

# K-complex Detection using Sparse Optimization

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This work describes a method using sparse optimization for the detection of K-complex in sleep EEG. K-complex is an important feature in sleep stage identification, which is helpful to sleep disorder diagnostics process. In this work, a discrete-time sleep EEG signal  $\mathbf{y} \in \mathbb{R}^N$  is modeled as:

$$\mathbf{y} = \mathbf{x}_1 + \mathbf{x}_2 + \mathbf{w}, \quad (1)$$

where  $\mathbf{x}_1$  is the baseline trend,  $\mathbf{x}_2$  is composed of K-complexes, and  $\mathbf{w}$  presents noise. More specifically,  $\mathbf{x}_1$  is piecewise smooth comprising a lowpass signal component  $\mathbf{f}$ , and a sparse order- $K_1$  derivative component  $\mathbf{g}_1$ , i.e.,  $\mathbf{x}_1 = \mathbf{f} + \mathbf{g}_1$ . Further,  $\mathbf{x}_2$  is assumed as a transient waveform with a negative wave followed by a positive wave, and modeled as a ‘wavelet’ (e.g. Fig. 1(b)). Moreover,  $\mathbf{x}_2$  is modeled as the output of a high-pass filter, i.e.,  $\mathbf{x}_2 = \mathbf{H}_2 \mathbf{g}_2$ . In addition, we assume the order- $K_1$  derivative of  $\mathbf{g}_1$  is sparse, and we likewise assume the order- $K_2$  derivative of  $\mathbf{g}_2$  is sparse. In another word,  $\mathbf{g}_1$  and  $\mathbf{g}_2$  are sparse-derivative signals, where  $\mathbf{u}_1 = \mathbf{D}_1 \mathbf{g}_1$ , and  $\mathbf{u}_2 = \mathbf{D}_2 \mathbf{g}_2$  are both sparse. Adopting the zero-phase filter design techniques discussed in Ref. [3], and the idea of morphological component analysis (MCA) [4], we formulate the optimization problem:

$$\{\mathbf{u}_1^*, \mathbf{u}_2^*\} = \arg \min_{\mathbf{u}_1, \mathbf{u}_2} \frac{1}{2} \|\mathbf{H}_1 \mathbf{y} - \mathbf{A}_1^{-1} \mathbf{B}_1 \mathbf{u}_1 - \mathbf{A}_2^{-1} \mathbf{B}_2 \mathbf{u}_2\|_2^2 + \lambda_1 \sum_n \rho_1([\mathbf{u}_1]_n) + \lambda_2 \sum_n \rho_2([\mathbf{u}_2]_n). \quad (2)$$

where  $\rho_1$  and  $\rho_2$  denote penalty functions. The high-pass filters are expressed as  $\mathbf{H}_1 = \mathbf{A}_1^{-1} \mathbf{B}$ ,  $\mathbf{H}_2 = \mathbf{A}_2^{-1} \mathbf{B}$ , with  $\mathbf{B} = \mathbf{B}_1 \mathbf{D}_1 = \mathbf{B}_2 \mathbf{D}_2$ . Using the solution from (2), we recover  $\mathbf{x}_1$  and  $\mathbf{x}_2$  by:

$$\hat{\mathbf{x}}_1 = \mathbf{y} - \mathbf{H}_1 \mathbf{y} + \mathbf{A}_1^{-1} \mathbf{B}_1 \mathbf{u}_1^*, \quad \hat{\mathbf{x}}_2 = \mathbf{A}_2^{-1} \mathbf{B}_2 \mathbf{u}_2^*. \quad (3)$$

Problem (2) both decomposes the data  $\mathbf{y}$  into  $\mathbf{x}_1$  and  $\mathbf{x}_2$ , and performs denoising. It can be solved iteratively by majorization-minimization (MM) [2]. Further, the proposed algorithm is computationally efficient as it makes use of banded matrices. We use an asymmetric penalty function to capture the morphology of K-complex, and implement a simple detector by thresholding the local energy of  $\mathbf{x}_2$ . We test the proposed method by the public dataset collected in [1]. It achieves a better accuracy (F-measurement) than the result reported in [1]. An example is illustrated in Fig. 2.

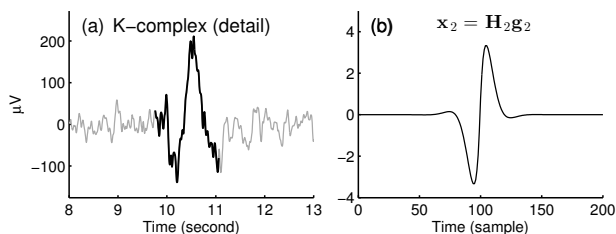


Fig. 1. (a) K-complex detail, (b) transient component signal model.

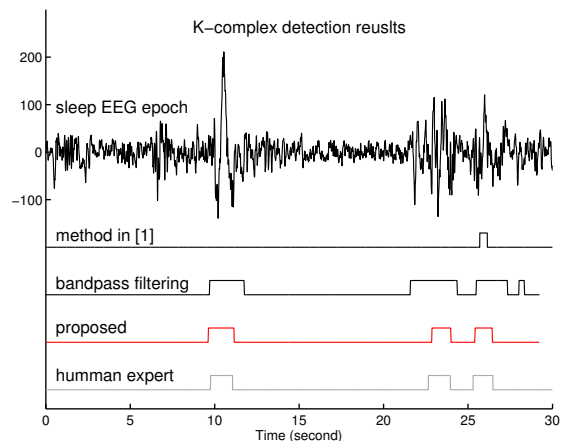


Fig. 2. Comparison of detection results: method proposed in [1], bandpass filtering, our proposed method, expert.

## REFERENCES

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