Stress Detection of Human Using Heart Rate Variability Analysis Based on Low Cost Camera

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***Abstract*— The article presents a non-contact solution to a stress detection. Computer human interfaces must be able to consider human's emotions. Being able to detect a stressful situation has several applications: Secure and assist Computer -Human Interfaces, telemedicine, driving assistance. This capacity allows to detect the user's state and improve the interface 's performance. We proposed a method based on a stress classification system with a sensor in contact and we compared with different classification methods based on sensors in contact. Our solution is based on a facial analysis obtained by image processing.**

Keywords-Vision; Stress; Photoplethysmography; Neural network; SVM; K-NN.

I. Introduction

Stress is a physiological response to a disturbing situation. Stressful situations can compromise not only our quality of life, but also our health, our ability to control when we are in a human-machine loop, for example man-vehicle interaction. The ability to detect a hazard is very important, but the human being is not able to objectively perceive physiological symptoms of this situation in real-time. This ability would have a lot of applications: medical, security, driving assistance, etc, and especially in the field of interactive systems. For example, for a human to be able to safely interact with new technologies (with a man-machine interface), it would mean to have the capability to detect his apprehension towards this new technology, or simply to be able to assist a novice use.

Today, there are many tools for person's stress detection. Two categories of devices can be distinguished: in-contact devices called invasive, and without-contact devices called non-invasive. Each solution may have advantages or disadvantages compared to others depending on the desired application. ElectroCardioGraphy (ECG), for example, is used for clinical applications; it measures the electrical activity of the heart to study its functioning. It can actually detect stress from variations in heart rate [1][2]. This method allows to calculate the statistical characteristics related to the intervals RR (the duration between two heart's beats) and to be able to deduce the various behaviors related to the heart (precisely to the heart rate). This solution is not adapted for an embedded application given the cost constraints and the invasiveness of this system. Electrodes are placed on the body of the person using adhesive patches to make the necessary measurements. This in-contact instrumentation is a psychological barrier since the solution is causing irritation and discomfort. There are also other solutions as Galvanic Sensor Response (GSR), which is not the subject of the article, but it is used for the test.

The purpose of this work is to show that it is possible to classify a person's stress from the physiological data captured by a low-cost camera. The main challenge of this solution is to have a sufficiently powerful system while considering the constraints related to the change of brightness of the environment especially for embedded applications and movements related to the system and the user.

The article is organized in several parts: In Section 2, we present the different solutions around the estimation of heart rate and stress. In Section 3, we describe in more detail the chain of acquisition set up to estimate the stress of a person from a camera. In Section 4, we present the evaluation protocol and the different results obtained by classification methods to build a model and the comparison between these different methods. Finally, a conclusion summarizes current findings, limitations and future work.

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II. CONTEXT AND RELATED WORK

In recent years, several studies have been conducted on the use of cameras as a system for measuring cardiac activity to assess a person's stress. It is now possible to measure the fine colorimetric variations of the skin generated by the heartbeat, using a conventional camera. This process, already used by optical sensors in contact, is now exploitable using standard equipment such as the basic camera provided on laptops accessible to the public. Researchers as Poh [3], Takano [4] and Verkruysse [5] have shown that it is possible to estimate heart rate from a person's face images. More recently, more complex solutions have been developed, not only allowing a simple estimate of heart rate, but a much more thorough analysis of cardiac activity. This analysis is based on the Heart Rate Variability (HRV), which is the study of the time's variation between the heart's beats. We choose to study the HRV because the set of measurements that compose it provides relatively diverse information, both in terms of cardiac activity, breathing or even the autonomic nervous system. Works like those of Bousefsaf [1], McDuff [6], Park [7] and Kaur [8] have shown that camera can be used to achieve a viable system of measurement of HRV to detect person's stress. This is a big step forward compared to a simple estimate of the heart rate.

Several reasons led us to choose this solution. It is a non-invasive method which clearly increases the user's comfort: the sensors in contact can generate discomfort, and even constitute a risk factor for medical applications. In addition, this solution does not require any tool to be developed, all computers are now equipped with a camera. For example, the camera used for our prototyping is a Pi camera [9]. Finally, the use of a camera allows us to perform other simultaneous processing such as example the detection of emotion from the facial expressions using the same images.

III. SYSTEM ARCHITECTURE

The objective is to show that it is possible to estimate a person's by classifying the physiological data from processed images of a low-cost camera that is accessible to everyone for various applications. The challenge of this choice of solution is the use of a low-definition camera that can present a loss in terms of performance. We propose a chain of acquisition (presented in Figure 1), which uses a camera to classify the physiological data to estimate the stress by ensuring comfort and a non-invasive solution. We also compared this solution with the results obtained with a PPG contact sensor (PhotoPlethysmoGraphic sensor) that allows us to estimate the heart rate and to study its variability to estimate the stress of a person. The first step in our work will therefore be to create a reliable system for measuring heart rate variability from a camera. From this measurement, we can extract parameters on the variability of the heart rate, which informs us about the stress of the person. The variation in time between heart beats represents the HRV, which offers many useful measures in the study of stress.

Figure 1. General method

The last step in our acquisition chain is the classification of stress indirectly through the classification of physiological data from processed images of a camera.

A. *PPG Signal Acquisition and Training*

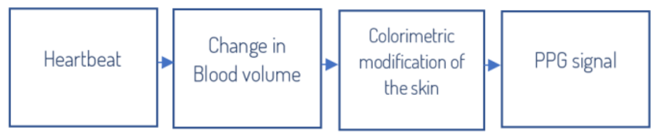


Figure 2. Principle of PhotoPléthysmoGraphy (PPG)

PhotoPlethysmoGraphy (PPG) is an optical measurement technique that allows you to observe blood volume's variation in a non-invasive way [10].

Figure 2 illustrates the principle of PhotoPléthysmoGraphie: the cardiac activity causes fluctuations in blood volume that result in fine variations in the light reflected by the skin, and more precisely in the blood capillaries. It is this fine variation that we will seek to measure.

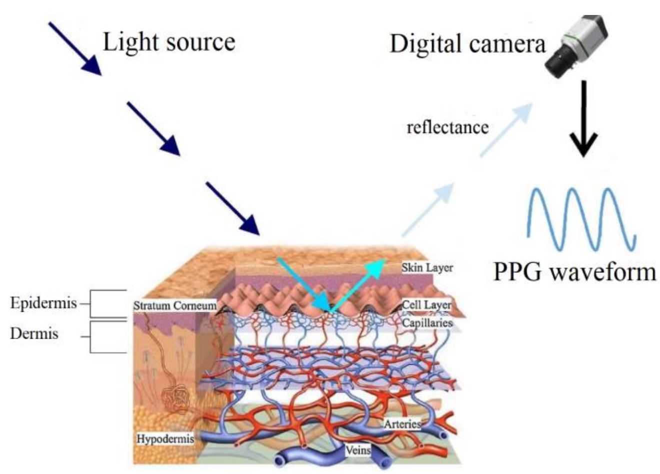
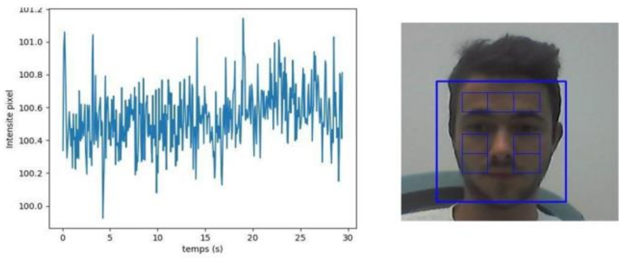


Figure 3. Description of the PPG concept [11]

As we can see in Figure 3 [11], the acquisition of a PPG signal requires two optoelectronic components: a light emitter and a light receiver. Today, cameras have become full-fledged PPG sensors, with ambient light acting as the light emitter, and the photosensitive cell matrix of the camera being the photodiode.



(a) **(b)**

Figure 4. PPG signal formation from the regions of interest of the face

To form the PPG signal (Figure 4a) from person's face (Figure 4b), several steps were followed:

- **Face's Detection**: This step is very important. To have a responsive and robust system it must be fast. The result of the system depends on good detection. We used the OpenCv library given the low execution time compared to other algorithms.
- **Creation of Regions of Interest (ROIs) on Face:** It is possible to define ROIs on the cheeks and the forehead (Figure 4b). This choice is to maximize the number of pixels belonging to the skin and obtain a PPG signal with minimum signal-to-noise ratio [12].
- **Chrominance Extraction *u:** We choose to use the space L*u*v more precisely the chrominance *u. This component represents the colors between red and green: wavelength interval in which photoplethysmographic variations are better observable [13].
- **Spatial Average:** Once the chrominance is extracted, we calculate the pixels' spatial of the ROIs. This average consists in summing all the pixels' intensities different from 0 and divide by this number of pixels. A point of the PPG signal represents the spatial average of a single captured frame.
- **PPG Signal Formation:** in order to have a raw PPG signal (Figure 4a), we do a normalization of the values obtained after the calculation of the spatial average as follows:

$$\dot{x}_i = \frac{x_i - \mu}{\sigma}$$

with $i \in \mathrm{N}$: number of signal's points after spatial average, σ et μ : standard deviation and mean.

A raw PPG signal is obtained at the output of the acquisition chain. We must filter it to make it more exploitable.

B. Filtering

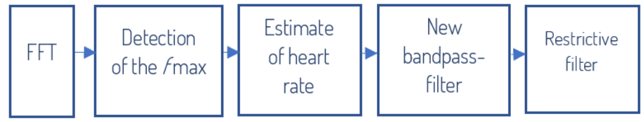


Figure 5. Signal filtering chain

Our algorithm of stress detection will be based on the study of the different peaks of the filtered PPG signal. The signal PPG is filtered in a sliding window of 30 seconds with a step of one second following the chain of Figure 5:

- After removing the continuous component, we apply a Butterworth filter with cutoff frequencies set at 0.8 Hz and 3 Hz, which corresponds to the usual heart rate in humans
- A Fast Fourier Transform (FFT) [14] is applied to determine the maximum heart rate, so we deduce the average heart rate.
- Another selective bandpass filter is applied from the average heart rate since the first filter applied does not allow to study the variability of the heart rate, we applied this second filter more restrictive to define the cutoff frequencies of the heart. filtered.

The objective of the filtering is to obtain a signal comprising distinct peaks that can be analyzed by a detection algorithm while avoiding "bad detection" as much as possible, since between each peak, there is a fixed amplitude and mean interval which eliminates any other spades that do not respect this constraint. Our algorithm of stress detection will be based on the study of the different peaks of our filtered PPG signal.

In the manner of the R-peaks of an ECG, it is possible to use the peaks of the signal PPG, which are not R-peaks indicated in (Figure 6a), but the P-peaks indicated in (Figure 6b) variability of the heart rate. The study of the variability of the heart rate via the PPG wave, is a reliable alternative and that leads to almost identical results to that of the ECG as shown [7].

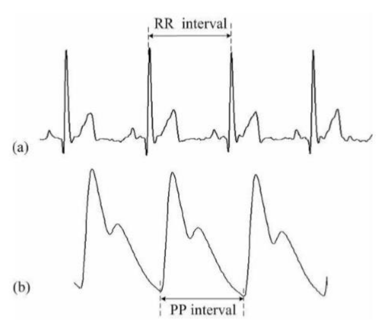


Figure 6. Analogy between R-R interval et P-P interval

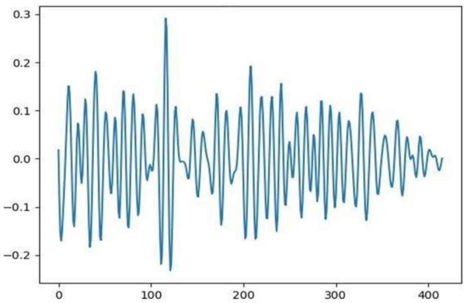
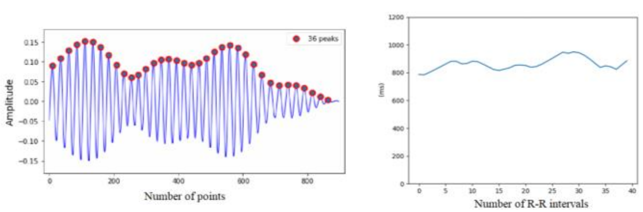


Figure 7. Filtered PPG signal



(a) (b)

Figure 8. Detection of PPG signal peaks and graphical representation of RR

The filtering method used seems adequate: The filtered PPG signal obtained (Figure 7) with the detection of the peaks (Figure 8a) corresponds to the adequate rate validated by the measurements made by a PPG sensor in contact; on the other hand the filtering is carried out in a sliding window of 30 seconds with a step of one second in parallel with the other operations: detection of the face; PPG signal extraction.

Once the R-R intervals of the filtered signal have been extracted and corrected, we have drawn the Tachogram (Figure 8b) which is the graphical representation of the R-R intervals.

C. Heart Rate Variability and Stress

Several studies show that heart rate variability is a marker of stress. The reference [15] shows that HRV of a person immediately drops in response to a stressful stimulus. This decrease is also observable in the case of chronic stress if we study the HRV over a longer period. The HRV presents a great informative value, it informs on the activity of the autonomic nervous system and more precisely on the balance between: The sympathetic system which helps to increase heart rate and the parasympathetic system which helps to decrease it. The reference [16] describes the autonomic nervous system which is the mechanism in charge of the regulation of stress, in the case of a stressful situation. Thus, an increase in sympathetic tone is observed together with a decrease in parasympathetic tone. Variations in sympathetic and parasympathetic tone can be seen in low frequencies and high frequencies, respectively. We will observe a decrease in high frequencies accompanied by an increase in low frequencies and therefore an increase in the ratio LF / HF in response to a stressful stimulus. We use the name Sympatho-Vagal Balance (BSV) to qualify this relation BF/HF.

It is important to note that heart rate is not a stress marker when studied in isolation. This is the interest of the HRV which has a much more informative value since it is based on the study of the variation of the time between heart beats. It is also a risk marker for many pathologies. Several studies indicate that a decline in HRV is associated with the risk of cardiovascular and coronary heart disease, hypertension and heart failure [15]. We have seen that the HRV provides information on the activity of the autonomic nervous system, vagal tone, respiration and of course the activity of the heart and its ability to adapt. That's why it can be used as a stress marker [17]. There are no normal values for the quantities of the HRV. They are modulated by a lot of parameters, including age or physical condition so they are intrinsic to each person. We choose to use 4 parameters to build our stress estimation and classification model. There are multiple combinations of parameters used to classify stress in the literature. Our choice was Beats Per Minute (BPM), Root Square of the Successive Differences (RMSSD), BSV and the Standard Deviation of all the intervals beats (SDNN). These indicators are used in recurring ways for this type of study:

- BPM: Number of beats per minute

- RMSSD: root square of squared differences of successive RR intervals which also expresses high frequency variability mainly of parasympathetic origin, modulated by respiration.

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_{diff}\, i)^2}$$

- SDNN: standard deviation of intervals between beats

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - \overline{RR})^2}$$

- BSV:

$$BSV = \frac{LF}{HF}$$

However, we have chosen to limit ourselves to these 4 quantities to limit the number of input parameters of our classification model, which reduces the processing time and makes the system more responsive.

In the case of a stressful reaction, several phenomena are observable:

- An increased BSV: Increased sympathetic tone and decreased parasympathetic tone corresponding to a stressed state.

- Decreased RMSSD and SDNN: During a stressful situation, the respiratory cycle is faster, which reduces the value of the R-R intervals. Since both RMSSD and SDNN are based on these ranges, their values are also reduced.
- Increased BPM and instant heart rate

D. Implementation of the Protocol and Creation of the Stress Classification Model

Once our cardiac activity measurement system was defined, we began the creation of our stress classification model. Machine Learning tools are now the ones that lead to the best results in classification tasks through models that are used to predict qualitative variables like quantitative, data separation is more complex as data are separated into different groups in a more precise manner. The main constraint of this type of method lies in the need for relatively large amounts of data to build a robust "classification model". Since there is no publicly available database of measures of heart rate variability annotated as being in a stressed or unstressed state, we chose to create our own database.

1) Test Protocol: Inducing Stress

Our experimental protocol aims to collect cardiac activity data corresponding to stressed and unstressed states. The main difficulty is to succeed in inducing stress in a maximum of participants.

Method: Comparison between GSR + in-Contact PPG sensors and image analysis

Inclusion: After presenting the test protocol, each participant has given their consent to participate by signing a consent letter.

Test: Our test consists of three stress phases separated by relaxation phases. The chosen protocol is to broadcast a video of 6 minutes including so-called relaxation phases, as well as stress phases (Figure 9). The 6 minutes are organized in alternating phases of 1 minute. During the relaxation phases, the videos broadcast are videos of soothing natures constitute the relaxing stimulus. The videos broadcast during the stress phases correspond to the Stroop test, presented in [18]. It is common to use the Stroop test as an inducer of mild stress, which is the stressful stimulus used by Bousefsaf [13].

We chose to have participants fill out a questionnaire during the protocol, to measure their level of anxiety, in order to filter the data collected, and understand some results. Each participant had to complete the State Trait Anxiety Inventory (STAI) presented in [19] before starting the test. These psychological questionnaires also allow us to exclude some participants by correlating the GSR sensor data with the test results.

Figure 9. Stress induction test

2) Database of Physiological Measurements

We used data from the 15 participants. We initially had data from 21 participants. Participants 9 and 15 were excluded as they showed no evidence of physiological responses to the stressful stimulus. Finally, participants 7, 18, 19 and 22 were excluded for material reasons (sensor that breaks off during the test, etc.). We used data from the remaining 15 participants.

As shown in Figure 10, we have for each participant a set of three sensors:

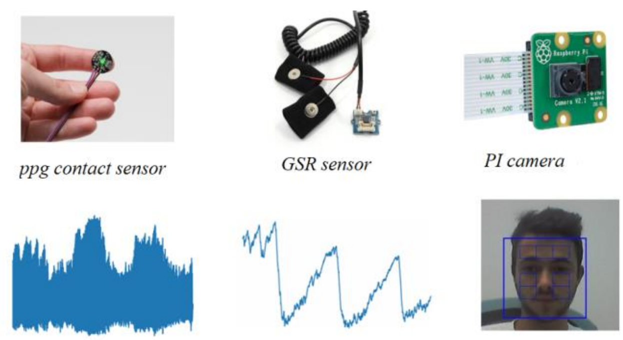


Figure 10. Test sensors

The PPG and GSR sensor to build a stress estimation model, then we will compare this model with the model established with the PI camera solution.

i. Detection Chain to Validate

- The video of the participant's face: it validates our PPG signal acquisition chain from the video, by referring to the measurements of the PPG contact sensor.

ii. Comparison Chain

- Measurements of the GSR sensor in contact: This sensor provides information on sweating of the skin, during a stressful situation, a person is supposed to have a different sweating than during a rest phase. It allows to determine if there was stress or not and therefore to select the participants to include in the training data.
- The measurements of the PhotoPlethymographic Sensor (PPG) in contact: allow to train our classification model.

iii. Validation of Learning Data

Once we have these data, we excluded participants who did not show signs of a stressful reaction, for which the GSR sensor data was used. This sensor provides information on sweating of the skin. During a stressful situation, a person is supposed to have a different sweating than during a rest phase. Our test consists of three stress phases separated by relaxation phases, the signal returned by the sensor must have (Figure 11) three separate spades, in the case where the subject has stressed.

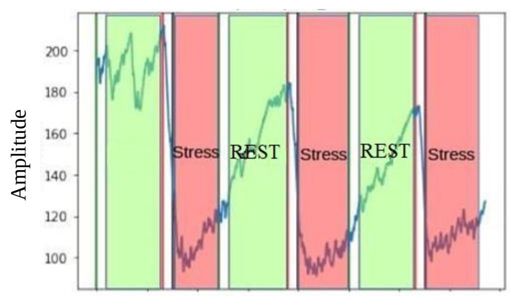


Figure 11. Representation of selected signal portions

The test consists of three stressful periods which implies that the participant should have three times a lower rate of sweating. The spectra that do not show pikes at the moments corresponding to the beginning of a stressing phase, therefore did not stress. It was therefore relatively easy to exclude the participants without any reaction, it was enough to visually grasp the data of the GSR sensor.

IV. Resultats & Discussion

The method proceeds in two steps:

A. Step 1: Comparison of Classification Methods

This step consists in creating a reference classification model based on the physiological data of the participants coming from the PPG contact sensor. This classification model is used to validate the model created from the physiological data from the camera.

i. Description of Methods

In order to classify the data from the PPG contact sensor and annotate them, we compared three different methods. We want to generalize a classification of unknown samples from a learning database. We compare three methods of supervised learning; this choice is based on a bibliographic analysis: neural network; K-NN et SVM. These are the methods with the best results in terms of classification. The reference [18] used the KNN method and obtained a classification accuracy of 95%. Reference [19] tested the SVM and the KNN method and obtained better results with the SVM with an RBF core function, they reached the 85% accuracy. Reference [20] has shown that it is possible to classify measures of cardiac variability according to 4 levels of stress using an artificial neural network.

Neural Network (Supervised learning method): an input layer with 4 neurons which are the 4 input parameters (SDNN, BSV, RMSSD, BPM); the next three layers are hidden (the number of hidden layers is defined according to the optimal percentage of precision obtained); the last layer composed of neurons corresponding to the two outputs (stressed state; non-stressed state)

K-NN (Supervised learning method): is an algorithm based on training data that it stores in memory; it is a memory-based algorithm. This method is therefore suitable for problems with a small database. In our case, we have a few thousand samples which allows us to use this method.

SVM (Supervised learning method): This method is used for regression problems, as in our case, it can also be used for classification. It separates a dataset into two categories: using a hyperplane separator which is linear; or using a kernel function that is non-linear.

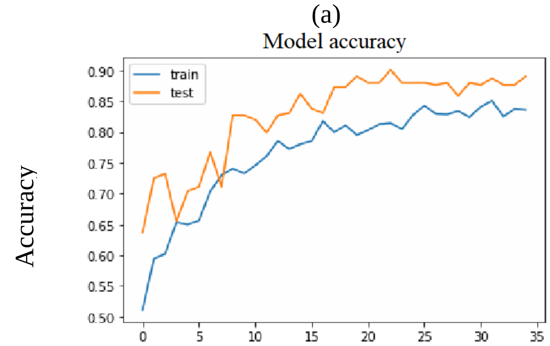
ii. Database for Classification

After acquisition of the test data, we have 1418 samples that have been split into two data sets.

Training and Validation Data: 80% samples of 1134 were used for the training and validation of the model.

Test Data: To test the model, it is necessary that the data were never injected into the model in order to evaluate the real performances of the model, 20% of the samples so 284 were used for that.

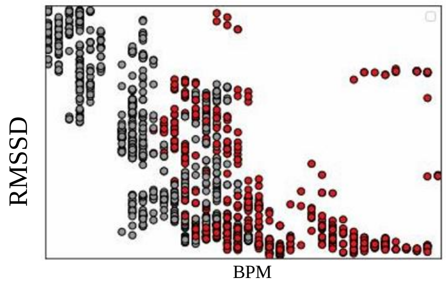
(a)



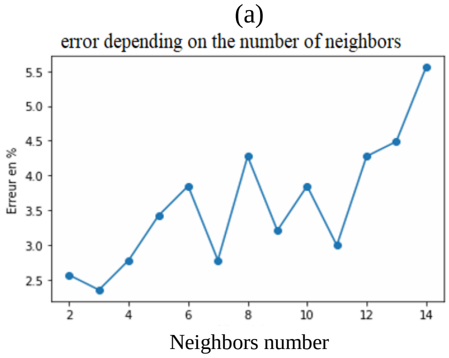
(b)

Figure 12. Neural network method

Figure 12 illustrates the performance of the model built using a neural network; the rate of loss of training and testing (Figure 13a); the training accuracy rate (Figure 13b).



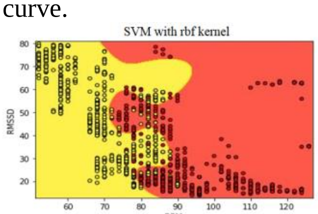
(a)

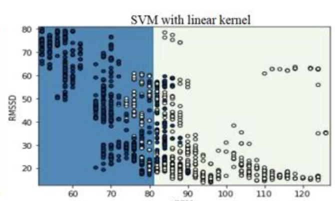


(b)

Figure 13. K-NN method

Figure 13a illustrates a classification obtained using the K-NN method, the number of neighbors is chosen which minimizes the error on the test data. It suffices to increment this hyper-parameter in a loop (Figure 14b) to determine its optimal value by visual apprehension of the curve.





(a) (b)

Figure 14. SVM method

Figure 14 illustrates the use of a linear SVM to classify our data (Figure 14b); and an SVM with a kernel function (Figure 14a).

iii. Discussion:

TABLE I. PERFORMANCES OF THE THREE METHODS

Algorithm	Accuracy test – data learning	Accuracy test on the second dataset
Neural network	**89,1 %**	**83,3 %**
K-NN	**97,6 %**	**77,4 %**
SVM	**97,2 %**	**75,2 %**

Table 1 summarizes the results obtained after the evaluation of the three classification methods. If we analyze the results: We note that the k-NN method is the one that presents the best classification results on the 284 samples from the learning dataset. The accuracy rate is 97.6% which is relatively high. However, this accuracy is not indicative of the performance of the algorithm under real conditions. In the test data set, measurements are almost identical to those of training, which explains why, with the k-NN method or with the SVM, it is possible to obtain such high results. That's why we have injected the second set of test data. This test database will allow us to really evaluate the performance of our models and compare them together.

We note that the neural network method presents the best classification performance on this new dataset, with an accuracy of 83.3% against 77.4% for the k-NN algorithm and 75.2% for the SVM. We can deduce that the best solution available to us the neural network solution. In fact, it has the best capacity for generalization and therefore brings us good results in real conditions.

B. Step 2: Comparison with the Non-Invasive Non-Contact model: camera

The first step made it possible to obtain the physiological data of the participants coming from a PPG sensor in contact. This acquisition was synchronized recording a video of their face. Once the classification model of the data from the contact PPG sensor is done, we will be able to analyze the quality of the acquisition chain and test our classification model only from the camera's data.

We used three classification methods to classify the data obtained from the camera; SVM; Neural network and temporal averaging method.

- Time Averaging: We made an estimate of the heart rate every second. The goal is to calculate the right heart rate estimated by choosing the one with the highest number of occurrences. In this method, the historical aspect (evolution over time) is considered to calculate the heart rate.

TABLE II. DATA CLASSIFICATION PERFORMANCE FROM THE CAMERA

Algorithm	Properly classified samples
Neural network	59,2 %
Time averaging	61,1 %
SVM	56,3 %

Table 2 shows the results of the three methods used to classify the camera dataset; 56.3% of good classification is obtained using SVM, slightly more with neural network method 59.2% and 61.1% with temporal averaging.

C. Error Calculation: Contact Model - Contactless Model

We compared the classification results obtained from the camera with the classification results obtained from the PPG contact sensor.

We used two parameters for the comparison:

- RMSE: Root Mean Square Error
- Correlation: the Pearson correlation coefficient r used to study the intensity of the link that exists between the results obtained with the model of the PPG contact sensor and the data obtained with the model of the camera.

a. Neural Network Method

TABLE III. COMPARISON OF THE NEURAL NETWORK METHOD

	RMSE	Correlation
BPM	12,057	0,37 *avec p-value <0.01
RMSSD	36,87	0,06
BSV	0,65	0,02
SDNN	28,11	0,11

b. Time Averaging Method

TABLE IV. COMPARISON OF THE TEMPORAL AVERAGING METHOD

	RMSE	Correlation
BPM	12,24	0,15 *avec p-value <0.01
RMSSD	33,4	0,05
BSV	0,7	0,04
SDNN	29,12	0,09

c. SVM Method: Injection of two second signal portions at the input of the model to predict the parameters of the HRV

TABLE V. COMPARISON OF THE SVM METHOD

	RMSE	Correlation
BPM	9,61	0,11 *avec p-value <0.01
RMSSD	43,5	0,03
BSV	1,3	0,06
SDNN	36,2	0,04

Discussion:

The results presented in Table 3, Table 4 and Table 5 correspond to the three main methods. The neural network method (Table 3) is relatively close to the temporal averaging method (Table 4). The filtering and signal processing algorithms used are strictly identical. The third method is relatively different (Table 5) since it does not require prior signal processing. The idea is simply to inject signal portions of 2 seconds into input of a classification model and the parameter to predict (BPM, RMSSD, etc.) from the sensor. The model will predict the parameter in question: the BPM, SDNN, RMSSD, BSV since the objective is to inject the raw signal from the camera without specific treatment (filtering) and to predict the heart rate with the associated HRV parameters. The most interesting results in terms of quadratic error are those obtained with the SVM method, however, the correlation rate is relatively low compared to the basic method, for BPM at least (Table 5).

The two methods to be considered are those using temporal averaging and SVM since they present more promising results. The SVM could be used more judiciously than to predict the parameters directly at the output of the model. This is a solution that was recently developed [20].

For the temporal averaging method, the histograms of the predictions show that the correct estimates are the most recurrent, however the algorithm implemented is not yet well adapted to perform a correct arbitration as to the correct estimate to be chosen when the signal is of poor quality in some areas of interest. One possible improvement would be to set up an algorithm to assign a coefficient to each estimate based on the signal-to-noise ratio (SNR) of the region of interest from which it is derived, which would be low in the case where the SNR is low and vice versa.

V. CONCLUSION AND FUTURE WORK

The objective of this work is to show that it is possible to classify the stress of a person from the physiological data captured by an accessible camera and embeddable.

The developed method allowed us to compare different methods of classification but the use of the camera as a tool for measuring cardiac activity is still in its beginnings.

To estimate the stress of a person using a sensor without contact: camera. First, we propose an acquisition chain in order to estimate the heart rate and calculate the parameters of the HRV that will be used as inputs for the stress classification model. We have put in place a test protocol to create our own database that will be used to create the stress classification model. Data acquired during this test are: sensor data in PPG contact synchronized with video recordings, and a GSR sensor.

A classification model from the PPG sensor data was created using different supervised learning methods; the method that shows the best results is the neural network method.

Then, we evaluated the performance of our acquisition chain with the camera by comparing the built classification model with the camera data.

There are many constraints brought by this tool, which today represent the main barrier to its use on embedded systems. The two main constraints are movements and light variations, constraints which are difficult to overcome even in laboratory conditions. Both are closely related since a movement will necessarily result in a change in the illumination of a person's face. These are two of these areas that we will strive to improve. Nevertheless, this solution is more accessible and especially embeddable since it is non-invasive. We will try to minimize the impact of light variations on the accuracy of our measurements. Today, light variations are one of the main challenges in computer vision on embedded systems. Since computer vision and signal processing techniques have been evolving in recent years, particularly with the advent of machine-learning tools, it is certain that the measurement of cardiac activity via the extraction of the PPG signal by a camera will improve and one day, will become a recognized alternative measurement system. It can be imagined for many applications: driver assistance, telemedicine or biometrics.

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