ACOUSTIC INTERFACE FOR TREMOR ANALYSIS

David Pirrò[1], Alexander Wankhammer[1], Petra Schwingenschuh[2], Alois Sontacchi[1], Robert Höldrich[1]

1 - Institute of Electronic Music and Acoustics,
University of Music and Performing Arts Graz, Austria
2 - Division of Special Neurology, Medical University of Graz, Austria
pirro@iem.at, wankhammer@iem.at, petra.schwingenschuh@medunigraz.at
sontacchi@iem.at, hoeldrich@iem.at

ABSTRACT

In this paper we introduce new methods for real-time acoustical tremor diagnosis. We outline the problems of tremor diagnosis in the clinical context and discuss how sonification can complement and expand the existing tools neurologists have at their disposal. Based on three preliminary sonification experiments upon recorded tremor movement data, we show how temporal as well as spectral characteristics of tremor can be made audible in real-time.

Our first observations indicate that differences among tremor types can be made recognizable via sonification. Therefore, we suggest that the proposed methods could allow for the formulation of more confident diagnoses. At the end of the paper, we will also shortly outline the central topics of future research.

1. INTRODUCTION

Tremor is the most common movement disorder. It is defined as a rhythmic and involuntary oscillation of a body part, caused by reciprocal nervous innervations of muscles [1]. The wide spectrum of tremor forms is summarized in the 1998 consensus statement of the Movement Disorder Society [2], whereas the most common forms include the essential tremor, parkinsonian tremor, dystonic tremor and psychogenic tremor. It is well known that each different tremor form can be the symptom of a specific disease [1]. Therefore, reliable classification and quantification of different tremor types is of strong clinical interest. A correct tremor diagnosis early in a diseases course is crucial in order to provide adequate treatment and medication for the patient.

In many cases a confident clinical diagnosis mainly based on the visual analysis of a tremor by neurologists experienced in movement disorders is possible. Nevertheless, these neurologists have to be highly specialized in this form of diagnosis and in some situations uncertainty remains. Therefore, further investigations based on structural and functional imaging, video analysis, accelerometry and other electrophysiological investigations can be necessary. Although such methods offer important additional information for a final diagnosis, the ex-post analysis and interpretation of recorded data is typically very time-consuming and hard to implement in the daily routine of clinical examinations. Besides, these methods do not support the neurologist during the personal contact with the patient.

The sonification experiments presented in this paper aim at extending established tremor analysis methods by an acoustical interface for tremor diagnosis. Based on real time sonification of acceleration data, detailed information on the temporal as well as spectral characteristics of tremor could be made audible to the neurologist while interacting with the patient. As sonification could provide an additional modality to perception, it would allow for a holistic analysis of the observed tremor avoiding the major drawbacks of ex-post analysis methods.

2. AUDITORY DISPLAY FOR MOVEMENT DATA

Sonification of movement data in the medical context is being employed in different areas and in conjunction with various motion capturing technologies. For example in virtual rehabilitation [3], sonification provides objective real-time information for analysis. In physiotherapy, sonification has been used to offer clear feedback for therapists and patients during rehabilitation exercises, e.g. with the sonification of EMG (Electromyogrphy) data [4]. Further, the auditory channel can be employed to augment the perception and proprioception of the subjects to heighten their motivation [5]. From a more general perspective, auditory data displays also gain increasing interest in multimodal biomedical data representation [6], caused by the growing number of simultaneous data streams that have to be perceived and analyzed. However, the sonification of tremor movements as a diagnostic tool is a novel research topic that has not been addressed until now.

The sonification studies we present here concentrate on tremor in Parkinson's disease, essential tremor, and psychogenic tremor. From a medical point of view these are clinically sometimes difficult to distinguish and therefore a clear discrimination by means of acoustical tremor analysis would be of great importance.

Since sonification will serve as a tool for neurologists, not sound specialists, our principal aim is to make differences between tremor types perceivable as clear as possible. To avoid auditory information overload, we try to lower the complexity of the sonification, by associating only the most significant and well-defined qualities of the data with distinct sound attributes. At the same time, we try not to oversimplify but to preserve all relevant information present in the data.

The preliminary experiments presented in this paper have been carried out on pre-labeled tremor data that has been captured by one of the authors during previous clinical studies. To evaluate the quality of the proposed sonification methods as diagnostic tools, a prospective clinical study with multiple neurologists who have been trained with the sonification system will be carried out at the Medical University of Graz in 2012. The neurologists will be asked to classify 30 different tremor patients with known diseases (approx. 10 per tremor form), basing their diagnoses solely on audio files representing sonifications of recorded tremor data. Although such an "audio only" restriction does not reflect a real-world situation, it allows to asses the quality of the proposed method, when compared to the established standard of clinical tremor diagnosis.

3. SONIFICATIONS

In the following sections, we describe the three sonification experiments carried out on the data set we have at our disposal. At the end of each section, we briefly outline how the different tremor forms could be distinguished by the respective sonification approach.[1]

The acceleration data we work with has been captured with a sampling rate of $f_s = 1\ kHz$ using a 3-axes accelerometer[2] taped to the backside of the proximal phalanx of the index finger of a patient's hand. As the typical frequency range of pathological tremor lies approximately between 3 and 15 Hz, we apply a DC removal filter and a low pass filter with a cutoff frequency of $f_{cL} = 70\ Hz$ to the acceleration signals and upsample the data to $44.1\ kHz$. When the system will later be integrated as real-time diagnostic tool, the data will be captured using the same sensor, but already at audio rate. Therefore, real-time capability of the designed system has already been a crucial requirement for our preliminary studies.

3.1. Frequency-Shifted Audification

In our first approach we aim at translating the acceleration data into sound in a simple and direct way i.e. without any sophisticated pre-processing. As the signals we are confronted with exhibit frequencies mostly below the audible range and our system has to be real-time capable, direct data audification (e.g. transposition via sample rate conversion) is not a viable option. However, as the ear is very sensitive to changes in amplitude and frequency, ranging from loudness fluctuations to different forms of roughness, the tremor signals turned out to be especially well-suited to serve as modulators of fixed frequency carriers. To highlight the rhythmic structure of the observed tremor signals, we apply simultaneous amplitude (AM) and frequency modulation (FM) to the carrier signals. Since maxima in frequency coincide with maxima in amplitude of the resulting modulated signal, rhythmic or dynamic changes of the tremor become clearly audible.

The following formula describes this sonification approach for one axis:

$$x_{son}(n) = \hat{x}(n) \sin\left(2\pi n(f_x + kx(n))\right) \tag{1}$$

where $\hat{x}(n)$ represents the half-wave rectified acceleration signal $x(n)$ along the x-axis to avoid a doubling of the perceived modulation frequency in relation to the observed tremor movements and the frequency f_x of the carrier is fixed. The amount of FM can be controlled by the modulation index k, resulting in a pure amplitude modulation with suppressed carrier when $k = 0$. The signals $y_{son}(n)$ and $z_{son}(n)$ can be computed in the same way, but with different carrier frequencies f_y and f_z. The simultaneous sonfication of all three axes can then be defined as follows:

$$tot_{son}(n) = a_x x_{son}(n) + a_y y_{son}(n) + a_z z_{son}(n) \tag{2}$$

where the amplitudes a_x, a_y and a_z can be controlled separately, allowing to isolate single acceleration axes or planes for the sonification; the squared sum of these weighting parameters is normalized to one.

Though quite basic, this approach allows us to rapidly explore the data and get a glimpse of how the different tremor typologies can be characterized. In particular, a first distinction between tremor types can be based on their temporal characteristics. While the parkinsonian tremor shows a regular pulsation that can remain steady for long time intervals (10 $\sim$ 20 seconds), there seems to be no regularity of any kind in most essential tremor cases as the sine is modulated by a quite noisy signal. In psychogenic tremor, pulses appear for short time intervals, but the beats do not present a steady repetition rate; they seem to falter, generating hesitating rhythms.

3.2. Spectral Features

As amplitude and frequency of a tremor are two very important parameters for the detection and quantification of tremor types, spectral analysis of recorded accelerometry and EMG data has been used widely by neurologists [7, 8]. Typically a spectral representation of the investigated tremor signal (e.g. the power spectrum) is computed based on the Fourier transform, followed by the extraction of specific spectral descriptors. Since many neurologists are familiar with these descriptors we want to make them audible in a real-time sonification.

The most commonly used parameters in the context of human tremor analysis are the peak tremor frequency, the total power of the spectrum between 1 and 30 Hz and the half-width power, where the half-width is defined as the frequency interval between the two values left and right to the main peak, at which the spectral power density is half of the peaks' power (see Figure 1). It is important to note that for clinical ex-post analysis, these features are typically computed over relatively long observation periods (e.g. 30 seconds), which practically eliminates any temporal information inside the signal.

When analyzing the power spectra of different tremor forms, we can basically distinguish three different scenarios (see Figure 1): a nearly harmonic spectrum, mostly in the Parkinson's disease (top); no narrow or clear peaks, but a broader region in the lower part of the spectrum, recurrent in the essential tremor (middle); only one prominent peak, frequent in the psychogenic tremor (bottom). To parametrize the sonification algorithm, we therefore decided to use features similar to those depicted in Figure 1. We extract the central frequency of the main peak (if present), its half-width power and we detect the presence of side peaks or harmonics.

As the relevant tremor frequencies lie in a very low and narrow part of the spectrum, we have to perform the real-time spectral analysis inside sliding windows of at least one second, in order to achieve the necessary frequency resolution. That way, the temporal structure of the signal is preserved, but its level of detail is limited to the selected window length.

In the sonification, where each axis can be sonified individually, we use a Karplus-Strong [9] algorithm. The excitation signal of the algorithm is pink noise and the base frequency is proportional to the central frequency of the main peak. The location of the main peak is determined by parabolic interpolation between neighbouring bins: this way, "jumps" of the base frequency are avoided when the the main peak of two consecutive frames resides

[1] Examples: http://iem.kug.ac.at/index.php?id=13661

[2] Sensor details: http://www.biometricsltd.com/accelerometer.htm

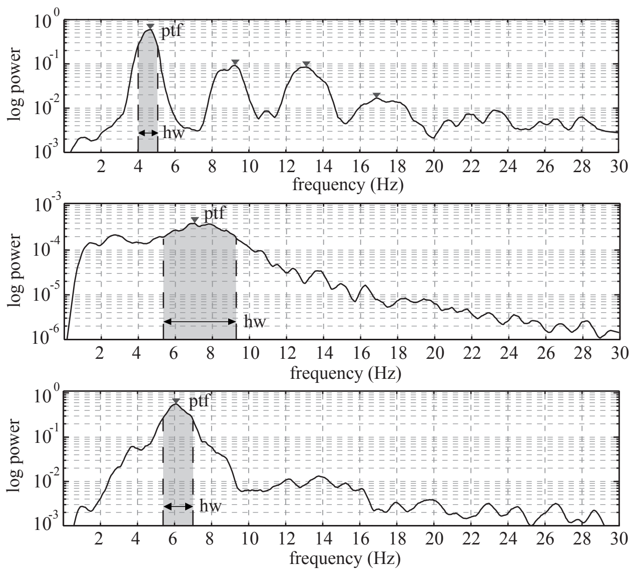

Figure 1: Typical power spectra of tremor signals with indicated peak tremor frequencies (ptf), half widths (hw) and side peaks.

in different bins. The width of the main peak is used to control the feedback factor of the delay line in the algorithm. If the peak is narrow, the feedback factor is nearly equal to 1.0. Instead, if the peak gets broader, the feedback factor is diminished and gets down to 0.0 when no clear peaks are detected. The output is then passed through a low pass filter: if harmonics of the main peak are detected, the cutoff frequency of the filter is adjusted to be eight times the base frequency and set to be equal to it if no significant side peaks appear in the spectrum.

The resulting sound presents a clearly pitched tone, if the spectrum exhibits one or multiple peaks. When sonifying acceleration data of a parkinsonian tremor, the spectrum of the tone has more overtones and the pitch remains quite stable over longer time intervals. On the contrary, when sonifying psychogenic tremor data, the generated tone can have more noise mixed in. It has a tighter spectrum and its base frequency moves quite frequently. Essential tremor generates a more noisy sound from which occasionally tones pop out but immediately disappear.

3.3. Translation and Rotation

For the final sonification approach we analyze the spatial movement pattern of the trembling hand. Since a sonification based on detailed information on the exact hand movement would presumably provide too much auditory information, we developed a method to separate the observed motion into its major components.

Assuming that the main components of a hand movement are typically located on a slowly changing plane in space, we project the three dimensional acceleration vectors onto this plane, in the following referred to as the ”plane of movement”. This projection does not only reduce the dimensionality and amount of data we have to process, but also offers important information on the investigated motion.

To identify the plane of movement of a motion in real-time, we have to detect its major acceleration components during short observation periods. As the spatial spread of successive acceleration vectors directly represents the amount of acceleration into the respective directions, Principal Component Analysis (PCA) is a suitable method to identify the two main axes of acceleration. PCA basically detects the direction of the greatest variance of the data and places a first axis in this direction (the first principal component). The next axis (second principal component) is chosen perpendicular to the first axis along the direction of the next greatest variance. Hence, the first two principal components directly represent the vectors defining the plane of movement.

As we have to process the captured data in real-time, the principal components are computed based on an iteratively updated covariance matrix $\mathbf{\Sigma}(n)$. The first two eigenvectors $[\boldsymbol{\gamma}_1(n), \boldsymbol{\gamma}_2(n)]$ of $\mathbf{\Sigma}(n)$ represent the principal components that are used to project each three dimensional input sample $\boldsymbol{a}(n) = [x(n), y(n), z(n)]^T$ onto the plane of movement. The resulting transformed input samples $\tilde{\boldsymbol{a}}(n)$ are called score vectors.

$$\tilde{\boldsymbol{a}}(n) = \begin{bmatrix} \tilde{a}_1(n) \\ \tilde{a}_2(n) \end{bmatrix} = [\boldsymbol{\gamma}_1(n), \boldsymbol{\gamma}_2(n)]^T \boldsymbol{a}(n) \qquad (3)$$

Successive score vectors now define a two dimensional trajectory that offers important information on the amount of translation and rotation inherent to the observed motion. This becomes clear, when we analyze the characteristic data distributions related to purely translational and rotational movements: a translational movement will lead to a “line-like” distribution of acceleration values, as only the sign and magnitude of the acceleration vectors changes over time, while a rotational movement will lead to a “circle-like” data distribution, as only the direction of the acceleration vectors constantly changes.

Considering these characteristic distributions projected onto the plane of movement, we can now make two important observations: any progression along the axis defined by the first principal component can be caused by rotation and translation, while changes along the second PCA axis can only be caused by rotational components. Therefore, the second element of the score vector directly represent the rotational signal component $r(n)$ of an observed motion. To get a definition of the translational component $t(n)$, the influence of the rotational component has to be removed from the first element of the score vector. Hence, after calculating the Root Mean Square (RMS) of each element of the score vector, the translational component can be obtained as follows

$$t(n) = \frac{RMS\{\tilde{a}_1(n)\} - RMS\{\tilde{a}_2(n)\}}{RMS\{\tilde{a}_1(n)\}} \, \tilde{a}_1(n) \qquad (4)$$

In the sonification we use the translational and rotational components, $t(n)$ and $r(n)$, and the smoothed sum $s(n)$ of the x, y and z components of the acceleration signal.

$$t(n)HPF\{s(n), 1000\} + r(n)s(n)sin(2\pi fn) \qquad (5)$$

In the first part of the sonification we pass the signal $s(n)$ through a second order high-pass filter $HPF\{s(n), 1000\}$ with a cutoff frequency of 1000 Hz and multiply the result with the translational component; this generates clicks or sort of thumping beats. In the second part we use it to modulate the amplitude of a fixed frequency sine and multiply the result with the rotational component.

This way, we try to sonically separate and enhance translational or rotational qualities of movements by associating them with two contrasting sound qualities that can be easily distinguished. Further, as the signal $s(n)$ contains all the temporal details of the movement itself, we do not loose this information in the sonification and can rely on it when making distinctions between the three tremor forms.

Applying this analysis and the related sonification to the acceleration signal, we can point out some important observations. In the essential tremor, the rotational component is most pronounced; even if the movement is highly disordered and not regular, the major component is typically rotational, as the irregular clicks generated by the translational component remain in the background. The psychogenic tremor is mostly characterized by a strong translational component; the rotational component can also be present and even dominate, but only for short time intervals. In parkinsonian tremor, both components can be present, but in most cases clear and regular beats can be heard, helping to identify this tremor.

4. DISCUSSION

Our first experiments showed that sonification could indeed be a promising extension to the diagnostic tools already used by neurologists. In particular, the temporal qualities of tremor movements, which are transported by all our sonification approaches, seem to bear important information that can be crucial in the distinction between the various forms. Besides, our approach to separate translational and rotational movement components is a novel analysis method and could also be an interesting step forward in clinical tremor research.

Even if most of the tremor forms can be identified via the sonification, some cases remain unclear and a certain amount of ambiguity is inherent to all of the sonifications we presented. Although complementing one sonification with another can sometimes be useful, it often leads to more confusing results, as it packs too much information into one sound.

Considering the quite limited set of data examined so far, the new recordings that will be made in the next months will help us to sharpen the tools we created. Still, a different analysis approach that could eventually give us a more holistic view of tremor would be desirable. In the next section we will therefore introduce an analysis method that could possibly meet our needs in this respect.

5. OUTLOOK

As the preliminary evaluation results are very promising, we are planning to extend the current system with a more sophisticated data analysis method. In particular, the correct separation of simultaneous movement patterns or tremor modes inside overlapping frequency bands would offer valuable information for the sonification process.

Depending on the investigated tremor type, the frequencies of individual tremor modes may significantly vary throughout a tremor recording. When using traditional spectral analysis methods (see section 3.2), it is often impossible to determine if different peaks inside a spectrum represent the coexistence of separate tremor modes, one mode residing in multiple frequency bands or if they are caused by local oscillations during the observation period.

To overcome these difficulties, recent studies [10] propose to use empirical mode decomposition (EMD) [11], a relatively new time-frequency analysis method for nonlinear and non-stationary data, for the analysis of tremor signals. Unlike Fourier analysis, where signals are assumed to be a composition of linear, stationary components, EMD decomposes any arbitrary time series into a set of superimposed oscillations (AM/FM modulated signals), called intrinsic mode functions (IMF). Practical investigations on tremor data have shown that individual IMFs carry important information on the investigated tremor movement, as they adaptively follow the nonlinearities and non-stationarities inside the signal.

Considering our observations presented in section 4, we are planning to apply EMD not only to the three dimensional accelerations vectors, but also to the rotational and translational signal components. The resulting IMFs could then serve as new input parameters for a temporally as well as spectrally detailed sonification approach.

6. REFERENCES

[1] K. Wyne, “A comprehensive review of tremor.” *JAAPA*, vol. 18, no. 2, pp. 43–50, 2005.

[2] G. Deuschl, P. Bain, and M. Brin, “Consensus statement of the movement disorder society on tremor,” *Movement Disorders*, vol. 13, no. S3, pp. 2–23, 1998.

[3] G. Burdea, “Keynote address: Virtual rehabilitation- benefits and challenges,” *1st International Workshop on Virtual Reality Rehabilitation VRMHR*, 2002.

[4] S. Pauletto and A. Hunt, “The sonification of emg data,” *Proc. of the 12th ICAD*, 2006.

[5] K. Vogt, D. Pirrò, I. Kobenz, R. Höldrich, and G. Eckel, “Physiosonic - movement sonification as auditory feedback,” *Proceedings of the 15th International Conference on Auditory Display*, 2009.

[6] E. Jovanov, D. Starcevic, V. Radivojevic, A. Samardzic, and V. Simeunovic, “Perceptualization of biomedical data. an experimental environment for visualization and sonification of brain electrical activity,” *Engineering in Medicine and Biology Magazine, IEEE*, vol. 18, no. 1, pp. 50 –55, jan.-feb. 1999.

[7] J. Timmer, M. Lauk, and G. Deuschl, “Quantitative analysis of tremor time series,” *Electroencephalography and Clinical Neurophysiology/Electromyography and Motor Control*, vol. 101, no. 5, pp. 461–468, 1996.

[8] P. Mansur, L. Cury, A. Andrade, A. Pereira, G. Miotto, A. Soares, and E. Naves, “A review on techniques for tremor recording and quantification,” *Critical Reviews™ in Biomedical Engineering*, vol. 35, no. 5, pp. 343–362, 2007.

[9] K. Karplus and A. Strong, “Digital synthesis of plucked string and drum timbres,” *Computer Music Journal*, vol. 7, no. 2, pp. 43–55, 1983.

[10] E. Rocon de Lima, A. Andrade, J. Pons, P. Kyberd, and S. Nasuto, “Emd: A novel technique for the study of tremor time series,” in *World Congress on Medical Physics and Biomedical Engineering 2006*. Springer, 2007, pp. 992–996.

[11] N. Huang, Z. Shen, S. Long, M. Wu, H. Shih, Q. Zheng, N. Yen, C. Tung, and H. Liu, “The empirical mode decomposition and the hilbert spectrum for nonlinear and nonstationary time series analysis,” *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, vol. 454, no. 1971, p. 903, 1998.