Automated Validation of Capillary Refill Time Measurements Using Photo-plethysmogram from a Portable Device for Effective Triage in Children

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***Abstract*—Capillary refill time (CRT) is an important tool for the clinical assessment of trauma and dehydration. Indeed, it has been incorporated into advanced life support guidelines as part of the rapid assessment of critically ill patients. However, digitalized CRT techniques are not readily available and the standard assessment based on the visual inspection of CRT lacks standardization and is prone to a high inter-observer variability. We present an algorithm for the automatic validation of the CRT measurement on the finger using photo-plethysmogram recordings on a small portable device. It is based on a set of deterministic rules for the classification of finger pressure and regular plethysmographic pulses. Validation studies using the classification of 93 pediatric recordings from Canada and Uganda showed that the novel algorithm reliably detects invalid CRT measurements (sensitivity 98.4%). This includes patterns such as insufficient pressure, low perfusion signals, and artifacts. Since our device consists of widely available components already in use, the promising results suggest that the algorithm could be readily integrated in operating rooms and intensive care units around the world. This more robust assessment of CRT would produce a more powerful diagnostic tool for clinical triage in critical care settings.**

***Keywords*-photo-plethysmogram, capillary refill time, pulse oximeter monitoring, anesthesia, children, segmentation, classification**

I. Introduction

Capillary refill time (CRT) is defined as the time taken for a distal capillary bed to regain its color after pressure has been applied. Endorsed by the Word Health Organization [1], CRT has been an integral part of the clinical assessment of both adults and children since 1981, when it was introduced as an element of a trauma score [2]. Along with other clinical signs, CRT can assess the circulatory status of a patient[3] and correlates well with the degree of dehydration in children [4], [5]. Indeed, the clinical measurement of CRT was found to be the best individual sign for diagnosing children with 5% dehydration [6].

Different body sites have been proposed for CRT measurement. While most studies use the pulp of the distal phalynx of the finger or the nail bed to perform CRT, many pediatric health care providers use the chest [7]. Other studies suggest using the soft tissue at the kneecap or forearm [8]. CRT measurements on the same patient, however, can vary depending on the measurement site: CRT is significantly longer at the heel than the finger [4], [9]; and CRT measurements on the heel or palm produce a uniform distribution while those on the forehead or chest produce a Gaussian distribution [10].

A major limitation of CRT measurement is the low inter-observer reliability [9], [11], [12]. Human limitations in estimating short time intervals likely compound additional issues with technical in-consistency in visual CRT assessment. Despite CRT varying with both the duration and the amount of pressure applied, advice regarding application of pressure has been inconsistent. For example, it has been suggested that moderate pressure be applied for five [9], [13] or three seconds [1], or until the capillary bed just blanches[6]. Applying pressure for less than three seconds, however, results in a lower CRT than longer times. While a consistent CRT may be found when applying pressure for between three and seven seconds [10], stronger pressure can prolong the measured CRT [4]. Intra-observer differences can also be affected by ambient lighting conditions, with CRT measurement being challenging under poor lighting conditions [13]. The level of training of the observer is also relevant for the accuracy of CRT.

To eliminate the subjectiveness of this visual CRT assessment procedure, optical sensing devices have been used to objectively measure CRT. One potential approach uses digital videography [14], which replicates the visual observation method by substituting the human eye with an electronic image sensor array. Although it has shown promising results, the CRT reading from such devices remains dependent on ambient light and requires the development of custom sensor equipment [14]. An alternative device is a blue LED photo-

978-0-7695-4595-0/11 $26.00 © 2011 IEEE
DOI 10.1109/GHTC.2011.19

plethysmographic (PPG) sensor that can detect changes in blood flow [15]. Indeed, three measures for quantifying CRT have been derived from a PPG sensor based on a blue light emitter: *1*) time to reach the initial DC level; *2*) time to reach the DC signal maximum after pressure release, and; *3*) time of return from the DC maximum to its initial level [15]. While the low wavelength of light makes this sensor particularly sensitive to changes in blood flow in capillaries at the surface of the skin, its lack of testing and commercial development limit its current application. Developing a reliable CRT test using an alternative, existing PPG sensor that is more widely available and affordable would overcome these practical constraints. Integrating this into a small portable device would make this diagnostic tool broadly accessible.

We are working towards this goal by harnessing the potential of PPG from commercial pulse oximeter sensors that are commonly used in the operating room and intensive care unit. Since pulse oximeter sensors are designed to measure blood oxygen saturation (SpO2), the method of estimating CRT will be based on the standard recording of the PPG in the red and infra-red spectrum. Given that these commercial plethysmographs have been designed with a different objective (measuring SpO2), their sensor systems present some restrictions that need to be overcome in order to measure CRT. For example, lack of access to raw PPG recordings from most sensor systems prevents the computation of the three CRT quantification methods suggested for the blue PPG sensor [15]. Even when "raw" PPG recordings can be accessed using remote devices such as computers, it is often normalized and has had an auto-gain applied. Since the DC component of the signal cannot be retrieved for comparison with the amplitudes of the AC component, the quantification methods remain impossible.

The effects of zero-mean normalization, however, present an alternative opportunity to measure CRT. The normalization produces a unique signal pattern with large spikes where the sensor DC value abruptly changes (Figure 1). Since the presence of the AC component (pulses) is not affected by the filtering methods used in some commercial devices, it can be used to detect the pressure exerted on the sensor during a CRT test. Indeed, the pulses of the PPG signal have been shown to re-appear within 1-2 seconds after pressure release [15].

In this paper we will describe the development of an algorithm for the automatic detection of errors in the CRT measurement with a pulse oximeter probe, and its validation using data from a small portable device.

II. Materials & Methods

A. Algorithm

Two components in the PPG signal need to be extracted to perform automated CRT validation: 1) regular PPG pulsations characterized by a maximal volume peak and the possible presence of a dicrotic notch; and 2) a CRT pressure pattern characterized by a negative and a positive high amplitude spike separated by a signal at baseline level without pulsations (Figure 1). In order to extract these features, we have chosen

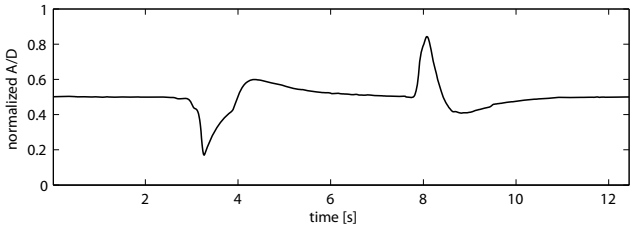

Fig. 1. Typical PPG pattern during a CRT test recorded on a finger with the blood flow occluded. The effects of the zero-mean normalization are seen after pressure has been applied to the sensor and then released. A sudden decrease or increase in the DC value caused by an increase or decrease in the distance between LED and photo-diode, respectively, is compensated by normalizing the signal to baseline within two seconds. Blood flow to the finger has been prevented by elevating the hand above the heart.

a segmantation algorithm. Since both of these elements are based on morphological shapes that can be characterized by consecutive lines, this algorithm will permit further signal processing and classification.

1) Segmentation: An Incremental-Merge segmentation method, a mixture of Iterative-End-Point-Fit [**?**] and Incremental algorithms [16], has been used. Because of its sliding-window structure, the Incremental-Merge algorithm is simple, fast and can be computed on-line. Segments were constructed by connecting the first and the last points of the segment (End-Point-Fit) and by computing the angle of this line. The segments extracted from a typical PPG during the measurement of CRT present characteristic slopes that are distinct from segments extracted from regular PPG pulses (Figure 2 bottom).

2) Segment classification: In a next step, the lines are validated and classified into different classes using a rule based algorithm (Algorithm 1). The algorithm uses the lines' basic characteristics: angle (α_z), length ($\parallel line_z \parallel$), first and last ordinate of the line ($start_z, end_z$). Algorithm 1 characterizes a normal PPG pulse as an up-slope and a down-slope line (Figure 2 bottom).

3) Pattern classification: The goal of the pattern identification is the recognition and classification of typical patterns inside the PPG time series. Consecutive valid segments are analyzed to form distinctive patterns (Algorithm 2). Typical patterns are: *regular* PPG pulses, *start pressure*, and *end pressure*. Between the start and end of pressure a flag is set (Figure 2). In addition, the PPG was classified for four abnormal states:

- Low perfusion signal
- Signal corrupted by artifacts
- Insufficient pressure
- No pressure.

Algorithm 3 describes the classification rules for abnormal PPG. Time segments are checked for typical patterns and segment classes obtained from Algorithm 1 and 2.

B. Experiments

Following ethical board review and written parental consent, 31 children (1-5 years old) who were to undergo general anesthesia at a Canadian health institution and 62 children

Algorithm 2 Pattern classification

if $class_{z-2}$ == down-slope & $class_{z-1}$ == up-slope & $class_z$ == down-slope **then**
  $pattern_z \leftarrow$ regular
  $pressureflag_z \leftarrow 0$
end if
if $class_{z-2}$ == up-slope & $class_{z-1}$ == down-slope & $class_z$ == up-slope **then**
  $pattern_z \leftarrow$ regular
  $pressureflag_z \leftarrow 0$
end if
if $class_{z-4}$ == regular & $class_{z-3}$ == regular & $class_{z-2}$ == down-slope & $class_{z-1}$ = spikeLow & $class_z$ == down-slope **then**
  $pattern_{z-2} \leftarrow$ start pressure
  $pressureflag_{z-1} \leftarrow 1$
end if
if $pressureflag_{z-1} == 1$ & $class_{z-2}$ == baseline & $class_{z-1}$ == spikeHigh & $class_z$ == down-slope **then**
  $pattern_{z-1} \leftarrow$ pressure release
  $pressureflag_{z-1} \leftarrow 0$
end if

Algorithm 3 PPG classification

if spikeHigh $\in class_{[0s...4.5s]}$ | spikeLow $\in class_{[0s...4.5s]}$ **then**
  $ppg \leftarrow$ artifacts
end if
if (regular $\notin pattern_{[0s...4.5s]}$ & $ppg \neq$ artifacts) | plateau $\in class_{[0s...4.5s]}$ **then**
  $ppg \leftarrow$ low perfusion
end if
if start pressure $\notin pattern_{[4.5s...8s]}$ | pressure release $\notin pattern_{[8s...12s]}$ **then**
  $ppg \leftarrow$ no pressure
end if
if start pressure $\in pattern_{[4.5s...8s]}$ & pressure release $\notin pattern_{[8s...12s]}$ **then**
  $ppg \leftarrow$ too low pressure
end if

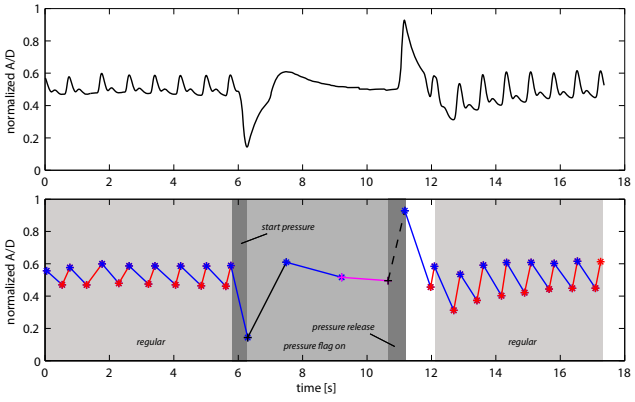

Fig. 2. Top: PPG during a CRT measurement. Pressure began at 6 seconds with a large negative spike (photo-diode closer to emitter diode). During pressure the signal recovered to baseline without detecting a pulse wave. At pressure release, a large positive spike was detected. Bottom: Extracted and classified segments from the PPG (blue: down-slope; red: up-slope; black: extreme up-slope; and magenta: plateau). Gray boxes are the result of the pattern classification.

(1-6 years old) who were hospitalized for malaria, burns, or dehydration in an Ugandan institution were recruited. A standardized clinical measurement of CRT was initially obtained: the right index finger was raised to chest level and pressure was applied to the pulp of the distal phalynx to cause blanching of the capillary bed for five seconds. The time to return of normal color was measured with a stopwatch to a precision of 0.1 seconds. A PPG pulse oximeter sensor was then placed on the same index finger. The device consisted of a PureLight medium soft pulse oximeter probe connected to an Xpod OEM module (both Nonin, Plymouth, USA), which was in turn linked to an iPod Touch 2^{nd} generation (Apple, Cupertino, USA), which displayed the waveform and recorded the data stream. The PPG was recorded with a 16 bit resolution at a sampling rate of 75 Hz. Pressure was applied to the sensor and CRT was measured following: *1*) five seconds of regular PPG, *2*) five seconds of pressure application, and *3*) 15 seconds of recovery. The iPod application guided the user automatically through these steps. This procedure was replicated three times on each patient. In addition, on 16 patients from Canada, one minute of normal PPG without applying CRT pressure was

Algorithm 1 Segment classification algorithm

if $\| line_z \| < minimallength$ **then**
    $class_z \leftarrow$ not a valid segment
else if $\alpha_z > 0 + \varepsilon$ **then**
    $class_z \leftarrow$ up-slope
else if $\alpha_z < 0 - \varepsilon$ **then**
    $class_z \leftarrow$ down-slope
else
    $class_z \leftarrow$ plateau
end if
if $class_z$ == up-slope & $start_z < thres_{low}$ **then**
    $class_z \leftarrow$ spikeLow
else if $class_z$ == up-slope & $start_z == thres_{baseline}$ & $end_z < thres_{high}$ **then**
    $class_z \leftarrow$ spikeHigh
else if $class_z$ == plateau & $end_z == thres_{baseline}$ **then**
    $class_z \leftarrow$ baseline
end if

Where $minimallength$ is the length of a segment in nb. of samples, $class_z$ is the class for segment z, ε is the range of tolerance for low angles, and $thres_{low}$, $thres_{high}$ and $thres_{baseline}$ are threshold values that characterize spikes or baselines.

taken.

C. Performance Measure

Sensitivity and specificity were calculated for each PPG class and for each CRT measurement rejection. To put sensitivity and specificity into relation, a receiver operating characteristics (ROC) plot was generated.

III. Results

Thirty-eight of the 93 clinical CRT measurements that we obtained were within the normal range for the age group tested (<2.5 s). The remaining CRT measures ranged from 2.5 s to 5.6 s. A total of 336 PPG segments were collected. Three random PPG segments were used to calibrate the classification algorithm[1] and were discarded. Table I shows the distribution of the PPG classes in the remaining reference measurements obtained by the visual observation of a technician. The results of the automatic classification of the PPG segments are shown in Figure 3. The classification of low perfusion showed a high specificity (94.5%), but relatively low sensitivity (35.8%). On the other hand, artifacts were detected with a sensitivity of 95.6% and a specificity of 66.5% (Figure 4). Most importantly, only four failed CRT were not recognized as such (sensitivity 98.4%).

IV. Discussion

We showed that a rule-based classification based on segment features can be applied to classify PPG signals. The pattern

[1] $thres_{baseline} = 0.5$, $thres_{high} = 0.65$, $thres_{low} = 0.35$ $\varepsilon = 3 * 10^{-4}$, $minimallength = 8$

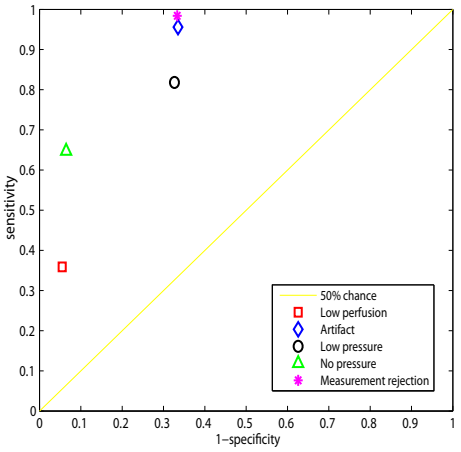

Fig. 3. Receiver operating characteristics plot for the PPT segment classification. A classifier with optimal performance would be located at the upper left corner (0,1). A classifier located above the diagonal performs better than random.

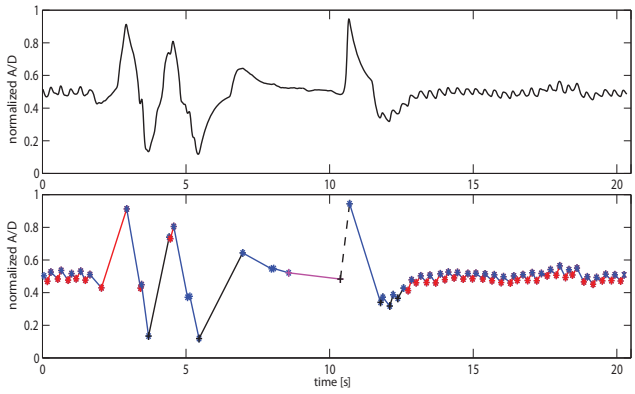

Fig. 4. Top: Movement artifact in the PPG before a CRT measurement. Bottom: Extracted and classified segments from the PPG (blue: down-slope; red: up-slope; black: extreme up-slope; and magenta: plateau).

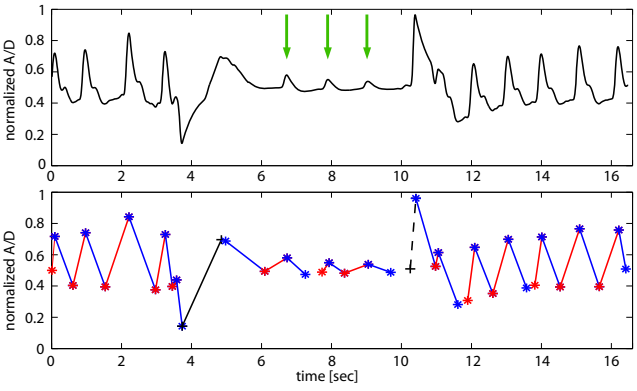

Fig. 5. When insufficient pressure was applied, pulses reappeared in the PPG during pressure application (top, arrows). The segment classification algorithm detected these pulses (bottom) and could not identify the pressure release pattern since no flat baseline was detected.

TABLE I
DISTRIBUTION OF PPG SEGMENT CLASSES FOR THE REFERENCE MEASUREMENTS

	Low perfusion	Corrupted by artifacts	Insufficient pressure	No pressure	CRT rejection	Total measurements
Nb. of PPG segments	78	136	88	85	252	333

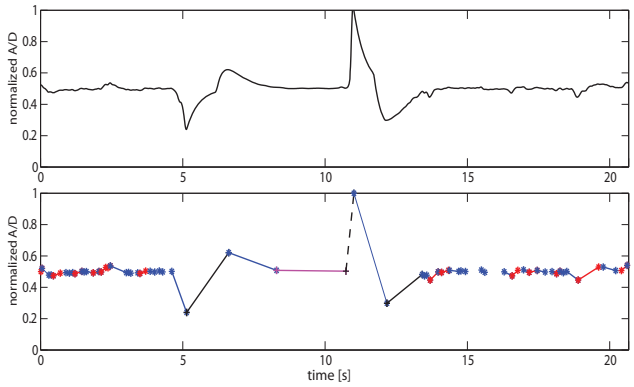

Fig. 6. Top: Low perfusion PPG during a CRT measurement. Bottom: Extracted and classified segments from the PPG (blue: down-slope; red: up-slope; black: extreme up-slope; and magenta: plateau).

and PPG classification rules are an efficient way to discriminate the PPG used for CRT into five classes, notably: *1*) low perfusion signal, *2*) artifacts, *3*) insufficient pressure, *4*) no pressure, and more general *5*) invalid CRT.

The high sensitivity for detecting invalid CRT patterns achieved with the automatic validation algorithm suggests that this algorithm is a reliable tool to accurately validate CRT using a single measurement in a clinical environment.

In addition, the device was able to identify when pressure applied to a finger was insufficient for an accurate reading; detection of cardiac oscillations or movement artifacts during the period where the pressure was applied to the finger identified inadequate pressure (Figure 5). The detection of low perfusion was less reliable. Baseline drifts due to movement with low amplitude were difficult to distinguish from small pulses (Figure 6) and misinterpreted as such.

In future versions of the classification algorithm, additional PPG classes could be implemented. For example, exact duration between start pressure and end pressure could be assessed and validated against a standardized duration.

The algorithm followed the assumption that the user performed the CRT measurements according to the guidance from the iPod application. CRT measurements that were not aligned in time with the target were rejected. For more usability, future versions of the algorithm could include the automatic pressure pattern detection within the PPG, without the need for an application with a specialized user interface.

The filtering functions of the proprietary sensor introduce a limitation which needs to be studied further. Variation in filters used by different manufacturers might influence the typical morphology of the pressure pattern; a change that could negatively influence the classification of the CRT pattern and the CRT measurement. Additional experiments with other devices will be needed to investigate these effects and to guarantee universal application.

In a next step, we will develop an algorithm for a completely automated measurement of CRT. So far, we have observed a high rate of low perfusion states in children with prolonged CRT. Further investigations are required to elucidate the correlation between low perfusion and long CRT, and whether this property impacts the automated calculation of CRT with a PPG recording. Other reasons for low perfusion readings are improper sensor placement or increased tissue absorption due to pigmentation.

We have tested this algorithm only on PPG recordings from children. We plan to extend the study to other age groups, such as elderly people, whose normal CRT values tend to be higher [17].

V. CONCLUSION

We have proposed an automated method for objective CRT measurement validation using a small portable device based on photo-plethysmography. The release of pressure from the finger could be automatically detected with the implementation of a Incremental-Merge segmentation algorithm and a multi-stage, rule based classification algorithm.

Our validation studies showed that the novel algorithm reliably detects no and insufficient pressure, low perfusion signals, and artifacts. Since our procedure could be applied to any clinical pulse oximeter, the promising results suggest that the algorithm, when combined with an automated assessment of CRT, could be readily integrated into operating rooms and intensive care units around the world. By improving the practice of health care workers, the automatic measurements of CRT would produce a more powerful diagnostic tool for clinical triage in critical care settings.

VI. ACKNOWLEDGMENT

This project was funded by the University of British Columbia Martha Piper Research Fund. We would like to acknowledge Jennifer Gow and Richa Anand for helping to edit this manuscript.

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