample to be an inlier in the distribution of pattern c, is calculated as $p_{ic}(A_{ic})$. Linear interpolation is used to calculate intermediate values. Finally the probability of the test vector to be a KC is calculated as the maximum probability across all clusters.

The training and testing phase are performed independently for each set of time series, x^t and x^f, representing signal and frequency content. The two probabilities, let's denote them as p_i^t and p_i^f for sample i are fused and thresholded to reach the final decision. Fusion is performed by Fisher's method [14] which combines p-values from several independent tests into one test statistic that has a chi-squared distribution:

$$p_i = F_{chi2}(-2(\ln(1 - p_i^t) + \ln(1 - p_i^f)) \tag{2}$$

where p_i is the total probability combing signal and frequency content and F_{chi2} is the cumulative distribution function evaluated at the test statistic. We used $(1 - p_i^t)$ and $(1 - p_i^f)$ as the p-values of each probability. The total probability p_i is used for ROC analysis of the results.

III. Results

A. EEG Data

The data used in this work were acquired during a whole-night sleep EEG of a healthy volunteer without a history of neurological or psychiatric disorder, or sleep disorder. Nocturnal sleep was recorded using 58 EEG tin electrodes positioned according to the extended international 10–20 system on an electrode cap (ElectroCap International Inc, Eaton, OH, USA). Electrophysiological signals were AC recorded, amplified (×1000), band-pass filtered (0.05–500Hz), and digitized (16-bit A/D conversion) at 2500Hz. In order to reduce the computational load, only 10 electrodes across the midline were used for KC detection. Manual cursor marking offered by Scan software was used in order to place time-markers over the KCs. The KC was visually identified as a >500 ms well-delineated negative sharp wave

TABLE I. DETECTION ACCURACY

	FN	FP	TP	TP/P	FP/P
after 1st step	39	2218	240	86%	795%
after 2nd step	47	1330	232	83%	477%

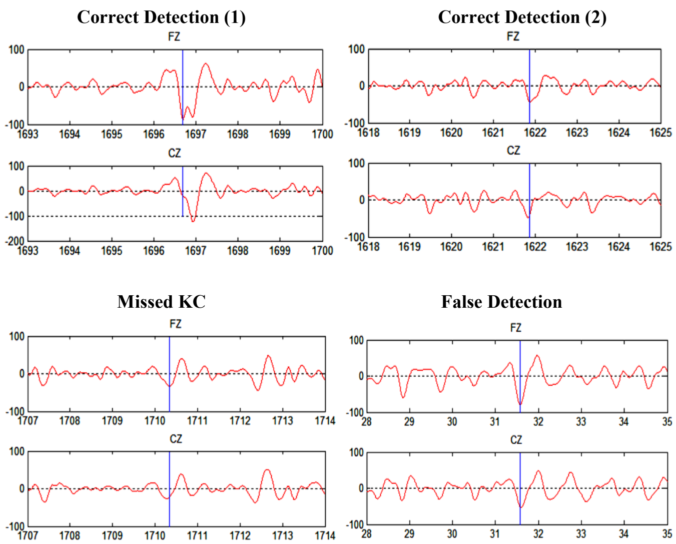

Figure 3. Examples of two correct detections (top panel), one missed KC (bottom left) and one false detection (bottom right). The recordings of the 'FZ' and 'CZ' electrode are shown for each case. The vertical blue line indicates the location of the marker or the detected KC for the FP case.

usually followed by a positive phase that stands out of the EEG background [1]. It was visually marked at the peak of the negative phase [11]. Later on, during data preprocessing, imprecise markings were corrected by shifting them to point the largest negative value within a predefined neighborhood (±0.35sec) around the original marking.

B. Detection Performance

Assessment was performed by examining the temporal coincidence of the manually and automatically detected KCs. The maximum time interval between an automatically detected peak and the closest marker (detection latency), that allows a detection to be characterized as TP, was selected as 0.5sec. Automatic detections with higher latency were characterized as FPs, whereas manual detections with higher latency were characterized as FNs. The 2nd step of the method was assessed by 3-fold cross validation on the data consisting of 13 excerpt files (of 0.5h sleep each), i.e. each time 2/3 of the sleep recordings were used for training and 1/3 for testing. The total number of marked KCs for all excerpts was P=279, while the total number of candidate KCs after the 1st step was 2458.

Table I shows the results after the 1st and 2nd step of the proposed method and reports the average (over all excerpts) FP rate (=FP/P), as defined in [9], for a given level of sensitivity (=TP/P). It can be observed that the outlier detection scheme applied in the 2nd step reduces significantly the FPs by only slightly reducing the TPs. The 2nd step of the method was additionally assessed by performing ROC analysis. The average area under the curve (AUC) was 0.62 and the highest (for varying thresholds) classification accuracy (number of correctly classified candidates) was 84%. As a comparison to our results, the method in [9] reported a sensitivity of 61.7% and 60.9% for two visual scorers, for FP rates 19.62% and 181.25%, respectively. However based on our evaluation criteria (detection latency = 0.5sec) and the provided results [15], which contain the time instant of each detected KC, the method achieved a sensitivity of 56.3% and 59.4% for the two scorers, for FP rates 43.0% and 215.6%, respectively.

Some illustrative examples of two correctly detected KCs, one missed KC, and one false detection, are illustrated in Fig. 3.

IV. CONCLUSION

An automatic scheme is proposed for detecting a specific brain waveform in EEG, the K-complex. After the application of knowledge-based rules for extracting candidate waves, a one-class classification method was applied which reduced false detections by 60% with only 3% reduction in TPs. The presented methodology is generalizable for any waveform providing a computationally efficient tool for outlier detection.

REFERENCES

[1] P. Halász, "K-complex, a reactive EEG graphoelement of NREM sleep: an old chap in a new garment," *Sleep Med Rev.*, vol. 9, no.5, pp.391–412, 2005.
[2] A. Rechtschaffen, A. Kales, *A manual of standardised terminology and scoring system for sleep stages in human subjects*. U.S. Government Printing Office, Washinghton, DC; 1968.
[3] A. Loomis, E. Harvey, G. Hobart, "Distribution of disturbance patterns in the human electroencephalogram, with special reference to sleep," *Journal of Neurophysiology*, vol. 1, pp. 413-430, 1938.
[4] M.H. Silber, S. Ancoli-Israel et al. "The visual scoring of sleep in adults," *Journal of Clinical Sleep Medicine*, vol. 3, 2007.
[5] A. Kam, A. Cohen, A. Geva, A. Tarasiuk, "Detection of K complexes in sleep EEG using CD-HMM," *IEEE IEMBS*, 2004.
[6] D. Moloney, et al., "Detecting K complexes for sleep stage identification using nonsmooth optimisation," *The ANZIAM Journal*, vol. 52, no. 4, pp 319-332, 2011.
[7] D Migotina, A Rosa, A. Fred, "Automatic K-complex detection using Hjorth parameters and fuzzy decision," *ACM SAC*, 2010.
[8] C. Richard, R. Lengelle, "Joint Time and Time-Frequency Optimal Detection of K Complexes in Sleep EEG," *Computers and Biomedical Research*, 1998.
[9] S. Devuyst, T. Dutoit, P. Stenuit, M. Kerkhofs, "Automatic K-complexes Detection in Sleep EEG Recordings using Likelihood Thresholds," *IEEE EMBS*, 2010.
[10] A. Erdamar, F. Duman, S. Yetkin, "A wavelet and teager energy operator based method for automatic detection of K complex in sleep EEG," *Expert Systems with Applications*, 2012.
[11] F. Saccomandi, L.Priano, A. Mauro, R. Nerino, Guiot C. "Automatic detection of transient EEG events during sleep can be improved using a multichannel approach," *Clinical Neurophysiology*, 2008.
[12] V. Kokkinos, GK. Kostopoulos, Human non-rapid eye movement stage II sleep spindles are blocked upon spontaneous K-complex coincidence and resume as higher frequency spindles afterwards. *J Sleep Res.,* vol. 20, no.1, pp.57-72, 2011.
[13] A.Y. Ng, M.I. Jordan, Y. Weiss, "On Spectral Clustering: Analysis and an algorithm," *Advances In Neural InformationProcessing Systems*, pp. 849–856, 2001.
[14] R.A. Fisher, *Statistical Methods for Research Workers*. Oliver and Boyd (Edinburgh), 1925.
[15] http://www.tcts.fpms.ac.be/~devuyst/Databases/DatabaseKcomplexes/