CamPressID: Optimizing Camera Configuration and Finger Pressure for Biometric Authentication

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***Abstract*—To protect sensitive information on smartphones, state-of-the-art (SoA) studies exploit the built-in camera to capture PPG signals from fingertips as a hard-to-forge biometric. However, those studies do not provide a comprehensive analysis to optimize the camera parameters and finger pressure, leading to distorted and unstable PPG signals that degrade the authentication performance. To overcome these limitations, we propose the *CamPressID* framework. First, we analyze various camera parameters and optimize their configuration to obtain PPG signals with a high signal-to-noise ratio. Second, we investigate different finger pressures to identify the best pressure for every subject, in order to avoid signal distortion. To evaluate the performance of CamPressID, we collect a diverse dataset with 58 subjects. Our evaluation results show that CamPressID can improve the average balanced accuracy (BAC) by 10%. Moreover, the BAC reaches 90%, which is similar to the accuracy reported in the SoA using *a dedicated PPG sensor* for authentication.**

I. Introduction

To protect user privacy, current smartphone authentication systems leverage external biometric features such as fingerprints and facial structures. These external biometrics, however, can be forged. For example, fingerprints can be recreated in latex from touched objects [1]; and pictures from the Internet can be used to fool face recognition systems [2].

To address the fundamental drawback of *external* features, researchers are investigating *internal* biometric features concealed under our skin, which are harder to forge. An internal biometric feature that is attracting interest is the *cardiac pattern* because they are uniquely defined by the heart, lung and vein structures of an individual. Cardiac signals can be captured with a photoplethysmogram (PPG) sensor, which measures the changes in the blood volume via the absorption of light. PPG sensors rely on two key factors: 1) the use of LEDs and photodiodes in *the near infrared spectrum*, and 2) *a steady pressure* guaranteed by a finger clip, as shown in Figure 1(a). These two properties allow capturing stable cardiac signals, as illustrated in Figure 1(b).

The flashlight and camera on smartphones can also be used to capture PPG signals, as shown in Figure 1(c). However, the signal quality degrades significantly, as depicted in Figure 1(d), because the required spectrum and finger clip are no longer present. Some SoA studies using PPG signals *from the camera* report unsatisfying performances, with an equal error rate of around 20% [3]). Although some studies have optimized part of the camera parameters, such as in [4], they still need to collect PPG signals in a *controlled manner* to achieve a good performance. None of these studies have conducted a comprehensive analysis over the camera parameter configuration or the pressure control on the camera.

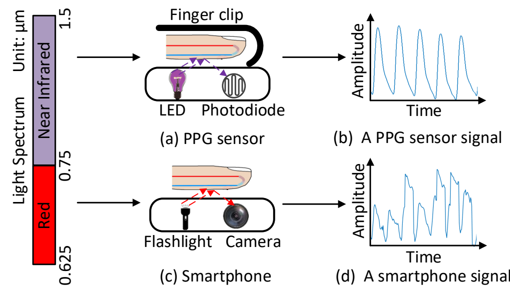


Figure 1: Cardiac signal obtained with a PPG sensor and a smartphone.

In this work, we analyze the effect of PPG signals captured with cameras for authentication. Our contributions are:

Contribution 1: Camera Configuration [Section III]. Cameras are designed for taking pictures and recording videos. Using cameras to capture PPG signals leads to poor signal quality as shown in Figure 1(d). We investigate and configure all camera parameters to render a PPG signal that is as similar as possible to the one captured with a dedicated sensor.

Contribution 2: Pressure Control [Section IV]. Pressure plays an important role in signal distortion. Without a finger clip, SoA systems using cameras have no control on pressure. We investigate the optimal pressure and provide feedback to the user to maintain such pressure. By doing so, we achieve stable PPG signals for every subject *without any add-ons*.

Contribution 3: Thorough Evaluation [Sections VI & VII]. We collect a dataset with 58 subjects. This dataset is bigger and more balanced than other datasets used in SoA [4], [5]. Our results show that the average balanced accuracy is above 90%, matching the performance of SoA studies using PPG sensors, which is 10% superior to SoA systems using cameras.

II. System Overview

To improve the quality of the signals captured from cameras, we propose two methods that can be easily added to existing authentication solutions: *camera configuration* and *pressure control*. First, we analyze the effect of all camera parameters to configure the camera for PPG signal collection (as opposed to optimizing it for pictures and videos). Second, the system asks the subject to use different pressure levels. Based on these levels, the system identifies the optimal pressure and provides feedback to the subject to maintain such level. After

Table I: Camera configurations in the SoA [3]–[5]. The table shows the default camera values for light and dark skin, and our optimized configuration. The parameters in red means it is studied and controlled. (DC: default configuration; γ: gamma correction; DPS: dynamic pixel selection; $-$: hardware-limited; $\times$: not evaluated; $\checkmark$: evaluated but the value is not reported.)

Configuration	Smartphone	Frame rate	Frame resolution	Flashlight	Aperture	ISO	Shutter speed	White balance	γ	ROI
[3]	Iphone X	240 fps	1280*720	$\times$	$-$	$\checkmark$	$\checkmark$	$\checkmark$	$\times$	$\times$
[5]	Iphone 7	60 fps	$\times$	$\times$	$-$	20	200	$\times$	$\times$	selected pixels
[4]	Iphone 7	60 fps	1280*720	$\checkmark$	$-$	$\checkmark$	$\times$	$\times$	$\times$	DPS
DC for light skin	Moto G7 plus	30 fps	320*240	$-$	$-$	100	1/729	4474 K	$\times$	All pixels
DC for dark skin	Moto G7 plus	30 fps	320*240	$-$	$-$	100	1/611	4858 K	$\times$	All pixels
Our configuration	Moto G7 plus	30 fps	320*240	$-$	$-$	100	1/400	6600 K	1	Central 1/4

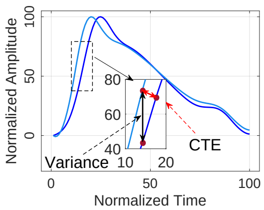


Figure 2: Comparison between variance and CTE.

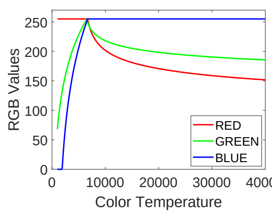


Figure 3: RGB values in different color temperature [6].

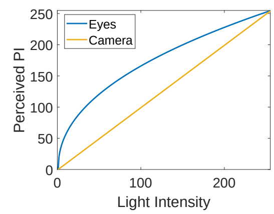


Figure 4: Gamma correction maps camera curve to human perception.

Table II: PPG amplitude (in pixel intensity) under different camera settings.

	Shutter Speed			
ISO	**1/200**	**1/400**	**1/800**	**1/2000**
100	10.032	**11.1327**	5.594	2.3122
200	4.7356	6.0337	10.659	3.2671
400	2.0377	4.2761	9.5248	8.1455
800	0.0102	2.7351	7.3982	7.4224

these steps, our system processes the PPG signals and uses the authentication methods reported in the SoA.

The accuracy of authentication systems depends on two factors: i) the shape of PPG periods *from the same subject* should be similar (short intra-class distance), and ii) the morphology *of different subjects* should be distinct (long inter-class distance). In this work, *we refer to the shape of PPG periods as* ***morphology***. If the morphology of each subject diverges, morphologies from different subject will overlap with others, which will lead to a huge decline in the authentication performance. Therefore, a stable morphology for each subject is essential to PPG authentication.

To check the morphology convergence, we need a high signal-to-noise ratio (SNR) to detect the PPG signal. Consequently, we introduce two indicators to assess the improvement of our two methods: PPG amplitude and cross-track-error (CTE). PPG amplitude can map to SNR. Within the duration of a PPG signal, the PPG amplitude captures the average peak-to-peak values of all periods. For CTE, it calculates the shortest Euclidean distance from points on one signal (points on a period in a given subject) to a reference signal (the average morphology in a given subject like the red lines in Figure 5). That can be used to measure the similarity between periods in one subject (morphology convergence). Note that CTE is a better metric to measure similarity than the variance, because the variance can penalize heavily small misalignments between periods, as depicted in Figure 2.

III. Optimizing the Camera Configuration

A comprehensive study of camera configuration for biometrics application is still missing. In Table I, we summarize the camera configurations in the SoA. Without a thorough study, it is hard to achieve optimal signal quality for authentication.

A. Camera Parameters Optimization

Two camera parameters have been analyzed in the SoA: the frame rate and resolution. The frame rate represents the sampling frequency of a PPG signal. According to [7], a frame rate between $[30\text{ Hz}, 60\text{ Hz}]$ leads to comparable PPG signals as using frame rates above 60 Hz. To reduce the computation load in our system, we use a frame rate of 30 frames per second (fps). Regarding the resolution, selecting the lowest value allows real-time processing without affecting the signal quality much (given the millions of pixels present).

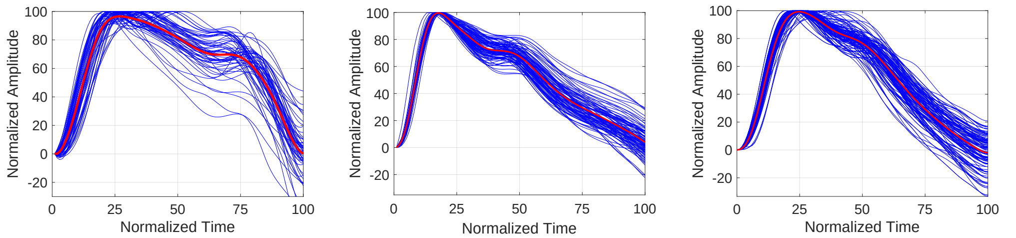
There are, however, two camera configurations that have not been analyzed much but affect the quality of cardiac signals: light exposure and image processing.

1) Light exposure: Four important parameters are related to light exposure: flashlight intensity, aperture, ISO, and shutter speed. They affect the pixel intensity in cameras. Whereas, in most smartphones, flashlight intensity and aperture (impact the amount of incoming light) are fixed.

We can only configure ISO and shutter speed. ISO controls the pixel's sensitivity to light. Shutter speed controls the shutter open interval, during which cameras integrate the light energy in each pixel to calculate its value. We should assess all ISO and shutter speed combinations and select the best one for our system. Taking the smartphone Moto G7 Plus for example, there are four values for both ISO $(100, 200, 400, 800)$ and shutter speed $(\frac{1}{200}, \frac{1}{400}, \frac{1}{800}, \frac{1}{2000})$. For each combination, we use 10 subjects to collect 120 seconds of PPG signals. To determine the best combination, we adopt PPG amplitude (SNR) as the metric. The experiment results are shown in Table II. In high light exposure (ISO: 800, shutter speed: $\frac{1}{200}$), PPG signals saturate most of the time, which renders an almost zero PPG amplitude (0.0102). In low light exposure (ISO: 100, shutter speed: $\frac{1}{2000}$), pixels are insensitive to light change, which renders a low PPG amplitude (2.3122). Among all combinations, ISO 100 and shutter speed $\frac{1}{400}$ provide the highest PPG amplitude. Therefore, on Moto G7 Plus, these values are optimal. The proper configurations of ISO and shutter speed on other smartphones can be identified similarly.

2) Image processing: Due to the differences between cameras and human eyes, a camera-captured raw picture is distinct from the perception of human eyes. To mimic human eyes' perception, engineers introduce the parameters *white balance* and *gamma correction* to modify the raw RGB values in a picture, which leads to the distortion in camera PPG signals.

White balance adjusts color intensity to render "correct" colors to human eyes. It depends on the color temperature.



(a) Overlapping periods under default configuration (CTE=4.67).
(b) Overlapping periods under our configuration (CTE=3.42).
(c) Overlapping periods under PPG sensor (CTE=3.44).

Figure 5: Comparison of overlapping periods. The red lines represent the average of all overlapping periods.

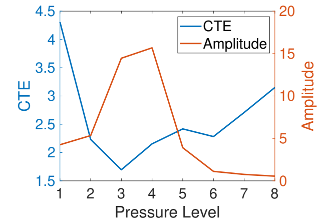


Figure 6: The CTE and amplitude change along with pressure levels.

Figure 3 shows modified RGB values for the white color in different color temperatures [6]. We can see that except for color temperatures in $[6500\text{K}, 6600\text{K}]$, the intensity of two colors will be attenuated under white light. This will clip the signal and lose all information. To gain the raw RGB values, we set the white balance to $6600K$.

Gamma correction is a non-linear mapping that maps the light intensities in cameras to those in human eyes. A camera's response to light changes is linear, while human eyes are sensitive to light changes in a dark environment but resilient in bright scenarios, as shown in Figure 4. To approximate human eyes, smartphones apply gamma encoding. Its equation is $Y = 255\,(X/255)^{\gamma}$, where X is the raw pixel intensity, γ is a constant and Y is the pixel intensity in human eyes. In most cases, our cameras use $\gamma = 0.45$ [8]. From the equation, we can observe that the non-linear mapping for human eyes amplifies the light change by *different factors* at *different intensity levels*. The fluctuation of the pixel intensity level is inevitable during the data collection due to the fingertip movements or pressure changes. Therefore, the PPG morphology from the same subject will suffer a considerable distortion. To restore the linear mapping, we set γ to 1.

B. Region of Interest Selection

Among all pixels in camera, only a fraction can capture the changes caused by cardiac signals. Some studies select the best areas by analyzing each pixel [4], but such a process is too demanding to attain a real-time response on the smartphone. In this work, we use *only* the central $\frac{1}{4}$ region of each frame as our region of interest (ROI). This can avoid the influence of the ambient light change on the outer regions in each frame. Furthermore, to exclude noisy pixels in the RoI, we use α-trimmed mean filtering [9], with $\alpha = 0.1$ to consider only the mean of pixel values between the 10th and 90th percentile.

C. Preliminary Evaluation

We use the camera of Moto G7 Plus and optimize the configuration in the last row of Table I. To showcase the improvement of our camera configuration, we perform measurements with a dedicated PPG sensor (SDPPG from APMKorea) as a baseline, the default camera configuration (optimized for photography like [10]), and our optimized camera configuration.

The metrics for the improvement evaluation are PPG amplitude and CTE. Given that the PPG amplitude is sensitive to the spectrum (infrared/visible) and system circuit (PPG sensor/camera), the comparison between the PPG sensor and a camera would be unfair. Accordingly, we only compare the PPG amplitude between different camera configurations. The default configuration (ISO 100 and shutter speed $\frac{1}{721}$ for light skin; ISO 100 and shutter speed $\frac{1}{611}$ for dark skin) has a pixel intensity of around 5.6. Our camera configuration, instead, reaches a pixel intensity of about 11. Thus, we can conclude that with our optimized camera configurations, the improvement in the PPG amplitude is notable.

Table III: Notations of our used pressure levels.

Notations	L1	L2	L3	L4	L5	L6	L7	L8
Pressure (newton)	0	3	6	9	12	15	18	21

The CTE measures the similarity between periods. As an example, we demonstrate the CTE comparison for one subject, as shown in Figure 5. The overlapping process consists of two steps. First, we normalize the duration and amplitude of each period to 100. Second, we set the starting point of all periods to (0,0) to align them. We can see that the CTE under the default configuration is higher and the periods are diverging, making it hard for a system to learn the morphologies of the signals. The CTE under our camera configuration is reduced by 27% and the periods are converging, leading to more stable morphologies. In the end, compared to the CTE obtained under our optimized camera configurations, the CTE in the PPG sensor is slightly higher and the periods are slightly looser. This demonstrates that our configuration can compensate for the camera disadvantages to obtain a close resemblance to the PPG sensor. More evaluations of our camera configuration will be presented in Section VII-A.

IV. Optimizing the Pressure on Camera

PPG signals are generated by the blood flow. The contacting pressure on sensors can change the blood flow through altering the cross-section area of the fingertip's blood vessels. In this section, we study its impact on *PPG morphologies*.

A. Pressure Influence

We study the influence of pressure through experiments. We put the smartphone on a scale with the rear camera facing up and ask a subject to put his fingertip on the camera. At the starting state, no active pressure is applied to the camera. After every 45 seconds, we add a 3 Newton (i.e., 3 $kg \cdot m/s^2$) pressure to the subject's fingertip until the pressure reaches 21 N. The notation of each pressure level is shown in Table III. This pressure range can simulate situations from no pressure to over-pressure. Figure 7 illustrates the pressure's impact on the amplitude and morphology of PPG signals. The corresponding CTE and amplitude values are shown in Figure 6.

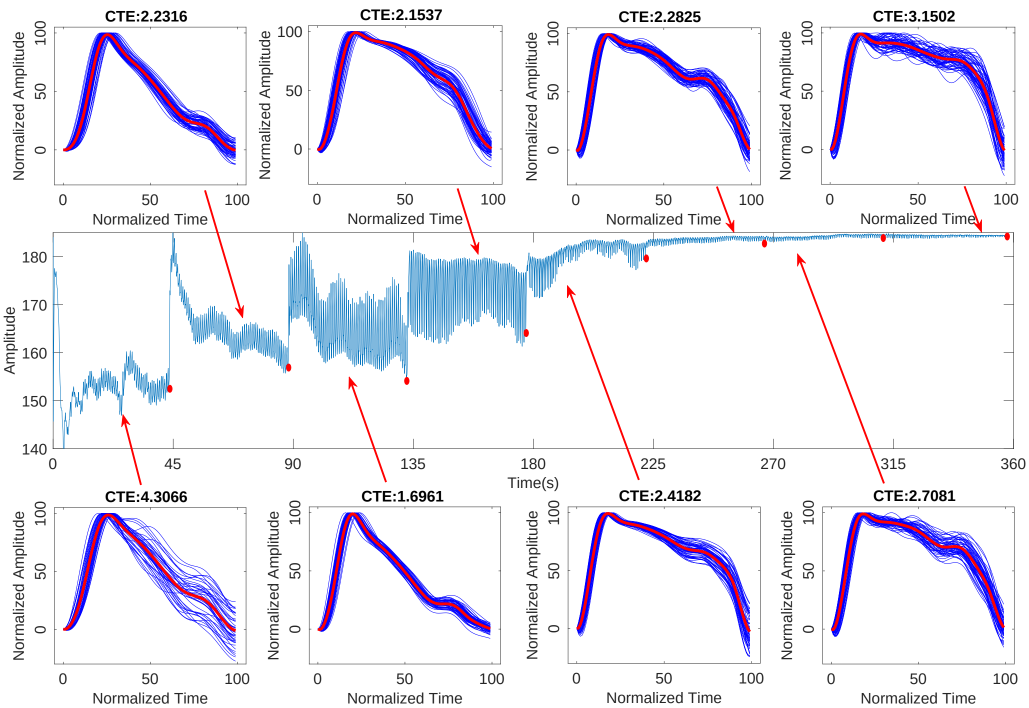


Figure 7: In our experiment, we apply 8 pressure levels on the fingertip of a subject in an increasing order from contact without active pressure to 21 N (2.1 kg). The increased pressure step is 3 N (300 g). Each pressure level lasts for 45 seconds. Red dots on the PPG signal indicates the end of a pressure level.

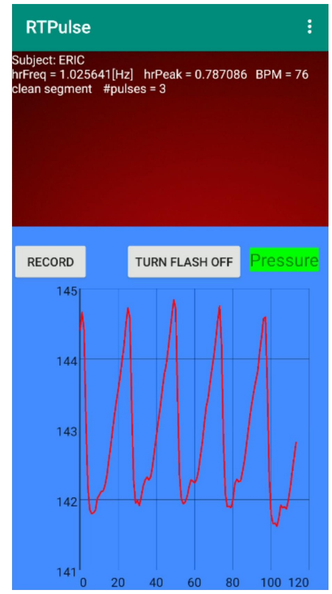


Figure 8: The online feedback interface during signal collection of our smartphone APP.

Under pressure level L1 (before the first red dot in Figure 7), without active pressure, parts of the fingertip surface detach from the camera. When a subtle movement happens, the detaching surface notably affects the light intensity on the camera. Thus, we can see that, within level L1, the PPG amplitude is low and CTE is high (divergent periods). This PPG signal prohibits our system to learn its morphology.

Under pressure levels L2 and L3 (from the first red dot to the third red dot), the added pressure on camera facilitates the PPG amplitude and CTE. Especially under pressure L3, the resulted PPG amplitude is close to the highest value and the CTE is the lowest. These convergent periods with high SNR will help the system to abstract the PPG morphologies.

Under pressure level L4, the PPG amplitude reaches the maximum value, but the CTE increases visibly. Compared with morphologies obtained under pressure L2 and L3, the morphology under L4 is distorted. The right part of these periods are lifted, making the morphology distinct from previous ones. The fingertip under L4 is slightly over-pressed because we will see later that the morphologies from over-pressed scenarios are similar to the morphology obtained under L4.

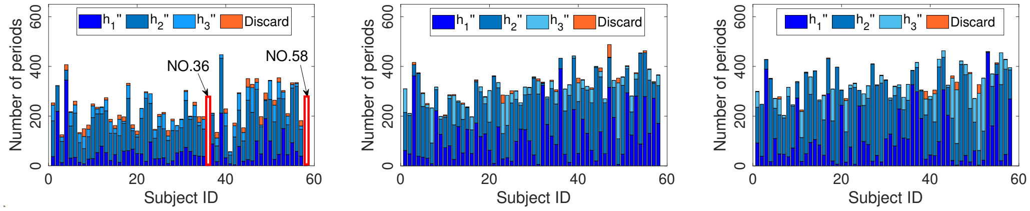
After pressure level L4, larger pressure changes the blood flow by suppressing the vessels. The camera cannot sense the visible fluctuation of pixel intensity as before. The PPG amplitude swiftly decreases to around 2 in the end. The low PPG amplitude makes periods vulnerable to noise, amplifying the discrepancy between periods. Thus, there is an increasing CTE trend in the last four pressure levels. Along with the increasing pressure, although the general PPG morphologies are consistent, their shapes become more and more “square”. These distorted morphologies are far away from reflecting the real situation of blood flow and cardiac system.

B. *Pressure Control*

From the analysis of pressure influence, we see that a subject generates multiple morphologies under various pressures. Without pressure control, those morphologies from the legitimate subject can increase the chances for attackers to breach the authentication system. Thus, controlling the pressure at the best level is essential for camera-based authentication systems.

First, we need to determine the best pressure for each subject. Given the situation in Figure 7, pressure levels generate two groups of morphologies: the triangle shape and trapezoid shape morphology. *Within one group of morphologies*, the best pressure level is the one with the highest amplitude and lowest CTE. Whereas, between morphology groups, we must compare the authentication performances for best pressures in each group. Accordingly, we form a dataset with 10 subjects’ pressure processes as Figure 7. For each subject, we select the pressure providing the highest amplitude and lowest CTE as the best one in triangle (L3 in Figure 7) and trapezoid group (L4 in Figure 7). The first 80% of the best pressure durations are for the training and the rest are for testing. Exploiting the authentication method in [5], we obtain the BAC result of triangle shape reaches 93.47%, while that of trapezoid shape only reaches 85.89%. Consequently, we choose the triangle morphology with the highest amplitude and lowest CTE as the best pressure level (L3 in Figure 7) for each subject.

Second, we must stabilize the pressure at that level during the data collection. To avoid the unconscious fingertip movement or pressure change, we design an Android APP as shown in Figure 8 to assist users during the data collection. After obtaining the best pressure level, a subject can know their



(a) Our CamDefault dataset. (b) Our CamConf dataset. (c) Our CamPress dataset.

Figure 9: The period numbers of morphologies in our datasets. h_1'', h_2'' and h_3'' are three dominant morphologies in our datasets; others are discarded.

PPG amplitude and morphology through the APP's real-time feedback in Figure 8. Then in both the training and the testing phases, a subject can stabilize the pressure to achieve similar PPG amplitude and morphology assisted by the APP. When there is abrupt fingertip movement or pressure change, the subject can easily adjust the PPG signal back.

V. Authentication Method

We present our feature collection and authentication method briefly. More details can be found in our previous work [5].

In feature collection, let $s(t)$ denote the collected PPG signal. To stabilize $s(t)$, we only preserve the spectrum of $s(t)$ within $[2f, 5.5f]$ (f is the heartbeat frequency) to obtain $h(t)$. To accentuate subtle fiducial points on $h(t)$, we obtain its second derivative $h''(t)$, which has three dominant morphologies h_1'', h_2'', and h_3'', as shown in Figure 7 in [5]. In our three evaluation datasets (cf. Section VI), those morphologies contribute more than 95% periods in each dataset, as shown in Figure 9. In our system, we only exploit h_1'', h_2'', and h_3''.

There are two other observations from Figure 9. First, from the CamDefault dataset to the CamPress dataset, we observe a clear increase in period number, which reflects the improvement in signal quality. More periods with a better signal quality help authentication considerably. Second, two subjects (#36 and #58) have no periods detected in the CamDefault dataset. This is because signal from those subjects saturated constantly without camera configuration and pressure control. More analysis on our datasets are introduced in Section VII-A.

We extract features from both $h(t)$ and $h''(t)$. The details of feature collection are illustrated in Section 4.2 in [5]. In authentication, we refine our features by PCA to gain new informative ones. After transferring samples on new features, we find that sometimes data points from *one subject* can have *a few* clusters. Thus, we apply wavelet clustering [11] to identify all clusters. At last, we select *Mahalanobis distance* [12] to measure the distance from new coming samples to all clusters. According to the distance, our system can verdict if the samples belong to the legitimate subject.

VI. Building the Dataset

To evaluate the performance of our methods, we first need suitable datasets. Existing ones such as in [4], [5] have a small population of subjects and narrow age range, which are not enough for thorough evaluation. In this work, the subject details are listed in Table IV. Compared with others such as [4], [5], we have more and better diverse subjects: our subject population (58) is the largest; the gender distribution is more balanced (22 females); our age range is wide enough to cover most smartphone users, while the mean (40.2) and standard deviation (14.6) can guarantee the subject age spreading wide enough to prevent overfitting on a narrow range of users. With these subjects, we build three datasets[1]:

Table IV: Subject details for different PPG authentication systems.

Studies	Sensor	# Users	# Females	Age range (mean/STD)
[10]	PPG sensor	12	4	22–51 (-/-)
[13]	PPG sensor	42/32	-	- (-/-)
[4]	camera	25	6	25–33 (-/-)
[5]	camera	43	16	12–79 (36.7/14.9)
CamPressID	camera	**58**	**22**	15–80 (40.2/14.6)

- *CamDefault dataset*: The data collection runs under the default camera parameters and without pressure control. This dataset can represent the data collection of most SoA authentication systems like [10].
- *CamConf dataset*: The data collection runs under our optimized camera configuration.
- *CamPress dataset*: The data collection runs under our optimized camera configuration and with pressure control.

In our data collection, we use a smartphone Moto G7 plus to extract PPG signals from all the subjects while they are sitting. Each dataset contains a 4-minute PPG recording for all subjects. 80% of each recording is used for the training while the rest 20% of each recording is used for the testing.

VII. Evaluation

In this section, we evaluate our datasets and authentication methods. Among SoA camera-based authentication systems, we select CardioID [5] and CardioCam [4] for comparison.

- *CardioID [5]*: It adopts *two types of sensors*: camera and PPG sensor. The sufficient number of subjects (43) and wide age distribution (average: 36.7, standard deviation: 14.9, and range: 12–79) guarantees that the result generalizes well. The camera-based result (*CardioID-Camera*) helps us to evaluate the improvement of our camera configuration and pressure control. The PPG sensor-based result (*CardioID-PPG*) enables us evaluate how close our CamPressID approaches the result of PPG sensors.
- *CardioCam [4]*: The number of subjects in this work is 25, which is only about 45% of ours. Thus, it is unfair to generalize their results in our evaluation directly. For comparison, we re-implement its signal processing chain (filters, features and PCA) and apply them to our datasets.

[1]The data collection activities related to these datasets have been approved by the Human Research Ethnic Community (HREC) in our University.

Table V: Performance comparison between multi- and single-morphology systems. N_{DS} is the number of detectable subjects.

Method/System	Dataset	Acquisition speed	Acquisition rate	N_{DS}	PPG amplitude	CTE
Multi-morphology[1]	CamDefault	0.73 (10167/13920)	95.15% (10167/10685)	55	4.03	4.82
	CamConf	1.06 (14774/13920)	98.73% (14774/14964)	57	9.41	3.74
	CamPress	1.13 (15755/13920)	99.17% (15755/15886)	58	9.41	2.32
Single-morphology[2]	CamDefault	0.25 (3468/13920)	32.61% (3468/10634)	40	4.98	4.73
	CamConf	0.62 (8695/13920)	62.62% (8695/13885)	48	9.44	3.34
	CamPress	0.79 (10977/13920)	69.61% (10977/15769)	48	9.42	2.32

1: Studies exploit multiple morphologies in PPG authentication, such as CardioID [5] and CamPressID in this paper.
2: Studies exploit only one morphology in PPG authentication, such as Seeing Red [3] and CardioCam [4].

A. Dataset Evaluation

We employ five metrics to evaluate our datasets: *acquisition speed, acquisition rate, N_{DS} (number of detectable subjects), PPG amplitude* and *CTE*. PPG amplitude and CTE have been introduced in Section II. Let S' denote the useful periods with morphologies h_1'', h_2'', h_3'' and S denote all detectable periods. The acquisition speed is S' collected per second; the acquisition rate is S'/S. The acquisition speed and acquisition rate can reflect the system's robustness for data collection, which is the basis of a real-time system (less authentication delay). N_{DS} shows how many subjects with $S' > 20$ can be detected by *a system* (subjects with less S' provide little information to learn). It shows the user inclusion of a system. In an ideal real-time system, the acquisition rate should be 1; the acquisition speed, N_{DS} and PPG amplitude should be high, and the CTE should be low. There are two ways of data collection: *single-morphology* and *multi-morphology*. The *single-morphology* system is commonly used in SoA; in this work, we re-implement the data collection in CardioCam as the representative of *single-morphology* systems. Our CamPressID is representative of *multi-morphology* systems. The details of the comparison are given in Tables V.

First, we compare the multi-morphology (CamPressID) and the single-morphology (CardioCam) systems under all setups. *Here, we fully focus on the same rows in different systems*. From single-morphology to multi-morphology, our metrics behave in three ways: 1) increasing remarkably on acquisition speed, acquisition rate, N_{DS}; 2) increasing slightly on CTE; 3) staying almost the same on PPG amplitude. This is because the stringent requirements on the PPG morphology in CardioCam (the morphology in Figure 8 in [4]) filter out periods with non-conforming morphologies. Therefore, its datasets have fewer periods, which results in lower first three metrics, and more unified morphology, which results in a lower CTE. For PPG amplitude, the advantages of CardioCam are visible in CamDefault datasets and negligible in CamConf and CamPress datasets. This is because only some good periods in noisy (CamDefault) datasets meet the requirements of CardioCam, while most periods in CamConf and CamPress datasets do. Given the higher CTE and more periods in our CamPressID system, it is more challenging for our system to perform well.

Second, we analyze the difference between datasets in each system. *This analysis fully focuses on the different rows in one system*. It is clear to see the significant improvement on all metrics from CamDefault datasets to CamConf datasets in each system. This reflects the contribution of our camera configuration on the signal quality. From CamConf datasets to CamPress datasets, except for CTE, the improvements on other metrics are limited. This is because our pressure control aims at obtaining stable morphology, which leads to a significant decline in CTE. The morphology, at which periods stabilize, is easy for most systems to detect. Therefore, the first three metrics also increase slightly. Since the pressure control prioritizes CTE over PPG amplitude, our systems obtain better CTE at the cost of PPG amplitude decline. In general, from CamDefault datasets to CamPress datasets, the improvements are comprehensive and significant, showing the contribution of our camera configuration and pressure control.

B. Providing the Right Context for Final Evaluation

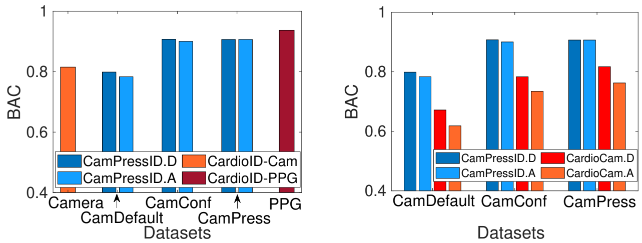
In PPG authentication, the small intra-distance (low CTE) and large inter-distance (small subject number) allow authentication systems performs well. Compared with CardioID-Camera, CamDefault dataset is 19% lower in CTE (5.97 vs. 4.8) and 35% more in subject number (43 vs. 58). Compared with CardioID-PPG, CamPress dataset is 46% lower in CTE (4.29 vs. 2.32) and 66% more in subject number (35 vs. 58). Considering the percentage gain in subject number overwhelms that in CTE, our datasets are more challenging.

We cannot fully reproduce the datasets and results in CardioCam, since we do not have their same smartphone and cannot find their detailed camera configuration. In our evaluation, we re-implement the signal processing chain of CardioCam and then evaluate its performance with our datasets. Our goal is to get as close as possible to CardioID-PPG (93.7%) with our CamPress dataset. In authentication, *an improvement in the order of 5%, or above, is already considered significant*.

C. Authentication Evaluation

From the results given in Tables V, we can see that except for the CamPress datasets under both setups, N_{DS} cannot reach 58. In the evaluation, if we only average the BACs on *detectable subjects*, it is unfair for our system because we detect more subjects. Therefore, we also include the undetectable subjects into the calculation to make a fair comparison among all systems. In this case, we assign every undetectable subject with 0.5 BAC, that is obtained under two assumptions: 1) systems will reject all testing periods for undetectable subjects, which is reasonable for a system lacking the information of these subjects; 2) the data from undetectable subjects will not confuse authentication systems to degrade the results of other detectable subjects, which is the ideal scenario. Therefore, the true positive rate is 0, and true negative rate is 1, which renders BACs of these subjects are 0.5. Consequently, for every dataset we present both results with detectable/all subjects.

Figure 10a shows the performance of the camera and PPG sensor datasets in our baseline [5] and the datasets in



(a) Comparison among our setups and camera and PPG sensor from [5].

(b) Comparison between our method and [4] on our datasets.

Figure 10: Comparison among our method, [5] and [4]. CamPressID.D/A stand for results with detectable/all subjects in CamPressID. CardioCam.D/A stand for results with with detectable/all subjects in [4].

our system. In the CamDefault dataset, our system has the lowest performance among all datasets. Even with a partial camera configuration, CardioID-Camera can perform better than it. With the CamConf dataset, the BAC obtained in our system surges to above 0.9, which is 10% higher than the previous one. Our camera configuration boosts the perform remarkably through enhancing the signal quality. With the CamPress dataset, our system performs similarly as one with the CamConf dataset and is inferior (about 3%) to CardioID-PPG. There are two reasons for the similar performance of our system in the CamConf and CamPress datasets. First, the performance limit of our system on our datasets is just above 0.9. This is because our CamPress dataset is harder than CardioID-PPG (discussed in Section VII-B), and the performance gap between CardioID-PPG and our system in the CamPress dataset is relatively small. Second, the majority pressure in the CamConf dataset is the best pressure. During the data collection in the CamConf dataset, 62.1% (36/58) subjects apply their best pressures in most of time.

In general, the improvement of the CamPress dataset over the CamDefault dataset is significant. Moreover, based on our optimized camera configuration and pressure control, our CamPressID system is superior to the system with a partial and simple camera configuration (CardioID-Camera) and close to the system with a dedicated PPG sensor (CardioID-PPG).

Figure 10b shows the performances of our system and CardioCam [4] on our datasets. There are two points to notice. First, the performance gain of our system over CardioCam is noticeable. The gain with detectable subjects is about 10%, while the gain with all subjects is about 15%. The reasons are explained in [5]. Second, both our system and CardioCam have a significant improvement (more than 10%) from the CamDefault to CamPress dataset. This shows the potential of CamPressID to facilitate different authentication methods.

VIII. Related Work

Camera-based PPG authentication systems. CardioCam [4] is the first work in this area. To obtain reliable cardiac patterns, the authors develop a gradient-based method to adjust *flashlight and ISO* and select sensitive pixels in each frame. CardioCam achieves a BAC of 95.8% based on single-period testing. We implement its *signal processing chain* as our baseline. CardioID [5], as our other baseline, considers a PPG sensor and a camera for authentication. They adopt fixed camera configuration without optimization. CardioID achieves a BAC of 93% with the PPG sensor and 82% with the camera. In CamPressID, we optimize the camera configuration and pressure for improving the system performance. Besides, Seeing Red [3] also aims at PPG authentication based on smartphone camera. They adopt fiducial and spectral features and achieve 20% EER with 15 subjects. Due to the low subject number, we do not use them as our baselines.

Pressure control for better PPG signals. There is no paper studying the pressure influence on camera-based PPG authentication. We only find two papers for healthcare considering pressure during PPG measurement. Chandrasekhar et al. [14] study the influence of contact pressure on a PPG sensor for blood pressure measurement. They use the pulse arrival time to estimate the blood pressure. PhO_2 [15] uses a smartphone mounted by an add-on to measure blood oxygen level. To mitigate the contact pressure impact, they design a light-based pressure detection algorithm by monitoring the PPG signal amplitude. In these papers, instead of morphology, they only focus on a part of the PPG signal. Moreover, their devices are tailored for the *infrared spectrum*. Thus, we cannot use their studies for authentication on normal smartphone cameras.

IX. Conclusions

The lack of optimizing camera configuration and pressure control is preventing current camera-based PPG authentication systems to achieve high accuracy. In CamPressID, we studied the impact of camera configuration and pressure control, and optimize them. In the end, CamPressID reached 90.6% BAC, approximating the performance of a dedicated PPG sensor, with a diverse 58 subjects dataset.

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