A NEW APPROACH TO THE K-COMPLEXES AUTOMATED DETECTION

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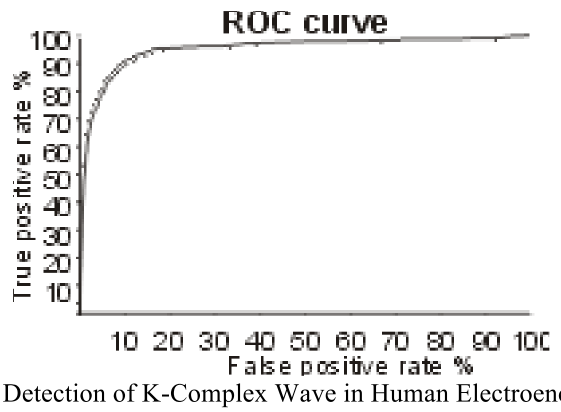
The automated detection of k-complexes in sleep EEG has already been the subject of several studies[1,2]. Most of time, the detection problem boils down to discriminate k-complex from delta waves that can easily be confused with k-complex. Then, various methodological solutions are described to sort out the both features in equal proportion. From this point of view, the numerical results seem to be actually convincing. Nevertheless, in practice, the situation is far more complicated. When doing a full-night EEG matched prefiltering, positive set accounts for 95% of clearly identified k-complexes. Yet, false positives are twenty times higher than true positives[3]. In these circumstances, existing discrimination methods are insufficiently selective.

Our study show a new approach based on Time-Frequency (Wigner transform) discrimination. In fact, we introduce a method of designing linear TF-based receivers from labeled training data. Accurately, this method enable to avoid large biases due to the small number of data[4]. Numerically speaking, 64 values are needed to model a k-complex feature (32Hz signal during 2 second) and the dimension of the Wigner transform is 64x64=4096. So, the direct receiver optimisation requires a very large quantity of learning data, out of proportion to the dimension of a realistic learning set. Our most important concern has been to ensure an effective complexity regulation of the problem. The basic idea has been founded on a very general methodology introduced by Fukunaga to design linear discriminants in the context of Pattern Recognition[5]. A interesting point that this theory is not very restrictive with regard to the distributions of the data sets. But, first and foremost, the Fukunaga theory reduces the optimisation problem to the optimisation of a single parameter. In addition, we regulate internal computation complexity of Fugunaga theory with classical methods called "brain damage" or "weight decay". In this way, we obtain a very coherent construction of an optimum linear receiver.

This new detector seems to be better than the other existing solutions to discriminate two equal size sets of k-complexes and delta waves[4]. And we can show the results in a practical case.

To make the learning set, the all-night sleep recordings of 3 healthy young volunteers have been scored by 6 experts. The testing set has been obtained in the same way with 3 other healthy young volunteers. K-complexes identified by at least 3 out of 6 scorers are kept for the analysis. We can estimate the average k-complex and build the matched prefilter that keep 95% of the two previous k-complex sets. The two false positive sets of the prefiltering on each 3 volonteers group give the two sets of non k-complexes elements, a learning and a testing one. The size of each non k-complex set is around 15000 and the size of each k-complex set is around 600. In that case, the performances of our discrimination method are presented in the following figure.



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