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ADVANCED METHODS FOR THE ESTIMATION OF HUMAN BRAIN ACTIVITY AND CONNECTIVITY

Automatizing detection of spectroscopic features

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Abstract. We are involved in the investigation and development of methods for the automatized localization, extraction, analysis and comparison of features in spectra of biological signals. With diverse applications, different feature attributes turn out as significant and as characteristics of the investigated phenomena. Individual tunes and music representation in brain signals have attracted our attention since early nineties and the possibility to use inner tunes in the brain for the Brain Computer Interfaces, BCI. There were some of the motives for the present study, but applicability of the developed algorithms is broader.

Keyword: Spectral feature automatic detection; Inner Tones and Music; Brain Computer Interface;

1. Introduction

Automatized recognition of spectroscopic features can announce serious cardiac crisis in the monitoring of cardiologic parameters. In EEG it can announce epileptic seizures and is used in brain computer interfaces BCI. We experimented with EEG recordings of externally generated and inner tones, the imagined tones which are not sung aloud and inner music, [Jovanovic 1997; 2001; Jovanovic and Perovic 2007]. Inner tones can be taken as the basis for the command language for the BCI. The BCI became reality in recent years. Impressive are achievements of Babiloni and his group [Babiloni et al., 2007; Cincotti et al., 2002], other groups as well. Some researchers have suggested high - HF frequency EEG for the BCI applications, e.g. [Jovanovic 1998; Zattore and Halpern, 2005; Watkins et al., 2006; Kroger et al., 2006]. Here we present some examples from our practice where the automatic recognition of spectral features is applicable and useful, describing method applied and its effects on the patterns of interest.

Some examples of real time spectrograms with a sort of features we are dealing with are given in the presented figures. We have developed systems for the real time acquisition and analysis of large number of signals. Shown is acoustic recording of a hump back whale song, then spectrograms of inner tones recorded with 8 channels EEG at 4 KHz, Figure 1. Blood pressure - BP spectrogram features are shown on Figure 2.

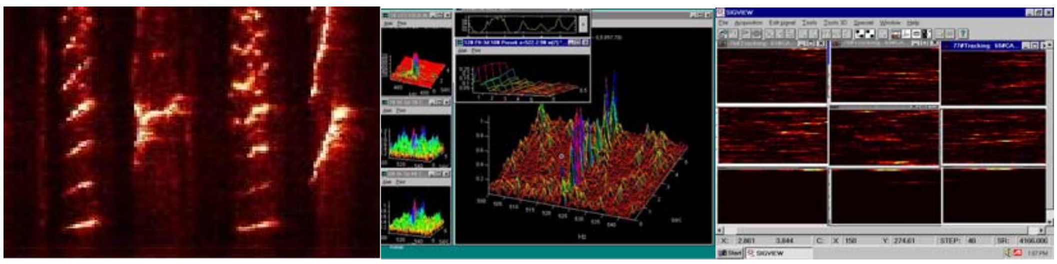

Figure1.*Examples of spectrogram features. Left: spectrogram of a humpback whale song; large structures correspond to melodious patterns which change in both frequency and rhythm. Center: extracted dominant feature in a composite spectrogram of EEG with inner- imagined tone c2. Right: spectrograms of EEG containing features corresponding to the traces of inner tones.*

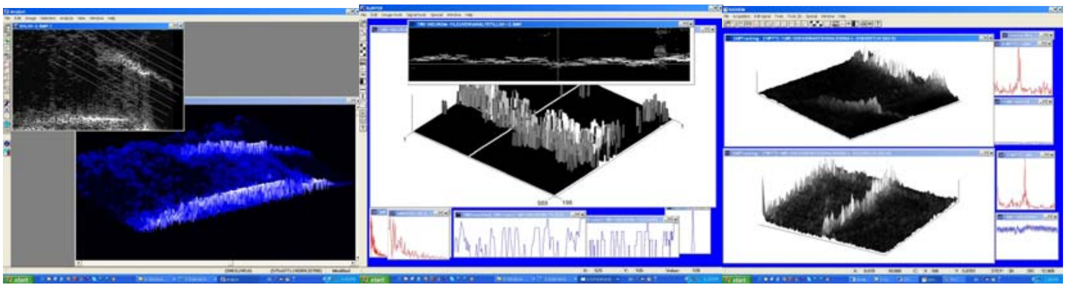

Figure 2. *Features in the spectrograms of long recordings of blood pressure - BP.*

2. Methods

For certain aspects in automatized feature recognition we treat our real time spectrograms and composite spectrograms with tools more related to image processing. First, we have automatic threshold reduction, as shown on Figure 3, left. This step can be subjected to the preliminary learning. Following, depending on the application, we have a criterion of minimum spectral stability, i.e. localization of sets of dots - spectral lines in consecutive spectra with topologic invariants that would distinguish them as features against, e.g. smaller granular objects or random dot clouds. The key parameters are defined prior to application. For example, the shortest music tonal feature we are localizing is around 0.1 second. After feature localization, we apply the contour stabilization-smoothing, and then we trace the topology of features by two alternative processes. Geodesy of embedded isophotic (closed) curves determines the gradients around features local extremes and defines the features “meridian”. Alternatively, orthogonal vectors on points of the contour, will provide “ribs and a back bone” of the curved coordinate system, tailored to the topology of the feature. The results of the two methods are compared, with error reduction. Then, within tunable, reasonable approximation, the feature local extremes are marked in the curved coordinate system. This is the basis for further normalizations and for the automatized measurement of similarity with the etalon objects and feature classification to the context dependent criteria. These steps in the automatic feature recognition are illustrated in Figures 2. and Figure 3, left. For the investigation of some dynamic feature characteristics, e.g. those related to both rhythmic and frequency changes, or metric invariants, or those involving second order spectra, necessary is the analysis of features in the original shape, together with some normalized form, obtained by mapping the original topology representation to a suitable, like projections or “rectifications”, as well. This is partly illustrated on Figure 3.

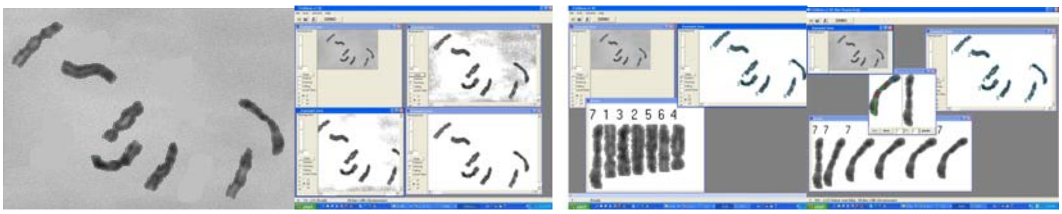

Figure 3. *Example of threshold elimination in automatized procedure leading to the feature-object localization, left. Automatic feature contour detection, topology definition, normalization following its topologic structure, right.*

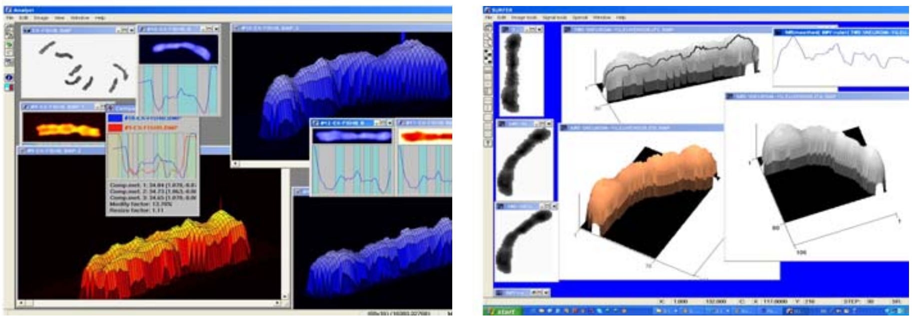

Figure 3. *Feature normalization and automatic comparison, on the left. The same feature step by step normalization with longitudinal sections exhibiting rhythmic change, right.*

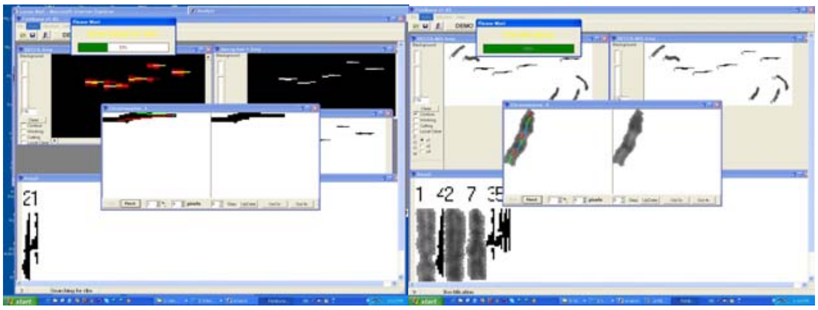

Figure 4. *Automatized feature recognition. Left: real time spectrogram of a simple melody (deccg) played on an electric organ. Right: the same melody expanded with continuous non-constant frequency patterns, treated by the algorithm for automatic feature recognition.*

One example of a spectrogram with locally well defined and well separated features processed through the steps of the above described procedure is given in the Figure 4.

3. Discussion

With some examples from our practice we presented the automatized real time spectrogram feature recognition system. Of course, real experimental practice always offers nice counter examples that do not fit well into predefined conceptual scheme, like parts of the features in the BP spectrograms on the Figure 2, top left. The lower feature contour is heavily fuzzy. The left part of the top structure can hardly be called feature at all, rather a sort of random cloud of dots. But the complete set of dots is definitely structurally related. We are witnessing emergence of a feature out of randomness, a sort of a phase shift, which is characterizing some micro phenomena which are still not tightly semantically bound. This is a kind of reality where here presented method performs poorly, needing improvements. Nevertheless, as it is, it can be well applied in a variety of different cases of real time spectrogram features. We are developing extension of this method, based on nonlinear analysis, see [Klonowski 2007], [Dobosz , Duch 2008]

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