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Heart Rate Measurement Using Video in Different User States for Online HCI Applications

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Abstract :
In this paper we implemented an unobtrusive and non-invasive method to measure pulse rate and heart rate variability. A Ballistocardiography technique has been used which describes ballistic force applied by heart on blood vessels. Ballistocardiography depicts repetitive motion in human body against blood flow because of the ballistic force. In this process videos of human head have been recorded and feature points using Lucas - Kanade point tracker are calculated. After filtering the resultant signal to remove noise (unwanted signals) trajectories are decomposed into elementary components. Component that best corresponds to pulse frequency is selected. Detected peaks correspond to beats in the signal and hence the Heart Rate Variability is calculated. The algorithm was tested with many videos of 12 subjects (10 males and 2 females) with variations in skin color , sex, subject's state. We found that user state and activities affect Heart Rate Variability which can be calculated through our algorithm. It is concluded that extensive research and development of this unobtrusive and non-invasive technique can yield new tools for various online and adaptive HCI applications.

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*Keywords:*BCG; PCA; Heart Rate Variability; Pulse Rate;Histogram.

1. Introduction: Ballistocardiography (BCG), originally derived from the Greek (*βάλλω* (*ballō*) "throw" + καρδία (*kardia*) "heart" + γραφία(*graphia*) "description"), is a method for obtaining a description of repetitive movements of human body due to accelerated blood ejected by heart during each systolic operation to blood vessels[1]. Isaac Starr, who performed first experiment in 1936, was inspired by the work of Handerson and built a system to fix flaw of Handerson's design which restricts subject to hold breath during recording[2]. Extensive experiments by Starr has given physiological interpretation to BCG and described malfunctioning of heart using BCG[1]. After standardization

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of BCG in 1956 and development in sensor technologies namely piezoelectric sensors, a lot of bed and chair based systems embedding these sensors developed by researchers and use of these sensors transitioned early development of BCG namely displacement or velocity BCG to acceleration BCG. Systems implemented on Doppler Radar concept to transmit BCG signals wirelessly[3]. With the increasing trend of wearable, ubiquitous and unobtrusive technology BCG became one of the main research focuses. A wearable heart monitor based on BCG and ECG is designed in MIT in which 3D accelerometer was worn by subject at ear to record motion in head[4]. Relation between 'R' wave (ECG) and analogous 'J' wave (BCG) was found and stroke volume and pre-ejection period parameters were derived. In experiment 3-dimensional BCG obtained and two conclusions were drawn. First conclusion was suggesting that head moves in y axis due to blood ejection and second conclusion was suggesting interference of head - neck joint structure in movement. Because of the ventricular depolarization heart applies ballistic force on blood to flow it throughout the body and through Carotid Artery to head. Blood vessels follow Newton's third law of motion and react to this blood flow. Because of this action by blood flow and reaction by vessel walls head moves. Movement in head due to blood ejection is corrupted by cervical discs in head-neck joint. These Discs are arranged in stack form. Each disc has analogy with spring fixed at both the ends. This stack organization is supported by facet joints which provide stability and movement. Vibration in head is created due to concept called dynamic equilibrium which says "net force on mechanical system is zero". Two equal and opposite forces called displacement force and restoring force applies on discs and create vibration in head. Above two conclusions were utilized by Guha et.al and they captured this vibration in head by recording video of head[5]. Guha measured Pulse Rate and Heart Rate Variability. Heart Rate Variability is recognized as an important tool for detecting risk factors of Cardiovascular Diseases (CVD) as supported by many studies and researches. According to the report of World Health Organization (WHO) CVD are major cause of death worldwide[6]. Detection and understanding of risk factors of CVD can help to reduce the death statistics given by WHO in report. Pathological conditions of heart can be predicted by Imbalance in autonomic nervous system and there is a clear association between HRV and autonomic nervous system as it regulates pacemaker (Sympathetic branch which increase rate of contraction whereas Parasympathetic branch does opposite) according to the requirement of body for blood[7, 8, 9, 10]. Long term monitoring of HRV in different-2 states like resting, running, stress, standing can give important information to predict CVD like coronary artery disease, congestive heart failure, cardiac arrhythmia, angina pectoris, myocardial infarction[9]. Along with CVD prediction HRV has importance in predicting user's state and behaviour. Julian et.al performed a meta-analysis of association of HRV with Amygdala and Medial Prefrontal Cortex. They found that HRV may approximate behaviour and health by giving information about "vertical Integration (Integration of three regions Cortex, Brain Stem and limbic area)" of the brain mechanisms that control behaviour[11]. Deniel et.al concluded HRV as a novel marker to recognize emotions by finding positive association of HRV with emotion recognition task while experimenting with different age groups[12]. In 1998 an experiment conducted to find relationship between HRV and mental effort. In same experiment user has to play game and simultaneously ECG had recorded. It was found that HRV is affected by mental effort[13]. Studies and experiments summarized above suggesting importance of HRV in diagnosis of CVD in emotion recognition and in assessing interface friendliness. Traditional way of cardiac monitoring requires physical contact with any part of human body like for ECG, electrodes should be placed at right spot on chest with irritating chemical solution for conductivity, pulse oxy-meter needed to be worn at ear or at finger. Electrocardiography can lead to skin irritation if used for long term monitoring or used for heart monitoring of old age persons. ECG could also causing skin damage of newborn babies, which is very sensitive to any chemical solution. Importance of HRV and need of unobtrusive measurement of heart related parameters inspired us to develop an unobtrusive and non-invasive method which at the same time requires less setup and technician unlike ECG and also easily accessible. We developed method for unobtrusive and non-invasive measurement of pulse rate and HRV. We tested our technique with subjects varying in skin colour, sex, and activities. To record variation due to uncomfortable state we compelled our subjects to wear napkin and To record variation after physical activity we recorded videos of subjects after 100 meter running. Obtained results suggest that the technique can measure the HRV correlating them to various activities and hence making it appropriate for various HCI applications. Rest of the part describes methodology in section 2, the experimental setup in section 3, result and analysis in section 4 and discussion is given in section 5.

2. **Methodology**: Flow chart of implemented method is presented in figure 1. Flow chart is clearly describing input and output after applying different modules. In following subsections all modules are explained.

2.1 *Face Detection and Region Selection:* We used Viola-Jones face detector to detect face in a video frame. Viola - Jones object detection framework has three basic modules. First module is "Haar feature calculation". Second module is Ensemble or Ada-Boost method to select features that are predicting face well. Third module is "Attentional cascade" which is a method of combining weak classifiers. It is trained with database of million faces and has 99.99% accuracy in face detection. Face region detected by face detector includes whole face, but our region of interest is some part of face that's why face region needs to be adjusted to include required part of face only and exclude others. Center location (nose tip) of face region detected by face detector is considered as reference point to get required ROI. Width and height factor for ROI can be selected by user interactively. Default Width of ROI is 40 percent of face region and Height of ROI is 55 percent of face region. Width and height of ROI should be selected such that it is not too wide and should exclude nostrils, eye, and hair region as they can introduce noise due to breathing, eye blinking and air blow respectively. With the consideration of above norms a selected ROI is passed to feature extractor module to extract features.

2.2 *Feature Extraction*: Good feature selection is very important to acquire useful information. Feature were selected from first frame and in subsequent frames these features were tracked using optical-flow point tracker. Features selected should be easy to track and should not lead to "aperture problem". Although corners are very good features for tracking, but texture under ROI which we were using for feature extraction don't give too many corners. There is also problem of skin tone and fairness which varies from person to person, so in some cases it is very rare to get a point where two edges meet. That's why we have used edges as appropriate features and detected these edges by "Canny Edge Detector" in region of interest. These edge points collectively defines the feature set for normal and running case. For the case in which subject was wearing mask; corner detector were used. We used "Harris Corner Detector" to detect corners in frame which served the purpose of feature for the subject wearing mask.

2.3 *Tracking:* Feature points were changing position from frame- to- frame due to head vibration. We tracked these feature points using Lucas - Kanade point tracker algorithm. Optical flow equation shown in equation 1 was being calculated to get flow vector (u, v)at each feature point by getting optimal solution for matrix shown in equation 2. We added u and v with previous location co-ordinates x and y respectively to get new locations co-ordinates x' and y'. Head movement due to pulse arrival is periodic because heart contraction and relaxation is a cyclic event. It is like pendulum is moving in two directions. That's why tracking was performed by calculating point correspondence between first frame and all other frames 2,3,4.........m in video. Parameters like height of Pyramid, Error threshold and block size are selected to capture small movements and global flow i.e. flow due to head movement rather than flow due to local patch variation. Muscle movements and sudden changes in light patterns can corrupt the signal. So we processed the tracking results to recognize these movements. Due to blood flow head moves in upward and downward direction i.e. in y direction that's why we recorded only y co-ordinate. Recorded trajectories of feature points were not in same scale. So we calculated zero mean trajectory and normalized amplitude between -5 to 5. We recognized those points which were deviating from flow pattern and eliminated these feature points.

Optical Flow Equation: $$f_x u + f_y v = -f_t \qquad (1)$$

f_x = Spatial derivative of image with respect to x axis. (Known)
f_y = Spatial derivative of image with respect to y axis. (Known)
f_t = Temporal derivative with respect to time. (Known)
u and v are optical flow vectors. (Unknown)

Values in the following matrix were derivatives of neighborhood pixels which were incorporated in optical flow calculation for one feature point. For every feature point optimal solution for matrix containing respective neighborhood pixel derivatives for each feature point was calculated. This calculation was iterative in every pyramid level until error threshold was reached. Optical Flow values obtained in higher level of pyramid were passed to lower level of pyramid to facilitate initial guess for lower level till original dimension encountered. Finally obtained optical flow vector with original dimension was added to previous location of feature point to get new locations.

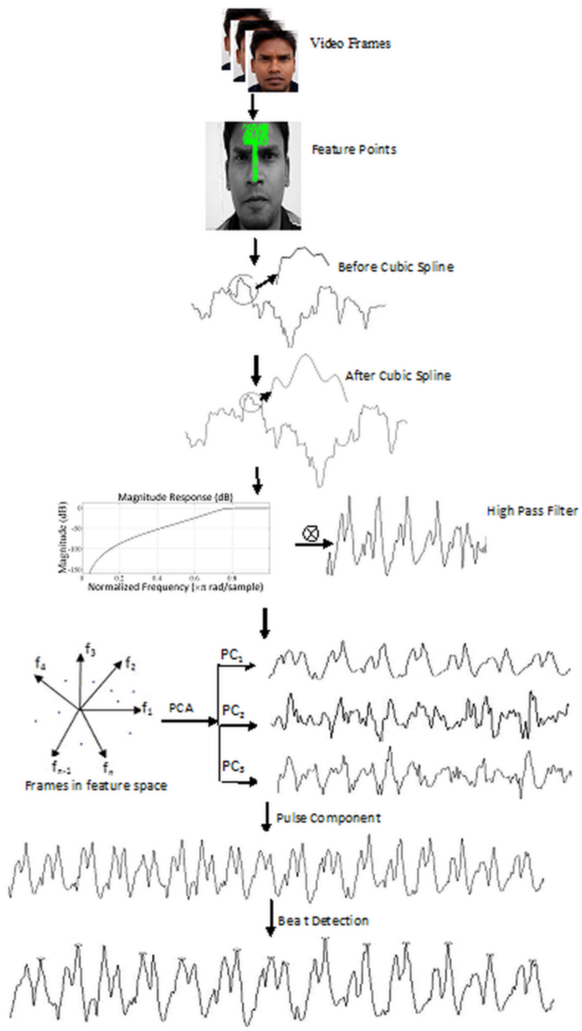

Figure1 Flow Chart of Proposed Methodology

$$\begin{bmatrix} f_{x1} & f_{y1} \\ f_{x2} & f_{y2} \\ | & | \\ | & | \\ | & | \\ f_{xn} & f_{yn} \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} f_{t1} \\ f_{t2} \\ | \\ | \\ | \\ f_{tn} \end{bmatrix} \quad (2)$$

New Co-ordinates: $x' = x + u$ and $y' = y + v$

After getting trajectories we performed point elimination by eliminating those points which were deviating from trajectory followed by other points. This was done by first normalizing trajectories and then removing outlier based on the standard deviation.

2.4 *Cubic Spline:* Sudden change in amplitude of the signal due to pulse arrival is sum of high frequency components. We captured 30 frames per second. According to Nyquist criteria one can recover maximum 15Hz component, which is not enough to get sharp peaks. That's why we up sampled the signal by 5 samples using Cubic Spline interpolation to capture sharp peaks. Normally ECG records signals at 250Hz to recover sudden electric impulse due to ventricular depolarization. This impulse is so quick, but movement in head due to pulse arrival is not this much quick. So we increased sampling frequency of signal from 30Hz to 150Hz.

2.5. *Filtering:* Movement due to respiration causing base line drift and present throughout the trajectory. Other than respiration head vibrations interfere with the signal randomly. We used Butterworth high pass filter with cut-off frequency is 0.75Hz. Cut-off frequency was selected such that along with other noise, base line drift should be filtered, without loss of desired information. Passed signal with cut-off frequency less than 0.75Hz was dominated by breathing movement in case of physical exercise. We used Butter-worth filter because it gives maximally flat Pass-band" with controlled transition period tuned by its order. As we go high in order transition period reduces. But there exists trade-off between stability and transition period, so we used 5th order Butterworth high pass filter'. We had to recover peaks due to pulse arrival that's why instead of Band-pass filter, we used High-pass filter.

2.6. *Principal Component Analysis:* We observed that even after above processing like filtering, point elimination; still we left with corrupted signals. This signal was corrupted due to three reasons; a)first reason is random variation in signal due to head vibration subjected to head neck connection by stack of cervical disks, b)second reason is variation due to involuntarily muscle movements and c)third reason is variation in local surface texture, consequently variation in optical flow pattern. Position of feature points was varying not only because of blood flow but because of respiration and above three movements also. Respiration frequencies were filtered out by filter. Here we were using PCA to getting signal which is maximally varying due to pulse component. Since signal has various elementary movements along with pulse movement and these elementary motions are components of original signal, using "Principal Component Analysis" we got principle components of variations. Formally we have n feature points f_1......f_n representing n dimensional position of head and m frames O_1.......O_m. At a particular time t frame O_t was represented by a column vector of features $[f_1(t),f_2(t),f_3(t),..........,f_n(t)]^T$. We need to calculate mean and covariance of m x n dimension matrix using following formula:

$$\text{Mean:} \qquad \overline{F} = \frac{1}{m}\sum_{i=1}^{m} F_i$$

$$\text{Co-Variance:} \quad \Sigma_m = \frac{1}{m-1}\sum_{i=1}^{m} (F_i - \overline{F})'(F_i - \overline{F})$$

Eigen vectors of Co-Variance matrix are Principal axes of variation and linear combination of feature points. Eigen vector corresponding to maximum Eigen value represents axis of maximum variation. PCA returns matrix ϕ_n (n x n) of n non-zero Eigen vectors ϕ_1, ϕ_2, ϕ_3,........ϕ_n and Ψ_n Diagonal matrix of Eigen values λ_1, λ_2, λ_3, λ_4,............, λ_n. These two are Inner Product of each 1 x n dimensional frame with 1x n dimensional Eigen vector is giving a signal, varying because of one elementary motion component. Likewise we calculated signal corresponding to all principal components. Before passing signals to PCA, we processed these signals to find outlier frame. Outlier frames are causing deviation in regular pattern and sudden increase in amplitude because of superficial muscular movements, posture adjustment. We calculated median of vector length corresponding to each frame and reduced vector length of vectors greater than this median value by 0.75.

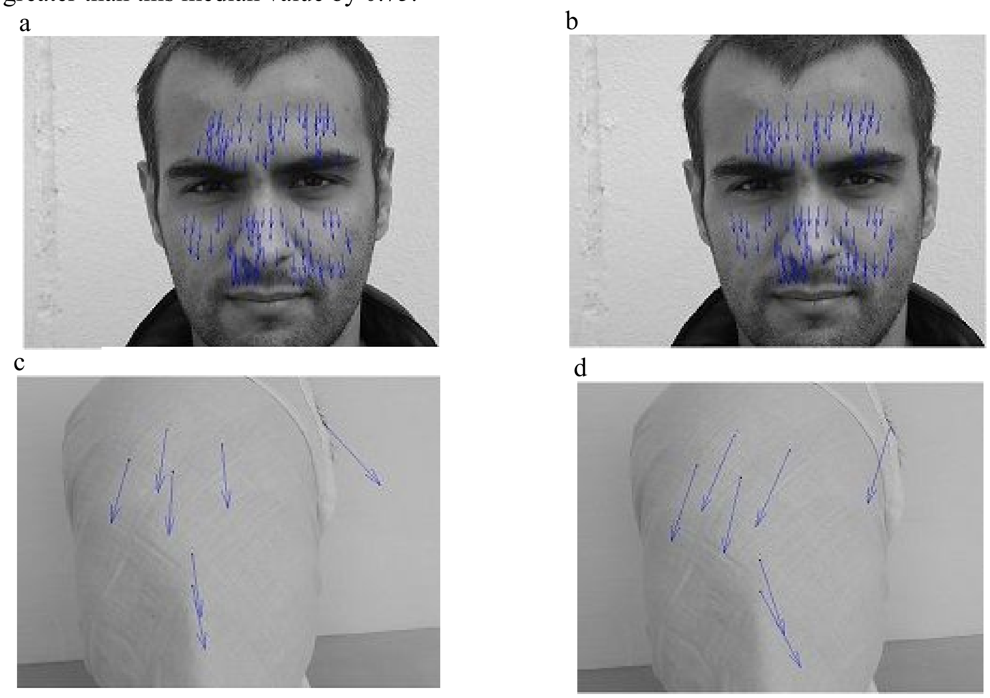

Figure2 Principal Components: (a) and (b) Without Mask; (c) and (d) with Mask

These Eigen vectors are representing signals corresponding to different - different source of movements. One of the Eigen vectors is representing maximum variation in signal due to pulse. We were calculating power spectrum of projected signal on these components. Signal with new dimension for variation whose total power is maximally contributed by frequency within the decided bandwidth is recognized as desired signal. And this frequency is determined as pulse frequency. Component which was corresponding to pulse frequency is depicted in figures 2, where images belongs to videos of same person taken after some interval and with and without mask. It can be observed clearly that co-ordinates of pulse component are varying. We inferred from this observation that Heart functionality varies based on the subject's state and context (Like with and without mask).

2.7. *Beat Detection:* To detect beat, we used window whose size is calculated using following formula.

Size of Window = Sampling Frequency / Pulse Frequency

This window we are shifting through signal. A point within the window is qualifying as beat if it is following two criteria. First criteria is if it is greater than at least 10 leading points and 10 following points. Second criteria is its value should be greater than one-fourth of maximum value of signal. Time between beat to beat can vary because of natural variation in heart cycle.

3. Experimental Setup: We have recorded videos using Nikon Coolpix L820 with frame rate of 30 fps. Camera and subjects were not allowed to move. Length of recording was 1 minute. We counted pulses manually and calculated average pulse rate. Videos of 12 subjects (10 males and 2 females) aging between 23 to 28 have been recorded. Dataset has variations in skin colour, sex, visuals, physical activity and environment (sun light and room light). Distance between camera and subject was maintained approx. 1 meter for every subject. Background of recorded videos was not same because they have not been recorded at the same location.

4. Result and Analysis: The frequency contributing maximum power in the power spectrum of the traced component was calculated which corresponded to the pulse frequency. This frequency gives information about average pulse rate in one minute. With the beat detection algorithm we detected beat and calculated beat lengths. Table 1 is showing pulse rate detected manually (actual) and calculated using our algorithm. The difference between the two readings is very small (minimum 0.03 percent and maximum 2.48 percent). The mean error is only 0.96 % with 16 observations. We also calculated mode and standard deviation for HRV. Mode is calculated to check which beat length is dominating in HRV graph. We Observed that beat length corresponding to average pulse frequency has more occurrences than other beat lengths. This validates our approach. In order to further validate our method we superimposed 20 windows centered at beat location to obtain BCG signal (as shown in fig 3a and 3b). The obtained BCG wave has similarity with the standard BCG wave[2] including information related to "IJK" complex and other useful nomenclature. By observing histograms (as shown in fig. 3c and 3d) we found that there is maximum no. of beats for those bins which represent time intervals inverse of average pulse frequency. These histograms belong to the same subject in two different states, i.e. first without any napkin (fig. 3c) and second with napkin tied on the face (fig. 3d). First histogram is showing beat distribution when subject has no napkin on face and in normal state and second histogram is showing histogram when subject's face tied up with napkin causing irritation.. There are variations in beat length in the two histograms because of variation in heart rhythm which may be because of irritation due to tied face with napkin. It can be observed in the histograms that some beats (1 or 2) are

Table 1. Average Pulse Rate Detected by our method and by Manual counting

Subject ID	State	Sex	Avg. Pulse Rate (Beats/min.)			HRV(seconds)	
			Actual	Motion	Error	Mode	Standard Deviation
S01	Resting	M	89	88.53	0.52	0.67	0.163
S02	Resting	M	75	75.29	0.39	0.79	0.182
	Running		108	109.61	1.49	0.54	0.023
S03	Resting	M	79	79.23	0.29	0.75	0.186
S04	Resting	M	67	68.66	2.48	0.87	0.214
S05	Resting	M	76	75.2	1.05	0.79	0.189
	Running		103	105.12	2.05	0.57	0.081
S06	Resting	M	82	81.07	1.13	0.74	0.114
S07	Resting	M	88	87.23	0.87	0.69	0.091
	Mask		94	93.76	0.26	0.64	0.081
S08	Resting	M	70	70.02	0.03	0.86	0.136
S09	Resting	M	100	101.23	1.23	0.59	0.092
S10	Resting	F	95	95.08	0.08	0.63	0.034
S11	Resting	F	68	67.19	1.19	0.89	0.206
S12	Resting	M	82	81.21	0.96	0.73	0.112
	Mask		88	88.66	0.75	0.68	0.092

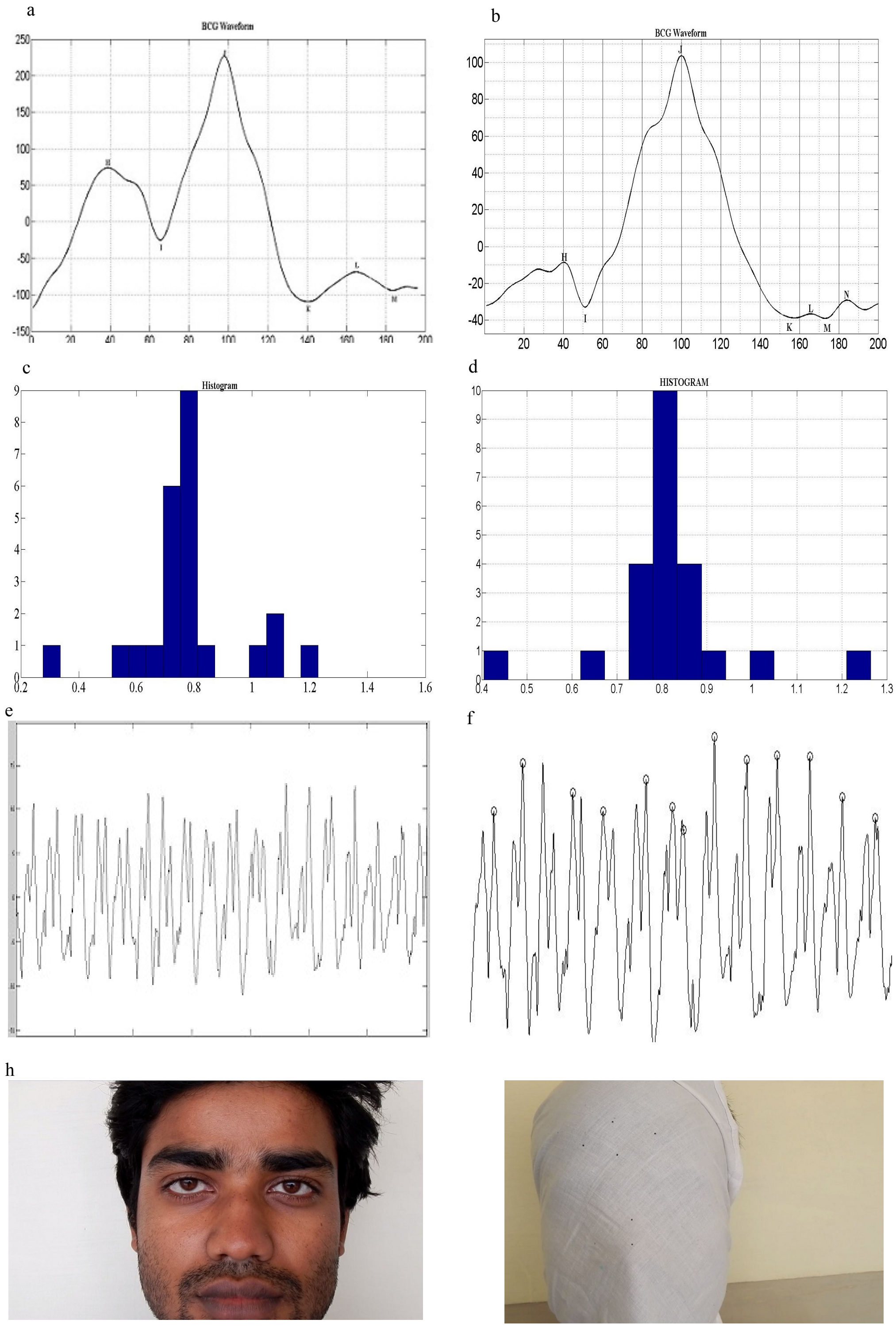

Figure3 (a) and (b) BCG waves; (c) and (d) Histograms; (e) and (f) BCG signals of same subject without mask and with mask.

appearing randomly here and there. This can be because of some noise still present in the signal due to head vibrations or involuntary motions. BCG signal which we got is the trace of the principal component obtained by principal component analysis of each subject video (as shown in fig. 3e and 3f).

5. Discussion: We successfully recorded HRV and pulse rate and achieved very satisfactory results with mean error of 0.96% in measurement of average pulse rate. Encouraging result for Beat length distribution could be justified by statistical measures mode and standard deviation. Mode is ensuring that we are getting good count for beat length corresponding to average pulse frequency. Standard deviation is ensuring us about beat length distribution with low values. Since all our subjects are healthy that's why low standard deviation value is meaningful. For some cases we obtained large deviation in HRV values, it could be because of three reasons. First reason may be less frame rate in video recording where videos were recorded with only 30 frames/second whereas traditional ECG machines record signals with at least 128Hz sampling frequency and cubic Spline may not be able to address this issue completely. Second reason is filtering and component analysis technique which may be unable to remove involuntary motions completely. Third reason is tracking visual patterns which can be affected by non-uniformity of light on the face surface and feature points selection. To get good tracking results features should be unique, but unique features like corners are very rare in human face. Most of the times corners, i was getting, were on the places which were sensitive to involuntary motions like eye movement, respiration and lip movement. That's why i took edges instead of corners. Above three reasons may be cause of error in our approach. These errors can be reduced by further research regarding every module. Unobtrusive and Non-Invasive characteristic of Ballistocardiography directs towards future where this technique could have application in Video surveillance, Lie detection, software or interface assessment, in heart monitoring of severely burn patients, with more sophisticated filtering, tracking and analysis techniques to detect and remove involuntary movements and other unwanted motions. HRV is very simple and informative parameter, good understanding of HRV in relation with Nervous system is good predictor of CVD and Heart functioning. In future exact correspondence between BCG signal and ECG signal can be obtained to justify applications of BCG in prediction of CVD and heart functioning using HRV parameter.

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