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Preprocessing of PPG and EDA signals for detection of emotional and cognitive states via physiological signals

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Abstract. *Presented in the current paper is a methodology for approaching the preprocessing of Photoplethysmography and Electrodermal activity for the detection of emotional and cognitive states in humans via physiological signals. Examined closely are the effects of downsampling and segmentation of the PPG, the segmentation and separation of the Skin Conductance Level (SCL), and Skin Conductance Response (SCR) components of the EDA signal with both median and low pass filters. The results from the research indicate that the most appropriate preprocessing with regard to emotions and cognitive load classification is segmentation of 2 minutes which is the recommended length for frequency analysis of heart rate variability. Recommended, furthermore, is the downsampling of the PPG to 64 Hz, which proved to be the lowest sampling frequency that doesn't introduce errors in the systolic peak detection, neither does it drastically affect the length of the Inter Beat Intervals (IBIs). Proposed, as to the separation of the SCL component of the EDA, is the usage of median filter with window length of 75% of the sampling frequency, which introduces negligible artefacts, mainly at the start of the signal.*

Keywords: PPG, EDA, preprocessing, emotions, cognitive

1 Introduction

Modern human life is characterized by increased intensity and the constant strain on the mind can lead to health degradation – both mental and physical. In our everyday life we are in the habit of using a wide variety of devices and electronics, which, in turn, can also be used for running close checks on our emotional and cognitive states. This monitoring, when combined with the latest advances in wearable devices, can easily provide the much-needed instrument for prevention of health degradation.

Every act of monitoring, as suggested above, could be successfully achieved through the use of sensors and systems for acquisition of physiological signals such as Electrodermal Activity (EDA), Photoplethysmography (PPG), Electrocardiography (ECG), etc. The easiest and most accurate physiological signals for out-of- the- lab monitoring prove to be the EDA (**Yang, 2021**) and PPG, which outperforms ECG in dynamic scenarios (**Bradke, 2021**). There are many databases with physiological signals adapted for emotional and cognitive states detection, for example, DEAP (**Koelstra, 2012**), CASE (**Sharma, 2019**) and CLAS (**Markova, 2019**).

For the detection of emotional and cognitive states, the researchers use different machine learning techniques, supporting real-time applications (**Li, 2020**), that require a parametrization of the utilized physiological signals, involving a specific processing for the EDA (**Geršak, 2020**), which is found to be very useful for emotion recognition (**Ganapathy, 2021**). The most commonly used parameter for the PPG (**Moressi, 2021** is Heart Rate Variability (HRV), of which multiple methods for calculation are available (**Kalinkov, 2020**).

The usage of the physiological signals in real time applications and in wearable devices brings forward the need of fast and accurate processing of the signals. There are various ways of reducing the data size, such as downsampling, which is critical for PPG **(Béres, 2021**). Normally, the wireless transmission of the signals and their processing may lead to artefacts that must be accounted for or removed. It is important to note that the artefact correction can affect the subsequent classification (**Cosoli, 2021**).

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2 Methodology of preprocessing of photoplethysmography and electrodermal activity

Explored, in the current section, are the selected number of methods for preprocessing of the PPG and EDA signals and the relevant approaches for preparing the signals for further feature extraction and parametrization for the needs of machine learning algorithms, tasked with the classification and detection of cognitive and emotional states in humans. The research is conducted on the CLAS Dataset.

2.1 Photoplethysmography

The PPG signal is carrying information about the heart activity, which is key in the detection of emotional and cognitive states. In our study the PPG signal is used as alternative to the ECG signal, which is harder for recording, as it is very sensitive to movement and interference.

2.1.1 Downsampling

The trend of wearable devices' minimization and the increasing decentralization of computing, poses serious challenges to the speed and energy efficiency of the signal processing. One of the principal methods for speeding up the course of action is decreasing the amount of data for processing. Such a method is the downsampling (decimating) of the signal. In our testing we have a PPG signal sampled at 256 Hz. The experiments aimed at decimating the signal from the original 256 Hz to 128 Hz, 64 Hz, 32 Hz and 16 Hz. An example of a PPG signal with a duration of 5.0313 seconds and different decimation rates can be examined in Figure 1.

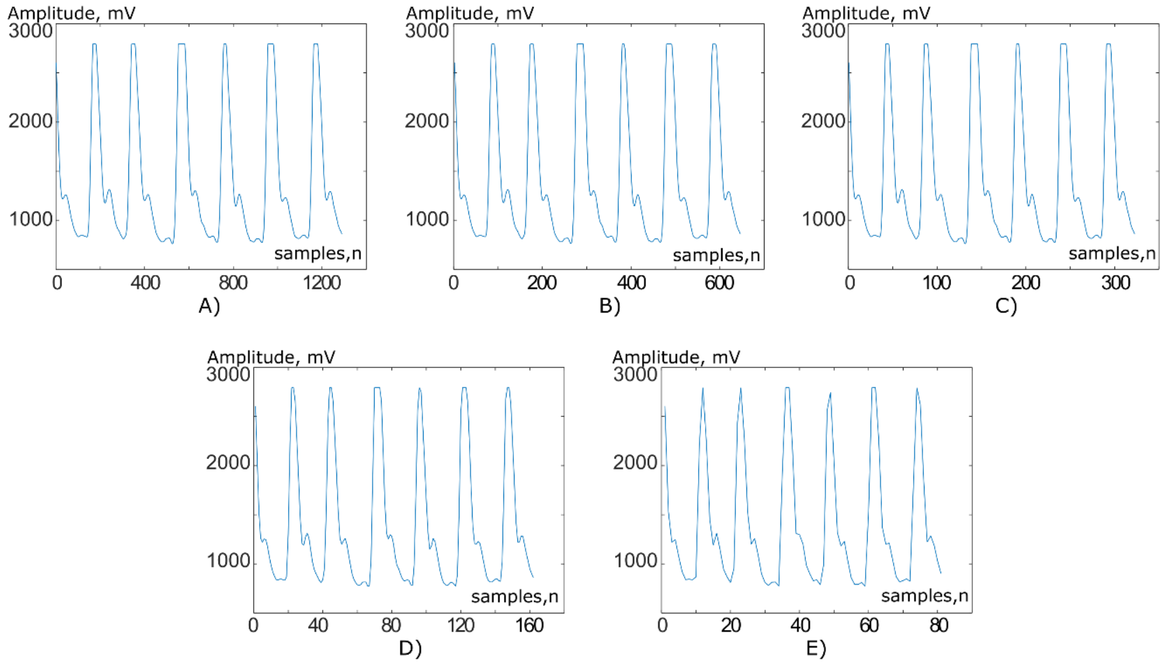

Fig. 1. PPG signal with original sampling rate of 256 Hz (A) and downsampled to 128 Hz (B), 64 Hz (C), 32 Hz (D) and 16 Hz (E)

Seemingly, there are no significant differences at the different sampling rates, but under the surface, certain changes occur to be fully examined and represented in the results section.

2.1.2 Segmentation

Another approach for immediate decrease in the amount of data processed at once is to segment the signal. The recommended length for the recognition of emotions and short-term cognitive states of the mind is 2 minutes. This length, as specified by the calculations of the great number of spectral features

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obtained from the PPG signal, is also considered suitable for achieving good spectral resolution during the Fast Fourier Transform.

On the other hand, the segmentation of the signal and the undertaken overlapping of the different segments allows the researchers to increase the population of the separate classes, thus, feeding more useful data into the machine learning algorithm, responsible for the classification and creation of models for the detection of emotional and cognitive states.

2.2 Electrodermal Activity

The EDA signal has invariably proven to be invaluable in the detection and recognition of human emotional and cognitive states. Therefore, the general usage of EDA signal in the polygraph is not a mere coincidence. The effects of the galvanic skin response (GSR) are not hard for detection and processing, despite the fact that the physiological processes and the EDA signal are quite complex.

2.2.1 Downsampling and segmentation

The EDA signal, similarly to the PPG signal, can also be subjected to data reduction. Downsampling is often omitted because of the native low sampling rates, mostly of 16 Hz, for that type of signal, due to the relatively slow changes in the signal. If the sampling rate is higher, downsampling causes no noticeable changes and/or artifacts to the signal.

As regards the segmentation, it is used for similar reasons as the segmentation of the PPG signal – providing data reduction for simultaneous analysis and increasing the population of the separate classes during the process of classification and model creation.

2.2.2 Separating EDA components

The raw EDA signal (on figure 2) consists of two components – SCL (Skin Conductance Level) and SCR (Skin Conductance Response). The SCL carries information about the slow changes in the electrodermal activity (known also as the tonic level), while the SCR represents the fast changes in the signal. The two components constitute the principal source of valuable data, with the SCR being more tightly connected to the emotional and cognitive states.

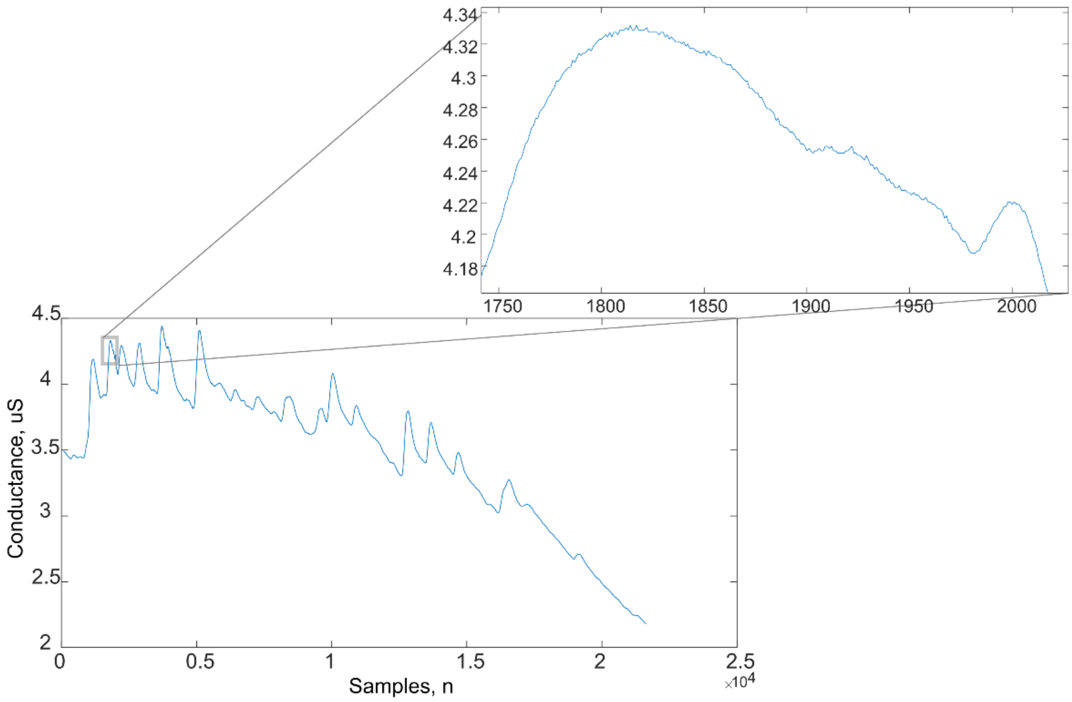

Fig. 2. Raw EDA signal

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The separation of the two components is easily achieved by subtracting the SCL from the raw signal. Thus, the first step is the separation of the SCL component from the raw EDA. There are two main approaches to the calculation of the SCL – passing the raw signal through median or low pass filter with cut off frequency of 0.2 Hz. After the separation of the SCR component, the signal is smoothed with the help of moving average and a window length of 15 samples in an effort to remove any artefacts caused by the separation process.

3 Results

The section summarizes the research findings as to the effects the selected preprocessing techniques have on the signals and their most important components and parameters.

3.1 Effects of the downsampling of the PPG signal

The most prominent features of the PPG signal are the systolic peaks. They are used for the calculation of the inter beat intervals (IBIs), which are one of the main parameters for the calculation of the heart rate variability, a parameter tightly connected to the emotional and cognitive states in humans.

Investigated, further, is its effect on four signal groups (SG) with different levels of interference and/or modulation. Examples for the four different signal groups are graphically represented in Figure 3.

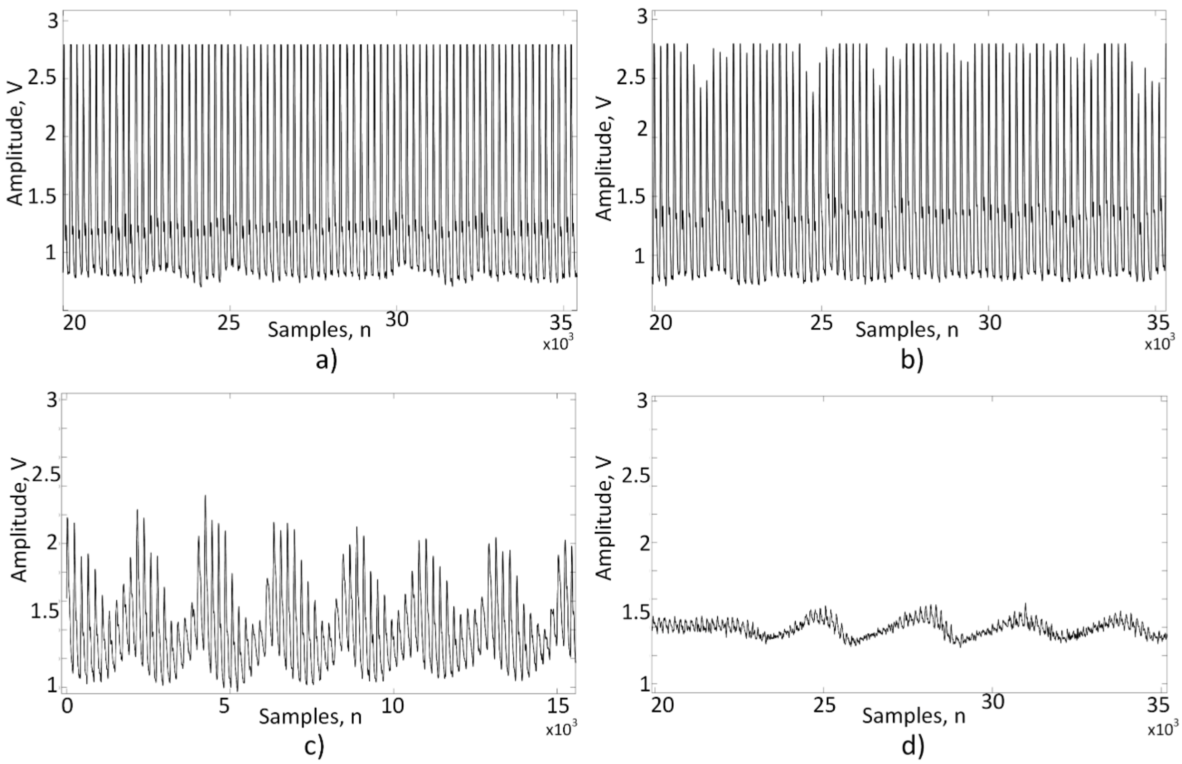

Fig. 3. Four groups of PPG signals, with different levels interference and modulation. The quality of the signal degrades from SG1 (a) to SG4 (d).

Outlined in Figure 4 are the results of the downsampling of PPG signal from 256 Hz through 128 Hz, 64 Hz, 32 Hz down to 16 Hz, its effect on the systolic peak detection (SPD) and the length of the mean IBI for the selected segment.

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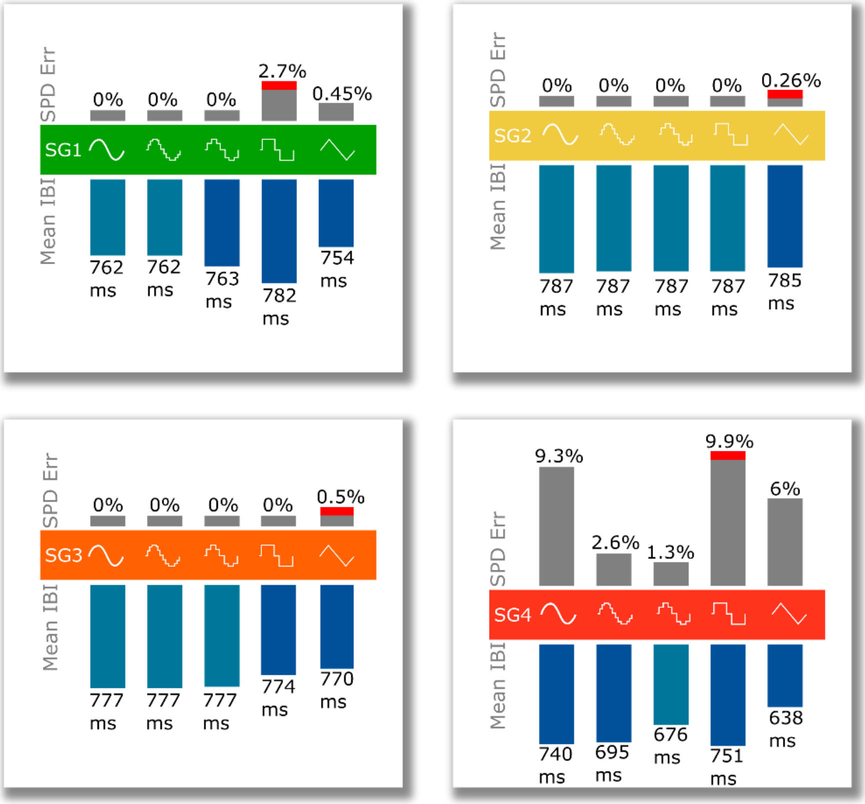

Fig. 4. Effects of downsampling in each signal group (SG) from 256 Hz through 128 Hz, 64 Hz, 32 Hz down to 16 Hz on the Systolic Peak Detection Error (SPD Err) and the mean length of the IBIs.

From the results in Fig. 4 it becomes clear that downsampling is likely to affect the SPD error and the length of the inter beat intervals. Accordingly, downsampling to 32 Hz has negative effect for the signals in SG1 and SG 4, while the signals in SG2 and SG3 remain unaltered. The results also show that the most effective downsampling for the applied database is that from 256 Hz to 64 Hz, thus, achieving 0% SPD Err in SG1, SG2 and SG3 and 1.3% wrongly detected systolic peaks for SG4. Additionally, downsampling to 64 Hz shows minimal change for the mean IBI length as the change is 1 ms in SG1, none in SG2 and 3 ms in SG3. As for SG4, downsampling produces good results for the length of the IBIs.

3.2 SCL and SCR separation

As already mentioned in section 2, we need to separate the SCL and the SCR components from the raw EDA signal. To that effect, the calculation of the SCL component (the tonic level) via median filter with window length of 75% from the sampling rate is contrasted with the 5th order Butterworth low pass filter with cutoff frequency of 0.2 Hz. The graphs can be observed in Figure 5, where the raw EDA signal is depicted at the top, the resulting signal from the median filter - in the middle and the SCL component resulting from the low pass filter – at the bottom. It becomes evident that the low pass filter creates noticeable artefacts in the signal. Additional experiments were conducted with different lowpass filters to discover that the Butterworth approximation is the one with less artefacts, and the decrease in the filter's order cannot clearly separate the tonic level, while an increase in the filter's order results in stronger artefacts, which proves to be a major obstacle as to the clean separation of the SCL and SCR components.

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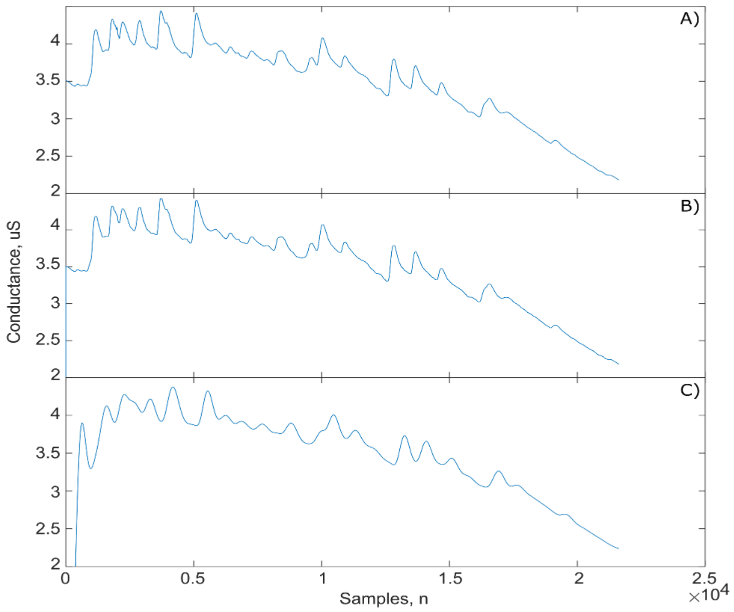

Fig. 5. EDA signal – raw (A), passed through median filter (B) and passed through low pass filter (C)

Consequently, the differences from the SCL separation lead to differences in the resultant SCR components as illustrated in Figure 6. Figure 6 (A) displays the SCR component directly after subtracting the SCL from the raw EDA. To smooth out the generated noise, applied is a moving average with a window length of 12% of the sampling rate, with the resultant SCR component being represented in Fig. 6 (B). The SCR resulting from the computation with the usage of low pass filter is indicated in Fig.6 (C). Discerned are some distinct artefacts, with the levels of the conductance being higher than the typical levels up to 0.1 μS for the SCR.

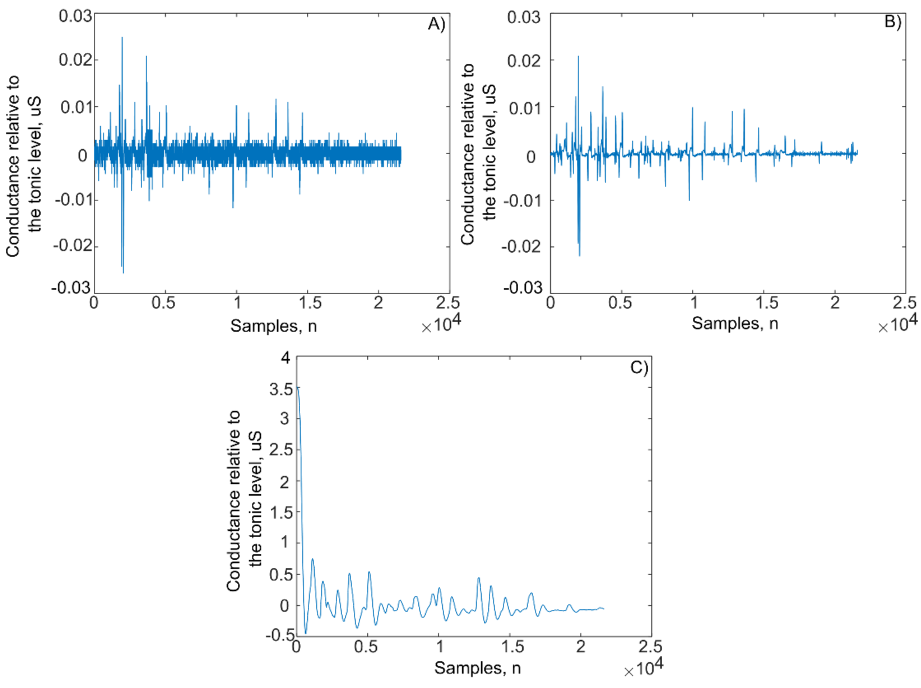

Fig. 6. SCR component from median filter (A) and then smoothed with moving average (B), SCR from low pass filter

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4 Conclusions

The results prove that the preprocessing of the physiological signals, such as PPG and EDA, is essential for the subsequent processing, parametrization, and prospective detection of emotional and cognitive states in humans. The research findings, hereto discussed, point to the conclusion that downsampling PPG from 256 Hz down up to 64 Hz does not pose a problem in the currently used CLAS Dataset. However, the separation of the SCR and SCL components is found to be crucial with respect to the EDA signals, and as mentioned throughout the paper, the usage of median filter proved to be the right approach.

Acknowledgments

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