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BLOOD PRESSURE MONITORING AND MANAGEMENT (J COCKCROFT, SECTION EDITOR)

Measuring Blood Pressure: from Cuff to Smartphone

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Abstract

Purpose of Review For measurement of blood pressure, using inflatable cuff-based technology can be inconvenient, uncomfortable, and requires special equipment. These issues could be overcome by using a contactless technology that measures blood pressure with the ubiquitous smartphone.

Recent Findings In a proof of concept study involving normotensive participants, Luo et al. demonstrated brachial blood pressure measurements from video of the face with accuracy comparable to traditional automated blood pressure monitors.

Summary There is still some way to go before contactless blood pressure measurement technology is sufficiently accurate and robust for clinical use. For example, variations in skin tone and lighting conditions must be addressed. Further, new predictive features will be necessary to reveal added information about blood pressure and thus improve prediction accuracy. New tools are likely to encourage blood pressure measurements in more people, in more places, and with more regularity than ever before.

Keywords Blood pressure · Hypertension · Blood pressure cuff · Smartphone · Medicine and smartphone · Selfie · New technology

Barriers to Measuring Blood Pressure for Hypertension Diagnosis and Management

Hypertension is a major but modifiable risk factor for cardiovascular disease. However, barriers to measuring blood pressure leave many hypertensives undiagnosed or with inadequately controlled blood pressure. The current standard for clinical examination and prediction of cardiovascular disease risk is to measure blood pressure via the brachial artery. Advantages are that the upper arm is easily accessible, and blood pressure can be measured noninvasively by using an inflatable cuff. Despite these advantages, using inflatable cuff-based technology can be inconvenient, uncomfortable, and requires special equipment. These issues could be easily overcome by implementing a contactless technology that measures blood pressure by using the ubiquitous smartphone.

Technological Basis for Contactless Determination of Brachial Artery Pressure

The ability to remotely discern arterial volume changes (pressure pulses) has existed for over a decade in video-based photoplethysmography [1]. This technique capitalizes on the fact that microvascular blood is compressed superficially toward the surface of the skin (and into range of ambient light) each time a pulsating artery expands as part of the cardiac cycle [2]. Blood hemoglobin absorbs specific wavelengths of this light and the remainder is reflected back out of the skin and captured by a consumer-grade video camera. The small attenuations of light captured on this video represent pressure pulses in the blood.

This technique provides a contactless (and therefore comfortable) alternative for obtaining blood flow information. It gathers rich and reliable blood flow information by obtaining a continuous signal, and by doing so from multiple skin regions simultaneously. Further, such information is interrelated throughout the body [3]. Therefore, signal captured in the face can provide information about brachial artery pressure, for

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instance. Further, such technology can be implemented on any device capable of capturing and processing video (e.g., modern smartphones).

Despite the apparent promise of this technique, it has remained difficult to extract robust signal in the presence of variable lighting conditions and motion. These difficulties have since been overcome to accurately measure heart rate [4]. However, oscillation frequency (heart rate) is a relatively robust feature of the plethysmographic signal. Other plethysmographic signal features are more difficult to extract and individually contain limited information about blood pressure, particularly without prior pressure calibration with a cuff. For these reasons, the ability to accurately and reliably measure blood pressure has remained elusive until now.

Luo and colleagues [5] recently took a major step toward attaining the "holy grail" of accurate video-based blood pressure measurement. In a proof of concept study involving normotensive participants, they demonstrated brachial blood pressure measurements from video of the face with accuracy comparable to traditional automated blood pressure monitors. This was achieved without prior calibration from a brachial pressure cuff. Their technology benefits from the combination of two major advancements. The first is a unique variant of video photoplethysmography called transdermal optical imaging (TOI), which facilitates the capture of highly robust and reliable video-based photoplethysmography signal (Fig. 1). The second is a robust set of novel blood flow features that are combined using advanced machine learning techniques to predict blood pressure.

Transdermal Optical Imaging

Transdermal optical imaging (TOI) builds upon state-of-the-art techniques for extracting blood flow signal from video. First, it tracks 17 unique regions of interest (ROI) on the face in the red, green, and blue color channels to generate multiple raw signals. In general, using multiple ROIs results in more robust and reliable signal. TOI specifically has the added benefit of ROIs that are under differential control of either sympathetic or parasympathetic vasomotor neurons. Such a feature provides rich information about the state of the neurovascular system. Further, unlike any other video-based technology, transdermal optical imaging separates each video image into multiple layers called bitplanes within the red, green, and blue color channels. It then uses a computational model previously trained with continuous blood pressure information to select bitplanes that contain hemoglobin-rich signals and discard uninformative visual information. This technique greatly enhances signal-to-noise ratio and protects signal from being influenced by factors such as skin tone and variable lighting conditions.

Upon extracting raw blood flow signal from video, TOI employs digital signal processing techniques to estimate the plethysmographic signal. Such techniques include digital filters (e.g., high-pass, low-pass, band-pass). This step is useful for removing high-frequency noise inherent to the signal acquisition process, as well as low and ultra-low frequency oscillations of physiological origin that naturally occur within humans (e.g., Mayer waves).

Predicting Blood Pressure from Plethysmographic Signal

Accurate blood pressure prediction requires extracting sufficient information about blood pressure from plethysmographic signal, and then, combining it effectively to predict blood pressure. Pieces of information extracted from signal are termed "features." A number of "classical" plethysmographic features have been elucidated over the years. They include pulse amplitude, dicrotic notch amplitude, augmentation index, pulse area, inflection point area ratio, systolic uptake time, systolic decline time, pulse frequency, and pulse transit time. While some features have known physiological correlates, newly created features are sometimes more abstract in

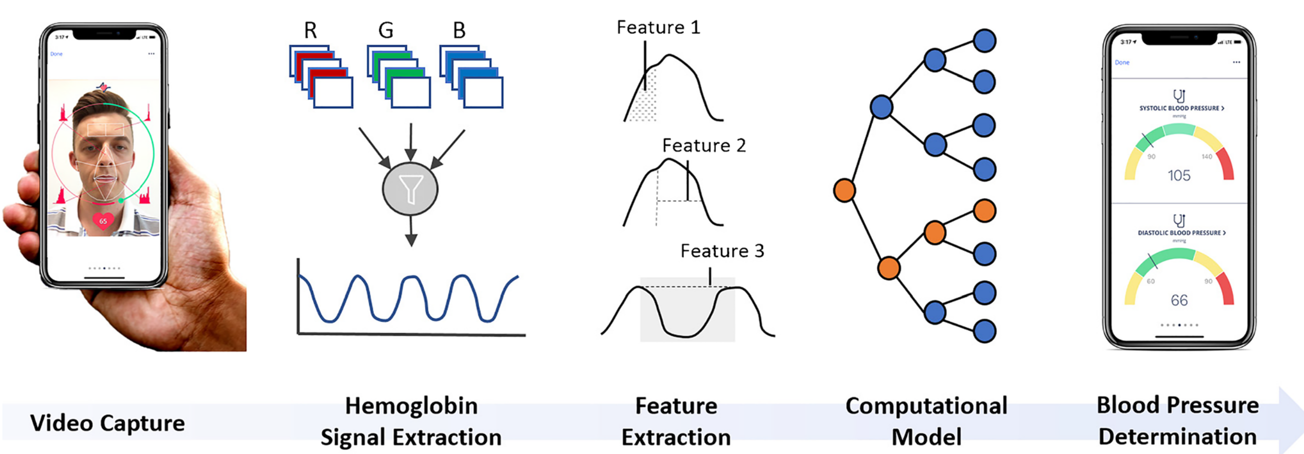

Fig. 1 Schematic of blood pressure prediction using transdermal optical imaging

nature. Growing feature sets are necessitating increasingly complex computational models and new optimization approaches to derive them. Recent advances in computational power have enabled the adoption of advanced machine learning techniques for this purpose (e.g., random forests, multilayer perceptron). However, blood pressure prediction accuracy has traditionally been poor with the models [6]. More information is needed in the form of new features.

In their work, Luo and colleagues went beyond classical features to extract many novel features. Of 155 features in total, 126 were blood flow features representing pulse shape (e.g., horizontal and vertical features including means, inverse means, standard deviations, maxima, minima, ratios of various measurements), pulse energy (rates of change in pulse shape), pulse rate, pulse rate variability, and pulse transit time. Together, these facial blood flow features contain information about brachial blood pressure over and above heart rate and demographic information [7]. This was most significant for systolic blood pressure. Aside from predicting blood pressure, many of these features provide information about other properties of the cardiovascular system, including cardiac output (e.g., pulse rate), arterial stiffness (e.g., pulse transit time), and sympathetic activity (e.g., pulse rate variability). The remainder of features used by Luo and colleagues consisted of readily available physical characteristics (e.g., age, gender, race, skin tone, height, weight), as well as meta-features to help normalize for different lighting conditions (e.g., colors, lighting gradients). The unprecedented quantity, novelty, and diversity of features, paired with large study size, are likely to have contributed to a comparatively high prediction accuracy relative to other work.

Challenges for Contactless Blood Pressure Measurement Technology

There is still some way to go before contactless blood pressure measurement technology is sufficiently accurate and robust for clinical use. It must become more robust to variations in skin tone and lighting conditions. This may be partly accomplished by developing blood pressure prediction models using ethnically diverse data, and data obtained under a diverse set of lighting conditions. Further improvement will come from explicitly controlling or normalizing for measurement conditions in the form of novel measurement constraints, camera calibration, light normalization, and skin tone normalization techniques. Further, new predictive features will be necessary to reveal added information about blood pressure and thus improve prediction accuracy. Accurate predictions will likely come from the convergence of multiple types of information [7], including pulse transit time [8], heart rate variability [9], and ballistocardiography [10] features. Non-blood flow features could be combined with blood flow features to create more personalized and thus more accurate models of blood pressure prediction.

For Luo and colleagues, the immediate next step will consist of collecting data from patients in the hypertensive and hypotensive blood pressure ranges and creating blood pressure prediction models using a full range of blood pressures. This is necessary to determine whether accuracy is maintained at clinically high and low blood pressures. From here, these models can be augmented with data from ethnically diverse subjects and with data collected under varying lighting conditions. The accuracy of these models can then be validated in a new set of participants according to an appropriate validation standard.

Into the Clinic

The clinical use of video-based blood pressure measurement will ultimately require regulatory approval according to an established set of design guidelines and validation procedures. The most appropriate standards currently are those developed for automated non-invasive sphygmomanometers. However, such guidelines are intended for cuff-based devices and do not adequately address the intricacies of video-based technologies. Factors like motion, lighting variations, and skin tone variation could impact the acquisition of blood flow signal and compromise the accuracy of blood pressure predictions. New standards are needed that consider this diversity of measurement conditions.

New Blood Pressure Measurement Tools

Contactless, video-based blood pressure measurement technology could be implemented on any device capable of capturing and processing video. Modern smartphones constitute such a device, and they are ubiquitously available. They have both a consumer-grade digital camera and the ability to either process video in place or upload signal to the cloud for processing. Blood pressure measurement on smartphones would be more comfortable and convenient than traditional cuff-based devices. Everyone with a smartphone would be able to measure their blood pressure anywhere and anytime without the need for special equipment.

There are significant advantages to having tools that can discern pressure pulse information continuously, as would be possible with video-based photoplethysmography. First, they can conduct more accurate measurements in less time. By averaging out slowly oscillating physiological waves (e.g., Mayer waves), they can determine blood pressure almost instantaneously without having to average across multiple measurements. Second, they can theoretically detect many arrhythmias, and indirectly collect information about stroke volume, arterial stiffness, cardiac output, and vascular resistance. Third, features of continuous traces could have yet undetermined prognostic significance in cardiovascular or other diseases.

Conclusions

New tools such as this are likely to encourage measurements in more people, in more places, and with more regularity than ever before. In hypertensives, they are likely to encourage more regular blood pressure measurements. They are also likely to make non-hypertensives aware of rising blood pressure, which could be addressed with lifestyle modifications before they reach hypertensive levels. A more comprehensive picture of patients' blood pressure throughout the day (e.g., akin to ambulatory blood pressure) is likely to have significant prognostic value. Such tools would revolutionize hypertension diagnosis and management, and begin to address the incredible burden of cardiovascular disease worldwide.

Compliance with Ethics Guidelines

Conflict of Interest Dr. Barszczyk declares no conflicts of interest relevant to this manuscript. Dr. Lee reports a patent System and method for detecting invisible human emotion (WO2016049757A1) pending, and a patent System and method for contactless blood pressure determination (WO2018112613A1) licensed to Nuralogix Corporation.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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