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NONINVASIVE CONTINUOUS BLOOD PRESSURE DETERMINATION

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Abstract: The determination of systolic and diastolic arterial blood pressures is very important for the diagnosis of cardiovascular diseases. Common principles for noninvasive measurements are the Riva-Rocci/Korotkow- and the oscillometric methods with inflatable cuffs around an arm, wrist or finger. In our approach we use the dependency between pulse wave velocity and arterial blood pressure to calculate systolic and diastolic pressures on a beat to beat basis. The advantage is a continuous blood pressure monitoring and the reduced stress for the patient due to the reduction of cuff inflations. Because of the required calibration for each patient, conventional measurements cannot be totally evaded but are minimized to only two readings. The method is under test in a children's hospital during excercise-ECG registrations. The data acquisition and experimental setups, the digital signal processing and blood pressure calculation are described and discussed.
Keywords: blood pressure, photoplethysmogram, pulse wave velocity, continuous monitoring.

1 INTRODUCTION

Arterial blood pressure (ABP) and its regulation during stress and other influences is an important characteristic of the human cardiovascular system. Noninvasive blood pressure measurement in the conventional way (Riva-Rocci, oscillometric) using an inflatable cuff around the upper arm, wrist or finger is quite simple but inaccurate and does not provide continuous readings. The repeatedly cuff inflations also yield stress to the patient. Continuous noninvasive arterial blood pressure measurement is possible [1] but expensive. An alternative is the evaluation of the dependency between pulse-wave velocity (PWV) and arterial blood pressure [2]. This method theoretically allows a determination of arterial blood pressure for each heartbeat and can be used for continuous monitoring during exercise electrocardiography [3] or sleep laboratory studies.

2 FEATURE BASED BLOOD PRESSURE DETERMINATION

2.1 Basics

The feature based blood pressure determination is based on the concept of estimating systolic and diastolic blood pressure by evaluation of blood pressure dependent features calculated from physiological signals. In our current implementation we use the pulse transit time (PTT) and the instantaneous heart rate as features and estimate blood pressures with an artificial neural network.

The two features are biased and scaled with individual reference data and fed into a multi-layer-perceptron network. The network is trained with a generalized transfer function between the features and systolic and diastolic blood pressure. The output of the network is again biased and scaled to match the individual calibration values. Figure 1 shows the principle of operation.

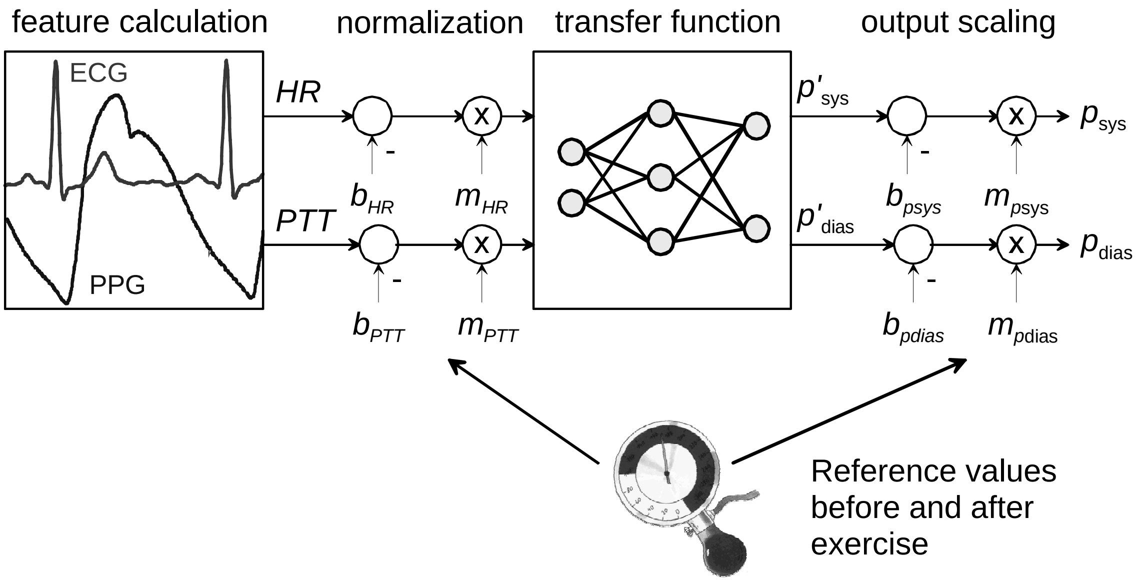

Figure 1: Principle of the feature based blood pressure determination

The pulse transit time as a measure for the mean pulse wave velocity can be determined by means of the simultaneous measurement of the electrocardiogram (ECG) and a photoplethysmogram (PPG). It is calculated as a time difference between one ECG reference point and a PPG reference point. As the time measurement starts in the ECG it consists of a pre-ejection period that can be assumed an individual constant value and the actual pulse wave delay time. The dependency between pulse wave velocity and blood pressure arises from the pressure dependent arterial elasticity and has been shown experimentally. If a linear relationship between pulse wave velocity and blood pressure in the physiological relevant blood pressure range is assumed [5] the pulse wave delay time is inversely proportional to blood pressure. Some authors have found a linear relation between blood pressure and pulse wave delay time. Both assumptions do not describe the actual relationship, which is non-linear because of the additional time components in the pulse transit time and the non-homogeneous pulse wave propagation through the arteries. The inverse proportional behaviour gives only a rough description.

The instantaneous heart rate has a strong correlation to systolic blood pressure [5] especially during ergometric exercise tests.

2.2 Feature calculation

The positions of the R-waves are extracted from the ECG and used to calculate the instantaneous heart rate in beats per minute. The index *i* corresponds to the *i*'th cardiac cycle in the registration and t_R is the position of the R-wave.

$$HR_i = 60/\left(t_{R,i+1} - t_{R,i}\right) \qquad (1)$$

The pulse transit time is calculated as the time from the R-wave in the ECG to the beginning of the rising slope in the PPG called t_P.

$$PTT_i = t_{P,i} - t_{R,i} \qquad (2)$$

Various definitions of pulse transit time are mentioned in literature. As the start reference point often the Q-wave or the R-Wave in the ECG are used. The R-wave has the advantage of being pronounced in the standard leads and therefore can be easily detected. The end point of pulse transit time measurement has to be a reference point in the photoplethysmographic signal measured at the finger or ear lobe. There are several possibilities in obtaining this value [4]. Some authors use the position with the highest gradient or they choose a midpoint between the 20% and 80% values of the signal. As the slope is variant in time and easily distorted by movement artefacts we are using an averaging procedure. After low pass filtering with 8 Hz cut off frequency we calculate the first derivative and search its maximum value to calculate a threshold. All consecutive signal samples around the maximum position for which the derivative exceeds the threshold are used to define a regression straight for the rising slope. In the same manner a second regression straight for the diastolic descending of the previous cycle is calculated. The intersection point is taken as the end of pulse transit time t_P. In addition to being robust another advantage is the improvement in time resolution. The intersection point can be computed with a higher precision than predetermined by the sampling rate. According to our measurement results a change in pulse transit time of 1ms roughly corresponds to a change in blood pressure of 1mmHg. Therefore, to achieve a blood pressure resolution better than 5mmHg the sampling rate must be higher than 200Hz.

The calculated features undergo a validity check. Heart rate should be in the range of 30 to 240 beats per minute and pulse transit time has a valid range between 75ms and 400ms regarding the measurement at the ear lobe or finger. Due to the dependency of the pulse wave delay time from the sensor placement the valid range has to be adjusted to higher values for a PPG registration at the foot.

As the absolute values of the features vary patient dependent we use an individual normalization and the features heart rate and pulse transit time are linearly transformed.

$$HR' = \left(HR - b_{HR}\right) \cdot m_{HR} \text{ and } PTT' = \left(PTT - b_{PTT}\right) \cdot m_{PTT} \tag{3}$$

The output of the neural network can be treated as normalized blood pressure values and it is biased and scaled to match the actual blood pressure values.

$$p_{\mathrm{sys}} = \left(p'_{\mathrm{sys}} - b_{p_{\mathrm{sys}}}\right) \cdot m_{p_{\mathrm{sys}}} \text{ and } p_{\mathrm{dias}} = \left(p'_{\mathrm{sys}} - b_{p_{\mathrm{dias}}}\right) \cdot m_{p_{\mathrm{dias}}} \tag{4}$$

The coefficients *m* and *b* are calculated from two calibration measurements carried out with conventional cuff techniques. The first calibration point incorporates the calculated features and the blood pressure values at rest. The second calibration point uses the values after an exercise test yielding features from a different blood pressure level.

2.3 Artefact detection

When using the method during exercise ECG registrations especially motion artefacts have to be considered. The ECG can be recorded nearly undisturbed using centralized electrode placement but the photoplethysmographic signal is frequently disturbed by movements of the patient. Artefacts can be reduced by an adequate sensor placement. During bicycle ergometry sensor placement at the ear lobe yields to a minimum of artefacts even though the perfusion in the ear is generally lower than in the finger.

Artefact detection is performed in two stages. First the signal level is evaluated. Regarding the input range of the analogue to digital converter lower and upper thresholds are calculated and cycles with too many samples exceeding the thresholds are neglected. Cycles that passed the first stage are further examined by comparing the signal shape to a user defined reference cycle. The algorithm is based on the expectation that the principle form of the pulse wave does not change during a registration. Due to blood pressure variations there is a time shift and also a change in amplitude. That’s why we examine the signal on a per cycle basis defined by two adjacent R-waves of the ECG. Because of the variable duration of each heart beat, the samples are interpolated to a normalized time. Amplitude normalization is performed with respect to the signal energy. Shape dependent criteria are derived from the cross correlation function between the reference waveform and each individual signal period. The maximum value and the position of the maximum value of the cross correlation function are evaluated with a threshold criterion.

2.4 System identification

To train the artificial neural network we performed exercise tests on patients different in age and physical condition. We used a standard bicycle ergometry test and an orthostatic stress test (Schellong test) to stimulate blood pressure reactions. To obtain a generalized transfer function the values of blood pressure and the calculated features are normalized with regard to the individual abilities. The normalized features and the conventional measured blood pressure values were used to train the neural network with the back propagation algorithm. Different numbers of hidden neurons were used and we found a good approximation and generalization with three neurons. As the target values we used Riva-Rocci based measurement.

Measuring dynamic blood pressure changes with the Riva-Rocci method is difficult because the systolic and diastolic values are measured at different points in time. It is not possible to interpret the measured values as taken at the end of the measurement because the systolic pressure is determined about 20 seconds before. This time shift becomes important when measuring after an exercise phase. As systolic pressure drops immediately the time position of systolic pressure has to be shifted for a correct measurement.

As the result of the different exercise tests we obtain an empirically derived transfer function between the heart rate and pulse transit time on the one hand and conventionally measured blood pressure on the other hand. In figure 2 the measurement results are shown for eight registrations from six individuals. In the left graph the normalized pulse transit time is interpolated with an inverse 4th order polynomial (dashed line). The behaviour is similar to the inverse proportional dependency mentioned in literature (solid line) [5]. In the right graph the dotted line is an interpolation with a 4th order polynomial for the dependency between heart rate and systolic blood pressure.

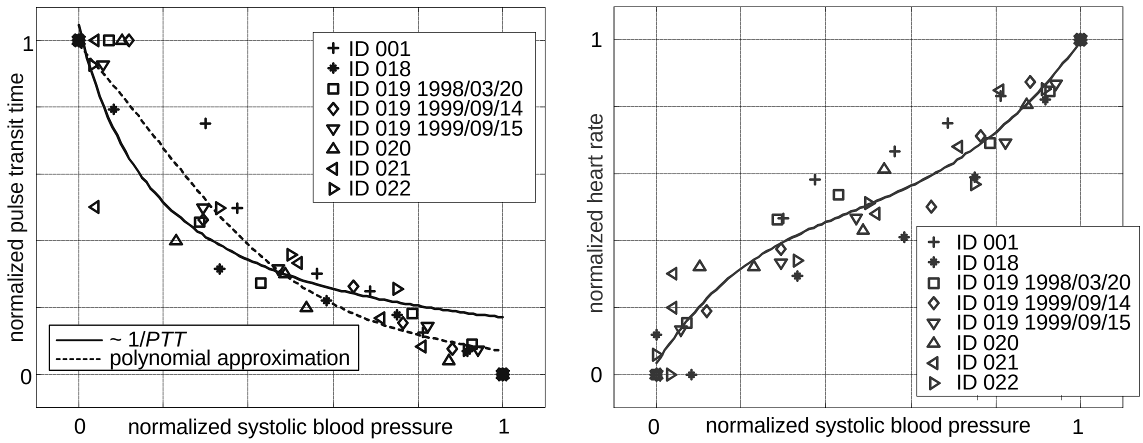

Figure 2: Measured relationship between blood pressure and features

Due to the normalization the non-linear transfer function can be used for several individuals and mapped linearly with individual calibration values as it can be seen in figure 2. Our measurements have also shown a long-term stability of the dependency for more than one year shown for patient ID 019 in figure 2.

The reproduction of the transfer functions with a neural network utilizes the generalizing effect of neural networks and gives a minimization of the individual error of each measurement. The neural network concept is also open for additional features like the gradient of the rising or falling slope of the photoplethysmographic signal or signal features like skewness or kurtosis.

3 RESULTS AND DISCUSSION

The system is being evaluated in the cardiologic department at the children's hospital Datteln as an additional blood pressure measurement system during exercise-ECG registrations using a bicycle ergometer. The patients' ages are in the range of 8 to 18 years. The conventional blood pressure measurement is carried out with an oscillometric device (DINAMAP 8100 [6]). In modification to commonly performed exercise-ECG registrations with continuous ergometric workload we use a test with interval load shown in figure 3. As the oscillometric measurement technique does not tolerate motion the exercise is stopped for a minute after a two-minute load to take an oscillometric blood pressure reading.

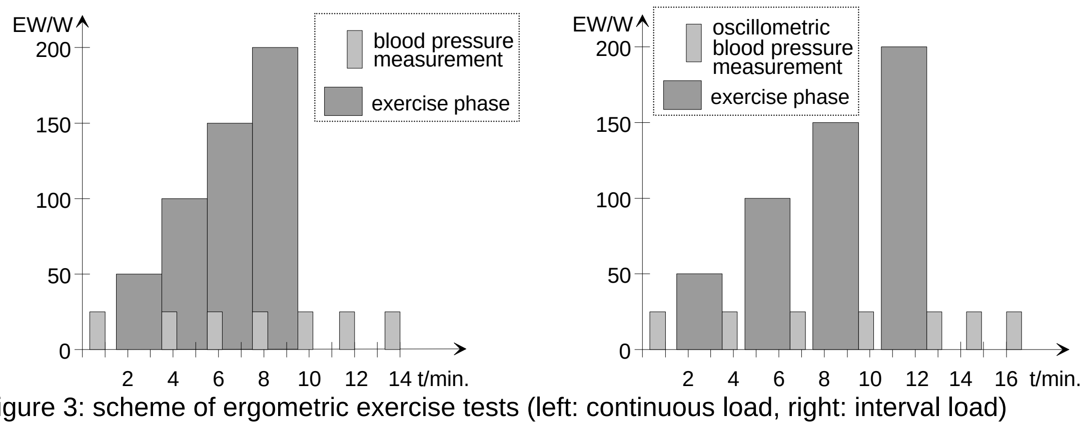

Figure 3: scheme of ergometric exercise tests (left: continuous load, right: interval load)

Two oscillometric readings are used as calibration values for the feature based blood pressure calculation. With the new system we have additional information about the blood pressure response during the exercise stages and in phases of relaxation. It can be seen in figure 4 that blood pressure drops also in the pauses between the exercise stages. This effect is not visible in the conventionally measured values and gives information about the cardiovascular regulating system.

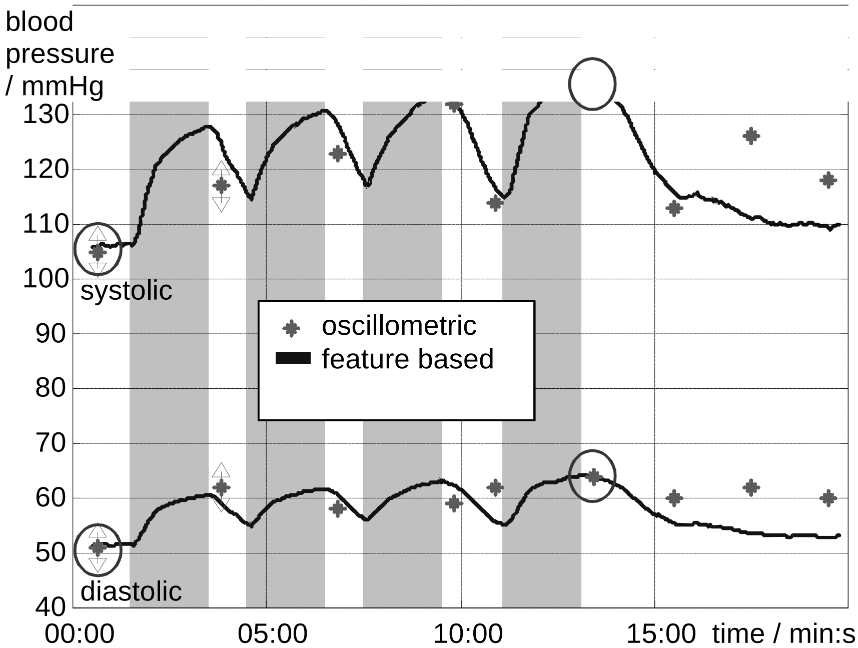

Figure 4: Blood pressure measurement during an exercise-ECG

We have also tested our system in comparison to the Portapres™ device during ergometric exercise; results will be published soon [8]. Especially systolic pressure measured with Portapres™ drops very fast after the exercise test. The Riva-Rocci measurements and our feature based method do not reveal such a fast relaxation.

For further improvement of the accuracy and reliability additional features should be added. This can be done easily by adding inputs to the neural net structure and retraining the net.

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