A mHealth solution for contact-less self-monitoring of blood oxygen saturation

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***Abstract*—Mobile health (mHealth) technologies play a fundamental role in epidemiological situations such as the ongoing outbreak of COVID-19 because they allow citizen to self-monitor their health status while staying at home and being constantly in remote connection with the physicians despite the quarantine. Special care should be given to self-monitoring vital parameters such as blood oxygen saturation (SpO2), whose abnormal values are a warning sign for potential infection by COVID-19. Measurement of SpO2 is commonly made through the pulse oximeter that requires skin contact and hence could be a potential way of spreading contagious infections. For this reason, contact-less solutions for self-monitoring of SpO2 would be beneficial. In this paper we present a mHealth approach to self-monitor SpO2 that does not require any contact device since it is based on video processing. Video frames of the patient's face acquired by a camera are processed in real-time in order to extract the remote photoplethysmography signal useful to derive an estimation of SpO2. Preliminary experimental results show that the SpO2 values obtained by our contact-less solution are consistent with the measurements of a commercial pulse oximeter used as reference device.**

***Index Terms*—Mobile Health, Self-monitoring, Blood oxygen saturation, Video processing, Photopletismography.**

I. Introduction

During the pandemic of COVID-19 (Coronavirus Disease 2019) citizens are advised to remain in home quarantine and not to leave their home unless it is necessary. In particular, patients should avoid to go outside of their home, even in case of suspicious symptoms. Nevertheless, patients may get worried about small health changes interpreted as symptoms of COVID-19 and may want to get in touch with their medical expert. Abnormal values of vital parameters, such as temperature, heart rate, breath rate and blood oxygen saturation may be early signs of many diseases, including COVID-19. Hence the possibility to self-monitor such parameters staying at home is of fundamental importance to assess in time the patient's health status, triage the patient to appropriate care, and determine potential diagnoses.

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In this scenario, the deployment of ICT technologies for personal healthcare is becoming essential not only to give people the possibility to self-monitor constantly their vital parameters but also to connect them with physicians in every moment. Using personal healthcare solutions, the physician can give his advice by remote leveraging the vital parameters self-measured by the patient and transmitted through a digital platform. The potential for using telematic solutions during disasters and public health emergencies has been highlighted in [1].

Recent developments in the field of Telemedicine have focused on Mobile health (mHealth) services as a new frontier for self healthcare that shifts the monitoring process to a new scenario where the patients use personal mobile devices to monitor continuously their vital parameters directly at home, through the use of smart-home technologies [2]–[4]. The use of self-monitoring systems can provide assistance without limiting or disturbing the patient‘s daily routine, giving greater comfort and well-being. In the specific case of Corona virus emergency, mHealth solutions can play a vital role in restraining the spread of the virus by favouring the early detection of the disease, the synchronization in care delivery, and the continuous patient-physician involvement.

Along with this new proactive paradigm for personal healthcare, in this paper we present a mHealth approach for self-monitoring vital parameters with a focus on blood oxygen saturation (SpO2) whose abnormal values may be a early warning sign of potential infection by COVID-19. Indeed, it has been observed[1] that low values of SpO2 ($< 90\%$) may appear in patients much more before Covid pneumonia first strikes. Usually patients do not feel short of breath, even if their blood oxygen levels are falling. Hence monitoring this vital parameter is of fundamental importance to avoid aggravation of the disease.

To derive an estimate of SpO2, the proposed method processes video frames of the patient's face acquired by a camera. Each frame is processed in real time to extract the remote photoplethysmography signal [5] that measures the

[1]https://www.nytimes.com/2020/04/20/opinion/sunday/coronavirus-testing-pneumonia.html

change of cardiovascular tissue coming from some regions of the face. By processing the photoplethysmographic signal we finally estimate values of blood oxygen saturation. Preliminary experimental results show that the SpO2 values obtained by our contact-less solution are comparable with measurements obtained using a commercial pulse oximeter, achieving measurement errors that are within acceptable margins according to the literature.

The paper is organized as follows. In section II we summarize related works. Section III describes the methodology for SpO2 contact-less measurement. Section IV presents preliminary results. Conclusions are drawn in section V.

II. Related works

Blood saturation indicates the intensity of oxygen in blood and represents the ratio between the oxygenated hemoglobin and the total amount of hemoglobin, i.e. oxygenated and deoxygenated. The medical device commonly used to measure SpO2 is the pulse oximeter (fig. 1), that exploits the different wavelengths of the light absorbed by the oxygenated hemoglobin and the deoxygenated hemoglobin. Specifically, the pulse oximeter exploits photoplethysmography to evaluate the changes in blood volume in the micro-circulation of the human tissues [6]. When a finger is inserted between the light source and the collector, the light passes through the epidermis and meets the blood vessels. Hemoglobin absorbs light and, according to Beer's law [7], the amount of light absorbed is proportional to the concentration of hemoglobin in the blood vessel. One limitation in the use of the pulse oximeter is that it requires direct contact to the skin and its correct use, especially in case of elderly people, may require the presence of a familiar to assist the patient or even the presence of a healthcare professional who knows how to place the device correctly on the patient's finger. In pandemic situations, where social distancing is mandatory, this could give rise to possible outbreaks of contagion, especially in presence of infected but asymptomatic people who come in contact though the use of the pulse oximeter. In this scenario, contact-less solutions for self-measurement of SpO2 would be highly preferable.

In the last years many devices and software systems that allow contact-less monitoring of the vital parameters (including SpO2) have been proposed [8]–[11]. These contact-less solutions are effective but difficult to employ in domestic daily life scenarios. More comfortable and easy of use solutions to support the daily management of diseases are steadily growing

Fig. 1. A pulse oximeter.

[12]–[14], but they require expensive or cumbersome devices, thus preventing their large-scale adoption for personal healthcare. Conversely, there is a need for low-cost and contact-less monitoring solutions that are easy to use, accurate, and can be easily applied at home as well as in other environments.

Among easy-to-use solutions, some attempts based on photopletismography using smarthphone apps have been proposed. For example [15] propose a solution based on a mobile phone to detect the color change signal of a fingertip placed in contact with its optical sensor. In [16] a prototype smartphone application (smartphone oximeter) is proposed to measure heart rate and oxygen saturation. In [17] SpO2 measurements are obtained using the built-in sensor and light source of a Samsung Galaxy S8 smartphone. However, the use of such contact solutions is not safe in a pandemic situation, since touching the smartphone may be a source of infection if the device has not been properly sanitized. Contact-less solutions are preferable during the spread of contagious infections like COVID-19 to avoid the risk of contagion.

Besides, according to the study in [18] smartphone apps that use non-contact photoplethysmography to measure vital parameters appear to have worse accuracy than those that use contact photoplethysmography. By analyzing the limited number of existing smartphone apps for oxygen saturation measurement, the authors suggest that smartphone apps are not very suitable tools for measuring oxygen saturation.

Other contact-less solutions using different sensors have been proposed for oxygen saturation measurement. For example in [19] a contact-less sensor to detect vital parameters is proposed as a useful solution in epidemiological situations like the ongoing COVID-19 outbreak. The sensor, called Impulse Radio Ultra-Wideband (IR UWB) enables measuring the change in the magnitude of signal due to displacement caused by human lungs, heart during respiration and heart beating. Hence the respiration rate and heart rate can be measured. However the blood oxygen saturation can not be measured using this technology.

The current state-of-art literature shows that the most suitable sensor for remote measurement of SpO2 is the video camera that satisfies both easy-of-use and contact-less requirements. There are many recent works using a camera combined with remote photopletismography (PPG) to evaluate vital parameters [20]–[22]. PPG techniques have been widely used in healthcare for monitoring purposes. In [23] for monitoring dialysis patients, in [24] for arrhythmia detection, in [25] for neonatal monitoring, just to mention few. Moreover, very recent works are going to improve photoplethysmography techniques [26] by modifying existing RGB cameras to make them suited for near infrared remote photoplethysmography (NIR-PPG). In [27] SpO2 is measured by processing videos acquired by a camera. The videos are analyzed through the Eulerian video magnification (EVM) method to amplify the skin colour changes due to the cardiac cycle. However SpO2 values are not evaluated in real-time, but on the basis of pre-recorded video. This makes this solution less usable for self-monitoring at home or for instant screening in hospitals.

Moreover, pre-recorded videos introduce privacy issues that should be taken into account when adopting such a solution. Rather, a real-time processing of videos is preferable.

Based on the above analysis, we observe that the most suitable sensor for remote measurement of SpO2 is the video camera that satisfies both easy-of-use and contact-less requirements. In this paper, we propose the use of a camera for non-contact and real-time measurement of the blood oxygen saturation based on face video processing and remote photopletismography. The resulting solution has the following key features:

- it does not require any specific or expensive medical device;
- it can run on any mobile device equipped with a camera (smartphone, laptop, tablet);
- it does not require storing of videos thus avoiding privacy issues or need for encryption;
- it can be easily used by the patient with no need of touching the device;
- it is extremely fast, providing a reliable SpO2 measurement in a couple of seconds.

III. Contact-less measurement of SpO2

Our approach for contact-less measurement of blood oxygen saturation is based on a combination of Signal processing and Computer Vision techniques. A short video frame sequence capturing the face of the user is processed to extract the remote photoplethysmography signal [5] that measures the change of cardiovascular tissue in some regions of the face. The underlying principle is that the impulse of cardio-vascular wave that flows through the body periodically, causes stretch in the vessel walls, with consequent fluctuations in blood volume. These fluctuations modulate the absorbency of light passing through a given volume of tissue, so it is possible to evaluate the variation of light during a normal cardiac cycle. According to [28], an estimation of SpO2 can be obtained by considering the cardiovascular pulse wave signal at two different wavelengths, namely the red and blue bands, being the blue band representative of the infrared wavelength used in the traditional pulse oximeter. Following this approach, we developed a method to measure SpO2 by processing frames in a short video. The method is composed of four main phases (fig. 2) that are detailed in the following.

A. Face detection

In the first step, real-time face video are acquired through the video camera and 24-bit RGB color representation is used. Three different channels, each of 8 bits/channel with a resolution of 480×200 pixel are extracted. A preliminary acquisition cycle of 26 seconds is performed to remove the initial camera distortion, and then successive frames are acquired every 2 seconds. The *OpenCV*[2] Python library is used for frame acquisition and processing. The pre-trained frontal face detector available with the Python library *Dlib*[3] is used to detect the face in the image frame. Given the detected face, we apply a Facial Landmark Detection[4] to obtain a set of 68 facial landmarks [29], [30].

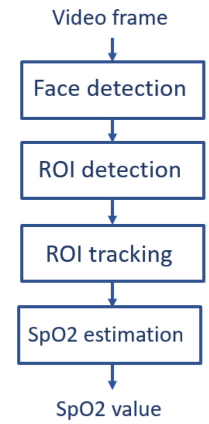

Fig. 2. Methodological pipeline.

B. ROI identification

The face landmarks obtained from the previous phase, are processed to localize regions of interest (ROIs). We consider three ROIs, one rectangular area (20×30 pixels) centered on each cheek and one rectangle (90×30 pixels) centered in the forehead. Indeed, the cheeks and the forehead are the most suitable areas to detect the photopletismographic signal [5]. Moreover the use of different ROIs enhances the effectiveness and the usability of the system. Indeed if one of the regions is totally or partially occluded, as for example hairs/hat on the forehead or beard and glasses on cheeks, the pletismographic signal can be still inferred from the remaining visible regions or from sections of regions that are not interested by the occlusion. Furthermore, ROIs have been located in the face so as to involve as much skin as possible. Figure 3 shows the location of the ROIs in the face frame. It can be observed that despite the presence of glasses occluding a small portion of the cheeks ROIs, there is still a large part of skin that is used for the analysis.

Rather than combining the three extracted ROIs, we select the most informative one to derive SpO2 values, after several pre-processing steps, as described in the following paragraphs.

C. ROI tracking

After initial localization, all the ROIs are tracked in subsequent frames so as to reduce undesired effects due to head movements and allow the user to be more natural and less static in front of the camera. To track all the ROIs in a robust way, an additional rectangular area sized 75×80 pixels (fig. 3) is considered in the centre of the face so as to join together the three ROIs (forehead and cheeks). Then a set of tracking points is extracted from the central ROI using the

[2]OpenCV: https://pypi.org/project/opencv-python/

[3]Dlib: http://dlib.net/

[4]Facial Landmark Detection: http://dlib.net/imaging.html#shape_predictor

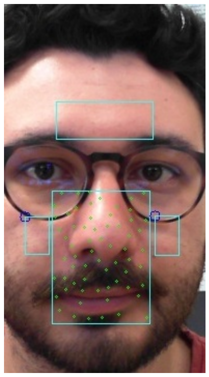

Fig. 3. Location of ROIs and tracking points.

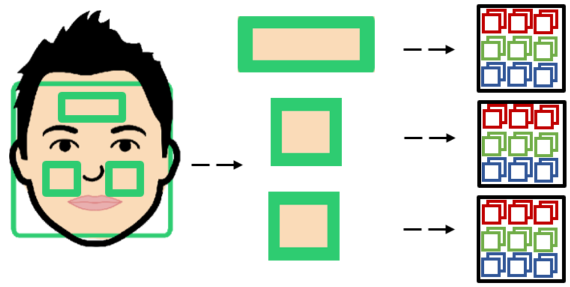

Fig. 4. Separation of ROIs into RGB channels.

method in [31]. These points are then tracked through the Kanade-Lucas-Tomasi (KLT) tracking method [32] using the APIs[5] implemented in OpenCV library. This method creates a transformation matrix that describes the movement of the face between subsequent frames. Using such a matrix, the coordinates of the tracking points as well as the corner points of all the ROIs in a frame are transformed into new coordinates in the subsequent frame according to the movements of the face.

D. SpO2 estimation

The next step is the analysis of the RGB signals coming from the ROIs marked in each video frame of a short sequence (here 2sec of video are considered) in order to estimate the oxygen saturation in blood. Each ROI is separated into the three RGB channels (fig. 4) and then each channel is averaged over all pixels of the ROI:

$$V_R = \frac{\sum_1^n \sum_1^m R_i}{nm} \quad V_G = \frac{\sum_1^n \sum_1^m G_i}{nm} \quad V_B = \frac{\sum_1^n \sum_1^m B_i}{nm}$$

where $n \times m$ is the dimension of the ROI. For each ROI, the average signals (V_R, V_G, V_B) are collected on the N frames of the sequence, hence we obtain a final signal matrix V_{RGB} with $3 \times N$ dimensions.

Signals in V_{RGB} pick up a mixture of the reflected plethysmographic signal along with other sources of fluctuations in light due to artifacts such as motion and changes in ambient lighting conditions. To avoid noise due to the motion and fluctuations in image lightness, the V_{RGB} signals are improved through a preprocessing phase. Firstly, to reduce the high-frequency noise in signals, a *Finite Impulse Response* (FIR) filter with window method[6] is used [33]. Then, to enhance the robustness to motion and illumination variations, the chrominance-based method [34] is applied. In addition, since during the real-time acquisition of video frames it may happen that the signal is not uniformly captured, a linear interpolation is applied to the acquired signal in order to guarantee a uniform sampling of the signal. Finally, we use Power spectral density (PSD) through Welch's method [35] to select the most informative ROI. Indeed, the ROI with the maximum value of PSD is considered for the SpO2 evaluation.

After the preprocessing phase, the signal of the selected ROI is processed in order to compute an estimate of the SpO2 value. As suggested in [28] SpO2 can be estimated by considering the cardiovascular pulse wave signals at two different wavelengths (660nm and 940nm), by comparing the red and blue bands. Precisely, SpO2 is estimated according to the formula:

$$SPO_2 = A - B \frac{AC_{RED}/DC_{RED}}{AC_{BLUE}/DC_{BLUE}} \tag{1}$$

where the AC_{RED} and AC_{BLUE} are computed as the standard deviations of the red and blue signals in V_{RGB}, while DC_{RED} and DC_{BLUE} are computed as the mean of red and blue values. We fix the coefficients $A = 125$ and $B = 26$ according to the empirical evaluation made in [28].

The above described process enables estimation of blood oxygen saturation in real-time, taking only a couple of seconds to obtain the SpO2 value.

IV. Experiments

In order to verify the effectiveness of the proposed method, a set of measurement comparisons has been carried out, by using pulse oximeter values as baseline. The adopted Fingertip Pulse Oximeter has a SpO_2 range of 70-99% with accuracy $\pm 2\%$ (for values below 70% the accuracy is undefined).

A total of 21 subjects, differing by age, gender, lifestyle, were involved in the study. In this preliminary work all the subjects were healthy, since due to the limitations imposed during the COVID-19 emergency, collecting measurements of sick people has not been possible. For a fair comparison, blood oxygen saturation of each subject was measured by using the pulse oximeter and our contact-less solution running on a laptop equipped with a camera. Microsoft LifeCam HD[7] has been used. This is quite small camera (3.44" length, 1.57" width) and it is provided with autofocus and with a HD

[5]KLT tracking method: https://docs.opencv.org/2.4/modules/video/doc/motion_analysis_and_object_tracking.html

[6]FIR filter: available through the Python library Scipy https://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.signal.firwin.html

[7]https://www.microsoft.com/it-it/p/lifecam-studio/91dt6wmfdlb3?activetab=pivot\%3aoverviewtab

1080p sensor that guarantees high sharpness and quality of the acquired images. An empirical study, with different cameras, has shown that autofocus and at least 30 fps are the minimum requirements for accurate results.

The experiments were conducted indoors and with a normal amount of sunlight as the only source of natural illumination. However, it is worth noting that, the influence of the light on the measurements has been minimized by using the chrominance method.

Each subject was asked to frame his face in front of the camera staying at a distance of approximately 50cm, resting in state of spontaneous breathing. The system has been designed to be user friendly. Icons and short messages have been used to communicate with the users. If the distance between the camera and the user is too short/long, a message will be eventually shown to communicate that the user needs to move closer or further to the camera. User position is continuously checked to assure the correct acquisition. However, since only two seconds are necessary to acquire the SpO2 values, once the user reaches a good position the system is ready to collect new measurements.

The tracking system allows more precise measurements by compensating possible head movements as rotation. Indeed in case of movements, thanks to the KLT method, the user face, together with the selected ROIs will still be tracked.

For each subject, ten successive measurements were taken (every 2sec) with both the devices. Figure 5 plots the average value of SpO2 computed on the 10 measurements obtained by our contact-less method and the pulse oximeter for each subject. Figure 6 shows the absolute error (AE) between these pairs of measurements. It is clear that on the average the proposed solution is able to estimate the SpO2 value with a good approximation of the baseline given by the pulse oximeter. Indeed for 8 measurements we observe $AE = 0.0$, for 6 mesurement $AE \leq 1.0$ and for the remaining 7 measurements $AE \leq 2.0$. We emphasize that the highest value of AE is still an acceptable, indeed SpO2 is valid if the mean bias is within $\pm 2\%$ [16].

Moreover, the Bland-Altman (B&A) analysis was conducted to assess and visualize Level of Agreement (LoA) between the proposed method and the pulse oximeter. Figure 7 shows the B&A graph that plots the differences in the SpO2 measurements between the pulse oximeter and the proposed solution and defines the intervals of agreements according to the B&A analysis. The solid line represents the mean bias. The two dotted lines represent the lower and upper limits of agreement (LoA). Typically B&A recommends that 95% of the differences are expected to be within these LoA for a reliable measurement. From fig. 7 we can observe that there is agreement between the two measurements since all the points except one are within the LoA.

Leveraging these preliminary results, we can conclude that SpO2 measurements obtained by the proposed contact-less solution approximate quite well measurements given by the pulse oximeter, with the added value of avoiding contact-based usage that could be a means of infection transmission.

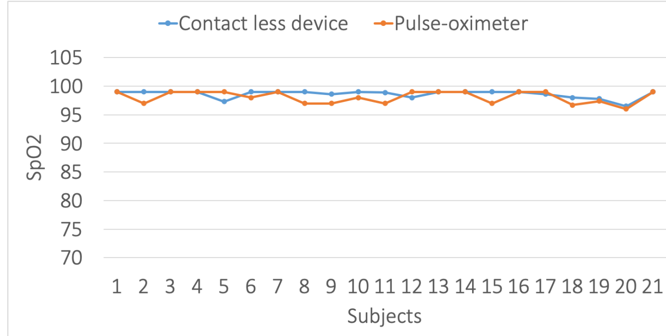

Fig. 5. Pulse oximeter and contact-less device measurements.

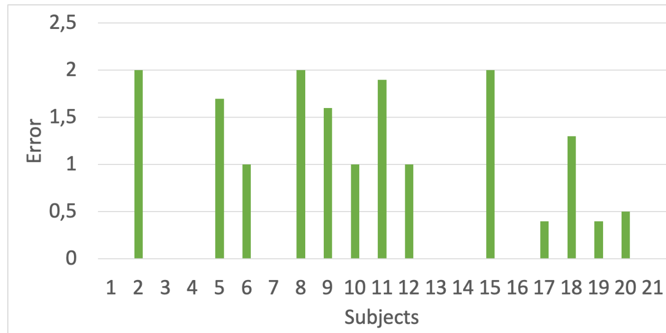

Fig. 6. Absolute errors.

V. Conclusion

In this paper a mHealth solution for self-measurement of blood oxygen saturation has been presented. The key feature of our solution is the use of a contact-less sensor (a video camera) that acquires video frames of the face from which the plethysmographic signal is extracted and finally an estimate of the saturation is derived. The proposed solution allows a continuous personal control of the blood oxygen saturation at the patient's home, avoiding the use of medical measuring devices (e.g. saturometers, pulse oximeters), but simply using a mobile device equipped with a camera. Microsoft LifeCam has been used for data acquisition, further experiments will be conducted to test how different features of the camera could affect the accuracy of the estimate of SpO2.

Preliminary experimental results on a small sample of users are encouraging, since they show that the SpO2 measurements obtained by our solution are comparable to those obtained by a commercial pulse oximeter. Of course, to better asses the reliability of our approach a larger number of tests should be carried out, by involving not only healthy people but also sick people, with special focus on patients with symptoms suggestive of COVID-19 infection. Moreover the influence of different factors such as healthy life style, smoke, disease family history, etc., on SpO2 measurements, will be investigated. These further experiments require special permission from healthcare organizations that we were not able to obtain due to this emergency period.

The proposed solution can be easily extended to find application in several healthcare scenarios. Firstly, if enriched with a videoconference tool, our solution may also allow a real-time remote interaction between the patient and the physician who can give his advice by remote leveraging the vital parameters self-measured by the patient. This is especially useful for patients that are not allowed to leave their home due to quarantine such as the one imposed by the current COVID-19 outbreak. In this view, our solution is suitable to intervene in continuity with the organizational model for emergency management, providing a valid tool to support the telephone triage of citizens and to facilitate what the latest Italian ministerial guidelines call ”Special Units of Continuity of Care (USCA)”.

Another possible extension that we foresee is to add the measurement of other vital parameters (e.g. temperature, heart rate,...) and use the enriched monitoring solution for COVID-19 screening of visitors including doctors, nurses, medical and non-medical staffs at entrances of hospitals or other places characterized by large inflows. In this case the solution could be well integrated in a social robot (equipped with a camera and a tablet) that measures vital parameters while welcoming visitors at the entrance. An example of this type of application has been recently experimented at the Fortis Hospital (Bangalore, India) as a bid to protect the healthcare workers from COVID-19 contagion[8].

Finally, it should be noted that the proposed solution can improve care non only for CoVid patients at home, but also for chronic patients, especially those affected by cardiovascular diseases. In this case more ergonomic devices could also be employed. An example is given in [36] where a variant of our method, including also heart rate measurement, runs on a laptop integrated in a mirror equipped with a camera. The resulting device is an object of daily use that enables a natural self-monitoring of vital parameters through the simple gesture of looking at oneself in a mirror. This is especially comfortable for elderly people who may have difficulty to auto-monitor their vital parameters through the use of common mobile devices.

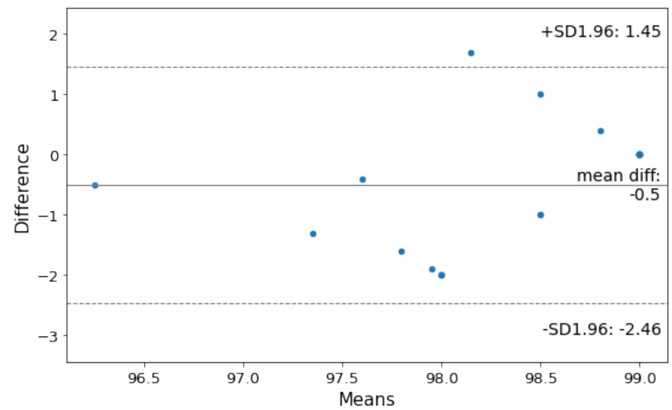

Fig. 7. Bland-Altman plot.

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