

## Exploratory Use of PPG Signal in Continuous Authentication

Júlio da Silva Dias<sup>1,4</sup>, Issa Traore<sup>2</sup>, Vitor G. R. A. Ferreira<sup>3,4</sup>, Julibio David Ardigo<sup>1,4</sup>, Carlos Roberto De Rolt<sup>2</sup>

<sup>1</sup>Universidade do Estado de Santa Catarina – Escola Superior de Administração e Gerência (ESAG/UDESC)

Av. Madre Benvenuta, 2007 – 88.035-001 – Florianópolis – SC – Brazil

<sup>2</sup>Department of Electrical and Computer Engineering – University of Victoria - Victoria, Canada.

<sup>3</sup>Universidade Federal do ABC – São Paulo, SP – Brazil

<sup>4</sup>Bolsista do CNPq - Brasil

{julio.dias, julibio.ardigo, rolt}@udesc.br, {traore}@uvic.ca,  
vitor.ferreira@aluno.ufabc.edu.br

**Abstract.** *One-time or static authentication is not sufficient in many applications and continuous authentication methods can provide a way to increase security in situations where an application could be compromised or misused after statically authenticating the user. The aim of this work is to evaluate the use of the Photoplethysmographic Signal (PPG) in continuous authentication and identify the requirements of the system that should be used to record and process the signal. Different types of sensors, sampling rates, and analog to digital conversion resolutions were tested in order to identify the configuration that best suits the application requirements. The algorithms used for processing the PPG signal as well as the size of the samples used in the authentication process were also analyzed during the experiments. In order to achieve the set objective, a dataset of PPG signals was developed since it was not possible to find open datasets with long term monitoring samples of individuals.*

### 1 Introduction

User authentication is performed usually at the moment of granting user access to resources. This service can be performed through something the user knows, has, is or even his/her location (Ghogare, Jadhav, Chadha, & Patil, 2012). The authentication based on what the user knows is performed using some information shared between the user and the system. In this case, the parties share a secret, e.g., a password or the answer to a security question. The authentication using something the user has is performed by the user presenting some physical device such as a smart card or a token

recognized by the system as being the property of a specific user. The authentication based on something the user is requires some kind of hardware capable of collecting biometric information from the user and matching such information with a pattern stored previously. It is also possible to combine two or more authentication methods in order to increase the security level.

Traditional approaches for user authentication consist of only checking the user identity once, typically at login time; however, this may allow a hacker to hijack the session after the authentication phase. Continuous authentication, which consists of repeatedly verifying user identity during a session, has been advocated as a way to address the above mentioned limitation. The principle of continuous authentication is to monitor the user behavior during the session while discriminating between normal and suspicious occurrences. In case of suspicious behavior the user session is locked or an alert is generated. The flag to prompt another authentication is based on time or the amount of data (delay between consecutive re-authentication). Continuous authentication has been applied for intrusion detection, network forensics, insider detection, and session security (Traore & Ahmed, 2011) (Brocardo, Traore, & Woungang, 2014). The process involves several key requirements including the need for low authentication delay, high accuracy, and the ability to withstand forgery. Additionally, the biometric capture device and environment, and the flexibility of the authentication process, play an important role in user acceptability.

Among the capture devices used (in continuous authentication) are not only traditional input devices, such as mouse and keyboard, but increasingly wearable devices, such as smartphones. The development of wearable devices has required new and improved sensors that along with Smartphone applications provide the infrastructure required to easily collect physiological data from users. This information has been used for monitoring fitness activities and also for personal healthcare. The devices developed allow the recording and storage of physiological signals such as electrocardiograms (ECG), plethysmograms and electromyograms and present the possibility of using these signals in other areas such as user authentication. The analysis of the plethysmographic waveform and electrocardiogram offers a low cost alternative for continuous authentication.

ECG is a graphical record of the electrical activity that is generated by depolarization and repolarization of the atria and ventricles. It is well suited for analysis by joint time-frequency and time-scale distributions. An ECG signal has a strong time-varying morphological characteristic, identified as the P-QRS-T complex. The signal frequencies are distributed by low frequency - P and T waves and mid to high frequency QRS complex (Haque, Ali, Kiber, & Hasan, 2009) (Islam, Haque, Tangim, Ahammad, & Khondokar, 2012).

There are several types of plethysmograph, however, photoplethysmograph (PPG) is usually seen as the most adequate for continuous authentication, as it is not invasive, it is cost-effective and can achieve high accuracy (Elgendi, 2012). PPG is used to estimate the skin blood flow using red or infrared light. Traditionally, it can be used for measuring the oxygen saturation, blood pressure, cardiac output, and for assessing autonomic functions. The PPG amplitude is measured using transmission-mode index finger pulse probe.

In this work, only the PPG waveform will be studied. Our goal is to explore the requirements of systems that perform continuous authentication based on PPG signals and also develop a dataset with PPG signals to be used in the development of a continuous authentication system. The remainder of the paper is organized as follows. In Section 2, related work is discussed. In Section 3, the architecture of the system is presented. In Section 4, the data collection procedures and datasets are presented. In Section 5, our biometric processing model is introduced. In Section 6, we analyze sample data and present obtained performance results. Section 7 presents some final considerations and discusses future works.

## 2 Related Work

Several papers have been published on using PPG signal in areas such as healthcare (Sriram, Shin, Choudhury, & Kotz, 2009), fitness (Gupta & Jilla, 2011), and also on research aiming to develop new sensors that explore the earlobe PPG (Yap Jiunn, Gi-Hyun, & Do-Un, 2011). A method of liveness detection based on pulse oximetry, proposed by Reddy et al. (Reddy, Kumar, Rahman, & Mundry, 2007), can also be used in the detection of fake fingerprints.

The use of ECG and PPG signals in authentication has also been studied for some time (Jianchu, Xiaodong, & Yongbo, 2007). Works by Biel et al. (Biel, Pettersson, Philipson, & Wide, 2001) and Singh and Singh (Singh & Singh, 2012) show that the use of ECG signals in biometric authentication is not new. There is also a few proposals on using these signals in continuous authentication (Bonissi et al., 2013; Coutinho, Fred, & Figueiredo, 2011; Guennoun, Abbad, Talom, Rahman, & El-Khatib, 2009). According to Hyun-Min (Hyun-Min et al., 2009) it is possible to use PPG or ECG signals in the monitoring of individual user behavior. Work from Labati *et al.* (Labati, Sassi, & Scotti, 2013) aims to prove that it is possible to use ECG signals once QRS complex is stable enough to achieve continuous authentication.

The increase in the volume of published articles indicates that this kind of devices presents some viability but it is yet to be shown that they can be used in a sustained way for continuous authentication. It is known that the ECG and PPG waveforms present a lot of variability when the individual under analysis is resting, and even more so when the individual is performing some kind of exercise.

However, there is no database with long term PPG waveforms and the published works are based only on individuals in resting state. Our goal, in this work, is to develop a dataset with both steady state and after exercise signals. A continuous authentication solution will only be possible if both kinds of signals are understood and can be used to uniquely identify a subject.

### 3 System Architecture

The system architecture used in the experiments is shown in Figure 1. The system consists of a sensor, a signal conditioning unit (Low pass and high pass analog filters) and digitization hardware (analog to digital converter) and a data processing algorithm (extraction and decision).

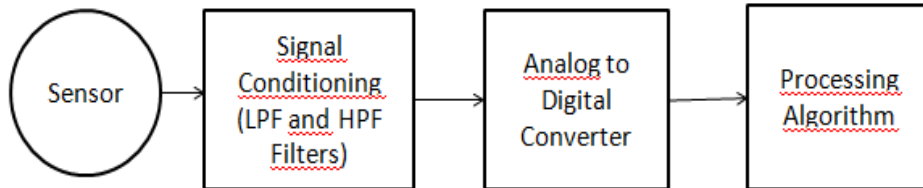


Figure 1 - System Architecture

In this work the sensor and the digitization modules were tested under different configurations to study the parameters of the system such as sampling rate, resolution and sensor specification. Only the infrared LED was used since reading the percentage of hemoglobin molecules in the arterial blood, which are saturated with oxygen (SaO<sub>2</sub>), was not our goal. A Nellcor DS-100A and a HRM-2511E sensors were used in the tests. The HRM-2511E is a transmission-mode sensor that uses only the infrared LED. The Nellcor DS-100A is a transmission-mode sensor that provides two LEDs, an infrared and a red widely used as a spo<sub>2</sub> sensor. Both sensors provided similar results. Consequently, the Nellcor DS-100A was chosen in the signal recording, since the use of the red LED could be useful in future work. Figure 2 shows a sample PPG signal recorded using the Nellcore sensor and a 12 ADC.

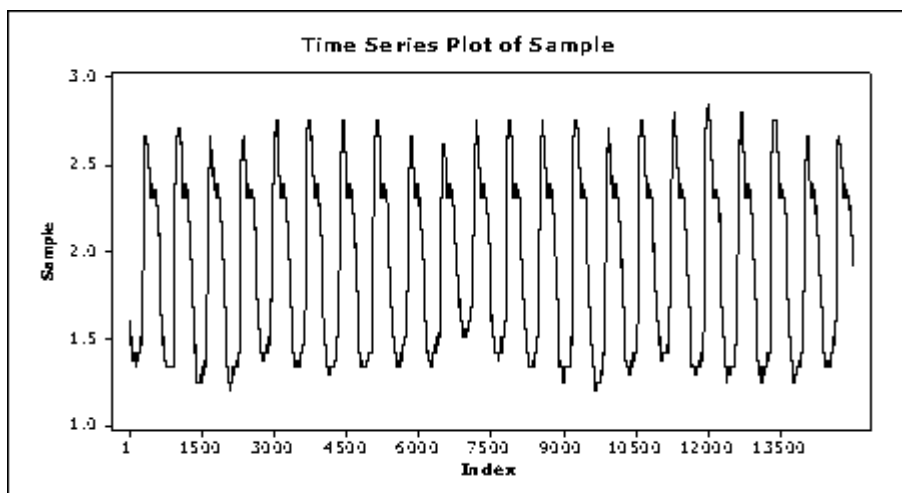


Figure 2 - PPG Waveform

The signal from the sensor must be amplified and filtered prior to digitization. Once the signal has been properly processed it is digitized using 8 or 12-bit analog to digital converter. The PPG waveform usually involves frequencies ranging from 0.5 to 2.5 Hz and the breathing rates modulating the PPG signal involves half those frequencies. As the waveform involves a low frequency, a high sampling rate is not required. We used a 750 Hz sampling rate that proved to be enough for the goal of the present research. In the initial phase of our research, higher sampling rates were tested, but it appeared that there was no real gain in using higher sampling rates, and that requires more processing time providing a lot of redundant data.

The resolution was also analyzed and it was found that 8-bit is enough for the present application. The tests using 12-bit resolution did not provide relevant information since the signal does not present fast amplitude variations.

We chose a transmission mode PPG sensor and an 8-bit analog digital convertor that could provide the data required and low power consumption. This might be a requirement, for instance, when the system is used as a wristband.

## **4 Experimental Data Collection**

In this section, we give an outline of our experimental data collection method and describe the collected data.

### **4.1 Data Collection Method**

In order to calibrate the process and collect consistent data, a specific procedure was established and used for both the subjects under analysis and the experimenter. Initially, the subject whose PPG signal was being recorded had to be seated in a relaxed position in front of a table. Next, the individuals had to lay their arms on the table and bend them parallel to their thoraxes. After placing the index finger in the finger clip the subject had to avoid abrupt movements due to the sensitivity of the equipment. Additionally, the subjects were asked to avoid changing their breathing in order to obtain more regular amplitude from the signal, even though the normalization process eliminates this concern. The PPG signal collected by finger pulse sensor presents variability due to arm position and movement.

The steps concerning the experimenter are related to the use of the software to collect reliable data. Firstly, it was necessary to evaluate whether the signal was stabilized, i.e., if its expected shape was being observed. Only after this check, the data recording could be started. Secondly, it was decided that the ideal recording time would be around one minute since the amount of data collected in this period provides a reasonable number of cycles taking into account the fact that some segments of the signal were affected by the sensitivity of the sensor.

### **4.2 Collected Data**

The data was collected in 2 phases: an exploratory phase and a follow-up phase. The data collected in the exploratory phase was used to identify possible problems that could

happen during the data collection, and design our biometric recognition model. The data collected in the follow-up phase, was used to test and validate our model.

Three subjects, at the ages of 15, 21 and 48, participated in the exploratory phase. Each of these subjects provided 2 sets of data samples at resting state and 1 set of data sample after exercising. The 3 data sets were collected consecutively at 5 days interval. Each of the resting samples consists of 1 minute data collected at 60 minutes time interval over 6 hours. The exercising samples were collected for 3 minutes starting from the end of the exercise.

During the follow-up phase, we collected another dataset from 7 additional subjects with ages from 21 to 30 years. Each of these subjects provided a single sample of one minute duration.

## 5 Data Processing Model

In this section, we present our biometric processing model by discussing about template matching and template size. The proposed model uses cross-correlation to identify similarities between the templates stored in the database and the PPG signal recorded from the user being authenticated.

### 5.1 Template Matching

For authentication, we need to compare a (received) sample against the template or pattern corresponding to the claimed identity.

Since the PPG signal presents a lot of variability due to physiological aspects such as respiration and also related to the way a sensor interacts with the individual it is necessary to pre-process it before using it to compare to other signals from the same individual. The signal before being used is normalized to zero mean and unit standard deviation. According to Lin *et al.* (Lin, Keogh, Lonardi, & Patel, 2002), this type of time-series normalization is the best known transformation of the raw time-series that preserves original time-series features.

Before using the PPG signal for authentication it is necessary to identify a common start point to be used in the signal processing. For this purpose, we calculate the first derivative of the normalized signal to find the minima used as the start point as shown in Figure 3.

The discrete derivative,  $\hat{x}_t$ , is calculated using the difference between the present value and the next value. The variability found in the signal makes it difficult to align two samples for the authentication process. This alignment problem translates into inaccuracies in the cross-correlation between the base signal and the signal under analysis.

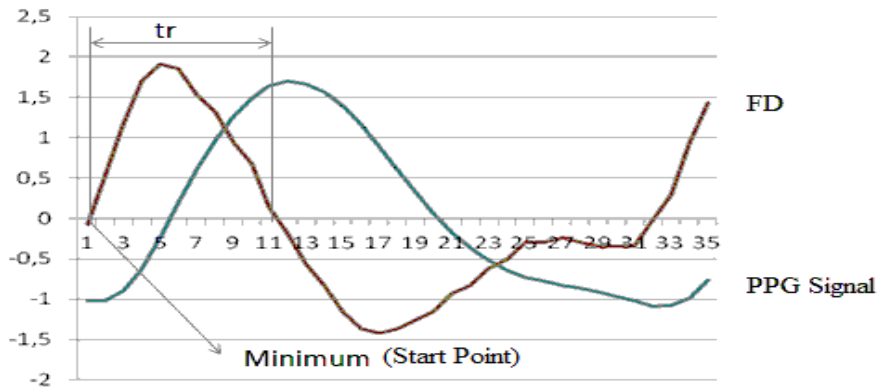


Figure 3 - First Derivative (FD) of a PPG signal

The last aspect to be adjusted is related to the alignment between the PPG signal used as template (or reference) and the signal to be verified. Such adjustment is expected due to the fact that the variability between two signals from the same subject creates some delay. A cross-correlation lag analysis provides information about de delay and shape similarity between two time series. Figure 4 shows a plot of a cross-correlation function of two signals where there is a small delay between the two time series.

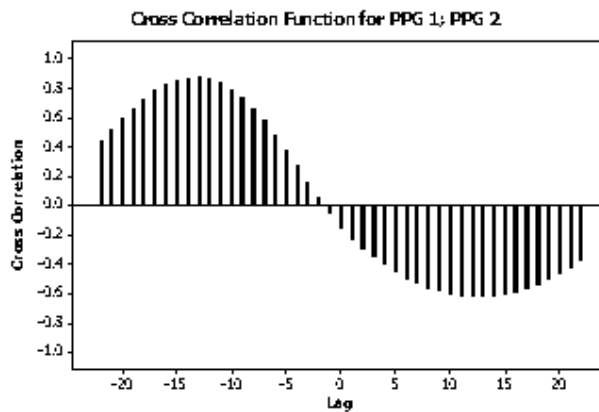


Figure 4 - Cross-Correlation function between two PPG samples

The information about the signal alignment can be obtained from the cross-correlation function (see Figure 4) or through the use of dynamic time warping. In order to compute the similarity it is necessary to align the two time series. It is expected that the two time series will present the same shape but no perfect alignment with respect to the X axis. The lack of alignment is due to the variability of the PPG signal and also to the error introduced by the quantization in the digitization process. Dynamic Time Warping is used for measuring the similarity between two PPG signals. Figure 5 shows the plot of two PPG signals seen as two time series. In order to compute the similarity between the two time series the library *dtw* from the statistical package R was used. The results are

similar to the ones provided by cross-correlation analysis. Both techniques can be used to quantify the lag between the signals. The information about the lag was used to align both time series as can be seen in Figure 5. Figure 6 shows the cross-correlation function between both time series after perfect alignment is achieved.

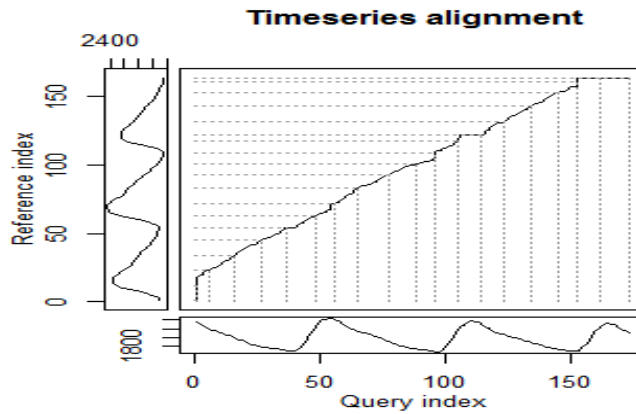


Figure 5 - Dynamic Time Warping for measuring the similarity between two PPG signals

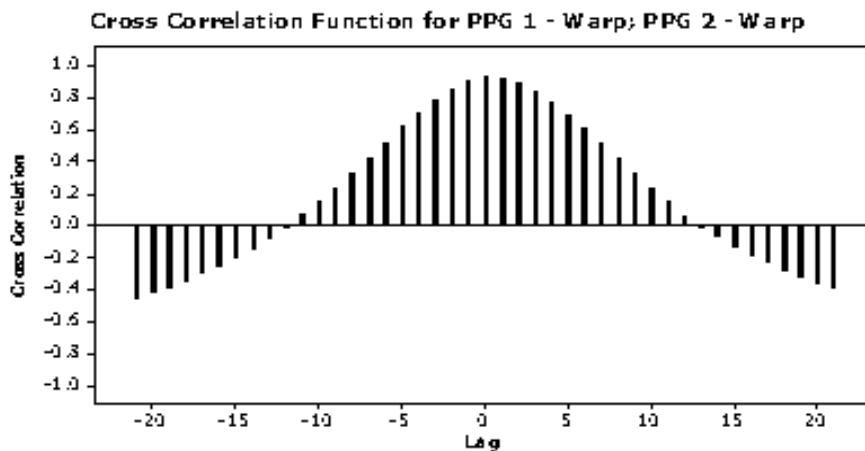


Figure 6 - Cross-correlation function showing a perfect alignment

After the pre-processing stage the PPG signal is stored in the database. The signal will be used to determine the number of heartbeat samples required for the authentication. The signal will also be used to study the impact of the variability due to exercise on the authentication process.

## 5.2 Template Size

Adequate subset of the heartbeats or cycles of the PPG signal must be used for enrolment or to build the biometric template. The variability makes it difficult to



correlate two waveforms from the same person when using many cycles from the PPG waveform.

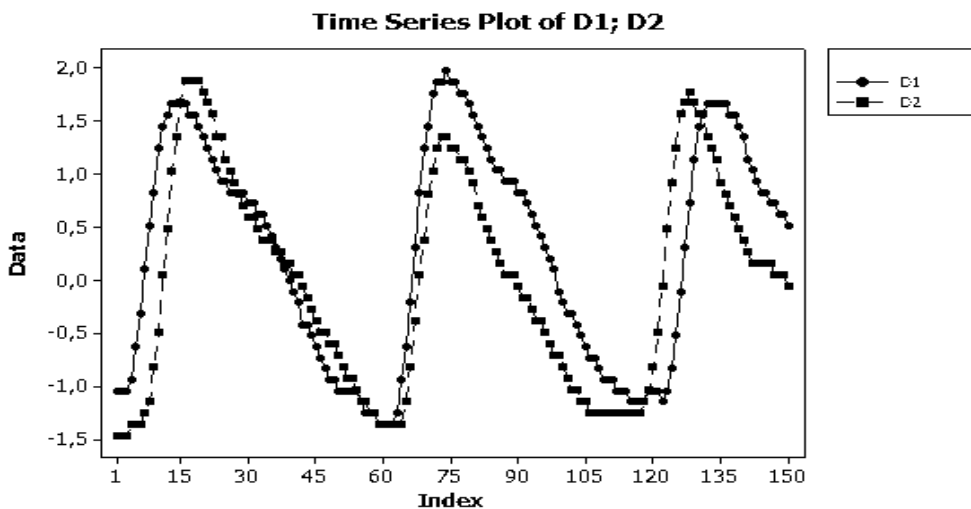
Using the exploratory datasets (involving 3 persons), tests were performed with different sample sizes, showing that it is possible to use 3 heartbeats to achieve the expected discrimination between samples from different users. It was found that the increase in the number of heartbeats will decrease the correlation between the base signal and the subject under analysis. This is due to the large variability found in PPG waveform. The increase in the number of heartbeats used in the authentication from 3 to 5, for example, decreases the cross correlation by about 6%. Using a lower number of heartbeats is desirable to save processing and power resources. However, using a number of heartbeats lower than 3 will decrease the cross correlation value as shown in Table 1.

**Table 1 - Cross-correlation values for different heartbeat numbers**

Number of Heartbeats	2	3	4	5
Cross correlation	0,86	0,903	0,889	0,840

## 6 Data Analysis and Results

Figure 7 shows two samples from the same subject but taken 7 days apart. The subject under test was in resting and relaxed state. The variations are mostly due to the respiration process. A 0.82 cross-correlation value was found between the PPG signal samples of these two days.



**Figure 7 - Two Samples 7 Days Apart**

Another test was performed to identify the impact of exercise on the cross-correlation function between different signals of a subject. PPG signals from the subject in resting state and after some exercise were recorded, as shown in Figure 8. The average cross correlation value between PPG signals from the same subject in resting state would be about 0.91. In this case the cross correlation was computed as 0.25 at the end of the exercise and 0.6 20 seconds after the end of the exercise. The monitoring of the subject under test showed that she would take about 2 minutes to return from exercise, a 15-minute walk or a 4-flight series of stair-climbing. Based on these tests it is possible to identify the individual since the database contains at least one sample from the rest state and another sample of the individual under exercise. The heartbeat variability increases during exercises and it was possible to verify that rise time is more stable than the fall time.

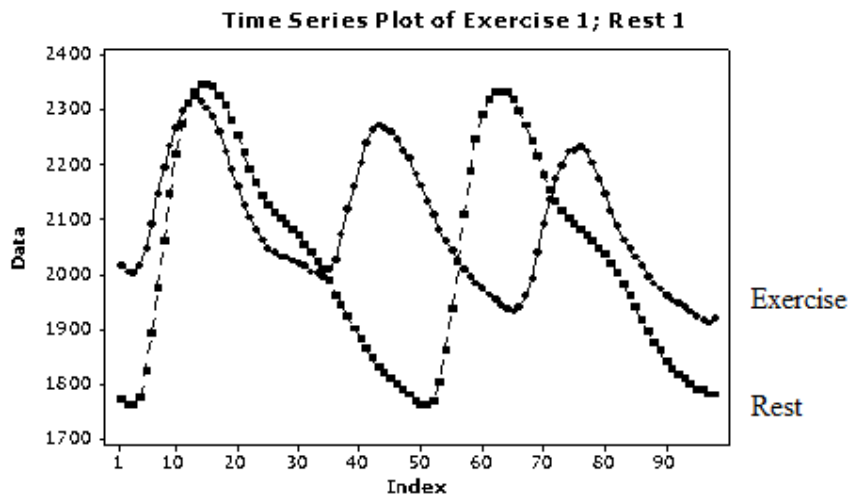


Figure 8 - PPG Signal at Rest and after Exercise

Table 2 shows the cross-correlation between base sample and consecutive samples from the same subject. The low cross-correlation found between S1xS4 and S1xS8 can be explained by problems related to interaction between the sensor and the user.

Table 2 - Cross-correlation between base sample and consecutive samples from the same user

	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
S1	0.84	0.8	0.5	0.85	0.82	0.93	0.76	0.9	0.87	0.89

Table 3 shows the evolution of the cross-correlation over a day. The data was collected each 4 hours and shows the variability present in the signal. The signal was collected in

a controlled way allowing the subject to rest for some time before collecting the data. So the noise due to movement is reduced and the variability is due mostly to respiration or mood.

**Table 3 - Cross-correlation for samples collected over 4 hours monitoring**

	S1	S2	S3	S4
S1	1	0.88	0.84	0.90
S2	0.88	1	0.95	0.94
S3	0.84	0.95	1	0.91
S4	0.90	0.94	0.91	1

Based on the above experiments the PPG signal yields encouraging results when used in continuous user authentication. It appears that is necessary to use at least two samples to allow user authentication along the time, one with the individual in rest state and another one after exercise.

Table 4 shows the cross-correlation between the samples for the 7 subjects involved in our test dataset. It can be seen that it is possible to discriminate the individuals in resting state using the cross-correlation values. The values are based on a 3 heartbeat sample (150 points) and more research must be done to verify the improvement when increasing the number of heartbeat in the sample.

**Table 4 - Cross-correlation values between 7 different users**

	U1-A	U2-B	U3-D	U4-G	U5-J	U6-JD	U7-MJ
U1-A	1	0.4	0.25	0.7	0.7	0.78	0.49
U2-B	0.4	1	0.5	0.5	0.5	0.45	0.6
U3-D	0.25	0.5	1	0.43	0.53	0.44	0.5
U4-G	0.7	0.5	0.43	1	0.66	0.6	0.7
U5-J	0.7	0.5	0.53	0.66	1	0.8	0.55
U6-JD	0.78	0.45	0.44	0.6	0.8	1	0.45
U7-MJ	0.49	0.6	0.5	0.7	0.55	0.45	1

Table 5 shows False Acceptation Rate (FAR) and False Rejection Rate (FRR) over the same 7 users for different cross-correlation values threshold. Lowering false acceptance rate makes false rejects more common, and vice-versa.

**Tabela 5 - Average Values for FRR and FAR over 7 Users**

<b>Threshold</b>	<b>FAR(%)</b>	<b>FRR(%)</b>
<b>0.95</b>	<b>0%</b>	<b>88%</b>
<b>0.90</b>	<b>0%</b>	<b>80%</b>
<b>0.85</b>	<b>0%</b>	<b>35%</b>
<b>0.80</b>	<b>2%</b>	<b>10%</b>
<b>0.75</b>	<b>6%</b>	<b>5%</b>
<b>0.70</b>	<b>18%</b>	<b>2%</b>
<b>0.65</b>	<b>24%</b>	<b>0%</b>

## 7 Conclusions

We have in this paper the use of finger pulse oximetry as a biometric data source for continuous authentication. The PPG signal recorded from this kind of device can provide information to ensure the user identity at the login time and throughout the session.

In this work, we collected data from 10 subjects using different system configurations in order to understand the best configuration to be used in continuous user authentication using this kind of signal.

It was found that lower sample rates and lower resolutions (an 8-bit resolution was used in this work) are enough to achieve proper user identification. This specification is in accordance with requirements to be fulfilled that are low power consumption, low cost and portability. The low power consumption requirement is one of the most important since it is necessary for the device to be incorporated in wearable devices such as a wristband. Also, continuous authentication requires the recording of the signal periodically. The components used in the prototype are low-cost, making it possible to develop a low cost sensor to be used in large scale.

The results obtained from the analysis of 10 users are encouraging, but it is better to acknowledge that these results are still not enough to draw a significant statistical conclusion. Further works will be carried out to maximize data collection with more users to be allowed to draw significant statistical conclusion and to address the noise and motion artifacts found in the PPG signal.

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