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# Cepstral Based Heart Rate Estimation

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*Abstract*—**Heart rate (HR) estimation is of crucial importance in human health evaluation and can be considered as valuable indicator of cardiovascular state. In this paper contact based system for heart rate is presented, where system for HR acquisition is consisted of a laptop and web camera. In such system heart rate variability (HRV) affects the changes in skin color of a fingertip while pressing the camera lens to make the full contact. HR value is estimated according to video sequence processing results. The proposed methodology uses local approach for feature extraction and cepstral based analysis. Experimental results are compared with referent pulse meter for healthy subjects. The average error of 5% is obtained.**

*Index Terms*—**Cepstrum, estimation, heart rate, image processing, web camera.**

## I. Introduction

THE resting heart rate of the body (commonly called RHR) is the number of contractions of heart that occur in a single minute while body is at complete rest. This number will vary depending upon the age, gender, and health condition of a person. In general terms RHR of a subject is a strong indicator of the person's basic level of fitness. A healthy heart beats 60 to 100 times per minute, which is necessary to supply oxygen-rich blood to the body [1]. Values outside this range of nominal values may indicate pathological health state. Thus, it is of importance to develop efficient and accurate heart rate (HR) detection techniques.

In the literature there are several approaches using web camera for HR detection [2]. One of them is contact based detection, where a subject is using a forefinger to cover the camera lens. Heart rate variability (HRV) causes micro changes on fingertip skin surface. As a consequence there is a modulation of light intensity falling on the camera lens. In other words, HRV is correlated with brightness changes found in video frames. The standard methodology for extracting information regarding HR is based on applying Fourier transform [3]. Maximum value is detected in calculated spectrum, where its position determines HR value. However, this approach has shown several disadvantages. One advantage of the cepstrum is that it is more capable of detecting those variations in phenomena that manifest themselves as periodic components in the Fourier spectrum. Such phenomena, which appear as repeated peaks in the Fourier spectrum, occur as a single peak in the cepstrum [4]. It is believed that advanced signal processing techniques provide new possibilities.

The main goal of a study presented in this paper is to examine the possibilities of cepstral analysis in HR estimation using previously described contact based system. The needed hardware is consisted of a laptop equipped with a web camera and the analysis is performed on five healthy subjects.

This and similar studies can be considered valuable for telemedical systems development. The methodology for HR detection should be considered along with the need of modern society. Data related to HR can be digitally recorded and sent directly to another device (desktop, laptop, mobile). It is expected that a member of medical personnel can have continuous access to such data and, thus, monitor the patient's health state.

The paper is organized as follows. In Section II the proposed methodology is described. Details regarding the video dataset acquisition can be found here, as well as further information related to HR detection algorithm steps. Section III briefly describes the simulation. Section IV is dedicated to obtained experimental results and proper discussion. The results are compared with referent pulse meter values. Finally, conclusion is given in Section IV.

## II. Methodology

For the acquisition of video sequences Lenovo Z710 laptop (Intel Core i5-4200M processor 3.10 GHz and 8GB RAM module) is used. Each recorded video sequence is 30 seconds long, i.e. 900 frames per record. Block diagram of the proposed HR detector is presented in Fig.1. Preprocessing is followed by cepstrum calculation step. After the calculation, peak detection is performed. Finally, HR value ($F_h$) is obtained.

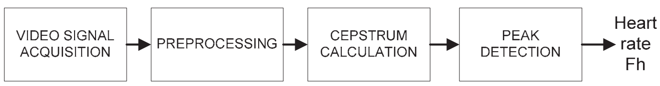


Fig. 1. Block diagram of the heart rate (HR) detector.

### A. Video signal acquisition

The laptop web camera is used in video signal acquisition. The upper HR bound of an adult subject is around 120 bpm (beats per minute), which can be related to tachycardia state [5]. This value can be interpret as $2Hz$ frequency, where

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according to Nyquist-Shannon theorem sampling frequency should be at least twice as high. Selected recording frequency of 30 $fps$ is far higher, so aliasing is certainly avoided.

Video sequence resolution is 320x240 pixels. Camera uses YUY2 (interleaved YUV format) color space, but the sequences are converted into RGB color space, where is frame is described by red (R), green (G) and blue (B) component.

### B. *Preprocessing*

Video signal acquisition is followed by preprocessing step. The main aim of the preprocessing step is to form one-dimensional signal adequate for further processing. Using R, G and B component of each frame, relative brightness $Y_k, \left(k=1..N_{frame}\right)$ is calculated:

$$Y_k = 0.2126R_k + 0.7152G_k + 0.0722B_k . \quad (1)$$

Each frame is divided on 12 blocks, where each size block is 80x80 pixels. In this way data regarding local brightness changes are gathered. Standard deviation is calculated for each block. Average of 12 standard deviation values is denoted as value $\mu_k$ for k-th frame [6]. Thus, RGB frames are mapped into an one-dimensional signal which may characterize brightness changes from one frame to the next one. Time interval between two successive samples is $0.033s$ .

Obtained signal is then analyzed using a sliding window. Window function should be properly selected in cepstrum calculation. The window is 6s long and applied with 8.33% overlapping (sliding increment is 0.5s). In Fig.2 j-th sliding window within a signal is illustrated. Two examples are shown, for j=5 and j=10. Hanning window function is applied in order to prevent spectral leakage phenomena.

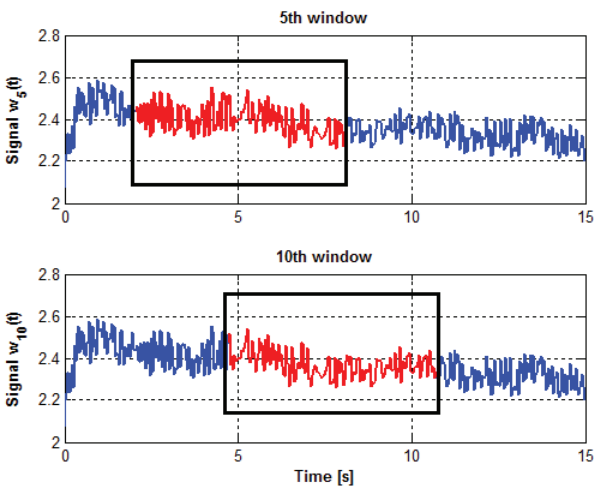


Fig. 2. Sliding window.

Window determines a 6s long segment of a signal. Further processing based on such segments. Consequently, multiple samples (frames) are employed in the evaluation of a single sample in a HR curve obtained in the evaluation process.

### C. *Cepstrum calculation*

Fourier transform, i.e. spectrum is usually calculated for the analysis [7]. The most of signal's energy is concentrated for low frequencies. As frequency increases contribution to the total energy of a signal decreases. There is a need to point out high frequency content. One of the nonlinear techniques is cepstral based approach. The term "cepstrum" is derived by reversing the letters "spec" in the word "spectrum". Cepstral analysis assumes applying logarithm transform on signal's spectrum.

Cepstrum approximation can be interpreted as inverse discrete Fourier transform of a Fourier transform magnitude logarithm:

$$c_p(n) = \frac{1}{N}\sum_{k=0}^{N-1}\log\left|X_p(k)\right|\exp\left(j\frac{2\pi}{N}kn\right), 0 \le n \le N-1 \quad (2)$$

Expression (2) defines a real cepstrum. Corresponding block diagram for computing the cepstrum is presented in Fig.3. If a logarithm basis is ten, ordinate axis scale is decibel. Signal $c_p\left(n\right)$ has temporal dimension called "quefrency" (an anagram of "frequency").


Fig. 3. Block diagram for computing real cepstrum.

In general, cepstral analysis is logarithm based method for detection of specific features of a signal structure [8]. One of them is periodicity.

### D. *Heart rate detection*

All of the processing is applied offline for the purpose of the study. Real cepstrum is computed, where Fourier transform is calculated for $N = 512$ . Two parts of a cepstrum structure can be noticed: "early" and "late" cepstrum. In this paper, the "late" cepstrum is important since it is related to high quefrency values. Quasiperiodic signals have a tendency to show significant local maximum in this part of a cepstrum. This is illustrated in Fig.4.

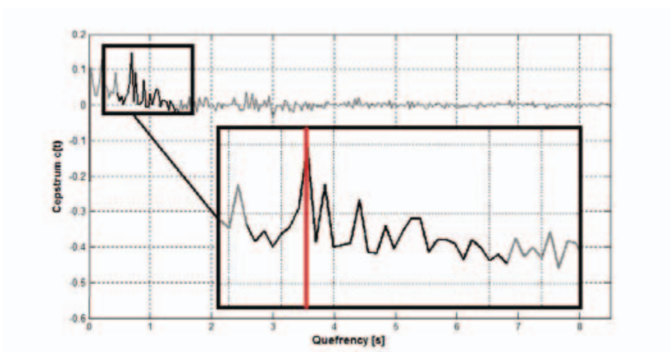


Fig. 4. The local maximum in a cepstrum.

Position of the significant local maxima corresponds to the reciprocal of HR value. The area in which the requested maximum should be found is bounded by maximum and minimum HR value.

The maximum detection in spectrum [9] is, here, replaced by cepstral maximum detection. Benefit is to improve signal-noise ratio in comparison to standard spectrum implementation [10]. To be more precise, in the significant maximum neighborhood there are no components close to its amplitude level. Due to this, it is easier to determine the maximum position in comparison to spectral components.

## III. SIMULATION

Dataset used in this paper is consisted of video signals acquired from five adult healthy subjects. The acquisition is completely automated. For each subject the recording is performed in several iterations. In different iterations the subjects were asked to be relaxed and in both sitting and standing position, as well as after specific physical effort. Referent HR is measured using a pulse meter.

Each signal passes through the same procedure described in Section II in order to detect the significant maximum within a cepstrum. The output of such procedure is HR curve which describes variability of HR in time.

Time interval between two successive samples in the curve corresponds to window analysis sliding increment. Median filter using neighborhood size 5 is applied on the curve. Finally, average value of the filtered curve, $\overline{X}_M$ , is compared with a referent value, $X_R$ .

$$\overline{X}_M = \frac{1}{M}\sum_{l=1}^{M} X_i \tag{3}$$

In order to quantitatively describe the error both absolute and relative difference is calculated. Absolute error, $E_A$, is a difference between average of an estimated HR curve and referent value obtained by a pulse meter.

$$E_A = \left|\overline{X}_M - X_R\right| \tag{4}$$

Relative error, $E_R$, is given in percent.

$$E_R = \frac{E_A}{X_R}\cdot 100[\%] \tag{5}$$

## IV. RESULTS

In Fig. 5 a typical HR curve obtained by cepstral analysis is presented. Shape of the curve is convenient for potential ECG representation synchronously with HR. For this purpose data can be exported in ASCII format. In this paper only HR curve average is considered.

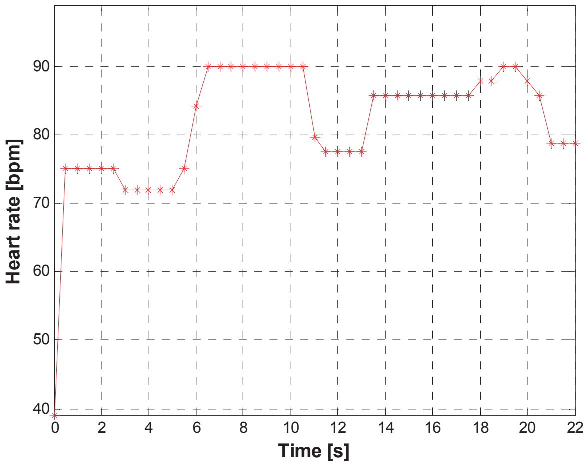


Fig. 5. Heart rate curve.

Based on the sequences obtained by the acquisition absolute and relative errors for each subject are calculated. Minimum and maximum values of the errors for five subjects are presented in Table I.

TABLE I
ESTIMATED PULSE RATE

| Subject | Absolute error [bpm] | | Relative error [%] | |
|---|---|---|---|---|
| | Min | Max | Min | Max |
| 1 | 1 | 6 | 1.19 | 7.41 |
| 2 | 1 | 5 | 1.67 | 7.94 |
| 3 | 2 | 8 | 2.35 | 8.70 |
| 4 | 2 | 4 | 2.25 | 4.44 |
| 5 | 1 | 4 | 1.19 | 5.00 |

The greater relative errors are found for the first, the second and the third subject, where the measured HR is closer to the upper bound (100 bpm). For the subjects where the HR is mostly in nominal range [60, 100] bpm, the errors are lower. In Fig.6 absolute error cumulative histogram is presented. Errors less than 3 bpm are most probable (relative cumulative frequency is over 70%).

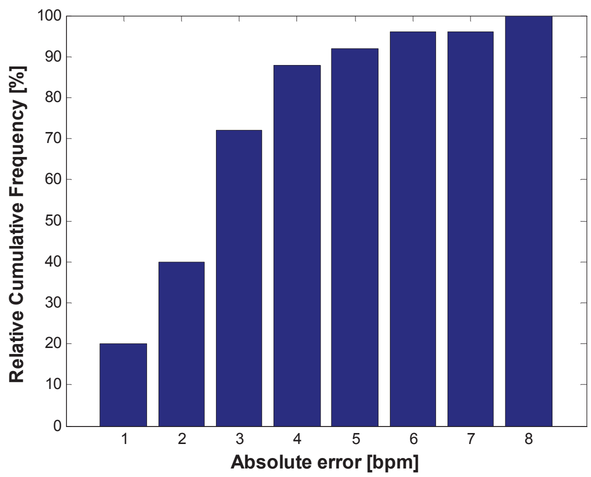


Fig. 6. Absolute error cumulative histogram.

The proposed methodology is just a step towards development of efficient and simple contact based pulse detectors. Even though satisfying results are obtained, the methodology need to be further improved.

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## V. Conclusion

In this paper a system for contact based HR detection is described. For the acquisition average quality web camera is used. A methodology is based on calculation of average of block standard deviation. This is a local approach for constructing one dimensional signal which is further used in cepstral analysis. By significant cepstrum maximum detection (instead of the detection of the first significant maximum in spectrum) HR is evaluated. Cepstral approach brings higher signal-noise ratio leading to an easier maximum detection.

In the comparison with pulse meter referent values, maximum error is less than 5% for nominal HR values (subject 4 and subject 5).

The future work regarding the contact based HR monitoring should be oriented towards increasing the dataset. Special attention should be given to pathological cases, such as tachycardia. Since the accuracy of HR detector depends on window function size and other parameters, adaptive possibilities need to be analyzed.

The most interesting aspect of implementation such detectors can be found place in telemedicine applications. Implementations on different platforms, like Android and iOS, can be considered.

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