Monitoring Cardiovascular Risk by Video Processing and Fuzzy Rules

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Abstract. To measure vital parameters, traditional devices are equipped with sensors that need to be used through contact with the subject's skin. In recent years photoplethysmography has been developed as a contactless method to monitor vital signs. Thanks to this method, difficulties concerning the detection of parameters through contact devices can be overcome, especially in elderly subjects. In this work we use remote photoplethysmography to estimate cardiovascular parameters through the use of a contactless device equipped with a reflective mirror and a webcam that captures video frames of people's faces. Besides, we use the clustering technique to automatically estimate the lips colour. Finally, the measured parameters are used as input to fuzzy inference rules integrated into our system, in order to predict cardiovascular risk.

Keywords: Contact-less monitoring · Photoplethysmography · Signal processing · Video imaging · Personal health care · Fuzzy inference system · Cardiovascular disease.

1 Introduction

According to a 2015 report[3], cardiovascular diseases are one of the leading causes of death in the world. Therefore, monitoring cardiovascular functions is essential to prevent the onset of chronic diseases and carry out therapies in an appropriate manner. In order to detect the risk level of cardiovascular diseases [5], it is essential to continually monitor vital parameters, such as heart rate, breathing rate and arterial blood oxygen saturation. One of the most common techniques to correctly estimate vital parameters is using a device such as an electrocardiogram (ECG). It is equipped with electrodes that require contact with the subject's skin. For this reason, ECG becomes an invasive device, whose intensive use, as well as the incorrect positioning of its electrodes, may irritate the subject's skin. Another low-cost non-invasive technique that detects the cardiovascular pulse wave through variations in transmitted or reflected light is photoplethysmography (PPG). Through PPG, it is possible to obtain values such as heart rate,

[3] www.who.int/healthinfo/global_burden_disease/estimates/en/index1.html (accessed on 2 March 2018).

arterial blood oxygen saturation, blood pressure, cardiac output and autonomic function [1]. In recent years, through the use of digital cameras and video image processing algorithms it has been possible to measure the values of heartbeats by PPG. Verkruysse's work [14] introduced the remote plethysmographic (RPPG) signal captured through a camera containing this signal. The vital parameters are then estimated through the use of image processing and blind source separation [11].

This paper provides a synthetic description of the ongoing PhD research activity of the author. A more detailed description can be found in [10, 3, 2]. The goal of the research is to develop an innovative solution for non-contact monitoring of vital signs that satisfies both low-cost and comfort requirements and acts as a decision-making system to support medical diagnosis of cardiovascular disease. The proposed monitoring system is based on a see-through mirror provided with a camera to acquire video frames of the mirrored face of the person. Using photopletismography, the video frames are processed in order to derive an estimate of vital parameters such as Heart Rate (HR), Breathing Rate (BR) and Oxygen Saturation in blood (SpO_2). As an additional vital sign, lips colour is automatically detected using clustering-based color quantization. Unlike other existing contact-less monitoring solutions, that are oriented only to measure vital parameters, the proposed solution integrates an intelligent component that provides for a support to medical diagnosis of cardiovascular disease. This component uses fuzzy IF-THEN rules to infer a cardiovascular risk level starting from the values of the vital parameters.

The proposed solution is a cheap device that is easy to use, lending itself very well for domestic use as well as for telemedicine applications.

2 Materials and Methods

This work proposes a solution for real-time estimation of cardiovascular parameters without the use of contact sensors, but with the use of a see-through mirror equipped with a HD camera that acquires the video frames of human faces and processes the signal from facial blood vessels to measure heart rate, breathing rate and blood oxygen saturation values. Our aim is to create a smart personal monitoring device made of a few assembled low-cost HW components. The principal device is a see-through mirror which has a 12" $\times$ 12" 3mm thick acrylic film that is partially reflective and partially transparent. A monitor is put in the darker side so that the output of the system can be displayed through the mirror. A Microsoft LifeCam has been used to ensure high images quality and sharpness. It is quite small and is equipped with autofocus and a 1080p HD sensor. This type of camera has been integrated with the see-through mirror to ensure quality video images. Two LED strips, each composed of 18 LED lights, have the following features: 12V, 6.0W, 0.5A and 120° beam angle. They have been placed on both sides of the frame to ensure good lighting during the acquisition phase of the video frames. The HW equipment is completed by a client/server architecture. The client is a Raspberry pi 3 board, which sends frames to the server that processes them to perform the signal analysis. In the current prototypical version of the system, the server is a desktop computer equipped with CPU Intel(R) Core(TM) i5-5200 2.20GHz 64 bit, 4GB RAM and 500GB hard disk.

The software architecture of the system includes a back-end and a front-end module. The front-end module acquires the video frames through a camera and sends them to the back-end module. The back-end module runs a face tracker within the video frames and localizes the region of interest (ROI) useful to estimate the vital signs. A pretrained frontal face detector is used to detect the face within video frames, which is available with the library Dlib [7]. Given the face region identified by the face detector, we localize the ROI [12] corresponding to a region with a strong passage of blood modulation, so as to enable evaluation of vital signs by means of PPG. Specifically, the ROI is separated into the three RGB channels and spatially averaged overall pixel to yield a red, blue and green measurement value for each frame. These values are processed to derive a PPG signal that is susceptible to motion-induced signal corruption and for this reason we applied a filtering phases [8, 13]. Then, we applied Independent Component Analysis (ICA) [4] and Fast Fourier Transform (FFT) to detect the vital signs. Finally, the values were sent back in JSON format to the front-end module, which shows them graphically to the user through the mirror.

In order to evaluate the health condition, lip color has been used as an additional parameter. Normal people show lips with a pinkish nuance, while altered states or illness may provoke a modification of this color. Using image processing techniques applied to a specific ROI acquired from an image of the patient's face, we automatically detect the lip color. ROI is processed after lips are detected and isolated. Then the dominant colour is classified as "regular", "altered" or "purplish". In order to quantify the lip color and detect the dominant color in the ROI, we apply a K-Means clustering with $k = 3$. Then, by means of K-Means algorithm, we obtain a histogram with the percentages of the three main colors expressed in RGB format. Finally, we convert the value of the dominant color into hexadecimal, associating it to a nominal label with the help of the library "$NameThatColor$"[4]. We developed a Fuzzy Inference System (FIS) with the help of the physician once all the parameters had been obtained. On the basis of the estimated vital signs, fuzzy rules have been defined to support the diagnosis of cardiovascular disease by assessing a risk level. The linguistic input variables created are HR, BR, SpO_2, $LipsColor$, which represent the measured vital signs. Furthermore, the output variable called *RiskLevel* represents the level of risk for cardiovascular disease. Besides, for each linguistic variable, we combined the linguistic terms with the relative fuzzy set. Finally, we obtained a total of 81 rules by defining a rule for each combination of input and output fuzzy values.

[4] `http://chir.ag/projects/name-that-color/`

3 Preliminary results

We have conducted two experiments. In the first experiment we involved healthy people, for a total of 25 participants (19 males, 6 females) from 18 to 65 years old and with varying skin colors. In the second experiment, we considered a sample of 10 subjects (5 females and 5 males) from 66 to 96 years old. All subjects were elderly people with cardiovascular diseases undergoing pharmacological treatment. During the experiments, HR and SpO2 values were collected simultaneously from our system and through a Finger tip Pulse Oximeter worn by the subjects. Then measurements from these two different sources were used for comparison. We considered the pulse oximeter for comparison because it is based on PPG that is the same principle underlying our device. A comparison with the use of ECG was avoided because it is based on a completely different approach.

In each test the subject was sitting in front of the mirror for 1 minute at a distance of 50cm ca. from the integrated HD camera. In Table 1 we summarize the statistics computed on the difference between the pulse oximeter and our device. The measurements obtained by our device are, in most cases, comparable to those of the pulse oximeter. It can be seen that the error increases in case of unhealthy people. This was due to the fact that most of unhealthy people involved in the tests were elderly subjects who had difficulties in standing still in front of the device because of their neurological problems (for example, Parkinson's disease [6]) . However, the results are in agreement with the literature [11, 9] since the average difference falls within 5 bpm, which is in an acceptable margin of error.

	all subjects	healthy subjects	unhealthy subjects
HR	3.45 ± 2.93	2.87 ± 2.39	4.90 ± 3.74
SpO_2	1.83 ± 2.43	1.54 ± 1.76	2.56 ± 3.63

Table 1. Mean absolute error and standard deviation obtained by comparing our contact-less system and the pulse oximeter.

We constructed a dataset by measuring and collecting the four vital signs of 116 people. In this way, the effectiveness of the fuzzy rule-based system in simulating the decision of the expert has been tested. A second physician, different from the physician responsible for building the fuzzy knowledge base, has been involved to label the dataset, have a different expert opinion and make a more reliable validation process. Thanks to his knowledge and experience, the physician first observed the measured life signs and then assigned them a risk label. The labelled dataset represents the ground truth for the evaluation of the diagnostic results obtained with the developed FIS. We have applied the inference of fuzzy rules to obtain a risk label (Low, Medium, High, or Very High) for each subject of the dataset.

Risk class	ACC	TNR	TPR	PPV	NPV	TP	TN	FP	FN
Low	0.83	1	0.77	1	0.6	66	30	0	20
Medium	0.75	0.76	0.57	0.13	0.96	4	83	26	3
High	0.91	0.94	0.50	0.4	0.96	4	102	6	4
Very High	0.88	0.96	0.40	0.6	0.91	6	97	4	9

Table 2. Classification results.

For each of the four output classes, we evaluated the accuracy together with additional measures that are commonly considered in classification tasks. In particular, while analyzing a single class c, we consider accuracy (ACC), true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

Moreover we considered:

Positive Predictive Value: $\text{PPV} = \frac{\text{TP}}{\text{TP+FP}}$ Ratio of correctly classified samples w.r.t. those identified as pertaining to class c

Negative Predictive Value: $\text{NPV} = \frac{\text{TN}}{\text{TN+FN}}$. Ratio of correctly classified samples w.r.t. those identified as not pertaining to class c

True Positive Rate: $\text{TPR} = \frac{\text{TP}}{\text{TP+FN}}$. Ratio of samples correctly classified as belonging to class c w.r.t. those actually belonging to class c

True Negative Rate: $\text{TNR} = \frac{\text{TN}}{\text{FP+TN}}$. Ratio of samples correctly classified as not belonging to class c w.r.t. those actually not belonging to class c

The values of these measures evaluated for each class are reported in Table 2. It can be seen that in general the TNR and NPV values are greater than those of TPR and PPV. This means that the fuzzy system is more effective in determining the non-membership to each class than the sensitivity to each specific class. This could be related to the unbalancement of the dataset.

4 Conclusion and future works

One of the main research areas in the field of biomedical engineering is the design of non-invasive and low-cost solutions for monitoring vital parameters. Our aim is to create easy-to-use accurate solutions that can be used both at home and in clinics. With our system, vital signs can be monitored at home in a comfortable way, without the need for additional invasive or even expensive medical devices. Our solution represents an innovative and smart object that can be of extremely useful in the field of Personal Healthcare. It was intended to be used for daily personal monitoring of vital signs. This system is a proof-of-concept methodology that still needs refinement. Nevertheless, results of experiments have shown that it provides effective measurements of vital signals as well as a reliable intelligent component based on fuzzy rules, which is able to simulate the expert physician decision. In our future works, we aim to improve our methodology through the acquisition of more data from ill people, and the integration of information such as demographic characteristics and patients and their family's history. We aim to carry out large-scale tests with patients suffering from cardiovascular diseases, through machine learning methods to automatically learn fuzzy rules from data.

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References

1. Allen, J.: Photoplethysmography and its application in clinical physiological measurement. Physiological measurement **28**(3), R1 (2007)
2. Casalino, G., Castellano, G., Castiello, C., Pasquadibisceglie, V., Zaza, G.: A fuzzy rule-based decision support system for cardiovascular risk assessment. In: Fullér, R., Giove, S., Masulli, F. (eds.) Fuzzy Logic and Applications. pp. 97–108. Springer International Publishing, Cham (2019)
3. Casalino, G., Castellano, G., Pasquadibisceglie, V., Zaza, G.: Contact-less real-time monitoring of cardiovascular risk using video imaging and fuzzy inference rules. Information **10**, 9 (2018)
4. Comon, P.: Independent component analysis, a new concept? Signal Processing **36**, 287–314 (1994)
5. Cook, S., Togni, M., Schaub, M.C., Wenaweser, P., Hess, O.M.: High heart rate: a cardiovascular risk factor? European heart journal **27**(20), 2387–2393 (2006)
6. Diaz, M., Ferrer, M.A., Impedovo, D., Pirlo, G., Vessio, G.: Dynamically enhanced static handwriting representation for parkinson's disease detection. Pattern Recognition Letters **128**, 204–210 (2019)
7. Kazemi, V., Sullivan, J.: One millisecond face alignment with an ensemble of regression trees. 2014 IEEE Conference on Computer Vision and Pattern Recognition pp. 1867–1874 (2014)
8. Kranjec, J., Begus, S., Gersak, G., Drnovsek, J.: Non-contact heart rate and heart rate variability measurements: A review. Biomed. Signal Proc. and Control **13**, 102–112 (2014)
9. Lam, A., Kuno, Y.: Robust heart rate measurement from video using select random patches. 2015 IEEE Int. Conf. on Computer Vision (ICCV) pp. 3640–3648 (2015)
10. Pasquadibisceglie, V., Zaza, G., Castellano, G.: A personal healthcare system for contact-less estimation of cardiovascular parameters. 2018 AEIT International Annual Conference pp. 1–6 (2018)
11. Poh, M.Z., McDuff, D.J., Picard, R.W.: Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. Optics express **18**(10), 10762–10774 (2010)
12. Rouast, P.V., Adam., M.T.P., Chiong, R., Cornforth, D., Lux, E.: Remote heart rate measurement using low-cost rgb face video: a technical literature review. Frontiers of Computer Science **12**, 858–872 (2016)
13. Tarvainen, M.P., Ranta-aho, P.O., Karjalainen, P.A.: An advanced detrending method with application to hrv analysis. IEEE Transactions on Biomedical Engineering **49**, 172–175 (2002)
14. Verkruysse, W., Svaasand, L.O., Nelson, J.S.: Remote plethysmographic imaging using ambient light. Optics express **16**(26), 21434–21445 (2008)