A Calibration-free Blood Pressure Measurement on a Scale: Concept and Challenges

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Abstract: Two health parameters are most relevant for self-monitoring of hypertension: blood pressure and body weight. Blood pressure is normally measured with a blood pressure cuff, whereas body weight can be measured with a simple body scale. If it is possible to integrate blood pressure measurement into easy-to-use body scales, patients will benefit from simpler use and lower overall price. The aim of this work is to develop a body scale with which blood pressure can be measured without calibration and without the need for additional devices. This can be realised by considering surrogate parameters for blood pressure. Starting from sensors such as electrodes, photo diodes and pressure transducers, various biosignals such as ECG, BCG, PPG or bioimpedance are extracted from the sole of the foot. The signal is reduced to morphological features which serve as input to a neural network for blood pressure determination. The integrated artificial intelligence (AI) is to be implemented in an energy-efficient way on an embedded system. In addition, the energy-efficient implementation ensures battery operation for several months with daily use. Besides the concept, the strengths, weaknesses, threats and opportunities of this concept are examined in detail within the framework of a SWOT analysis. This includes considerations of hardware, software, data and user experience.

1 INTRODUCTION

High blood pressure is one of the main causes of coronary heart disease, stroke and kidney failure. In the EU alone, more than 103 million people suffer from high blood pressure, which is a quarter of the population (European Commission, 2021). Excess weight in particular increases the risk of developing high blood pressure and the severity of possible secondary diseases. Therefore, it is very important to measure blood pressure regularly and above all in correlation with weight. In this way, appropriate countermeasures, such as the dosage of medication, can be initiated in time. Weight is usually recorded by a body scale which is easy to handle. Blood pressure, on the other hand, has to be measured with a blood pressure cuff.

The idea of this work is to extend the simplicity of a scale by the functionality of a blood pressure measurement and thus to avoid the complex measurement process by means of a blood pressure cuff. Thereby, the particular challenge is to develop a calibration-free blood pressure measurement method. Existing solutions for blood pressure measurement via a body scale require regular calibration with a blood pressure cuff. This is due to the individual physiological characteristics of the cardiovascular system of each person, which can change due to ageing and other influences. This is to be addressed by implementing machine learning methods based on biosignals such as ECG, PPG, BCG or bio-impedance. Furthermore, an energy-efficient implementation is necessary to ensure battery operation.

This paper is structured as follows: Section 2 reviews state-of-the-art methods for determining blood pressure. In the third section, we present our concept for determining blood pressure on a body scale. Based on this, a discussion of challenges and risks of this approach is given in section 4. In section 5, we summarise the results and give an outlook on further steps.

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2 RELATED WORK

Measuring blood pressure is necessary to draw conclusions about the condition and diseases of the cardiovascular system. There are different ways of measuring it. The most accurate method is the invasive method using an inserted catheter with a pressure sensor (Pielmus et al., 2021). In addition, invasive blood pressure measurement is characterised by continuous measurement, so that it is the method of choice during high risk surgeries and in the intensive care unit. However, there is a risk of bleeding or infection, which limits its use especially for daily usage.

The indirect measurement of arterial blood pressure, which is commonly used in everyday life, is carried out by measuring the pressure on the upper arm using a sphygmomanometer (Riva-Rocci method). By increasing and decreasing the pressure in the cuff, the blood pressure can be determined auscultatorily, palpatorily or oscillatorily. The measurement is less accurate than the invasive measurement and is not continuous. On the other hand, it is fast, inexpensive and without great risks. Nevertheless, regular measurements are perceived as burdensome for patients. This class of devices also includes blood pressure measurements on the wrist or fingers.

New approaches in research focus at the photoplethysmogram (PPG) more closely (Paviglianiti et al., 2020; Yan et al., 2019; Kachuee et al., 2017) and are less stressful to wear or even completely contactless (Nakano et al., 2018; Murakami et al., 2015; Fan et al., 2020; Jeong and Finkelstein, 2016). A distinction can be made between time-of-flight measurements and feature-based methods (Shin and Park, 2012). The analysis of the pulse transit time (PTT), which means the time delay of a pulse wave, and the pulse arrival time (PAT), which is the time between the electrical excitation of the heart and the arrival of the pulse wave, are two common methods for cuffless blood pressure measurement. PPG is used to measure the propagation time of the pulse wave between two skin sites or the temporal shift between ECG and PPG signal. A relationship between these values and blood pressure can be established via a regression analysis (Shin and Park, 2012; Oreggia et al., 2015).

Few works (Carek et al., 2019; Martin et al., 2016; Shin and Park, 2012) investigate and implement standing blood pressure measurement systems based on a combination of ECG, a ballistocardiogram (BCG) for recording the heartbeat or a PPG sensor, whereby all signals are measured at the foot. Shin and Park performed a synchronised averaging of the ECG signal based on the corresponding BCG peak location in order to reduce the influence of electromyogram (EMG) noise from leg muscles. The subsequent blood pressure estimation is based only on the temporal difference between the R-peak from ECG and the J-peak from BCG, where the correlation is established by a linear regression. Carek et al. and Martin et al., on the other hand, use PPG and BCG to calculate a delay. However, the drawback of these approaches is that their blood pressure determination methods are all based on an (regular) individual calibration of the regression curve to the specific characteristics (e.g. age, height, vascular stiffness) of the patient. They are therefore cumbersome to use and require maintenance. A single pulse delay value cannot provide enough information to determine systolic and diastolic blood pressure.

Yet, (Paviglianiti et al., 2020; Kachuee et al., 2017) show that it is possible to develop an universal model based on ECG and PPG that does not require individual calibration. Their models consider morphological signal features as well as the temporal relationship between PPG and ECG. Various studies (Sun et al., 2016; Singla et al., 2019; Lin et al., 2017) show that morphological PPG features can improve prediction accuracy compared to delay-based features only. While PTT and PAT exhibit a strong correlation with blood pressure, a single PPG signal can be sufficient for blood pressure estimation (Rundo et al., 2018; Xing and Sun, 2016). It has to be noted that their signals are measured at the wrist, finger or upper body, where ECG and PPG can be derived with higher quality than at the foot.

In parallel to the scientific publications, it was investigated which products and patents exist. There are scales, e.g. from the Withings company (Buard et al., 2016), which can determine blood pressure via a PAT measurement. However, all currently marketed scales require a calibration procedure and are therefore complicated to operate.

3 METHOD

3.1 Overview

In this section we present our idea of a calibration-free blood pressure measurement via a body scale and present the different steps of the processing. Figure 1 shows the single steps graphically. The process begins with the selection of suitable sensors, a computation unit, the embedded system, its electrical wiring and its placement and integration into the scale body. From these sensors, synchronised biosignals such as ECG, BCG or PPG are subsequently extracted. Based on these time and frequency signals, special morpho-

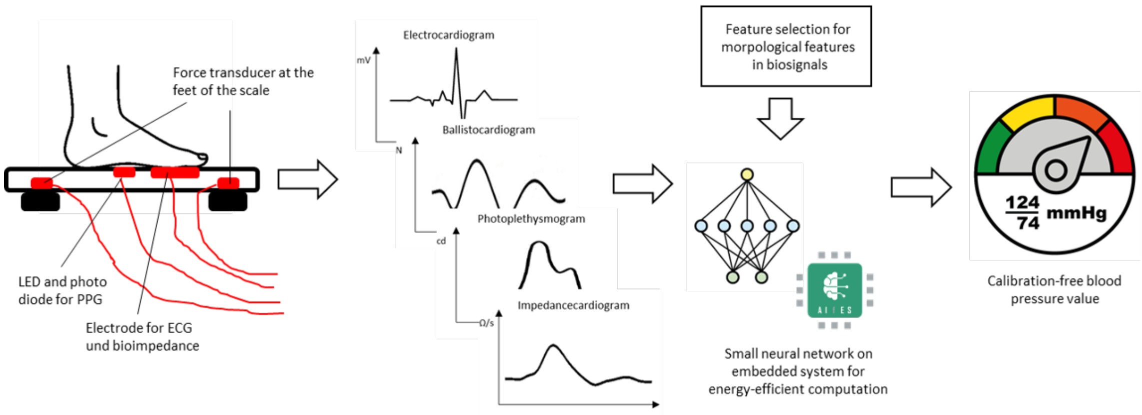

Figure 1: Overview of the single processing steps. From different physical sensors (pressure transducers, photo diodes and electrodes) biosignals such as ECG, BCG, PPG or bioimpedance are extracted. Based on them morphological features are extracted and the blood pressured is determined by a neural network. This is accompanied by an energy-efficient implementation.

logical features are extracted. Subsequently, the blood pressure is regressed by means of machine learning, whereby information such as age and body height should as well be taken into account. The final step is the energy-efficient implementation on the selected embedded system.

3.2 Mechanical Design & Signal Acquisition

The development starts with the design of the mechanical structure, the selection of sensors, their placement and the selection of an embedded system.

Since neither related work nor our previous experience provide information on exactly which feature of which biosignal will be most effective when measured at the foot, the first step is to collect information from as many different sensors as possible on the feet. In further consideration and after preliminary tests, the number of sensors should be reduced to the necessary level. The sensors we consider are pressure transducers for weight and BCG, PPG modules consisting of LEDs and photo diodes and electrodes for the ECG and the impedance cardiogram.

The placement and installation of the sensors proved challenging in preliminary tests. Especially with the electrodes and PPG modules, the foot should rest completely on the measuring point without an air gap. At the same time, the sensors must be attached in such a way that they do not exert pressure that interrupts blood flow in underlying vessels. Due to the arch of the foot, the inside is not suitable for measurements. In contrast, integrating the sensors on the outside of the sole allows for a robust measurement. For this purpose, a measurement prototype was made from PETG material using a 3D printer, see figure 2.

The plate has a size of 31 cm times 11.5 cm. This allows different foot shapes and sizes to be measured up to shoe size EU 48.5 or US 14.

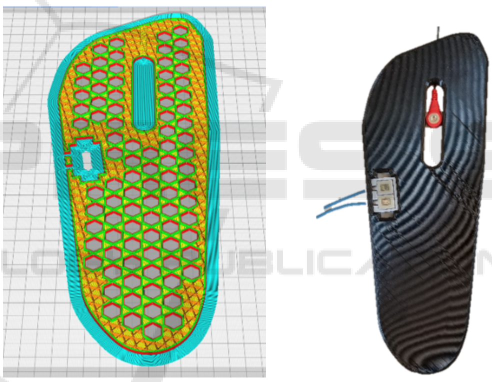

Figure 2: CAD model and 3D print of the measurement prototype with electrode and PPG module.

The individual sensor modules or preamplifiers can be connected directly to any microcontroller via protocols such as I^2C. Hereby, the selection of a suitable embedded system plays a crucial role. On the one hand, it should be sufficiently powerful to be able to determine blood pressure from various biosignals. On the other hand, the lowest possible energy consumption should ensure long-term battery operation. Another important point to consider is that the embedded system should be integrated into the scale body at a later date. For the first iteration, an Arduino Nano (ATmega328) was used, which requires a power consumption of 19 mA and weighs 7 g. This design decision is preliminary and can be corrected in subsequent iterations. Energy-efficient processing is essential and is considered separately in section 3.5.

3.3 Biosignal Generation

In total, at least the following four biosignals should be extracted: BCG, ECG, PPG and ICG (impedance cardiogram). From these, secondary parameters such as respiration rate, HRV or bioimpedance can be derived directly. Thereby, the challenge is that these biosignals are usually measured on the upper body (e.g. ECG) or the arms (e.g. PPG). At the feet, on the other side, the signal quality is significantly reduced. Between heart and feet lies the entire abdominal cavity as well as the lower extremities. This leads on the one hand to a reduced SNR of the useful signal and on the other hand to the coupling of bioartifacts from the corresponding body parts. In the following, the biosignals are discussed individually:

The ECG is derived via the electrodes on the left and right foot. Further electro-muscular activities e.g. of the leg muscles are coupled into the signal. This is because people automatically tense and relax their muscles to stand upright and keep balance. Figure 3 shows the difference in signal quality between the ECG derived from the upper body and from the feet. The ECG is hardly recognisable from this raw signal. Synchronised averaging of the ECG signal based on the corresponding PPG peak location (similar to (Shin and Park, 2012)) or a signal filtering based on a wavelet-transform should therefore be used to improve the signal. For the R-peak detection the possible temporal position can further be narrowed down by considering the other biosignals.

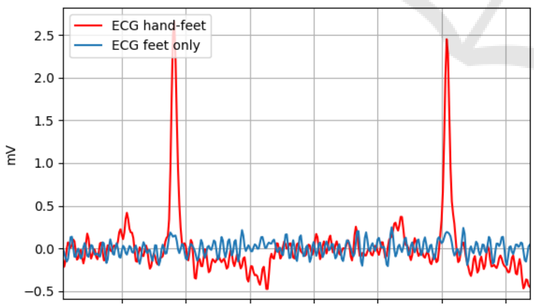

Figure 3: ECG signals simultaneously derived between the right and left foot (blue) and between feet and hand as reference (red).

Considering the mechanical attachment from the previous section, the PPG can be derived stably, see figure 4. Therefore, only a band pass filtering is needed for pre-processing. Note that PPG signals originate from different depths of the foot and thus maps multiple pulse waves slightly shifted in time. This leads to a smoothing of the overall curve.

The pressure sensors in the feet of the scale record the body movement over time, in addition to the weight of the person. Besides balancing movements for maintaining the upright position, the mechanical activity of the heart and the pulse wave can be measured as well. In accordance with Newton's third law, each application of force produces a counter-force of equal magnitude. The measured mechanical impulses can thereby temporally map the state of the heart and blood vessels and complement to the two previous methods. The main interfering factors are attenuation due to the distance from the heart as well as coupling muscle movements. In order to separate balancing movements from the impulses caused by heart contractions, the differences in the signals of the four sensors can be analysed.

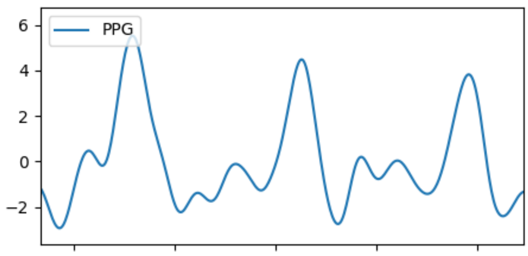

Figure 4: PPG signal measured at the foot. Placed on the outside of the sole of the foot, it provides a clear signal.

In ICG, voltage changes are measured when a small measuring current is introduced. From this, the impedance and its changes over time caused by heartbeats and blood volume changes can be recorded directly. In addition to recording the hemodynamic parameters such as stroke volume and cardiac output, it is also possible to make statements about the anatomy (e.g. tissue composition). A derivation of detailed hemodynamic parameters via the feet represents a novelty in this context, so that only assumptions can be made about the feasibility. A low signal amplitude is expected and a coupling of artifacts from the rest of the body.

As can already be seen in figure 1, the individual biosignals correlate strongly with each other or are shifted in time relative to each other, from which a difference in transit time can be determined. These interdependent influences are analysed subsequently.

3.4 Blood Pressure Determination

The determination of the blood pressure can be performed, as described above, via a time delay measurement (PTT or PAT) or the observation of the PPG signal morphology. For a final evaluation, both approaches should be combined. The PAT can be determined from the time difference between the R-wave of the ECG and the incoming pulse wave. While PAT alone does not allow any adaptation to or conclusions about the individual physiology, we will additionally analyse the morphology of the recorded signal courses. The morphology describes the entirety of the biosignal (e.g. times, amplitudes, slopes, shapes), which is difficult to capture in a model-based way, but describe important properties (e.g. vascular stiffness). In combination with ML methods, the blood pressure should thus be determined independently of the person and without calibration.

After the biosignals have been extracted, the question arises as to which information in the individual signals contains a contribution to the information about the blood pressure. Such features are, for example, the PAT, the diastolic width at 50 % of maximum or the rising area of systole. In addition, it must be noted that numerous features contain the same or similar information and are strongly correlated. However, the aim is to generate as few meaningful features as possible in order to keep the size of the subsequent neural network as small as possible. For this purpose, all features are subjected to a Sequential Forward Selection, which belongs to the wrapper methods of feature selection. First, all features are trained individually with a neural network of one input each to determine the blood pressure. The feature with the smallest error is kept. Afterwards, all remaining features are paired with the already selected feature and fed to a neural network with two inputs. This process is continued iteratively until all features have been selected. Now, we know exactly which feature combination will achieve which accuracy.

Additional information can be included such as age, gender and height to improve prediction accuracy (Kim et al., 2006; Luo et al., 2019; Lu and Dai, 2018). These values are already retrieved by commercially available body scales and are therefore easily accessible. Since only a small number of data points can be recorded in this experimental setup, transfer learning techniques will be used. There are databases with biosignals (Saeed et al., 2002; Johnson et al., 2016), which were recorded in intensive care units and also show continuous blood pressure values. These large datasets form a more diverse data source than just our own data. Based on this datasets, a transfer function is modelled, which transforms the signals recorded on the upper body from the dataset into the virtual biosignals on the feet.

3.5 Energy-efficient Implementation

Energy-efficient implementation is essential to keep power consumption low and thus enable battery operation on the body scale. In order to guarantee this, a trade-off between accuracy and complexity of the neural network must be found. The size of the neural network, together with the number of neurons, decisively determines the computational effort, since there is a full interconnection between the individual layers, which has a multiplicative effect. In addition, the number of features is formative for the number of inputs of the neuronal network. The smaller the input layer, the fewer neurons are needed in subsequent layers. Furthermore, the type of selected features and their complexity is a major influencing factor on computational cost. Another factor is the sampling rate at which the signals are recorded, processed and displayed.

In addition to accuracy, the calculation effort should also be included as a selection criterion in Sequential Forward Selection. This ensures that the calculation effort of the individual features is also taken into account. The specific weighting of these two parameters is to be carried out iteratively. In order to reduce layers and neurons, pruning is applied to the trained neural network. This removes the layers and neurons with only a small contribution to the output. The neural network is implemented in AIfES (Fraunhofer IMS, 2021), an open source framework for embedded systems. It is implemented directly in C, which is fast and executable on any small microcontroller. Furthermore, there is no need for an operating system, which saves overhead. The floating point values are to be quantised to an integer value (e.g. I32 or I8). Since only additions are carried out and no FPU, there is potential for energy savings. At times when no measurement is taking place, the Arduino is to be put into sleep mode with hardly any energy being consumed.

4 DISCUSSION

In the following, the previously presented concept is evaluated and classified within the framework of a SWOT analysis. A compact presentation can be found in table 1.

Strengths:

- One strength is the reduction of two devices (body scale, blood pressure cuff) into a single combined device, reducing hardware as well as costs and measuring time for the user.
- The calibration-free measurement ensures easy handling by the user.
- The ease of use (just standing on the scale) compared to the measurement requirements of the blood pressure cuff reduces the risk of incorrect operation.

Table 1: SWOT analysis of a calibration-free scale for blood pressure determination.

Strengths Reduction of devices Calibration-free Easy usage Higher comfort	**Weaknesses** Placement of feet low signal quality
Opportunities Regular measurements More vital parameters Cost reduction	**Threats** Availability of data Less accuracy Transferability Circulation disorders Exclusion of persons

- The overall result is increased comfort for the user.

Weaknesses:

- Precise placement of the feet is required so that the sensors have contact with the foot. This can be circumvented by placing markers on the top of the scale.
- The signal quality for some signals, e.g. ECG, is significantly reduced in comparison to attachment to the upper body.

Opportunities:

- The ease of use and increased comfort allow for more regular measurements and thus a more accurate picture of the state of health.
- In addition to blood pressure, there is the potential to directly measure other vital parameters such as heart rate, respiration rate, oxygen saturation or blood glucose level.
- It is expected that there will be a cost reduction due to fewer devices and cheaper sensors.

Threats:

- A major risk is the low availability of data. In particular, a large diversity in the training data is important to prevent bias. E.g., it can be expected that age has a very strong correlation with blood pressure. It must be ensured that such external factors do not dominate the predictions and that all possible cases are represented correctly in the model.
- There is a possibility that the blood pressure predicted by the scale is less accurate than the blood pressure cuff. However, since cuff-based methods also exhibit a relatively high error, reference measurements should be taken with a more accurate and continuous system for evaluation.
- Another risk is the applicability of transfer learning. Since some publicly available data is collected on the basis of intensive care patients, the transferability must be checked in a dedicated manner.
- In case of blood circulation disorders, there is a risk that the measured values are inaccurate or non-existent (where inaccurate readings are worse than no readings at all). Therefore, a plausibility check should be implemented.
- In case of employing bioimpedance measurements, due to the partially active measuring principle, certain groups of people (e.g. wearers of pacemakers) may have to be excluded from use.

5 CONCLUSION

In order to make the methodology of measuring blood pressure easier and to integrate it into everyday life, a concept for measuring blood pressure via a calibration-free body scale was developed. This includes the construction of hardware, the selection of sensors, the biosignal extraction, the determination of blood pressure via machine learning methods as well as the energy-efficient implementation. The calibration-free determination will be based on morphological features of biosignals in combination with a fully-connected neural net. In addition to the concept, we discussed and classified the strengths, weaknesses, threats and opportunities of the approach.

The next step is to implement the system itself. In several stages, a procedure for determining blood pressure with calibration is established. This is then further developed into a calibration-free method. The energy-efficient implementation is the final step. The biggest challenges are data availability, transferability and bias. Further work lies in ensuring the privacy of the user while respecting the legal requirements and the sensitivity of the health data collected.

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