QUESTION 1

How accurate is the blood pressure device that uses fingerprint scanning?

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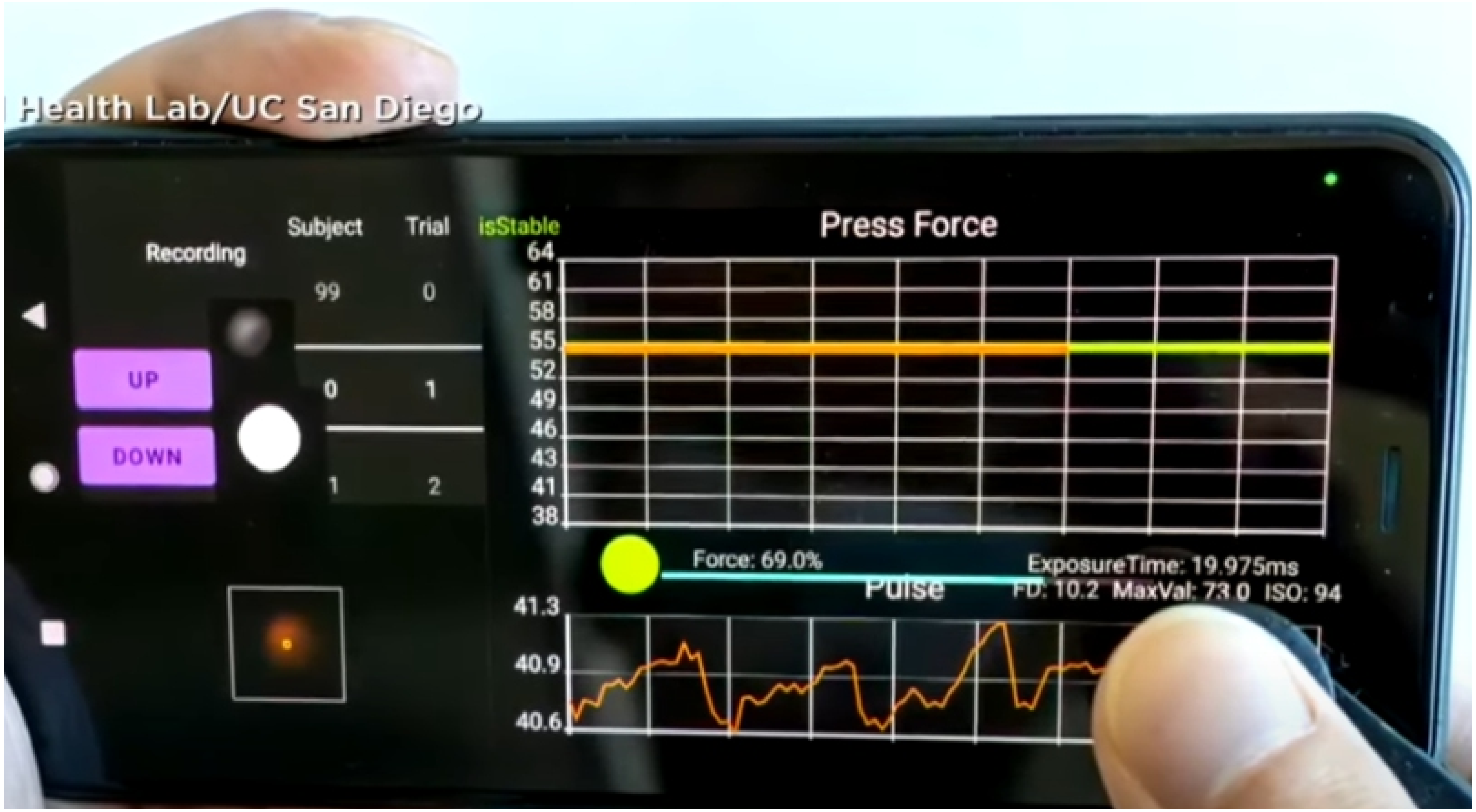
TED Talks | EDWARD WANG

https://www.youtube.com/watch?v=s_NizfAPcUM



BILLION LABS

TEAM

Edward Wang

Founder/CEO

NIH funded expert in the field of digital health technologies. On staff as an Assistant Professor of Engineering and Human Centered Design at UC San Diego

Colin Barry

Founder/CTO

A bio- and electrical computer engineer specialized in smartphone-based health monitoring. On leave as a Graduate Research Fellow of Engineering at UC San Diego

Chelsea Maples

CFO

Serial entrepreneur with years of experience starting and managing small businesses across diverse sectors.

Tatsuo Kumamoto

Software Engineer

Full stack mobile developer with experience in cross platform systems.

Chris Longhurst

Clinical Advisor (Systems)

Chief Clinical & Innovation Officer UC San Diego Health, Associate Dean, and Exec Director Jacobs Center for Health Innovation

Chris Arakawa

Clinical Advisor (Cardiology)

Cardiology Fellow Stanford Children's Health

Alison Moore

Clinical Advisor (Geriatrics)

Professor and Chief of the Division of Geriatrics, Gerontology and Palliative Care, Director of the Sam and Rose Stein Institute for Research on Aging, Center for Healthy Aging

Byron Fergerson

Clinical Advisor (Digital Health)

Staff Anathesiologist at UC San Diego with specialization in cardiothoracic anesthesia and echocardiography. Specializing in research on use of digital health for surgical success.

Ultra-low-cost mechanical smartphone attachment for no-calibration blood pressure measurement

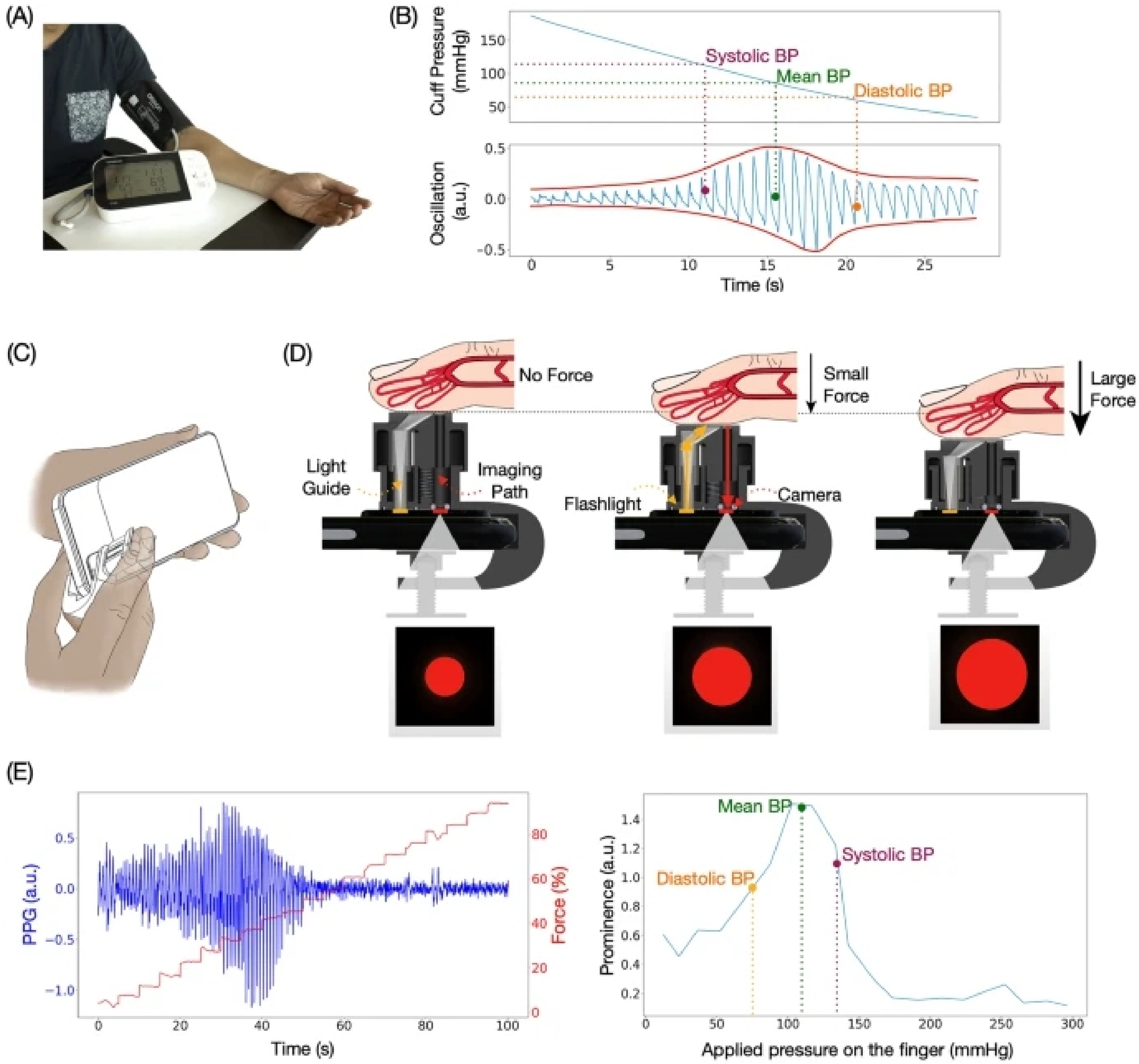
Yinan Xuan, Colin Barry, Jessica De Souza, Jessica H. Wen, Nick Antipa, Alison A. Moore & Edward J. Wang

Scientific Reports **13**, Article number: 8105 (2023) | Cite this article

Abstract

We propose an ultra-low-cost at-home blood pressure monitor that leverages a plastic clip with a spring-loaded mechanism to enable a smartphone with a flash LED and camera to measure blood pressure. Our system, called BPClip, is based on the scientific premise of measuring oscillometry at the fingertip to measure blood pressure. To enable a smartphone to measure the pressure applied to the digital artery, a moveable pinhole projection moves closer to the camera as the user presses down on the clip with increased force. As a user presses on the device with increased force, the spring-loaded mechanism compresses. The size of the pinhole thus encodes the pressure applied to the finger. In conjunction, the brightness

Figure 1



(A)
(B)
Cuff Pressure (mmHg)
150
100
50
Systolic BP
Mean BP
Diastolic BP
Oscillation (a.u.)
0.5
0.0
−0.5
0
5
10
15
20
25
Time (s)
(C)
(D)
No Force
Small Force
Large Force
Light Guide
Imaging Path
Flashlight
Camera
(E)
PPG (a.u.)
0.5
0.0
−0.5
−1.0
Force (%)
80
60
40
20
0
0
20
40
60
80
100
Time (s)
Prominence (a.u.)
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Mean BP
Systolic BP
Diastolic BP
0
50
100
150
200
250
300
Applied pressure on the finger (mmHg)

Figure 2


(A)
1. Notch
2. Flange
3. Cover
4. Rod
5. Tube
6. Spring
7. O-Ring
8. Base
9. Anti-Slip Pad
10. Screw Cap
11. Screw
Assembled Clip
(B)
Clip Fastened using Screw Pad
Channels Aligned with Flash and Camera
(C)
1.Notch
3. Cover
2. Flange
4. Rod
5. Tube
6. Spring
7. O-Ring
9. Anti-Slip Pad
10. Screw Cap
8. Base
11. Screw

Figure 3

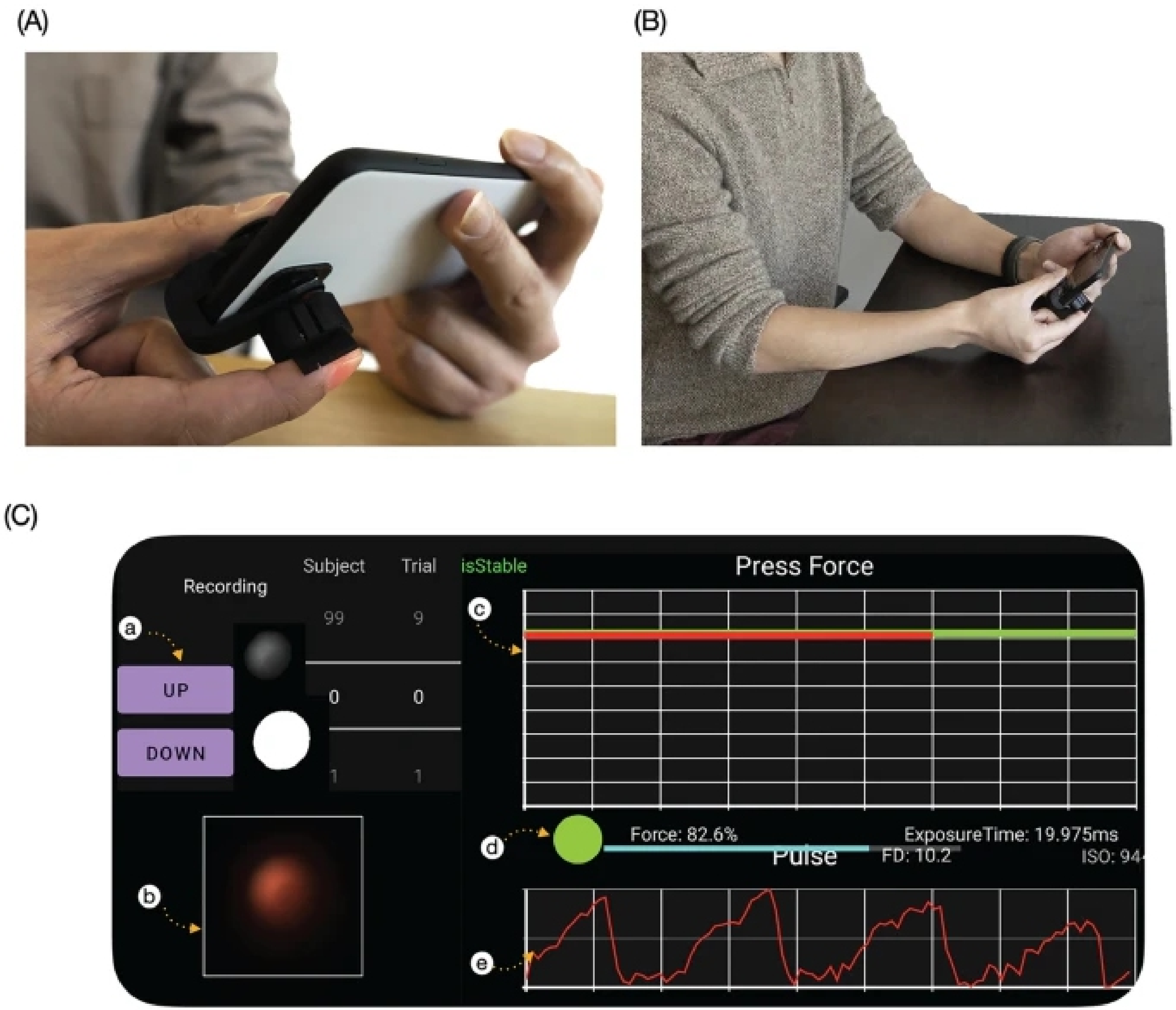
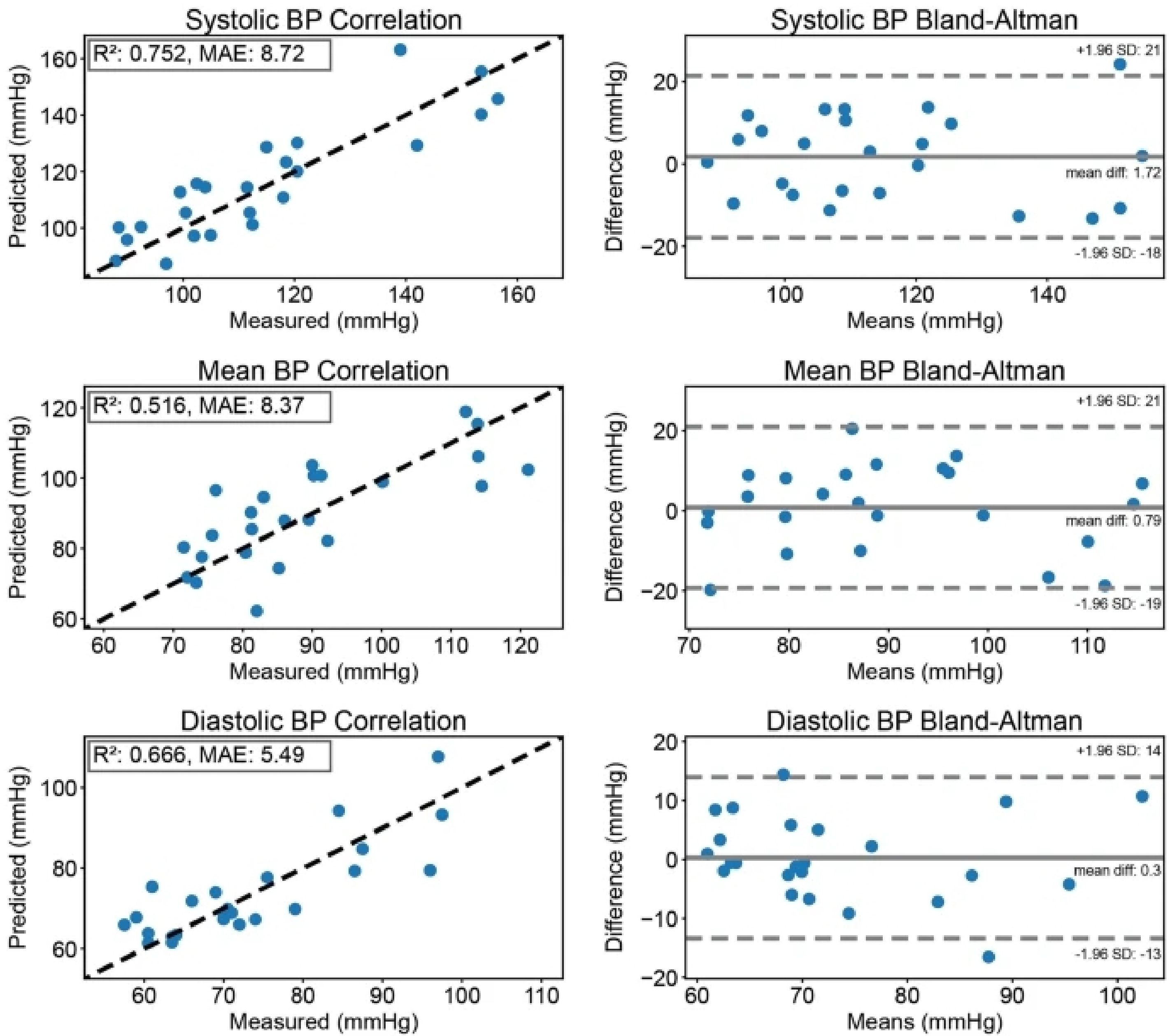

(A)
(B)
(C)
Recording
Subject
Trial
isStable
Press Force
99
9
0
0
1
1
UP
DOWN
a
b
c
d
e
Force: 82.6%
ExposureTime: 19.975ms
Pulse
FD: 10.2

Figure 4



CONTINUE: https://www.billionlabsinc.com/

A calibration method for smartphone camera photophlethysmography

Yinan Xuan[1,2*†] Colin Barry[1,2*†] Nick Antipa[1] Edward Jay Wang[1,2]

[1] Electrical and Computer Engineering, UC San Diego, La Jolla, CA, United States
[2] The Design Lab, UC San Diego, La Jolla, CA, USA

Smartphone camera photoplethysmography (cPPG) enables non-invasive pulse oximetry and hemoglobin concentration measurements. However, the aesthetic-driven non-linearity in default image capture and preprocessing pipelines poses challenges for consistency and transferability of cPPG across devices. This work identifies two key parameters—tone mapping and sensor threshold—that significantly impact cPPG measurements. We propose a novel calibration method to linearize camera measurements, thus enhancing consistency and transferability of cPPG across devices. A benchtop calibration system is also presented, leveraging a microcontroller and LED setup to characterize these parameters for each phone model. Our validation studies demonstrate that, with appropriate calibration and camera settings, cPPG applications can achieve 74% higher accuracy than with default settings. Moreover, our calibration method proves effective across different smartphone models ($N = 4$), and calibrations performed on one phone can be applied to other smartphones of the same model ($N = 6$), enhancing consistency and scalability of cPPG applications.

Article

Oscillometric Blood Pressure Measurements on Smartphones using Vibrometric Force Estimation

Colin Barry, Yinan Xuan, Ava Fascetti, Alison Moore, Edward Jay Wang

https://doi.org/10.21203/rs.3.rs-4033076/v1

Abstract

This paper proposes a smartphone-based method for measuring blood pressure (BP) using the oscillometric method. To measure BP, it is necessary to measure (1) the pressure applied to the artery and (2) the local blood volume change. This is accomplished by performing an oscillometric measurement at the finger's digital artery, whereby a user presses down on the phone's camera with steadily increasing force. The camera is used to capture the blood volume change using photoplethysmography. We devised a novel method for measuring the force applied by the finger without the use of specialized smartphone hardware with a technique called Vibrometric Force Estimation (VFE). The fundamental concept of VFE relies on a phenomenon where a vibrating object is dampened when an external force is applied on to it. This phenomenon can be recreated using the phone's own vibration motor and with powerthe resulting damped vibration measured using the Inertial Measurement Unit (IMU). A cross device reliability study with three smartphones of different manufacturers, shape, and prices results in similar force estimation performance across all smartphone models. In an N = 24 validation study of the BP measurement, the smartphone technique achieves a MAE of 9·35 mmHg and 7·94 mmHg of systolic and diastolic BP, respectively, compared to an FDA approved BP cuff. The vision for this technology is not necessarily to replace existing BP monitoring solutions, but rather to introduce a downloadable smartphone software application that could serve as a low-barrier hypertension screening measurement fit for widespread adoption.

RESULTS

Blood Pressure Study Participants

The full BP validation study recruitment included N = 30 participants, each with three resting smartphone BP measurements. From the 30 participants, 23 participants also participated in the exercise portion of the study for a total of 133 recorded smartphone BP samples. The participant population was 20% White, 67% Asian, and 13% Hispanic consisting of 50% males and 50% females. The mean age of the participants is 24·7 years with a standard deviation of 4·3 The average resting systolic and diastolic BP is 103mmHg and 70mmHg, respectively. Further details about participant statistics are included in Table 1. During the study, N = 29 participants were able to correctly apply force in at least 1 of their measurements as guided by the smartphone application. N = 24 participants contained at least 1 usable measurement (valid force and ppg signal combination) for BP prediction.

The 133 samples consist of 90 normal samples and 43 exercise samples. Of the 133 samples, 65 were excluded based on the criteria detailed in the final paragraph of the methods section. For first time participants and participants performing exercise during the measurement, user error is more common so the high exclusion rate is expected. For the exercise samples, which involved participants performing a wall sit while taking a measurement, 28 of the 43 measurements are excluded. This resulted in usable exercise measurements from only 11 of the 23 exercise participants. For the non-exercise measurements, 37 of the 90 measurements are excluded. The data included in the BP model training and testing consisted of 53 non-exercise measurements and 15 exercise measurements. For detailed information on exclusion criteria for participant measurements, please refer to the last paragraph of the methods section.

Table 1. Summary of Participant Demographics. This table summarizes participant demographic information including BP measurement statistics. Detailed information is available in the supplemental section.

	N	Min	Max	Mean	STD
Included Subjects	24	--	--	--	--
Male	12	--	--	--	--
Female	12	--	--	--	--
Age (years)	--	18	38	24.7	4.3
Ethnicity	--	--	--	--	--
Asian	14	--	--	--	--
White	6	--	--	--	--
Hispanic	4	--	--	--	--
Fitzpatrick Skin Type	--	--	--	--	--
I	0	--	--	--	--
II	6	--	--	--	--
III	13	--	--	--	--
IV	3	--	--	--	--
V	2	--	--	--	--
VI	0	--	--	--	--
Resting SBP (mmHg)	53	89	132	102.6	10.4
≤90	4	--	--	--	--
>90 & ≤ 120	47	--	--	--	--
>120 & ≤ 190	0	--	--	--	--
>130 & ≤ 139	2	--	--	--	--
>140	0	--	--	--	--
Resting DBP (mmHg)	53	60	84	69.8	6.6
≤60	3	--	--	--	--
>60 & ≤80	44	--	--	--	--
>80 & ≤89	6	--	--	--	--
>89	0	--	--	--	--
Exercise SBP (mmHg)	15	107	145	129.5	10.9
≤90	0	--	--	--	--
>90 & ≤ 120	3	--	--	--	--
>120 & ≤ 130	4	--	--	--	--
>130 & ≤ 139	5	--	--	--	--
>140	3	--	--	--	--
Exercise DBP (mmHg)	15	78	107	88.8	8.9
≤60	0	--	--	--	--
>60 & ≤80	3	--	--	--	--
>80 & ≤89	6	--	--	--	--
>89	6	--	--	--	--

Blood Pressure Proof-of-Concept Study

The BP proof-of-concept study comparing the smartphone to the FDA-approved BP cuff with a hold one participant out validation achieved a mean absolute error of 9·35 mmHg and 7·94 mmHg for systolic and diastolic, respectively. The Pearson correlation coefficient was 0·69 and 0·43 for systolic and diastolic measurements, respectively. The BP cuff measurements ranged from 89 to 147 mmHg systolic and 60 to 107 mmHg for diastolic. These results are depicted in Fig. 2.

In evaluating the proof of concept more specifically around hypertension screening, we categorize BP values based on the AMA/ACC standards[13], which involves determining if an individual is below 120mmHg (normal), between 120–130 mmHg (elevated), and above 130 mmHg (hypertensive). In categorizing the model results as normal (below 130mmHg systolic BP) or hypertensive (above 130mmHg systolic BP), the ROC analysis reveals an area under the curve (AUC) score of 0·92 for detecting high BP individuals, characterized by systolic BP greater than 130 mmHg. Under the same conditions, the model achieved a sensitivity and specificity of 0·91 and 0·69, respectively.

As shown in Fig. 3 part B, the oscillograms of each BP group contain characteristics supporting the clinical understanding of the oscillometric method. The most obvious characteristic is the peak of the oscillogram, often noted to represent the mean arterial pressure (MAP). As the MAP increases, the peak shifts right towards higher applied pressures..

Skin Tone and Ethnicity.

An ANOVA test is conducted to determine the impact of skin tone and ethnicity on performance. For both skin tone and ethnicity, the group variations are not statistically significant with p-values of 0·86 and 0·22, respectively. The skin tone and ethnicity of the participant population is listed in Table 1.

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Cross Device Validity

We ran a benchtop experiment demonstrating the force estimation technique across multiple models of phones. The accuracy of measuring applied finger force using VFE is evaluated across three smartphones: Google Pixel 4, Samsung Galaxy A53, and Motorola Moto G Power. The mean absolute error, standard deviation, bias, and correlation coefficient for the Google Pixel 4 is 0·77N, 0·90N, -0·46N, and 0·92, respectively. The mean absolute error, standard deviation, bias, and correlation coefficient for the Samsung Galaxy A53 is 0·55N, 0·64N, -0·18N, and 0·95 respectively. The mean absolute error, standard deviation, bias, and correlation coefficient for the Motorola Moto G Power 2022 is 0·39N, 0·53N, 0·01N, and 0·96, respectively. The average correlation coefficient across all phones is 0·92. These results are visualized in Fig. 4.