



## Quantitative Capillary Refill Time with image-based finger force estimation



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### ABSTRACT

Skin color observation provides a simple and non-invasive method to estimate the health status of patients. Capillary Refill Time (CRT) is widely used as an indicator of pathophysiological conditions, especially in emergency patients. While the measurement of CRT is easy to perform, its evaluation is highly subjective. This study proposes a method to aid quantified CRT measurement using an RGB camera. The procedure consists in applying finger compression to the forearm, and the CRT is calculated based on the skin color change after the pressure release. We estimate compression applied by a finger from its fingernail color change during compression. Our study shows a step towards camera-based quantitative CRT for untrained individuals.

### 1. Introduction

In recent years, there has been a notable increase in the number of emergency medical care (EMC) cases and a diversification of the types of EMC incidents, due to changes in societal conditions. However, in certain urban areas, there are instances where the number of ambulances is inadequate or hospitals capable of accepting patients cannot be located, resulting in a lack of appropriate medical care for truly urgent patients. Additionally, the recent outbreak of COVID-19 has further hindered the ability to respond to EMC cases [1]. There have been reports of patients who received care at home subsequently experiencing deterioration, leading to severe illness or death. In such emergency scenarios, there is a need for a method that can be performed by individuals without healthcare expertise and can quickly and accurately assess the urgency and severity of patients. One commonly used method for this purpose is triage, which involves classifying patients based on their degree of urgency and severity and prioritizing those with a higher degree of urgency. Triage allows for optimal medical care to be provided even in the presence of limited medical resources.

One indicator utilized in triage is Capillary Refill Time (CRT) [2,3] which is defined as the time required for a nail bed to return to its normal color after pressure is applied and released. CRT is a simple and non-invasive index that can be easily performed by anyone, however,

the CRT conventional method of compression varies among individuals and is evaluated visually, resulting in poor reproducibility and objectivity of measurement results [4–6]. To overcome the limitations of conventional CRT, quantitative CRT systems using optical sensors and devices for the application of controlled pressure have been developed [7,8]. These systems involve measuring light reflected from the finger to quantitatively calculate the changes in blood flow under the nail bed. These techniques have been shown to enable the quantification of CRT and to reduce measurement uncertainty [8,9].

Various sites of the body have been investigated for Capillary Refill Time (CRT) [5], such as the fingertip [10,11], the sternum [12], the forehead [13], and sites on the forearm [8,14], the knee [15], foot [16], and earlobe [17]. Measurements of CRT on the fingertip are affected by peripheral temperature [18,19], and while consistent results are obtained to assess normal/abnormal states, fingertip CRT variability [18] may hinder measuring the evolution of quantitative CRT in the same person as the person's health changes over time. In contrast, though not as stable as the forehead or the sternum, the forearm provides more stable quantitative CRT readings for different room temperatures [17, 18]. Indeed, further understanding of CRT in areas other than the fingertip will broaden the usability of CRT.

Quantitative CRT studies have shown CRT results for compression of the region of interest by mechanical arms and rigid surfaces [9,10,13,14],

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20]. Such artificial surfaces may not be a good surrogate to study the behavior of CRT with compression made by a live fingertip. The literature lacks a CRT study where the force was provided by real-life fingertip compression of volunteers, and compared to measurements made by a mechanical device. While other studies [21–23] have presented different methods to estimate force based on nail color, none have verified the influence of fingertip compression on the forearm in CRT measurements.

In this study, we analyze CRT on the forearm's inner side, examining how finger pressure impacts CRT measurements. To determine CRT we monitor the color shift in the compressed area post-pressure release using an RGB camera. We also present a technique to gauge the force applied by the fingertip on the forearm's inner side, by monitoring the color change caused in the fingernail while it compresses. The forearm is a more accessible location to apply pressure with a mechanical device than the forehead or sternum, enabling us to acquire measurements both with fingertip pressure and a mechanical device.

## 2. Methods

### 2.1. Regression model to correlate finger compression force with fingernail color

Fingertip pressure estimation using optical imaging has been extensively studied by Mascaro et al. [21–23]. Their method consists of analyzing the impact of force on blood flow distribution beneath the nail. Fallahinia and Mascaro [23], using RGB imaging, presented the most accurate force finger force predictions. However, this method requires contact-type 3-axis force sensors for model training due to a loss function that minimizes the difference between vectorial forces. In contrast, for simplicity and flexibility, we used a basic electronic scale as a 1-D force sensor for generating training data. In our setup, color change was captured using an RGB video camera (DFK33UX174, The Imaging Source, Charlotte, NC, USA), and force was measured with an electronic scale (Fig. 1a) as a dynamometer.

The region of interest of a fingernail ( $\text{CRT}_{\text{ROI}}$ ) was defined by a contour encompassing the lunula, and excluding the milky-looking nail tip area to reduce variability between fingernails [10]. To delineate the ( $\text{CRT}_{\text{ROI}}$ ), we manually identified 15 points on each finger image (Fig. 1b), which were then cubic-spline interpolated to 45 points (Fig. 1c). Next, a numerical mask zeroed out pixel values outside the  $\text{CRT}_{\text{ROI}}$  (Fig. 1d). This mask was retained for all measurements on the same finger. The resulting  $\text{CRT}_{\text{ROI}}$  was subdivided into nine equal nail-subregions (Fig. 2), from which R, G, and B mean pixel values were extracted. These nine nail-subregions may complement each other to help estimate pressure from fingernail color changes, despite being strongly correlated with each other [21–23].

We chose ridge regression for the fingernail-color-to-force prediction models instead of multiple regression which produces high uncertainties

in multicollinear data. We chose two different models to estimate the force applied by the fingernail (objective variable) on the electronic scale:

A ridge regression using 27 explanatory variables: the RGB channels in the 9 nail subregions.

A ridge regression using 9 explanatory variables: only the G channel in the 9 nail subregions.

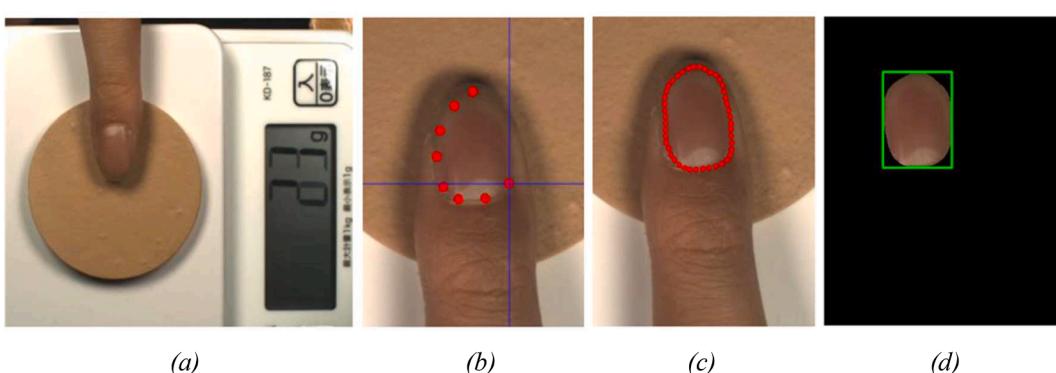
### 2.2. Experiment to build the model: force applied by the finger vs. fingernail color change

Eight Chiba University students aged in their twenties volunteered for finger force data acquisition experiments. They sat on a chair in a dark room and pressed their right index finger on an electronic scale on a desk (Fig. 1). The scale and finger were imaged by an RGB camera (30 fps; 1280 × 720 pixels), while illuminated by LED sources (5500 K; 2430 lx). Each volunteer participated in two experiments. The first experiment produced training data to build a model estimating finger compression force. As instructed by the experimenter, volunteers increased the finger compression force on the electronic scale every 10 s, targeting a pressure increase of 1 N increments, for a total acquisition time of 100 s. The second experiment produced the test data: for the first 30 s, volunteers freely applied finger compression force in the range of 3 N to 7 N; for 10 s more, they freely pressed the finger with a force of approximately 7 N or more.

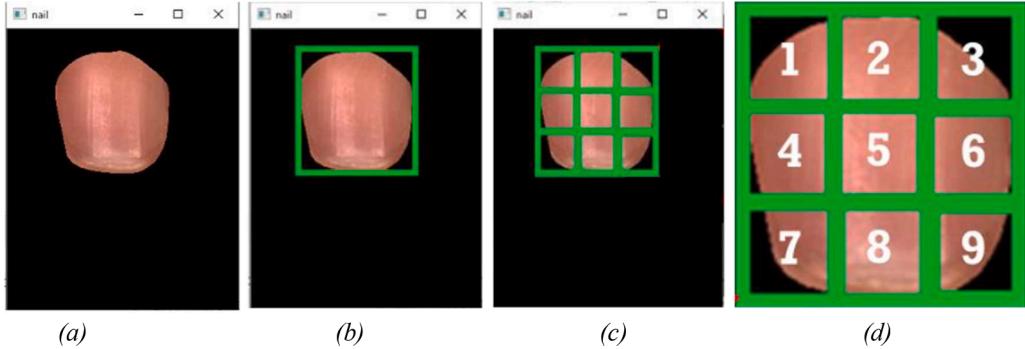
### 2.3. Experiment to measure crt by pressing a finger, or a controlled weight on the skin

Seven of the eight volunteers of the finger force model experiment (Section 2.2) participated in this part of the study. They sat on a chair in a dark room and placed their left arm on the measurement table (Fig. 3). We used the same camera and light source from the first experiment for two measurement sets. In the first set, each participant pressed their right index finger against a pen-marked area on their inner forearm for 5 s per trial. In the second set, a 5 N weight pressed on their forearm for 5 s per trial in the same marked area. Each measurement set consisted of five CRT repetitions with video acquisition throughout the experiment, with a 10 s baseline acquisition, followed by a 5 s compression, and 30 s resting before the next repetition. The volunteers themselves applied the compression on their forearms both when using the finger (Fig. 3a) or the weight (Fig. 3b), while the experimenter operated the camera and data acquisition.

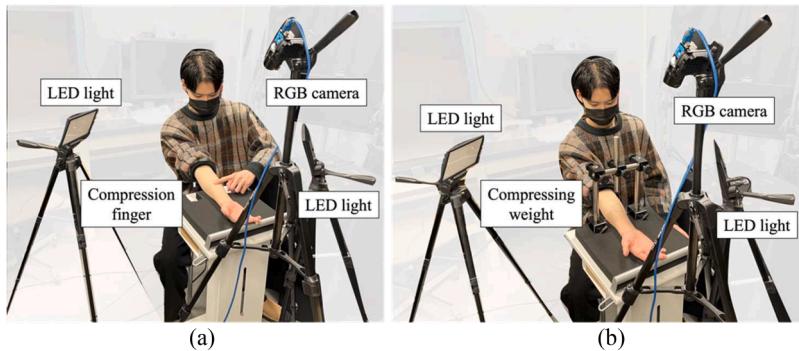
The 5 N weight consisted of a 3.1 cm<sup>2</sup> cross-section solid aluminum rod, terminated by a rubber insulator, similar to the one of reference [8]. The insulator minimizes heat transfer between the metal and the skin.



**Fig. 1.** Procedure for segmentation of the nail region. (a) Arbitrarily selected fingernail image. (b) Manually setting 15 points for the nail image. (c) Extension of the 15 points set in (b) to 45 points. (d) Extraction of nail region by mask processing.



**Fig. 2.** Procedure for analyzing RGB signals from the nail region. (a) Nail region after mask processing. (b) Setting a bounding box for the nail region. (c) Dividing the bounding box set in (b) into 9 regions (nail subregions). (d) Nail-subregions number.



**Fig. 3.** Experimental settings. Volunteer sitting with arm resting on measurement table. Positioning of light sources and camera. CRT measurement with two different compression methods: (a) an index finger, and (b) a 5 N cylindrical weight.

#### 2.4. Estimation of capillary refill time in the forearm using an rgb camera

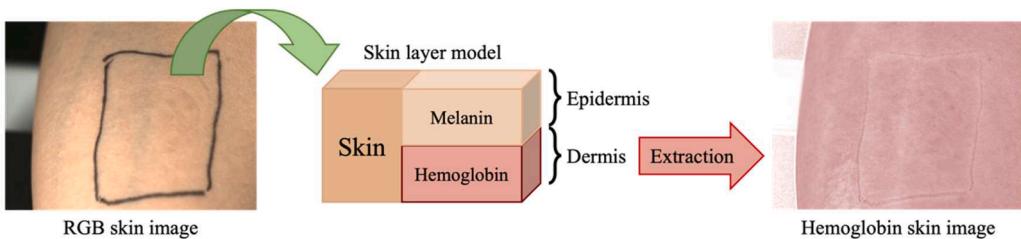
In RGB-camera-based quantitative CRT measurements, the G-channel often serves as a proxy for blood perfusion [8]. Green light is chosen due to its greater absorption by hemoglobin compared to red light, and its lesser absorption by melanin compared to blue light. However, blood perfusion data from the G channel is affected by noise due to uneven lighting, shading, and melanin, especially with illuminator movement, finger shadow changes during force application, or arm movement. Thus, before using the video for CRT determination, we reject all information unrelated to hemoglobin using a method described by Tsumura et al. [24] (Fig. 4). This method separates the skin RGB video into three monochromatic videos representing melanin, hemoglobin, and shading information, where shading takes into account penumbra and variations in lighting both in time and space. The hemoglobin signal is free from possible interference or noise caused, for example, by shading or penumbra as the finger moves back away from the ROI.

To determine CRT from the hemoglobin signal, we used a method described in detail in reference [8]. First, we need to estimate the exponential damping time constant of hemoglobin recovery after the

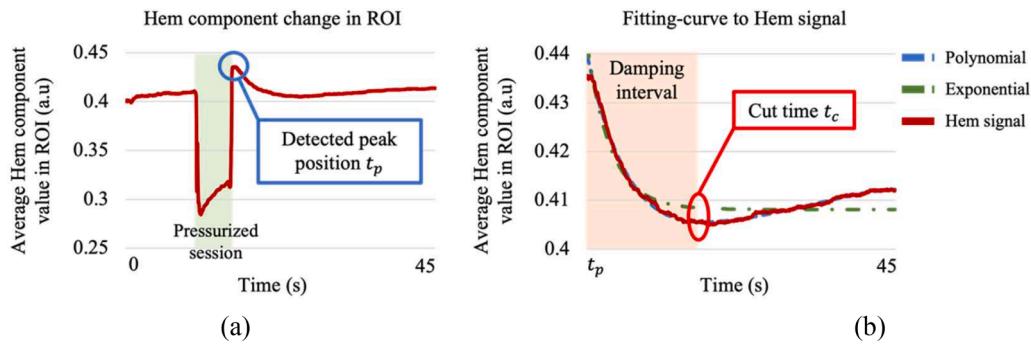
skin has been pressed. Next, the  $\text{CRT}_{\text{ROI}}$  pixel values are averaged, producing a time-dependent curve for the hemoglobin (Fig. 5). The video frame rate (fps) gives the time scale. The CRT curve follows approximately an exponential damping behavior immediately after the release of the compression ( $t_p$  in Fig. 5a) but deviates from an exponential damping for times beyond a cut time ( $t_c$ ). Following [8], we choose the cut time ( $t_c$ ) as the point of maximum difference between a provisional exponential regression (without a cut time) and the data smoothed by a sixth-order polynomial (Fig. 5b). CRT is defined here as the time constant of an exponential regression to the hemoglobin curve between the detected peak time ( $t_p$ ) and the cut time ( $t_c$ ).

#### 3. Results and discussion

The first step of this study was to estimate finger compression force, after calibration, from fingernail images. For the RGB model, the mean correlation coefficient between the estimated force and the ground truth was 0.73, with a mean root mean square error (RMSE) of 2.0 N. For the G-channel model, the mean correlation coefficient was 0.77 and the mean RMSE was 1.9 N for the same eight volunteers. In these results, the



**Fig. 4.** Pigment component separation by using a method by Tsumura et al. [24]. The region marked by pen ink (left image) delimits the region where the CRT experiment is performed.



**Fig. 5.** Procedure for cutting out damping intervals from the hemoglobin signal. (a) Detection of the maximum value ( $t_p$ ) after pressure release. (b) Definition of the cut time ( $t_c$ ).

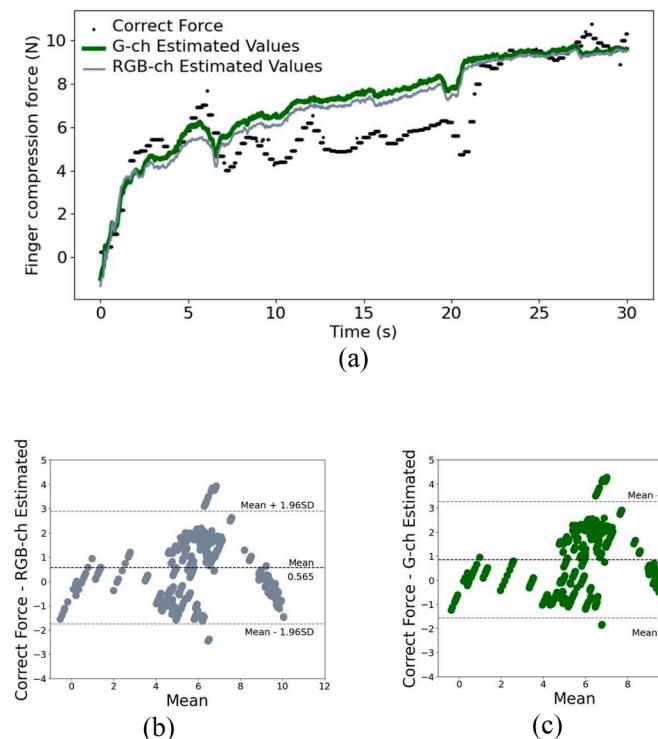
means are based on the values generated by five of the seven volunteers who participated in all the experiments. The reason we were unable to estimate the force applied by two of the volunteers will be explained later. A typical example of the results of the RGB and G-channel models for finger force prediction is shown in Fig. 6.

The partial regression coefficients used for the RGB and G models agree with the observed physiology of color change as an index finger is pressed against a surface (Fig. 7(a) and 7(b)). For example, the finger-tips, represented by nail subregions 1, 2, and 3, whiten as the finger compression force increases ( $R$  decreases or remains unchanged, while  $G$  and  $B$  increase). Nail-subregions 5 and 8 turn red as the finger pressing force increases ( $B$  and  $G$  pixel values decrease).

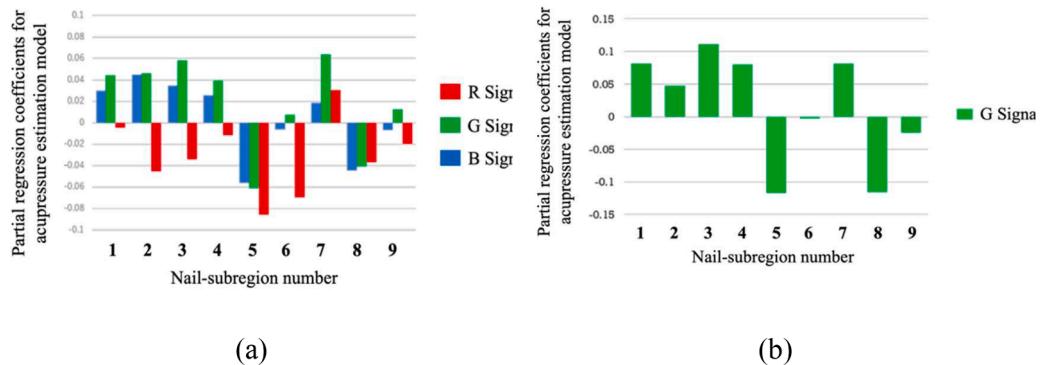
For the sake of parsimony, and because the mean correlation coefficient for the G model was slightly larger than the one of the RGB model (0.77 vs 0.73), we adopted the G model for further estimation of force applied by a finger in CRT measurements. However, no substantial differences were observed between the RGB and the G models for finger pressing force.

The CRT averages for all measurements of the seven volunteers are

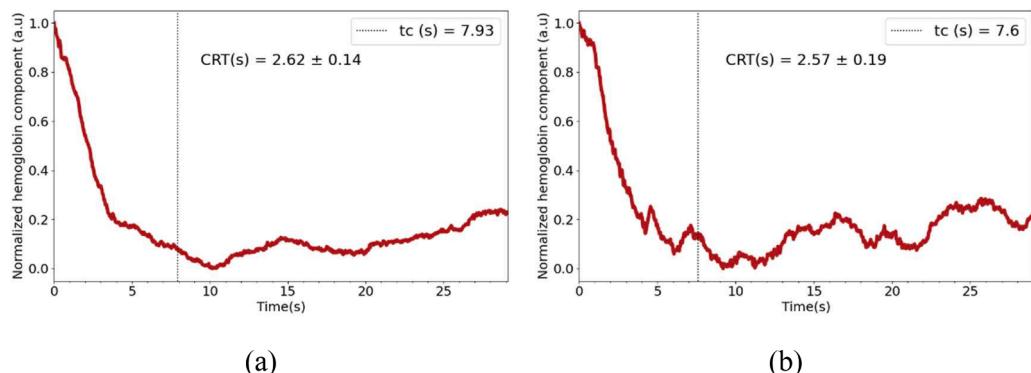
$(2.1 \pm 1.3)$  s for the compression by an index finger, and  $(1.6 \pm 1.3)$  s for the compressing weight, where the uncertainty is a standard deviation. Let us define a coefficient of variation (CV) as the regression 95 % confidence interval for a CRT found by exponential regression, divided by the corresponding CRT value. The mean CV for all measurements using an index finger for compression was 0.05, and the mean CV for all measurements using the compressing weight was 0.12. The lower CV suggests the CRT compression using a finger was more stable than using the rigid structure of the compressing weight. We observed that the compression by the cylindrical weight resulted in a noisier damping curve than using the finger to compress the skin (Fig. 8), for all volunteers. Such noise increases uncertainty (CV) in the fitting of exponential curves [8], despite the use of a cut time. The relatively noisy damping curve for measurements using the compressing weight (Fig. 8(b)) may be due to a lack of rounded edges, different from [8]. Thus, the compressing weight left a mark on the ROI of all volunteers, as may be seen in Fig. 4 (on the left). The areas where marks are left have different pixel values than other areas of the skin and may have caused noise in the measurement.



**Fig. 6.** Finger compression force: measured vs. estimated by ridge regression. (a) Typical time series for a volunteer. (b) Bland-Altman plot for ridge regression using all RGB channels in the 9 nail subregions. (c) Bland-Altman plot for ridge regression using only the G channel in the 9 nail subregions. In panels (b) and (c), the dashed lines represent the mean  $\pm$  1.96 SD, where SD is a standard deviation.



**Fig. 7.** Ridge regression mean partial coefficients for each nail subregion of the model to estimate finger compression force. (a) The model with RGB signal. (b) The model with G signal.



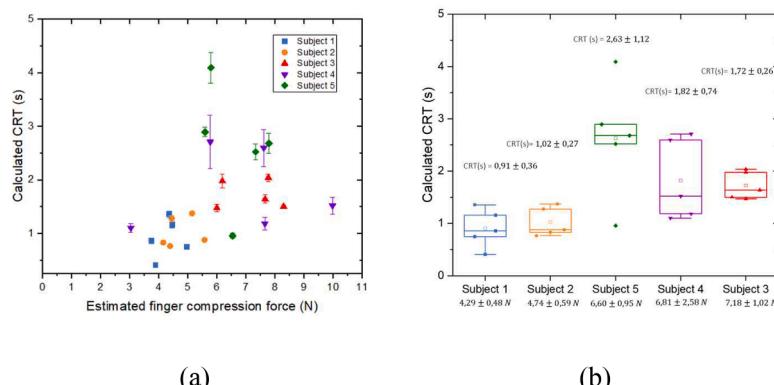
**Fig. 8.** Typical CRT signals of hemoglobin observed in volunteers (phototype I-II) after the release of compression on the forearm, calculation of CRT using the method [8]. (a) represents the response of the CRT during finger compression. (b) The response to the application of compressive weight. Note both CRT and the cutoff time ( $t_c$ ) are similar for both cases.

Compression applied by finger resulted in a longer CRT compared to compression applied by weight. (2.1 s vs. 1.6 s). The difference might be explained by the former being higher ( $3.0 \text{ N/cm}^2$ ) than latter ( $1.6 \text{ N/cm}^2$ ), as no real-time feedback on the compression by finger was given during the experiments. The longer mean CRT for higher compression, suggests that CRT may depend on the details of the compression procedure. Using the exponential damping of the hemoglobin signal, we also observed how CRT changed with applied finger force (Fig. 9). The CRT results are similar to our previous work which used the average G-channel signal to determine the exponential damping [8].

Limitations of this pilot study include insufficient evidence to determine whether an increase in compression force may result in an

elevation of CRT, and whether a higher finger compression force tended to cause more variability in the CRT measurements.

Also, for the simplified method we chose to use for force estimation, even small changes in fingernail positioning can degrade the accuracy of the estimate. We did not attempt to optimize our simple model or account for alignment errors. Notwithstanding, our ridge regression model (G-channel), chosen based on the results from 8 participants, yields a force estimation RMSE of 1.9 N, compared to 1.5 N for the more complex method of Fallahinia and Mascaro [23]. Admittedly Mascaro's method, applicable to any human fingernail, can achieve an RMSE of 0.5 N with training from 12 or more volunteers. Regardless, the potential for accurate force estimation demonstrated by Mascaro et al. renders



**Fig. 9.** Forearm CRT as a function of estimated finger compression force (5 s compression time). (a) All data points – no averaging for the applied forces. (b) CRT as a function of the average estimated applied force; the uncertainties are the standard deviations of five repetitions.

redundant a need to demonstrate here that force can be estimated accurately from fingernail images.

For two of the volunteers, we were unable to calculate the appropriate finger compression force because their fingernails were positioned either rotated or oblique compared to the training experiments done in the scale. Other limitations of this study are the lack of fingertip temperature measurement and the relatively small number of volunteers, which makes our study to constitute a pilot study. Our present report serves to stimulate discussion and lay the groundwork for future research, such as whether CRT may depend on the details (intensity, time, angle) of the compression applied to the ROI.

#### 4. Conclusion

We have used an imaging method to determine the force applied on the skin during the CRT test, which may help to standardize quantitative CRT measurements. We have also compared CRT results with compression established by a rigid cylinder, with CRT estimates using an index finger for ROI compression. In our experiments, the use of the finger to compress the ROI presented lower variability, despite lack of controlled force in our experiments. The reason for such an advantage needs further investigation.

#### Ethical approval

Work on human beings that is submitted to *Medical Engineering & Physics* should comply with the principles laid down in the Declaration of Helsinki; Recommendations guiding physicians in biomedical research involving human subjects. Adopted by the 18th World Medical Assembly, Helsinki, Finland, June 1964, amended by the 29th World Medical Assembly, Tokyo, Japan, October 1975, the 35th World Medical Assembly, Venice, Italy, October 1983, and the 41st World Medical Assembly, Hong Kong, September 1989. You should include information as to whether the work has been approved by the appropriate ethical committees related to the institution(s) in which it was performed and that subjects gave informed consent to the work.

#### Please state any sources of funding for your research

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

#### Does your study involve human subjects? please cross out whichever is not applicable

**Yes**

If your study involves human subjects you **MUST** have obtained ethical approval.

#### Please state whether Ethical Approval was given, by whom and the relevant Judgement's reference number

This study was approved by the Ethical Board of Kanazawa University School of Medicine (2018–154). All participants provided written informed consent for publication of the results from the study. All results are anonymized and individual participants cannot be identified.

This information must also be inserted into your manuscript under the acknowledgements section prior to the References.

#### Institutional review board statement

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#### Conflicts of Interest

None.

#### References

- [1] Park SY, Lee KW, Lee SH, Kim JK, Cho JW, Jeon JC, et al. Prevention of temporary emergency medical center closure through isolation zone and screening triage in COVID-19 outbreak. *Signa Vitae* 2022;18:34–40. <https://doi.org/10.22514/sv.2021.111>.
- [2] R, C Somogyi D, Sheridan D. Recent Advances in Bedside Device-Based Early Detection of Sepsis. *J Intensive Care Med* 2022;37:849–56. <https://doi.org/10.1177/0885066211044124>.
- [3] Sheridan DC, Cloutier RL, Samatham R, Hansen ML. Point-Of-Care capillary refill technology improves accuracy of peripheral perfusion assessment. *Front Med* 2021; 8:694241. <https://doi.org/10.3389/fmed.2021.694241>.
- [4] Shinozaki K, Jacobson LS, Saeki K, Kobayashi N, Weisner S, Falotico JM, et al. Does training level affect the accuracy of visual assessment of capillary refill time? *Crit Care* 2019;23:157. <https://doi.org/10.1186/s13054-019-2444-3>.
- [5] Pandey A, John BM. Capillary refill time. Is it time to fill the gaps? *Med J Armed Forces India* 2013;69:97–8. <https://doi.org/10.1016/j.mjaf.2012.09.005>.
- [6] Pickard A, Karlen W, Analgesia JA-A. Capillary refill time: is it still a useful clinical sign? *Journals LwwCom* 2011. n.d.
- [7] Morimura N, Takahashi K, Doi T, Ohnuki T, Sakamoto T, Uchida Y, et al. A pilot study of quantitative capillary refill time to identify high blood lactate levels in critically ill patients. *Emerg Med J* 2015;32:444–8. <https://doi.org/10.1136/emermed-2013-203180>.
- [8] Bachour RP dS, Dias EL, Cardoso GC. Skin-color-independent robust assessment of capillary refill time. *J Biophotonics* 2023. <https://doi.org/10.1002/jbio.202300063>.
- [9] Kawaguchi R, Nakada TA, Oshima T, Shinozaki M, Nakaguchi T, Haneishi H, et al. Optimal pressing strength and time for capillary refilling time. *Crit Care* 2019;23 (4). <https://doi.org/10.1186/s13054-018-2295-3>.
- [10] Mrgan M, Rytter D, Brabrand M. Capillary refill time is a predictor of short-term mortality for adult patients admitted to a medical department: an observational cohort study. *Emerg Med J* 2014;31:954–8. <https://doi.org/10.1136/emermed-2013-202925>.
- [11] Nickel AJ, Jiang S, Napolitano N, Yehya N, Fitzgerald JC, Bruins BB, et al. Full finger reperfusion time measured by pulse oximeter waveform analysis in children. *Crit Care Med* 2020;48:E927–33. <https://doi.org/10.1097/CCM.0000000000004506>.
- [12] Crook J, Taylor RM, Department P, Health Authority G, ward R. The agreement of fingertip and sternum capillary refill time in children. *Arch Dis Child* 2013;98: 265–8. <https://doi.org/10.1136/archdischild-2012-303046>.
- [13] Kerr E, Coleman S, McGinnity TM, Shepherd A. Measurement of capillary refill time (CRT) in healthy subjects using a robotic hand. *IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work.* 2018;1372–9. <https://doi.org/10.1109/CVPRW.2018.00176>. 2018–June.
- [14] Blaxter LL, Morris DE, Crowe JA, Henry C, Hill S, Sharkey D, et al. An automated quasi-continuous capillary refill timing device. *Physiol Meas* 2015;37:83–99. <https://doi.org/10.1088/0967-3334/37/1/83>.
- [15] Ait-Oufella H, Bige N, Boelle PY, Pichereau C, Alves M, Bertinchamp R, et al. Capillary refill time exploration during septic shock. *Intensive Care Med* 2014;40: 958–64. <https://doi.org/10.1007/s00134-014-3326-4>.
- [16] Ballalji HK, Correia R, Liu C, Korposh S, Hayes-Gill BR, Musgrave A, et al. Optical fibre sensor for capillary refill time and contact pressure measurements under the foot. *Sensors* 2021;21:6072. <https://doi.org/10.3390/s21186072>.
- [17] John RT, Henricson J, Nilsson GE, Wilhelms D, Anderson CD. Reflectance spectroscopy: to shed new light on the capillary refill test. *J Biophotonics* 2018;11: e201700043. <https://doi.org/10.1002/jbio.201700043>.
- [18] John RT, Henricson J, Junker J, Jonson CO, Nilsson GE, Wilhelms D, et al. A cool response—The influence of ambient temperature on capillary refill time. *J Biophotonics* 2018;11:e201700371. <https://doi.org/10.1002/jbio.201700371>.
- [19] Shinozaki K, Capilupi MJ, Saeki K, Hirahara H, Horie K, Kobayashi N, et al. Low temperature increases capillary blood refill time following mechanical fingertip compression of healthy volunteers: prospective cohort study. *J Clin Monit Comput* 2019;33:259–67. <https://doi.org/10.1007/S10877-018-0159-7>.
- [20] Bergkvist M, Henricson J, Iredahl F, Tesselaar E, Sjöberg F, Farnebo S. Assessment of microcirculation of the skin using Tissue Viability Imaging: a promising technique for detecting venous stasis in the skin. *Microvasc Res* 2015;101:20–5. <https://doi.org/10.1016/j.mvr.2015.06.002>.
- [21] Fallahinia N, Mascaro SA. Real-time tactile grasp force sensing using fingernail imaging via deep neural networks. *IEEE Robot Autom Lett* 2022;7:6558–65. <https://doi.org/10.1109/LRA.2022.3173751>.

- [22] Grieve TR, Hollerbach JM, Mascaro SA. Fingernail image registration using Active Appearance Models. Proc - IEEE Int Conf Robot Autom 2013;3026–33. <https://doi.org/10.1109/ICRA.2013.6630997>.
- [23] Mascaro SA, Harry Asada H. Photoplethysmograph fingernail sensors for measuring finger forces without haptic obstruction. IEEE Trans Robot Autom 2001; 17:698–708. <https://doi.org/10.1109/70.964669>.
- [24] Tsumura N, Ojima N, Sato K, Shiraishi M, Shimizu H, Nabeshima H, et al. Image-based skin color and texture analysis/synthesis by extracting hemoglobin and melanin information in the skin. ACM siggraph 2003 pap siggraph '03. 2003. p. 770–9. <https://doi.org/10.1145/1201775.882344>.