On the Classification of Acoustic Sequences for Intervention in Essential Hypertension

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Abstract

Acoustic signals are able to modulate the human metabolic and central-nervous functions and evoke physiological effects. The anti-hypertensive effect of certain iterative sound patterns, as a possible intervention in essential hypertension, has been examined in particular in many recent studies and has also been part of our own research work. There is evidence that the acoustic sequences and sound clusters used for intervention can decrease blood pressure significantly. For therapy, however, it is necessary to identify the active musical ingredients of the sounds in the context of active pharmaceutical ingredients. This article discusses the systematic analysis of the musical features that are responsible for the anti-hypertensive effect. More than 400 features were extracted and investigated in terms of their relevance concerning their anti-hypertensive effect. The 17 most significant characteristics were used to develop a classifier based on the discriminant analysis that decides whether a sound pattern has a sedative or a stimulating effect. This will be clarified in acoustic demonstrations. With this tool, it is possible to filter the most suitable therapeutic sound patterns from a large selection of music sequences. We now have the foundation for providing individualized and personalized therapies while respecting the personal preferences of every individual user.

Introduction

Arterial hypertension is one of the major endemic diseases present in all western industrialized countries. Apart from the classical anti-hypertensive medication, listening to certain pieces of music may also have an influence on hypertension. Many patients can learn how to actively control their blood pressure in conjunction with the telemedical and sensor-enabled acoustic biofeedback therapy system we are currently developing at the Heinz Nixdorf-Lehrstuhl für Medizinische Elektronik in Munich.

Aside from ergotropic music, which has a stimulating and emotionalizing effect on the body, trophotropic music has a stimulating effect on the parasympathetic nervous system. In many patients this produces a general sedative effect and also, among others, decreased blood pressure.

In order to be able to offer effective biofeedback therapy, it is essential to be aware of the active potential of the pieces of music and even certain parts of such pieces. Various parameters that may – at least if they overlay – have a trophotropic effect were described by Decker-Voigt [1]. In our study, we used - based on these principles - feature extraction to find out about musical characteristics and effects and their suitability for anti-hypertensive therapy. The characteristic features thus identified were subsequently used to define a classifier in order to be able to select music for acoustic biofeedback therapy that is both effective and adapted to individual preferences.

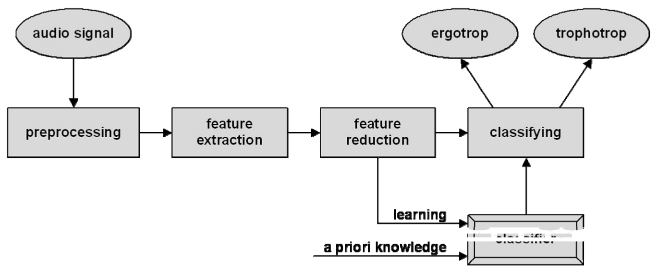

Figure 1: The process of signal processing

Materials and Methods

What kind of music was used?

Within the almost endless range of commercially available music recordings, we focused exclusively on classical music, since it is this genre that is considered to have the best therapeutic effect [2]. We selected 34 ergotropic and 34 trophotropic pieces from all musical eras from baroque to modernism.

Pieces were selected either due to their proven anti-hypertensive effects as described in literature [2, 3], or after it was shown in our own tests that they had such an effect. Examples for such pieces are J. Pachelbel's Canon in D major, or J.S. Bach's "Air" from Orchestral Suite No. 3.

One essential feature of this selection of music is its diversity: It covers all musical settings from solos and chamber music as far as full symphonic complement on the one hand, and a large spectrum of instrumental arrangements on the other. In this way, we could decrease the risk of the classificator being influenced more by formal, stylistic musical features, than by the hypotensive or hypertensive effects.

Feature Extraction

In order to decrease the dimension of the input quantities for the subsequent classification, we used the feature extraction method known from pattern recognition. Instead of considering the amplitude and the spectrum over time, only a vector $\vec{x}$ of features which is extracted from this information was used. A feature is a property that describes the characteristics of an object in a certain situation. In the present case, it is a musical parameter which characterizes the hypotensive or hypertensive effects of a piece.

Many features found in literature in other areas, such as genre classification, were adapted for use in the classification of anti-hypertensive music. In cases in which no suitable method could be found, it was necessary to program special feature extraction algorithms. A total of almost 60 algorithms provide about 270 significant musical features that were tested with respect to their anti-hypertensive effects.

The quality level of feature separation, i.e. the ability of an individual signal to separate ergotropic and trophotropic pieces of music, is calculated using a univariant analysis of variance Wilks' lambda Λ. The better the separation potential of a feature, the smaller Λ will be.

For the purpose of clear illustration, the features were grouped according to their musical significance (Fig. 2). There are groups including rhythmic, dynamic and harmonic features, and also a group of basic features. They include all features that are calculated directly from the spatial or spectral signal which cannot be attributed any clear musical significance.

The groups and their respective major features are described below.

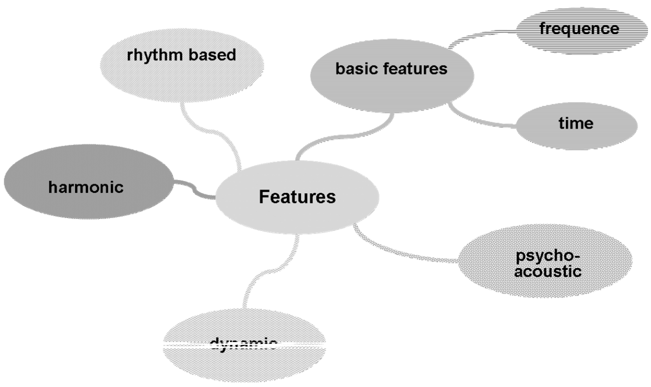

Figure 2: Overview of feature groups

Psycho-acoustic basic features:

This group comprises all features that can be calculated directly from psycho-acoustic models, such as loudness or acuity. The Mel Frequency Cepstral Coefficients (MFCC) frequently used in speech recognition represent a more complex model.

However, none of these features showed much correlation with an anti-hypertensive effect. Accordingly, the results for Wilks' lambda were high (> 0.64).

Basic features in the time domain:

This group includes all features that can be calculated directly from the amplitude waveform. Examples are the zero-crossing rate, the auto-correlation coefficients, or the signal energy. With Λ > 0.71, these features also make little contribution to the classification of anti-hypertensive music.

Basic features in the frequency domain:

These features can be calculated directly from the spectrum of the piece of music and mainly describe the form of the frequencies contained in the signal. Examples are the spectral centroid, the bandwidth or the spectral decrease. While almost all of these features have no particular significance with respect to an anti-hypertensive effect, uniformity [4] reached a firm value of Λ = 0.52.

Rhythm-based features:

These features are used to analyze the basic beat of a piece, as well as the periodic accent patterns resulting from the different time values of the notes. Analyzed frequencies were in the range of 0.33 to 5 Hz. There are primarily two types of extraction algorithms. Certain types are used to find periodicities in the signal and use them to deduct the rhythm, such as the Beat Histogram [5]. Other algorithms, such as the rhythm model by Zwicker and Fastl [6] try to detect the emphases in the time course of the piece which constitute the rhythm.

The best results are achieved by using the Periodicity Histogram from Elias Pampalk's MA Toolbox [7]. The periodicities present in the signal are calculated over forty resonators. The Center of Gravity of the Periodicity Histogram is the best feature in this category with Λ = 0.37.

Both with ergotropic and with trophotropic pieces of music, the basic beat is nearly always at 120 – 130 bpm (beats per minute), so it is not relevant as a differentiator.

Dynamic features:

This group includes all features related to changes in signal intensity over time and across the frequencies. In particular, we studied the dynamics of the signal energy, as well as of the psycho-acoustic parameter loudness within and between different frequency bands, namely the 24 bark channels. The best feature here reached a Wilks' Lambda of 0.45.

An even better result of Λ = 0.43 was obtained with the Spectral Flux, i.e. the change in two subsequent time frames in the spectral range.

Other dynamic features, such as change in the Mel Frequency Cepstral Coefficients (ΔMFCC) over time, are also suitable for differentiating between ergotropic and trophotropic pieces.

Harmonic features:

This group includes all features used for analyzing the harmony of the frequencies that are audible in the piece simultaneously. Many features in this group are suitable for differentiating anti-hypertensive music, demonstrating the importance of harmonics to an anti-hypertensive effect. Spectral Flatness [8] with a minimum Wilks' Lambda of0.27 in the mid-frequency bands is alone almost able to isolate the main unit.

Table 1 shows the 50 best features and their respective groups. While none of the basic features (with one exception) are sufficient for classifying anti-hypertensive music, the significance of the rhythmic, dynamic and harmonic features is almost equivalent, confirming Decker-Voigt's theories [1].

	basic features	dynamic features	rhythmic features	harmonic features
Top 10	0	2	4	4
Top 20	0	7	7	6
Top 30	1	13	8	8
Top 40	1	21	9	9
Top 50	1	27	10	12

Table 1: The best features and their category

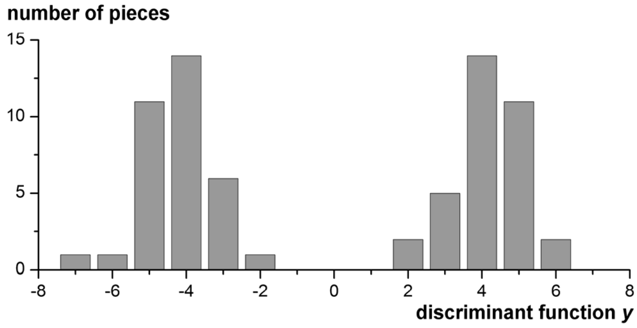

Figure 3: Distribution of the ergotropic (positive range) and trophotropic (negative range) pieces of music on the discriminant axis

Classification

After feature extraction we developed a classificator, a set of rules which calculates the correct class (ergotropic or trophotropic) from the extracted features $\vec{x}$. We opted for discriminant analysis and the Support Vector Machine from an abundance of possible methods, and compared them.

Despite the fact that the Support Vector Machine is basically more efficient and is also able to perform non-linear separation of objects, it was shown that for this application, equivalent results can be obtained with (linear) discriminant analysis, and that calculation proves to be much easier. In order to avoid overmatching, only 17 features, i.e. a quarter of the main unit, were included in the discriminant function. On the one hand these were selected according to their ability for separation, and on the other hand according to factually logical aspects.

With the selected features, we could calculate a discriminant function $y(\vec{x})$ which separates the centroids of the ergotropic and trophotropic pieces of music at a distance of 8.45 – with a standard deviation in each group from the centroid of $\sigma = 1$ (see histogram in Fig. 3). The result of the cross classification with the leaving-one-out method given in Table 2 shows that overmatching is at least so small that every object of the main unit may even be classified correctly if it is not an element of the training sample.

The distance of $y(\vec{x})$ of a piece of music to the zero point also indicates to what degree the analyzed piece fits into its group. If $y(\vec{x})$ is evaluated with time resolution, it is possible to calculate which parts of an anti-hypertensive piece of music particularly suit the other anti-hypertensive pieces; in this way it is possible to optimize the selection for the best possible therapeutic effect.

original group		predicted group		
		ergotropic	trophotropic	total
number	ergotropic	34	0	34
	trophotropic	0	34	34
percentage	ergotropic	100 %	0 %	100 %
	trophotropic	0 %	100 %	100 %

Table 2: Result of the Cross-Validation-Test with the Leaving-one-out-Method

As an example, Fig. 4 shows the time course of the discriminant function of Pachelbel's Canon in D major. It is indeed true that the parts at the beginning and the end of the piece have a higher anti-hypertensive potential than the parts in the middle which are more lively in character.

In this way, it is possible to detect supra-optimum sequences and to arrange these to form acoustic intervention sequences for therapeutic use.

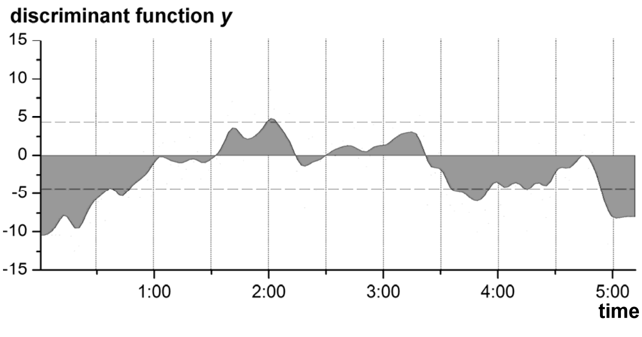

Figure 4: Discriminant function resolved per time unit for Pachelbel's Canon in D major

Conclusions

With the classificator we have developed, we are able - for the first time ever - to evaluate any piece of classical music the patient chooses with respect to its anti-hypertensive effect. Moreover, by extracting particularly effective parts from a piece that overall has an indifferent effect, they can also be used for acoustic biofeedback therapy. This allows for optimum blood pressure modulation.

Since not every patient responds to every piece of music in the same way, we recommend individual medical monitoring schemes for patients receiving acoustic biofeedback therapy. However, due to the fact that the patients can select their preferred music and can play an active role in this therapeutic concept, there is much better acceptance and compliance among the patients, which then results in a better therapeutic result.

Our work can be considered as the basis for the development of innovative therapeutic strategies. We are now able to design and offer a completely individualized and personalized therapeutic concept by taking the patient's personal preferences into account.

Acknowledgment

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