Creating Biosignal Algorithms for Musical Applications from an Extensive Physiological Database

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ABSTRACT
Previously the design of algorithms and parameter calibration for biosignal music performances has been based on testing with a small number of individuals - in fact usually the performer themselves. This paper uses the data collected from over 4000 people to begin to create a truly robust set of algorithms for heart rate and electrodermal activity measures, as well as the understanding of how the calibration of these vary by individual.

Author Keywords
Biosignals, EDA, HR, feature extraction, database, physiological signals, EDAtool, HRtool

ACM Classification
C.3 [SPECIAL-PURPOSE AND APPLICATION-BASED SYSTEMS] Signal processing systems, H.5.5 [Information Interfaces and Presentation] Sound and Music Computing

1. INTRODUCTION
Biosignals in the arts and in particular for music performance have been present for over fifty years, since artists in the 1960s started to experiment with medical instrumentation to create novel compositions. However, musical performances that use biosignals are generally calibrated with heuristic methods carried out by the performers themselves. It has only been until the last two decades that low-cost technologies and off-the-shelf physiological measuring devices for musical applications [9] have given the field a new impetus.

In this paper a new approach on the design of algorithms for bio-inspired systems for musical applications is presented. The extensive physiological database collected during the *Emotion in Motion* (EiM) series of experiments [6,7] has allowed the design and calibration of automatic feature extraction tools, with special consideration to automatic artifact detection and removal techniques.

EIM is comprised of a series of experiments deployed in museums and galleries to collect large amounts of physiological and self-report data of people listening to music. The experiments are designed as a testbed to study emotional response to music stimuli, where multiple research questions can be explored by looking at selected subsets of the database. In particular, these experiments aim to understand the relationship between what listeners report as felt emotions induced by music and their physiological manifestations via electrodermal and cardiovascular measures. Overall, EiM has collected physiological data from over 4000 people listening to music, from multiple locations on the world. This unique physiological database has allowed us to advance in two main areas:

a) The calibration of automatic feature extraction tools, including artifact detection and removal.

b) Start to see and understand certain relationships between the music, people's physiological reaction and their reported appraisal of the music content.

This paper focuses on the feature extraction tools developed using EiM database. To begin with, the two physiological channels utilized, electrodermal activity and heart rate are presented, describing their physiological origin, measurement techniques and the distinctive features that are extracted from them. To then continue with a thorough description of two physiological feature extraction tools developed to process biosignals, namely *EDAtool* and *HRtool*. Finally, the paper concludes summarizing the concepts presented in this document, and presents details on further work regarding these algorithms.

1.1 Electrodermal Activity
Electrodermal activity (EDA), also known as skin conductivity or galvanic skin response, is the measurement of electrical changes in the human skin. The psychophysiological origin of EDA is explained by the involvement of sweat glands in the skin, specifically the eccrine sweat glands, which are controlled by the sympathetic branch of the autonomic nervous system (ANS) [11,14]. Even though the primary function of the most eccrine glands is thermoregulation, the glands located on the palmar and plantar surfaces of skin have been suggested to be more responsive to psychological stimuli than to thermal [4].

Exosomatic measurements of EDA, usually preferred for being less invasive, involve passing a small electrical current through a pair of electrodes placed in the surface of the skin. The variation in skin resistance can be calculated by keeping the current or the voltage constant (and measuring the other), although most physiological recording systems use constant voltage [4].

Figure 1 shows a plot of an EDA signal, recorded during the screening of a short horror video clip. The plot shows a typical EDA signal, which can be separated in two components: tonic and phasic, which are believed to be originated by two distinct neurophysiological states of the organism [12]. The phasic component consists of relatively fast changes in the signal, which is seen as a series of responses to specific stimuli [4]. Each one of these responses, with a characteristic *Gestalt* shape, is called an electrodermal response (EDR or SCR for fixed voltage measurements).

The tonic or electrodermal level (EDL or SCL) component, is a relatively slow change in the conductance of the skin, and is less understood, mainly due to it being less reactive to experimental conditions [3]. EDL is not completely independent from EDR (see Figure 1), Dawson et al. state that "It is common

for SCL to gradually decrease while subjects are at rest, rapidly increase when novel stimulation is introduced, and then gradually decrease again after the stimulus is repeated" [4:164].

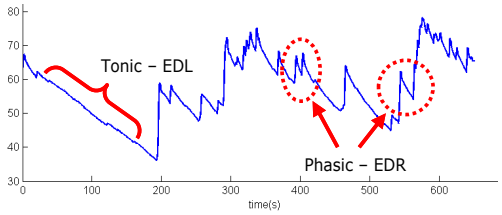

Figure 1. Example of a typical EDA signal for a single person, recorded during the viewing of a horror film clip.

1.2 Heart Rate

The heart, the central pump of the cardiovascular system, provides a consistent blood flow that reaches all the tissues of the body. Electrical waves cause the heart muscle to squeeze and pump periodically, on what is referred as the cardiac cycle. For centuries, humans have perceived in themselves and others the pulsations produced by the heart, and even associated these changes to emotionally significant experiences (e.g. fear) [5].

Several techniques have been developed to observe and analyze the cardiac cycle, each measuring different signals (e.g. sound, electrical impulses, changes in pressure, etc.). This paper will expand on Electrocardiography (ECG or EKG) and Pulse Plethysmography (PPG), as they are the measurements that are processed by our tool.

1.2.1 Electrocardiography (ECG)

ECG measures the small electrical impulses that trigger a heartbeat. These waves can be sensed by electrodes attached to the skin employing an instrument called electrocardiograph. The body acts as a conductor of the wave depolarization that travels the heart, transmitting this electrocardiac signals to the body surface, which can be detected by measuring the difference in potential across two or more electrodes positioned at either side of the heart [13]. Using a proper lead configuration, the output of the electrocardiograph depicts the electrical waves P, Q, R, S, and T. Nonetheless, Berntson et al. [1] postulate that for most psychophysiological applications, a simplified configuration that yields a relatively large R-wave is sufficient. ECG is quite robust to motion [13], however movement can produce changes in the ECG baseline [8]. Additionally, ECG can be affected by power line interference (e.g. 50[Hz]), which can be reduced with notch filtering.

1.2.2 Pulse Oximetry (POX)

During the cardiac cycle, blood is ejected from the ventricles and a pulse of pressure travels 10-15 times faster than the blood flow to the peripheral circulatory system. This change in pressure causes vessel-wall displacement and can be measured using a the photoelectric technique named pulse oximetry (POX) [8]. This method consists on shining infrared light from an LED on the skin, and measuring its reflection or transmittance with a photoresistor. The increased blood flow produced during the cardiac cycle interferes with the light transmission or reflection, particularly in the infrared band, causing changes that are analogous to the ventricular pressure [13]. Additionally, with each pulsation, there is a change in oxygen saturation of hemoglobin in arterial blood, which produces fluctuations in the absorption of red and infrared lights emitted from an LED [2,8]. POX sensors are affected by movement artifacts, due to the mechanical distortion of the skin [8].

2. Biosignal Algorithms

Two tools were developed in MATLAB to extract features from the physiological signals described above: *EDAtool* and *HRtool*. The extraction of features includes detection and removal of artifacts and abnormalities in the data. The output from both tools delivers the processed feature vectors (e.g. phasic EDA or HR) as well as an accuracy index (Q) that is defined as the percentage of the signal that did not present artifacts. This value can be utilized later to remove cases from the analysis (or the live performance) that fall below a specified confidence threshold. The EiM data has been used to both design and evaluate these algorithms.

2.1 EDAtool

EDAtool is a function developed to pre-process the EDA signal. Its processing includes the removal of electrical noise and the detection and measurement of artifacts. Additionally, it separates the EDA signal into phasic and tonic components. The processing of the EDA signal has several stages, which are detailed in the following sections, and illustrated in Figure 2. Additionally, *EDAtool* is available online.[1]

2.1.1 Revision of Input Parameters

The function has several input variables: the raw EDA signal as a vector, the sample rate (SR) of the signal, and options to adjust the parameters of the EDA processing such as the signal range, threshold adjustments, and interpolation options.

2.1.2 Pre-processing

Initially, the EDA signal is resampled to 50[Hz], using decimation or interpolation, depending on the original SR entered to the tool. This standardization is implemented in order to keep the filter coefficients constant for every signal, with a bandwidth that allows the detection of artifacts. Subsequently, any sample outside the sensor's range (specified in the input parameters) is limited, and counted as non-valid for accuracy purposes. Next, the start value of the signal is saved, and then the signal is shifted to start at zero in order to be filtered without DC component. Finally, the signal is normalized in accordance to the range of the EDA sensor specified by the user.

2.1.3 Removal of Electrical Noise

The next section removes any noise that is outside the EDA spectrum, typically electrical noise. For this, a 224 order low-pass FIR filter is used, with a cut-off frequency of 0.5[Hz] (stop frequency of 1[Hz] at -60[dB]).

2.1.4 Artifact Detection and Removal

EDA artifacts are typically caused by problems with the electrode-to-skin connection, which results in a discontinuity or rapid change in the conductivity measured by the sensor. Boucsein [3:140] gives a thorough overview of the physiologically and recording based artifact causes. He argues that due to the multiple origins of artifacts (e.g. loss of contact, change in contact pressure, subject's temperature, respiration induced SCRs, etc.), artifacts should be identified and corrected manually by researchers, yet this requires a significant amount of time for databases such as the EiM, and is not feasible for real-time applications. For this reason, automatic detection and removal of EDA artifacts induced by motion has been developed as part of the *EDAtool*. With regard to other source of artifacts, such as respiration induced SCRs or temperature, this needs to be controlled with additional sensors (e.g. thermistors), and are not currently considered in this tool.

[1] http://www.musicsensorsemotion.com/2012/06/21/edatool/

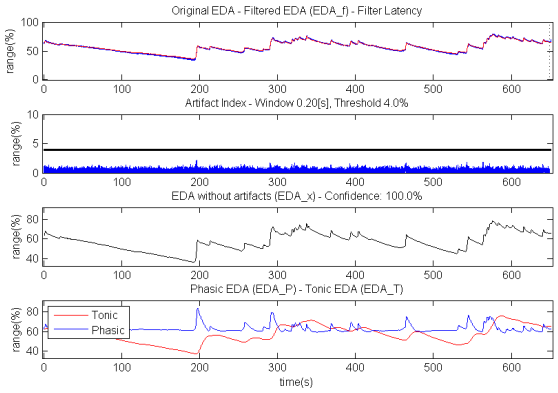

Figure 2. Stages of the EDAtool on an electrodermal signal.

The detection of artifacts consists of evaluating the gradient between the edges of a sliding window against a fixed threshold. Because the changes in EDA are slower than changes produced by artifacts, it is possible to separate both events with this method. If an artifact is detected, the algorithm replaces the adjacent samples with non-valid values using a 1.5[s] window, centered on the artifact.

A confidence index (Q) is obtained by calculating the ratio of non-valid values versus valid samples in the signal. After evaluating the values of Q against multiple examples of the EiM database, another variable was factored into the confidence index. It was noticed that on certain cases, the baseline of the EDA signal was shifted significantly before and after an artifact (see Figure 3). This may be due, for example, to the electrode not making a good connection initially, and after an adjustment (which triggers an artifact) the signal settles to the correct baseline. Instead of artificially correcting this difference, it was decided to consider this factor in the calculation of Q by decreasing its value proportionally to the difference between the EDA signal before and after the artifact.

2.1.5 Artifact Interpolation

If requested, the *EDAtool* interpolates between the detected artifacts. For this, the algorithm searches for any non-valid sample in the signal, identified during the previous sections, and implements a linear interpolation between the values before and after the non-valid sample.

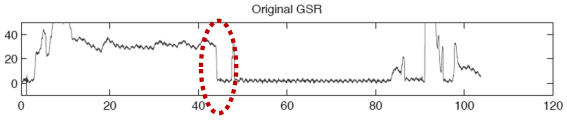

Figure 3. Example of a baseline shift in EDA before and after an artifact (circled).

2.1.6 Tonic and Phasic EDA

After testing several Finite Impulse Response (FIR) filters to separate the EDA signal into its tonic and phasic components, it was observed that the filter orders required to obtain the desired signals were producing extremely long latencies (over 15 seconds) with high processing demand. This created a problem for the EiM database analysis, which meant the loss of significant sections of the EDA vector, and also for any potential real-time applications that require faster processing times.

The solution was then to design an Infinite Impulse Response (IIR) Butterworth low-pass filter with a cut-off frequency of 0.001[Hz] (stop frequency of 1[Hz] at -60[dB]). Even though this option involves the inherent stability and phase (time dispersion) issues associated with IIR filters, the filter coefficients were manually calibrated against the EiM database in order to obtain stable results. Moreover, this filter is executed after the artifact and noise removal stages; hence it is applied to EDA signals with a similar frequency content, which will produce a similar dispersion from the IIR filter.

The tonic component is then extracted from the output of the IIR filter, while the phasic component is obtained from the difference between the original signal (supplied to the IIR filter) and the tonic component (see Figure 2 bottom plot).

2.1.7 EDAtool outputs

The final section of *EDAtool* returns each EDA vector to the original baseline (stored in the pre-processing section), and resamples each vector to the original SR (if requested by user). Originally, the output signals were all set to start in zero, but the relationship between the EDA baseline and the amplitude of phasic changes confirmed the importance of evaluating the changes in the EDA signal with respect to its absolute level [6].

2.1.8 EDAtool Parameters

The *EDAtool* parameters were calibrated using EDA signals from the EiM database. The range was set at the values of opened and closed circuit configurations of the BioControl sensor used.[2] The size of the artifact window, as well as the threshold levels were chosen after reviewing hundreds of signals, manually identifying artifacts and changing these parameters until they were recognized by the *EDAtool*.

2.2 HRtool

HRtool is a function developed to convert the data from an ECG or POX signal into a HR vector. The function identifies heart pulses in the input signal discarding artifacts and ectopic beats, to then generate a two dimensional matrix with the BPM value of each pulse and its relative location in time. The *HRtool* function and documentation are available online.[3]

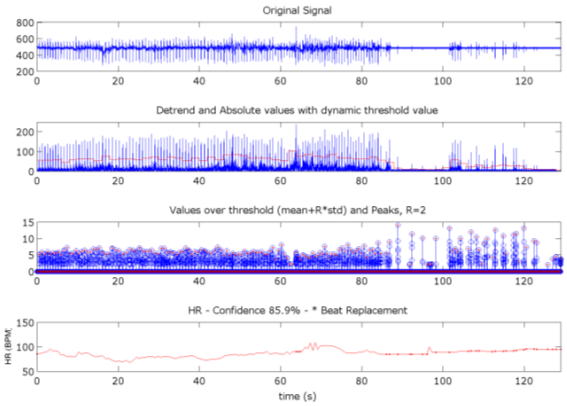

Figure 4. Stages of the HRtool on an ECG signal.

HRtool takes five input variables: The ECG or POX signal, the SR of this signal, a debug option, a parameter vector and the type of input signal. The parameter vector contains the minimum and maximum acceptable heart rate values, the maximum change ratio between two consecutive beats, and the threshold for beat detection; defined as the ratio between the beat values and the standard deviation of the ECG signal within a moving window. It outputs a vector with the HR values and the time in seconds where they occurred, relative to the start of the vector.

[2] http://infusionsystems.com/catalog/product_info.php/products_id/203

[3] http://www.musicsensorsemotion.com/2012/06/21/hrtool/

Additionally, it outputs the mean HR and confidence index Q. After checking input variables, the function processes the signal in three steps, described below and illustrated in Figure 4.

2.2.1 Pre-Processing

The first step for either signal, ECG or POX, is to remove any baseline trends in the signal. This is accomplished by subtracting the best straight-line fit trend from the vector.

For ECG, the signal is filtered using an FIR high-pass Kaiser Window, with cut-off frequency of 3[Hz] (stop frequency of 2[Hz] at -60[dB]). The filter coefficients are calculated each time the function is called, and they depend on the SR of the signal. After filtering, the ECG signal is time shifted to compensate for the filter's latency.

2.2.2 Threshold Calibration

For TTL POX signals, the algorithm computes a threshold for peak detection by calculating the signal's standard deviation plus a 20%.

The ECG signal is scanned by a moving window of 2-second duration. The signal for each window is z-normalized and the threshold is calculated by adding the mean value of the ECG signal inside the window with the product of the standard deviation and the threshold entered by the user. This allows having a dynamic threshold across the duration of the signal, as can be seen in Figure 4, 2nd plot from the top.

2.2.3 HR Extraction

In order to find peaks in the ECG signal, *HRtool* creates a sliding window of a size equivalent to the minimum beat-to-beat distance obtained from the maximum HR value entered by the user. The algorithm then searches for the highest value in the window (the R wave) and saves its position, to then calculate the interval with the subsequent peak value. For TTL POX signals, the first sample above the threshold is utilized.

After measuring the RR intervals between pulses and calculating each corresponding HR value in BPM, the algorithm evaluates the HR vector replacing any values that are outside the ranges entered by the user (e.g. values within the maximum and minimum HR range, and within the maximum change ratio between two consequent pulses).

Finally, the confidence index Q is obtained by calculating the ratio of replaced beats against normal beats.

2.2.4 HRtool Parameters

The HRtool parameters were set with the following boundaries for the processing of the EiM signals: Any RR intervals lower than 50[BPM] or higher than 130[BPM] were discarded. The maximum allowed change for a new beat with respect to the previous one was set to 20%. Regarding the decision on these parameters, the literature states that up to this date there is no clear standardization for short-term measurements of heart rate variability [15], and neither for which method should be used for interpreting ectopic beats and artifacts [18]. Moreover, the majority of the methods proposed in the literature use statistics extracted from the total duration of the recorded data to identify abnormal beats [10], which is incompatible with the real-time implementations intended to be used in musical applications. Nevertheless, there has been a thorough manual examination of the HR feature extraction tool, screening hundreds of different cases presented in the EiM database, in order to test the correct application of the above parameters.

3. CONCLUSIONS

This paper has introduced the development of two novel processing tools for bio-inspired musical applications, detailing the pre-processing, filtering, artifact detection and removal, and feature extraction process for both signals.

We believe that the tools presented in this paper offer a significant improvement to the creation of biosignal algorithms for musical performance applications, as well as for other artistic projects, as they have been calibrated and evaluated using the extensive physiological database from EiM.

The authors have been exploring the co-creation of music using audience's physiological response [10]. To increase the accuracy of these measurements, versions of the *EDAtool* and *HRtool* have been adapted for Max/MSP for real-time applications. These have been tested and successfully utilized in interactive concerts and in feedback for the EiM terminal.

4. REFERENCES

[1] Berntson, G.G., Quigley, K.S., and Lozano, D. Cardiovascular Psychophysiology. In J.T. Cacioppo, L.G. Tassinary and G.G. Berntson, eds., *Handbook of Psychophysiology*. Cambridge University Press, New York, 2007, 182–210.

[2] Bindszus, A. and Boos, A. Pulse rate and heart rate coincidence detection for pulse oximetry. 2001.

[3] Boucsein, W. *Electrodermal Activity.* Springer, New York, 2012.

[4] Dawson, M.E., Schell, A.M., Filion, D.L., and Berntson, G.G. The Electrodermal System. In J.T. Cacioppo, L.G. Tassinary and G.G. Berntson, eds., *Handbook of Psychophysiology*. Cambridge University Press, New York, 2007, 159–181.

[5] Gunn, C.G., Wolf, S., Block, R.T., and Person, R.J. Psychophysiology of the Cardiovascular System. In J.T. Cacioppo, L.G. Tassinary and G.G. Berntson, eds., *Handbook of Psychophysiology*. Holt, Rinehart and Winston, Austin, Texsas, 1972, 457–489.

[6] Jaimovich, J., Coghlan, N., and Knapp, R.B. Emotion in Motion: A Study of Music and Affective Response. In M. Aramaki, M. Barthet, R. Kronland-Martinet and S. Ystad, eds., *From Sounds to Music and Emotions*. Springer Berlin Heidelberg, 2013, 19–43.

[7] Jaimovich, J., Ortiz, M., Coghlan, N., and Knapp, R.B. The Emotion in Motion Experiment: Using an Interactive Installation as a Means for Understanding Emotional Response to Music. *Proceedings of the 12th International Conference on New Interfaces for Musical Expression, 21-23 May*, (2012), 457–458.

[8] Khandpur, R.S. *Handbook of Biomedical Instrumentation.* Tata McGraw-Hill Education, New Deli, India, 2003.

[9] Knapp, R.B. and Lusted, H.S. A Bioelectric Controller for Computer Music Applications. *Computer Music Journal 14*, 1 (1990), 42–47.

[10] Knapp, R.B. and Lyon, E. The Measurement of Performer and Audience Emotional State as a New Means of Computer Music Interaction: A Performance Case Study. *Proceedings of the International Computer Music Conference, 31 July -5 August*, (2011), 415–420.

[11] Malmivuo, J. and Plonsey, R. *Bioelectromagnetism: Principles and Applications of Bioelectric and Biomagnetic Fields.* Oxford University Press, New York, 1995.

[12] Van Olst, E.H., Orlebeke, J.F., and Fokkema, S.D. Skin conductance as a measure of tonic and phasic arousal. *Acta Psychologica 27*, (1967), 262.

[13] Siddle, D.A.T. and Turpin, G. Measurement, quantification, and analysis of cardiac activity. In Martin and P.H. Venables, eds., *Techniques in Psychophysiology*. John Wiley & Sons Ltd., New Jersey, USA, 1980, 139–246.

[14] Venables, P.H. and Christie, M.J. Electrodermal Activity. In I. Martin and P.H. Venables, eds., *Techniques in Psychophysiology*. John Wiley & Sons Ltd., New Jersey, USA, 1980, 3–67.