NIGERIAN COMMUNICATIONS COMMISSION 2019 RESEARCH GRANT:

FINAL REPORT

- Title of Research Project: Vital Signs Monitoring using Sparse Representation Based on Smartphone Video Camera
- Period of Reporting: 24 Months (August 2019 to July, 2021)
- Members of the Research Team indicating the Principal Investigator and his contact details:

1. Dr. Aliyu Nuhu Shuaibu (Principal Investigator)
2. Professor Danjuma Dajab Co-researcher
3. Sulaiman Muhammad Adejo Research Assistant

- Coordinating Institution: University of Jos
- E-mail Address & Mobile Nos. of Institution's Contact person: asnuhu@gmail.com, nuhua@unijos.edu.ng, 09063200704, Department of Electrical and Electronics Engineering

- Date of commencement of the Project: August, 2019
- Expected Date of Completion July, 2021
- Approved Project Budget: N14,500,000.00
- Grant Received so far: N12,325,000.00
- Balance remaining at NCC: N2,175,000.00

1.0 PROJECT IMPLEMENTATION

1.1 Brief Project Background

Cardiovascular diseases are on the list of top ten causes of annual global death in 2015 (Global Health Estimates: www.who.int/healthinfo/global_burden_disease/estimates/en/), hence regular assessment of the cardiovascular function is fundamental to prevent chronic diseases and to evolve treatment therapies adequately. The constant monitoring of vital signs, such as heart rate and arterial blood oxygen saturation, is the basis to detect a risk level of cardiovascular disease [1]. The heart is considered as an important organ of human body. The heart rate measurement is regarded as very essential in estimation of vital signs and physiological state of a person. The Normal heart rate is 60-100 beats per minute (bpm) while the abnormal heart rate is classify into two bands; above 100 bpm and below 60 bpm defined as Tachycardia and Bradycardia respectively. Clinically, Electrocardiogram (ECG) is the most widely adopted technique that provides correct and reliable values for cardiac monitoring and vital signs estimation. However, this technique realizes non-invasive acquisition mode, since it requires the contact between the electrodes and the skin, and an incorrect positioning of the electrodes on the skin can lead to error. More promising techniques consisted of a display and mounted electrodes on the chest.

Heart rate indicates the soundness of our heart and helps assessing the condition of cardiovascular system. In clinical environment, heart rate is measured under controlled conditions like blood measurement, heart voice measurement, and Electrocardiogram (ECG) but it can be measured in home environment. As a source of information about a subject's physical and affective state, heart rate measurement (HRM) is of interest to researchers, medical practitioners, and retail users alike. A classical application of HRM is for monitoring in a hospital environment. Electrocardiogram (ECG) is the most widely adopted technique to provide correct and reliable values for cardiac monitoring. However, this technique realizes an invasive acquisition mode, since it requires the contact between the electrodes and the skin, and an incorrect positioning of the electrodes on the skin can induce tissue irritation [2]. More promising techniques consisted of a display and mounted electrodes on the chest [3].

The demand for ubiquitous measuring of human physiological parameters is ever increasing not only in the field of medical sciences (e.g. monitoring of hospitalized patients, home health care, rehabilitation, nursing of elderly but also in several commercially oriented domain, such as automotive industry (vital sign monitoring of the driver), psychology (measure of stress response), sports (optimization of training) and even in the field of man–machine interface. In order to be able to conduct measurements in such diverse fields, the existing contact methods for obtaining parameter values with the known limitations would seem inadequate in some cases.

Recently, several innovative non-contact methods for measuring cardiovascular parameters, particularly the HR and HRV, have been studied world-wide. Some of the published results are promising and thus indicate that the non-contact measurements of certain human physiological parameters are indeed possible and will without a doubt have a great impact on many fields of application in the near future. There is an explicit air gap between the measuring sensor and the human body.

Photoplethymysography (PPG) is considered as a non-contact method for the detection of cardiovascular pulse waves within the human body. It works in accordance with the optical properties of vascular tissue using a probe, which consists of LED-photodiode configuration. The LEDs run as light emitters and the photodiodes (usually PINs, diode with a wide, lightly doped "near" intrinsic semiconductor region between a p-type semiconductor and an n-type semiconductor region) as light detectors (photo detectors, PDs). The probe can be placed on the periphery of human body, most commonly on a finger or a toe and can operate in reflectance or transmittance mode. The emitted light is reflected, absorbed or scattered by the blood and tissues. The intensity of the light reaching the PD is measured and the variations, caused by blood volume changes, are amplified, filtered and recorded as a voltage signal. This signal is extremely small, subject to noise and in addition to the PD, precise analogue amplifiers, high order filters and analogue-to-digital converters are required. Additional components not only increase the system complexity and cost, but also its size and power consumption. Additionally, the PIN detectors are not ideal as they are not spectrally selective and indiscriminately detect broad spectrum light ranging from near infrared to UV, and all that contributes to the noise and error levels.

As stated earlier, the conventional and well-established approaches to measure physiological information, like electrocardiogram (ECG) or photoplethysmogram (PPG), required the used of electrodes or transducers on the skin surface (e.g. wet adhesive Ag/AgCl electrodes) during the monitoring period. These approaches, although non-invasive, are bothersome, and perhaps irritating and distracting.

In this work, remote photoplethymysography (rPPG) is the backbone algorithm that was used with sparse reconstruction algorithm for non-contact methods. The progress so far made on non-contact heart rate measurement from facial videos has defined a new taxonomy in the field of telemedicine, healthcare, sport and biomedical engineering. The use of smartphone camera has proven more effective in heart rate estimation experiments using facial videos as compared to the use of PC's webcam camera and standard digital camera at significant confidence interval of 0.05. In addition, non-contact based method of HRM experiments have proven statistically the same with the conventional pulse measurement methods such as standard clinical pulse oximeter and android mobile device (Samsung health Apps).

1.2 Related Work

The physiological monitoring solutions are easy to use, accurate, and can be used in the home or ambulatory environment. Smart phones are becoming more popular, more powerful and have a variety of sensors/camera available to capture information from the outside world, transform the data, and transfer information via wireless communications. These factors make mobile devices better option as a “take anywhere” physiological monitor without the need for additional hardware, and their application has been explored for many biomedical devices [1, 2]. Optical visual monitoring of the skin with a digital camera contains information related to the subtle color changes caused by the cardiac signal measured based on pulse oximeter and can be seen to contain a pulsatile signal as reported in [4]. Given illumination of the area with a white light emitting diode (LED) mobile phone flash, this type of imaging can be described as reflection PPG imaging. In a related work, an overview of the approach for heart rate (HR) extracted signal from a sequence of video images is analyzed based on PPG, BCG and ECG [5, 6].

Another method based on Ballistocardiography (BCG) for heart rate monitoring was proposed in [7]. In this method, the HR is extracted by tracking the velocity of motion features in a facial video. An approach based on remote PPG was proposed in [8]. In a similar approach based on rPPG and sparse reconstruction algorithm in [9, 10]. The PPG signal is used to estimate the physical parameters using non-invasive camera. The reported result was compared with existing dictionaries such as discrete wavelet transform and discrete cosine transform for sparse signal reconstruction. The results in [10] produced better performance of Signal-to-Noise Ratio (SNR) as compared to the start-of-the-art methods.

Sparse signal reconstruction aims to calculate a high-resolution spectrum of the PPG signal, which is robust to noise interference and is advantageous over traditional non-parametric spectrum estimation algorithms and model-based line spectrum estimation algorithms. Sparse signal reconstruction (SSR) [10, 11], is an emerging signal processing technique, showing great potentials in many application fields. The SSR algorithm is helpful in improving the performance of HR monitoring signal. In SSR, the signal decomposition is achieved by singular spectrum analysis (SSA) that decomposes the time series into noise and oscillatory components; SSA helps to remove the motion artifact frequency components from the PPG signal. The signal is then temporally differentiated to make the heartbeat fundamental, harmonic spectral peaks more prominent and random spectrum fluctuations suppressed. A high resolution spectrum of the PPG signal is calculated by SSR. Heart rate (HR) is normally estimated by choosing the highest spectral peaks in a PPG power spectrum.

However, in our proposed approach HR measurements using a mobile phone camera based on rPPG-sparse representation algorithm has been compared with HR measured via pulse oximeter and android mobile apps in this work. The potential of monitoring the dynamics in the HR signal and extracting additional vital physiological parameters from the optical recordings has not been fully explored. It is widely known that the HR signal that can be captured by PPG contains vital information that are applicable in determining physiological conditions such as atrial fibrillation, blood loss, and cardiac autonomic function.

1.3 Project Objectives

The specific objectives of the research are to:

1. Develop non-contact heart rate monitoring algorithms based on sparse representation model.
2. Design and Implementation of heart rate pulse oximeter measurement validation system based on Adruino Uno Microcontroller IC.
3. Develop an android based application for the non-contact developed model.
4. Analyse statistically the significance of the results obtained from contact and non-contact devices.

1.4 Methodology

This section describes the proposed approach and methodology for non-invasive heart rate measurement using sparse representation based on rPPG [13] as shown in Fig. 1. The sparse signal representations are becoming more popular in computer vision applications. For simplicity and convenience, the face was detected with the aid of a face detector proposed by Viola and Jones (VJ) which is effective and efficient in locating the faces in frames. However, this face detector fails for non-frontal scene capturing. In this work, object detection toolbox (vision.CascadeObjectDetector) built in OpenCV based on VJ was used to detect the face in every frame. Moreover, simple skin color detection was used to ensure that the processed data were obtained from skin pixels.

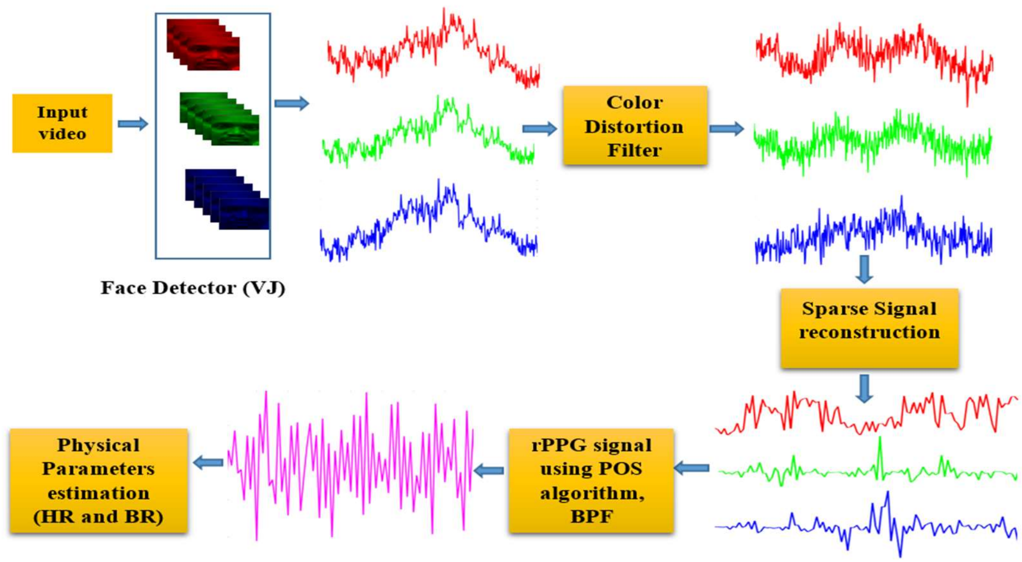

Fig. 1: Non-contact heart rate and breathing rate extraction based on Sparse-rPPG approach

a) Sparse Representation Algorithms

Sparse coding has been used widely in signal and image processing, machine learning, and neuroscience. The purpose of sparse modeling is to design a method used to represents signals as a linear combination of little distinctive patterns, called atoms extracted from a dictionary. For a given image or signal y∈R^n and a dictionary matrix D∈R^(n×k) that comprises K atoms as column vectors d_j∈R^n, j=1,…., K, the sparsest vector is found in such a way that x∈R^n, that y≅Dp. The problem is solved by using the optimization approach as shown in Eq. (1):

$$\min \|p\|_0 \quad \text{subject to } \min \|y-Dp\|_2 \leq \epsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where ∈ called the reconstruction error for given signal y based on dictionary D and the sparse coefficients p

The optimization problem can be solved based on the Eq. (2)

$$\min \|y-Dp\|_2 \quad \text{subject to } \|p\|_0 \leq \rho \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where ρ is a specified sparsity level. The vector p∈R^k comprises the representation coefficients of the signal y with respect to dictionary D elements. As compared with other methods such as PCA, the sparse coding calculates with the smallest number of non-zero coefficients vector. The sparse coefficients formulation usually used the n-norm which counts the non-zero entries of a vector. The formulation is an NP-hard problem, and can be solved by using optimization greedy algorithms. These algorithms are called matching pursuit (MP) or orthogonal matching pursuit (OMP). The pre-determined dictionary provides a fast and efficient solution for the sparse signal reconstruction. These dictionaries are based on Discrete Ridgelet Transform (DRT), Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT) basis function. Therefore for given training input dataset, the dictionary learns from given signal effectively in sparse representation.

b) POS Algorithm

There are numerous algorithms used in measuring the physical parameters with contactless video camera. One of the most important algorithm based on POS has been used in this experiment. Plane orthogonal to the Skin-tone method (POS) exploits the same skin reflection model as CHROM but uses a different color direction (i.e. a different distortion) for real-time projection tuning. The proposed method is using the plane orthogonal to the skin tone in the temporally normalized RGB space for pulse extraction. Therefore, the name POS is considered as a unique character distinguishing it from prior art.

The methods used IP camera based on face videos extracted from facial frontal view. The normalized RGB traces have an average spatial mean and concatenated in temporal way for all frames. Next, the skin pixels are constructed using YCbCr method. These traces are clean using color distortion filter. Furthermore, a sparse representation technique is applied on the filter RGB traces and compute the sparse coefficients using proposed dictionary elements for estimate signal extraction within the HR range of frequency spectrum. The sparse based signals are passed to the model based rPPG signals to measure the heart rate and other physiological parameters (Breathing rate and HR).

1.5 Experiment on Optimum Frame Rate Selection

The experimental set-up based on Fig. 2, was conducted at the following distances from the sensors 0.1m, 0.3m, 0.5m, 0.7m and 0.9m for the four devices; Samsung Note 8 smartphone (smp), Dell Desktop (dsk), Dell Laptop (lpt) and Standard Digital Camera (dcam). In each case, the minimum and maximum frame rates per seconds (fps) was recorded as shown in Table 1 and Table 2 respectively. During both experiments it was observed that the facial frontal region of interest (ROI) was out of bounding box (face outside ROI) at both odd and even sequences of 0.1m and 0.2m respectively.

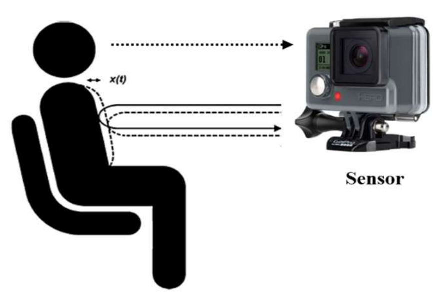

Fig. 2: Experimental set-up for non-contact heart rate measurement

Table 1: Experiment for minimum frame rates by varying sensor distance from the subject at controlled indoor illumination

S/No.	Distance (m)	Samsung Note 8 (fps), 640 x 480 resolution	Dell Desktop (fps), 640 x 480 resolution	Dell Laptop(fps), 640 x 480 resolution	Standard Digital Camera (fps), 300 x 300 face detector	Face ROI status
1	0.1	-	-	-	-	No reading
2	0.3	14.8	23.6	20.5	29.5	Detected
3	0.5	12.2	25.2	20.1	29.3	Detected
4	0.7	10.8	24.8	19.6	30.2	Detected
5	0.9	8.6	24.2	19.8	28.6	Detected

Table 2: Experiment for maximum frame rates by varying sensor distance from the subject at controlled indoor illumination

S/No.	Distance (m)	Samsung Note 8 (fps), 640 x 480 resolution	Dell Desktop (fps), 640 x 480 resolution	Dell Laptop(fps), 640 x 480 resolution	Standard Digital Camera (fps), 300 x 300 face detector	Face ROI status
1	0.1	-	-	-	-	No reading
2	0.3	15.6	24.8	20.2	30.6	Detected
3	0.5	19.2	26.8	22.4	33.2	Detected
4	0.7	18.2	25.5	22.0	33.4	Detected
5	0.9	19.0	28.4	22.2	32.2	Detected

The analysis suggests whether the difference between the minimum mean frame rates is significant, or not. A one-way analysis of variance (ANOVA) is performed. The purpose of one-way ANOVA is to determine whether the minimum frame rates recorded from the sensors or devices in Table 1 have a common mean or not. That is, one-way ANOVA find out whether different groups (sensors) of an independent variable have different effects on the response variable (frame rates). Let μ_i, and μ_j be respectively the mean frame rates of the aforementioned devices. Eq. (3) and (4) defined the hypothesis that ANOVA tests a null hypothesis that all group frame rates are equal (there is no significance difference between frame rates of the devices) versus an alternative hypothesis that at least one group is different from the others.

$$\text{(Null Hypothesis)} \quad \mathbf{H_0}: \mu_1 = \mu_2 = \mu_3 = \mu_4 \quad \ldots\ldots(3)$$

$$\text{(Alternative Hypothesis)} \quad \mathbf{H_a}: \mu_i \neq \mu_k \quad \ldots\ldots(4)$$

The probability value is obtained from a probability distribution table at the degree of freedom (n-1) and compared at the level of significance (α = 0.05). For any p-value greater than the critical value, the null hypothesis is correct whereas for any p-value less than the critical value the null hypothesis is rejected at the level of significance. Fig. 3 shows the box plot for the distributions of recorded minimum frame rates at 0.3m, 0.5m, 0.7m and 0.9 m from the subject.

a) A one way Analysis of Variance (ANOVA) for Minimum Frame Values:

The ANOVA Table 3 shows the inter groups variability (Column) and within-groups variability (Error) by the sum of squares (*SS*), the F-statistic for testing the significance of the variability, it is obtained by taking the ratio of the mean squared error (*MS*), $F = 228.396/1.956 = 116.78$. The MS is the ratio of sum of squares due to each source by the degrees of freedom (*df*) for each source, $MS_1 = 685.188/3 = 228.396$ and $MS_2 = 23.47/12 = 1.956$. Next, a hypothesis test is performed to evaluate the statistical significance of the minimum frame rates from the above four devices. The p-value is the probability that the test statistic can take a value greater than or less than the value of the computed test statistic, i.e., $P(F > 116.78)$. The small p-value of 3.81471e-09 indicates that the differences between the column means are significant. The results summary of performance at the level of significance ($\alpha = 0.05$) are presented in Table 3. In this analysis, the computed p-value which is less than α indicated that the null hypothesis $\mu_i - \mu_j \neq 0$ is rejected at significance value i.e. (there is significance difference between the minimum mean frame rates recorded from the devices).

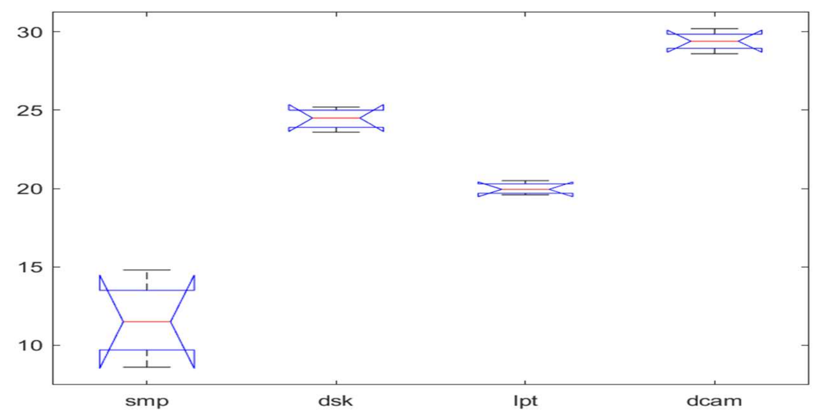

Fig. 3: Box plot for devices used in the experiments for minimum frame rates

Table 3: Result of one-way ANOVA test for minimum frame rates measured at significant value ($\alpha = 0.05$)

Source	SS	Df	MS	F	*Prob > F*
Column	685.188	3	228.396	116.78	3.81471e-09
Error	23.47	12	1.956		
Total	708.658	15			

b) Multiple comparison test between four devices:

Analysis of variance (ANOVA) techniques test whether a set of group means are equal or not. Rejection of the null hypothesis leads to the conclusion that not all group means are the same. This result, however, does not provide further information on which group means are different. The multiple comparison is applied to the stats structured obtained from the above ANOVA results. It involved multiple pairwise comparison of the group means. The options are Tukey's honestly significant difference criterion (matlab default option), the Bonferroni method, Scheffe's procedure, Fisher's least significant differences (lsd) method, and Dunn & Sidak's approach to t-test. The multiple comparison results of the above four sensors is presented in Table 4.

Table 4: Results of multiple comparison test between the devices at significant value ($\alpha = 0.05$)

Group (sensors)	Group (sensors)	Lower limits	Mean difference	Upper limits	p-value	Remark
smp	Dsk	-15.7859	-12.8500	-9.9141	1.0974e-07	Highly significant
smp	Lpt	-11.3359	-8.4000	-5.4641	1.0534e-05	Highly significant
smp	Dcam	-20.7359	-17.8000	-14.8641	7.7784e-09	Highly significant
dsk	Lpt	1.5141	4.4500	7.3859	0.0035	Significant
dsk	Dcam	-7.8859	-4.9500	-2.0141	0.0015	Significant
Lpt	Dcam	-12.3359	-9.4000	-6.4641	3.2369e-06	significant

In Table 4, the first two columns show the pair of groups that are compared. The fourth column shows the difference between the estimated group means. The third and fifth columns show the lower and upper limits for the 95% confidence intervals of the true difference of means. The sixth column shows the p-value for the hypothesis.

The first three rows show that both comparisons involving the first group (smp) have confidence intervals that do not include zero. Because the corresponding p-values (1.0974e-07, 1.0534e-05 and 7.7784e-09, respectively) are very small, those differences are highly significant.

Similarly, the forth to sixth rows show that the differences in the frame rates between the dsk-lpt, dsk-dcam and lpt-dcam are also significant with p-values (0.0035, 0.0015 and 3.2369e-06, respectively). The results of multiple comparison confirm that all devices showed appreciable level of significance. However, the use of smartphone Samsung Note8 (smp) in blue color legend with minimum average frame rates of 11.6 fps showed more significant than other three devices in red color legend at 0.3m, 0.5m, 0.7m and 0.9m distances from the sensors as depicted in Fig. 4.

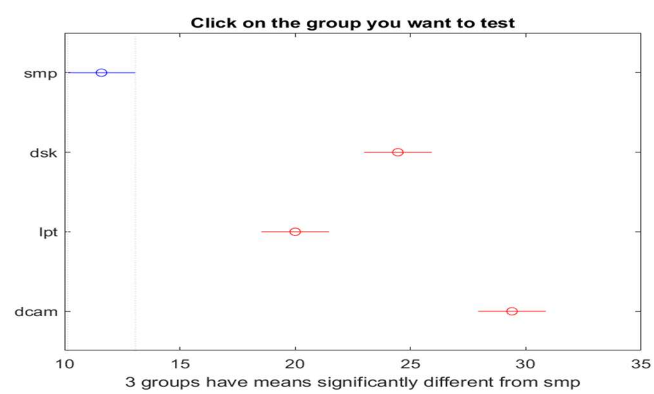

Fig. 4: Result of multiple comparison test for minimum frame rates

c) A one way Analysis of Variance (ANOVA) for maximum values:

The analysis followed the same hypothesis stated in statistical evaluation 1 using the maximum frame rates recorded in Table 2. The box plot for sensors distribution is shown in Fig. 5. The hypothesis test is performed to evaluate the statistical significance of the maximum frame rates recorded from the four devices. The p-value is the probability that the test statistic can take a value greater than or less than the value of the computed test statistic, i.e., $P(F > 77.56)$. The small p-value of 3.9938e-08 indicates that the differences between the column means are significant just as the case of minimum recorded fps. The results summary of performance at the level of significance ($\alpha = 0.05$) are presented in Table 5. In this analysis, the computed p-value which is less than α indicated that the null hypothesis is rejected.

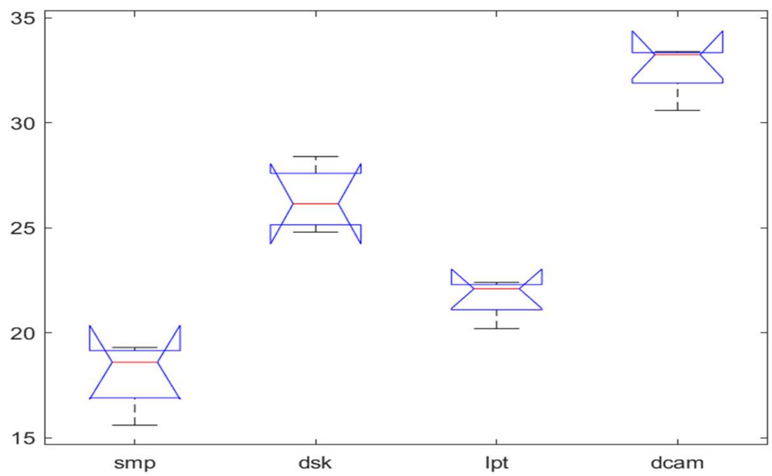

Fig. 5: Box plot for devices used in the experiments for maximum frame rates

Table 5: Result of one-way ANOVA test for minimum frame rates measured at significant value ($\alpha = 0.05$)

Source	SS	Df	MS	F	*Prob > F*
Column	476.662	3	158.887	77.56	3.9938e-08
Error	24.583	12	2.049		
Total	501.244	15			

d) Multiple comparison test between four devices

As stated early rejection of the null hypothesis leads to the conclusion that not all group means are the same, to prove that, we run a multiple comparison test on the computed ANOVA result, the outcome shown in Fig. 6 indicates that the group mean (smartphone Samsung note 8, smp) with blue color legend is significantly different from other three devices (dsk, lpt and dcam) as depicted in red color legend. The average maximum frame rates is 18 fps.

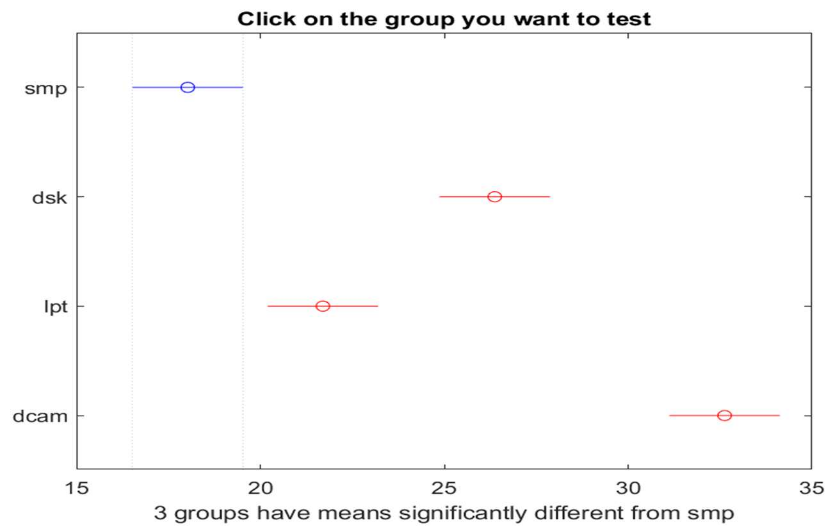

Fig. 6: Result of multiple comparison test for maximum frame rates

1.6 Experiment on Heart Rate Measurement and Validation

Heart rate was extracted for an average time window of 48 seconds. Noise due to illumination variance were observed and thereafter an advanced bandpass filter (cutoff frequencies of 0.7Hz and 4.0Hz, corresponding to min 42bpm and max 240bpm) was used to suppress both the lower and the higher spectrum noise levels. In our bandpass filter design, lower frequency ranges 0.7 * 60 sec = 42 bpm (lower peaks) and 4.0 * 60 sec = 240 bpm (highest peaks) were suppressed from the periodic signal spectrum. However, it was observed that this process affect the peak-peak signals that are responsible for computation of respiratory rate (RR).

It was also observed that the power spectrum of the peak pulses reoccurred after every ten samples. Therefore within the time window, an experiments was created to determine the optimal sample using an even periodic averaging sequence: 2, 4, 6, 8, 10, 12, 14, 16, 18 and 20 samples. A ten (10) samples of periodic signals yielded optimal and accurate bpm within the time window duration. Readings below 10 samples gave bpm below 50 while readings above 10 samples took longer computational time. Table 6 gives the summary of the optimal test experiment for heart rate measurement based on even samples.

Table 6: Experiments for computing optimal mean HR signal sample

S/No.	Samples	Mean HR (bpm)	Computational Time (Seconds)
1.	2	42	12
2.	4	35	12
3.	6	48	16
4.	8	49	22
5.	10	81	36
6.	12	68	39
7.	14	71	40
8.	16	73	42
9.	18	75	45
10.	20	70	46

The mean heart rate obtained with the proposed system was validated with the conventional methods; Samsung Health App and Pulse Oximeter as presented in Table 7. Readings from the three devices were recorded simultaneously on the subject for ten iteration (See Appendix A for pictorial view). Average value of the HR computed from each device was used for further analysis.

Table 7: Experiment for Contact and Non-Contact Devices in Terms of Computational Time at Resting Stage

S/No	Device	Time (seconds)	Mean HR (bpm)	Approach
1.	Samsung Health App	17	81	Contact
2.	Pulse Oximeter	60	87	Contact
3.	Proposed System	36	81	Non-Contact

Table 8: Result of one-way ANOVA test for HR measured between the three devices at significant value ($\alpha = 0.05$)

Source	SS	Df	MS	F	*Prob > F*
Column	240	2	120	162	9.15724e-2
Error	20	27	0.7407		
Total	260	29			

The ANOVA presented in Table 8 shows the variation between the groups in columns (Samsung health App, Pulse Oximeter and Proposed System) and within-groups variation (Error). SS is the sum of squares, and df is the degrees of freedom. The total degrees of freedom is total number of observations minus one, which is 30 - 1 = 29. The between-groups degrees of freedom is number of groups minus one, which is 3 - 1 = 2. The within-groups degrees of freedom is total degrees of freedom minus the between groups degrees of freedom, which is 29 - 2 = 27.

MS is the mean squared error, which is SS/df for each source of variation. The *F*-statistic is the ratio of the mean squared errors (120/0.7407). The *p*-value is the probability that the test statistic can take a value greater than the value of the computed test statistic, i.e., P(F > 162). The *p*-value of 0.09 greater than 0.05 indicates that differences between column means are not significant. In this analysis, the computed p-value which is less than ($\alpha = 0.05$) indicated that the null hypothesis stated in Eq. (4); $\mu_i - \mu_j = 0$ is accepted at significance value i.e. (there is no significance difference between the heart rate measured from the three devices).

2.0 GENERAL ACHIEVEMENTS

2.1 Achievements:

- Research guidelines, Reviews, software subscription, simulators.
- Data acquisition (publicly available data), data annotation and pre-processing.
- Purchase of equipment.
- Design, simulation, construction, prototype and testing of vital signs system
- Conferences (1 International conference, 1 International conference ongoing)
- Publications of Technical Papers (3 Journals: 2 Published, 1 Accepted)

3.0 PRELIMINARY IMPACT OF GRANT

3.1 Indication of preliminary impact of the project, as executed.

- The team has laid out the structure for significant aspects of the research by collecting, and preprocessing publicly available data
- Research related technical papers; 4 Nos. (3 Journals and 1 Conference)
- Several pieces of equipment and software have been procured

4.0 CONSTRAINTS/LIMITATIONS

1. The global lock-downs due to the COVID-19 pandemic caused significant delays in international shipping. This delayed research, research administration and procurement activities.
2. There were significant fluctuations and restrictions on forex usage during the period under review causing variations in the prices of items purchased.
3. Illumination variant due to difficulty to measure heart rate in darker environment or poor light source.

4. Distance between camera and the human body, susceptibility to environmental disturbances, movement artefacts etc. are among the factors that affect the accuracy of the heart rate and breathing rate measurement.
5. Respiratory rate reading was affected by the effect bandpass filtering during unwanted pulses suppressing within the heart rate periodic signal sample.

5.0 EVALUATION: OVERALL TARGETS

5.1 The level of project completion:

1. The equipment as well as necessary simulation software were purchased.
2. Deployment and the Prototype (APK) has been completed
3. Experimentations and testing of vital signs were completed

5.2 Outstanding activities:

1. Additional Conference paper will be presented in South Africa, Dec. 2021
2. Yolov4 mini Configurations will be done within the available fund

6.0 PROJECT FINANCIAL STATUS

6.1: Approved Grant for the Project

Milestone	Action	Duration	Payment Required in %	Amount
1st Milestone	Guideline, Reviews, Purchase of Laptop, Stationary, Articles, MATLAB Subscription, Software, Simulators, IP Camera, Smartphones	6 Months	20%	N2,900,000.00
2nd Milestone	Design of Prototype, Simulations, Purchase of equipment and components	6 Months	40%	N5,800,000.00
3rd Milestone	Construction, testing and modifications	6 Months	25%	N3,625,000.00
4th Milestone	Finishing of Prototype, Reporting Presentation and Submission	6 Months	15%	N2,175,000.00
Total		**24 Months**	**100%**	**N14,500,000.00**

6.2: Details of Expenditure of First Tranche (20%)

1.	DELL Precision Workstation M4800 Corei7, 16GB RAM	=	N750,000.00
2.	2019 MATLAB License with associated tool-kits	=	N600,000.00
3.	Samsung Smartphone Note8	=	N190,000.00
4.	IP Camera, accessories and stationaries	=	N110,000.00
5.	STIPS 3D and CAFFE Configuration	=	N950,000.00
6.	Researchers allowance (Each N150,000)	=	N300,000.00
	Grant Total	=	N2,900,000.00

6.3: Details of Expenditure of Second Tranche (40%)

1.	DELL Precision Workstation M4800 Corei7, 16GB RAM	=	N750,000.00
2.	2020 MATLAB License with associated tool-kits	=	N900,000.00
3.	HP Pavilion Corei7, 16GB RAM, 2GB GPU	=	N750,000.00
4.	Android Deployment, Testing and Modification	=	N1,400,000.00
5.	STIPS 3D and CAFFE Software Configuration	=	N2,000,000.00
	Grant Total	=	N5,800,000.00

6.4: Details of Expenditure of Third Tranche (25%)

1.	IEEE International Conference on Intelligent and Advanced Systems (ICIAS) 2021, Malaysia, Registration, Air Ticket, Hotel and Local Runnings	=	N1,743,920.00
2.	Journal Publication Charges (2 Papers) USD16+25,000 @N380	=	N31,080.00
3.	Darknet Deep Learning Configuration & Prototype	=	N794,000.00
4.	2021 MATLAB License with associated tool-kits	=	N1,056,000.00
	Grant Total	=	N3,625,000.00

6.5: Proposed Budget against the 4th Tranche (Final) Disbursement (15%)

1.	Yolov4 mini Configuration	=	N950,000.00
2.	International Conference on Electrical, Computer and Energy Technologies (ICECET) 2021, South Africa, Registration, Air Ticket, Hotel/Local Runnings	=	N1,225,000.00
	Grant Total	=	N2,175,000.00

7.0 CONCLUSION

This research work presented non-contact heart rate measurement based on physiological signals using smartphone IP camera. The heart rate has been estimated using rPPG signal based on sparse signal reconstruction technique. The proposed method produced reliable physical parameters estimation. The computed results based on rPPG and sparse representation technique provided less error rate as compared to methods without sparse signal reconstruction. The heart rate was computed with the existing rPPG technique by sampling the extracted periodic signals from the power spectrum. The mean of the periodic signal samples was obtained and validated with Samsung Health App and Pulse Oximeter.

The statistical analysis (one way ANOVA and multiple comparison test) for minimum and maximum frame rates have shown the effectiveness of the use of smartphone (Samsung Note 8) in heart rate estimation experiments using facial video as compared to the use of PC's webcam camera or standard digital camera at established statistical significant value. The average maximum frame rates used was 18 fps. In addition, heart rate extracted results were analyzed and validated using one way ANOVA. The p-value of 0.09 obtained which is greater than 0.05 indicates that the differences between column means are not significant. Hence, the heart rate measured by the non-contact device conformed to the standard bpm readings from contact devices. Therefore, statistical analysis based on ANOVA has shown that there is no significance difference between heart rate measurements obtained using non-contact (proposed) and contact approaches. The proposed method can be used in real time applications such as; (telemedicine, healthcare, sport etc.) that involves heart rate monitoring and vital signs estimation.

REFERENCES

[1] Cohen H, Kotler M, Matar MA, Kaplan Z, Loewenthal U, Miodownik H, Cassuto Y. Analysis of heart rate variability in posttraumatic stress disorder patients in response to a trauma-related reminder. Biological Psychiatry 1998; 44(10):1054-1059.

[2] Billman G. The LF/HF ratio does not accurately measure cardiac sympatho-vagal balance. Frontiers in Physiology 2013; 4(26).

[3] Lindh WQ, Pooler M, Tamparo CD, Dahl BM, Morris J. Delmar's comprehensive medical assisting: administrative and clinical competencies. Cengage Learning; 2013.

[4] Alexandra Fontaine, Arben Koshi, Danielle Morabito, Nicolas Rodriguez. “Reflectance-Based Pulse Oximeter for the Chest and Wrist”. A Major Qualifying Project Report Submitted to the Faculty of the Worcester Polytechnic Institute.

[5] Nedoma, Jan, Marcel Fajkus, Radek Martinek, Stanislav Kepak, Jakub Cubik, Stanislav Zabka, and Vladimir Vasinek. "Comparison of BCG, PCG and ECG signals in application of heart rate monitoring of the human body." In 2017 40th International Conference on Telecommunications and Signal Processing (TSP), pp. 420-424. IEEE, 2017.

[6] Das, Sangita, Saurabh Pal, and Madhuchhanda Mitra. "Real time heart rate detection from PPG signal in noisy environment." In 2016 International Conference on Intelligent Control Power and Instrumentation (ICICPI), pp. 70-73. IEEE, 2016.

[7] Pino, Esteban J., Javier AP Chávez, and Pablo Aqueveque. "BCG algorithm for unobtrusive heart rate monitoring." In 2017 IEEE Healthcare Innovations and Point of Care Technologies (HI-POCT), pp. 180-183. IEEE, 2017.

[8] Temko, Andriy. "Accurate heart rate monitoring during physical exercises using PPG." IEEE Transactions on Biomedical Engineering 64, no. 9 (2017): 2016-2024.

[9] M. M. A. Hashem, Rushdi Shams, Md. Abdul Kader, and Md. Abu Sayed. “Design and Development of a Heart Rate Measuring Device using Fingertip”.

[10] Zhang, Zhilin. "Photoplethysmography-based heart rate monitoring in physical activities via joint sparse spectrum reconstruction." IEEE transactions on biomedical engineering 62, no. 8 (2015): 1902-1910.

[11] Eduardo Pinheiro, Octavian Postolache and Pedro Girão, "Theory and Developments in an Unobtrusive Cardiovascular System Representation: Ballistocardiography", The Open Biomedical Engineering Journal, 4, 201-216,October 10, 2010.

[13] Benedetto, Simone, Christian Caldato, Darren C. Greenwood, Nicola Bartoli, Virginia Pensabene, and Paolo Actis. "Remote heart rate monitoring-Assessment of the Facereader rPPg by Noldus." PloS one 14, no. 11 (2019): e0225592.

Your faithfully,

Dr. Aliyu Nuhu Shuaibu (PI)
(09063200704)

APPENDIX

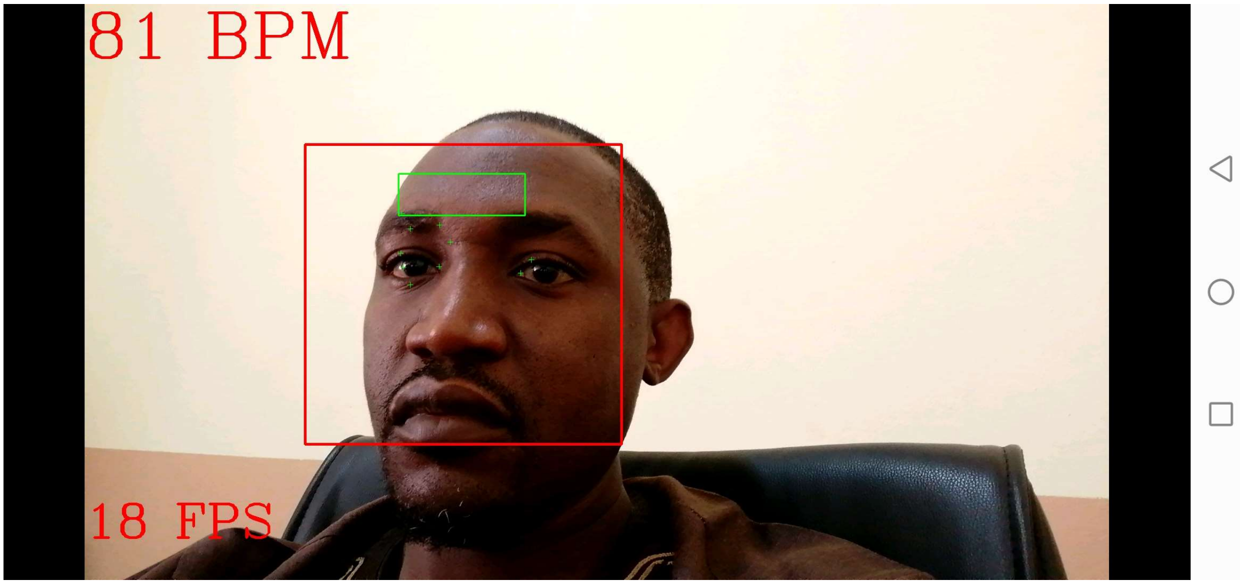

Fig. A1: Heart rate reading from the proposed non-contact system

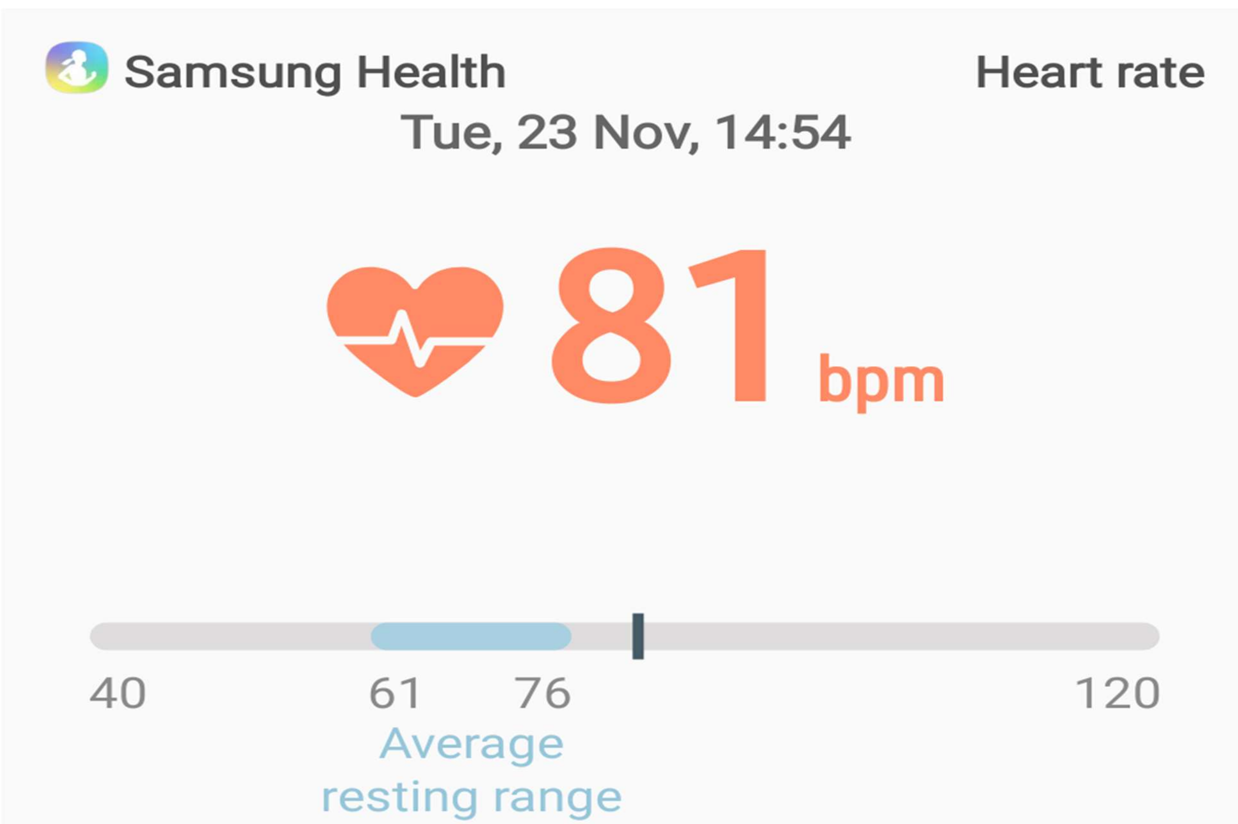

Fig. A2: Heart rate reading from Samsung health app (rear camera sensor)

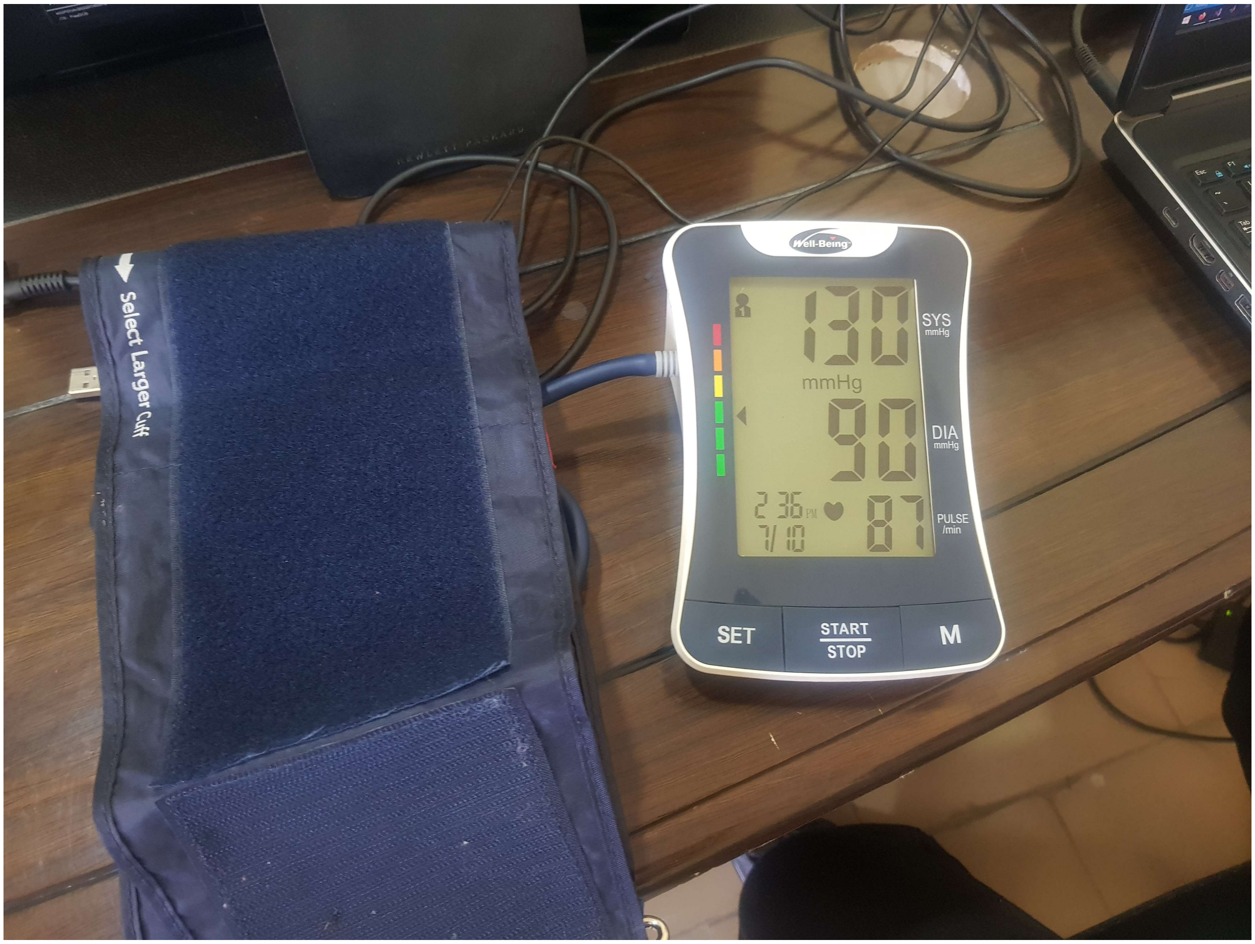

Fig. A3: Heart rate reading obtained from clinical pulse oximeter

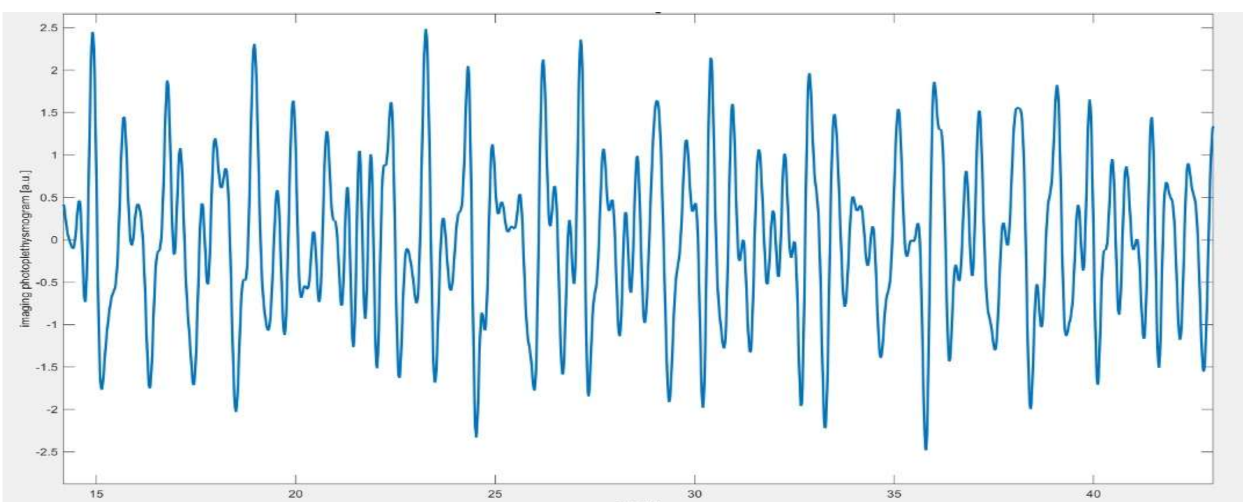

Fig. A4: Periodic Signal for non-contact heart rate measured

Table A1: Proposed sparse representation technique using rPPG signal for non-contact heart rate estimation

1	**Description: Signal reconstruction based on sparse modeling for sparse coefficients** $\mathbf{y}$ given rPPG signal samples; $\boldsymbol{D}$ dictionary matrix; $\boldsymbol{\rho}$ sparsity level chosen**;** $\boldsymbol{p}$ sparse coefficient
2	**FOR** $i = 1{:}\,Subjects$ **do**
3	Extract rPPG signal samples $\mathbf{y}$ using rPPG algorithms
5	Apply sparse coding on $\mathbf{y}$ to extract the sparse coefficients
6	$\min\lVert\mathbf{y} - \mathbf{D}\boldsymbol{p}\rVert_2$ subject to $\lVert\boldsymbol{p}\rVert_0 \leq \boldsymbol{\rho}$ $\min\lVert\mathbf{p}\rVert_0$ subject to $\min\lVert\mathbf{y} - \mathbf{Dp}\rVert_2 \leq \in$
7	Compute sparse coefficients $\boldsymbol{p}$ base on sparse modeling approach
8	$\boldsymbol{SrPPG(i) = p} \in \boldsymbol{R^{1xD}}$
9	**END FOR**
10	$F_M = [\boldsymbol{SrPPG_1}, \boldsymbol{SrPPG_2}, \dots, \boldsymbol{SrPPG_N}]$ sparse rPPG signals for subjects
11	**Apply Machine Learning Algorithm for classification**