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Mohammad A. Haque, Kamal Nasrollahi, Thomas B. Moeslund

Abstract. Different biometric traits such as face appearance and heartbeat signal from Electrocardiogram (ECG)/Phonocardiogram (PCG) are widely used in the human identity recognition. Recent advances in facial video based measurement of cardio-physiological parameters such as heartbeat rate, respiratory rate, and blood volume pressure provide the possibility of extracting heartbeat signal from facial video instead of using obtrusive ECG or PCG sensors in the body. This paper proposes the Heartbeat Signal from Facial Video (HSFV) as a new biometric trait for human identity recognition, for the first time to the best of our knowledge. Feature extraction from the HSFV is accomplished by employing Radon transform on a waterfall model of the replicated HSFV. The pairwise Minkowski distances are obtained from the Radon image as the features. The authentication is accomplished by a decision tree based supervised approach. The potential of the proposed HSFV biometric for human identification is demonstrated on a public database.

Keywords: biometric, identification, Radon transform, heartbeat, facial video

1 Introduction

Human identity recognition using biometrics is a well explored area of research to facilitate security systems, forensic analysis, and medical record keeping and monitoring. Biometrics provides a way of identifying a person using his/her physiological and/or behavioral features. Among different biometric traits iris image, fingerprint, voice, hand-written signature, facial image, hand geometry, hand vein patterns, and retinal pattern are well-known for human authentication [1]. However, most of these biometric traits exhibit disadvantages in regards to accuracy, spoofing and/or unobtrusiveness. For example, fingerprint and hand-written signature can be forged to breach the identification system [2], voice can be altered or imitated, and still picture based traits can be used in absence of the person [3]. Thus, scientific community always searches for new biometric traits to overcome these mentioned problems. Heartbeat signal is one of such novel biometric traits.

Human heart is a muscular organ that works as a circulatory pump by taking deoxygenated blood through the veins and delivers oxygenated blood to the body through the arteries. It has four chambers and two sets of valves to control the blood flow. When blood is pumped by the heart, some electrical and acoustic changes occur in and around the heart in the body, which is known as heartbeat signal [4]. Heartbeat

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signal can be obtained by Electrocardiogram (ECG) using electrical changes and Phonocardiogram (PCG) using acoustic changes, as shown in Fig. 1.

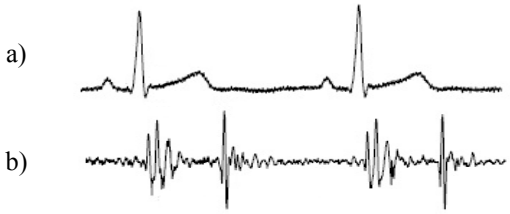


Fig. 1. Heartbeat signal obtained by a) ECG and b) PCG

Both ECG and PCG heartbeat signals have already been utilized for biometrics recognition in the literature. ECG based authentication was first introduced by Biel et al. [5]. They proposed the extraction of a set of temporal and amplitude features using industrial ECG equipment (SIEMENS ECG), reduced the dimensionality of features by analyzing the correlation matrix, and authenticated subjects by a multivariate analysis. This method subsequently drew attention and a number of methods were proposed in this area. For example, Venkatesh et al. proposed ECG based authentication by using appearance based features from the ECG wave [6]. They used Dynamic Time Wrapping (DTW) and Fisher's Linear Discriminant Analysis (FLDA) along with K-Nearest Neighbor (KNN) classifier for the authentication. Chetana et al. employed Radon transformation on the cascaded ECG wave and extracted a feature vector by applying standard Euclidean distance on the transformed Radon image [7]. They computed the correlation coefficient between such two feature vectors to authenticate a person. Similar to [5], geometrical and/or statistical features from ECG wave (collected from ECG QRS complex) were also used in [8]–[10]. Noureddine et al. employed the Discrete Wavelet Transformation (DWT) to extract features from ECG wave and used a Random Forest approach for authentication [11]. A review of the important ECG-based authentication approaches can be obtained from [12]. The common drawback of all of the above mentioned ECG based methods for authentication is the requirement of using obtrusive (touch-based) ECG sensor for the acquisition of ECG signal from a subject.

The PCG based heartbeat biometric (i.e. heart sound biometric) was first introduced by Beritelli et al [13]. They use the *z*-chirp transformation (CZT) for feature extraction and Euclidian distance matching for identification. Puha et al. [14] proposed another system by analyzing cepstral coefficients in the frequency domain for feature extraction and employing a Gaussian Mixture Model (GMM) for identification. Subsequently, different methods were proposed, such as a wavelet based method in [15] and marginal spectral analysis based method in [16]. A review of the important PCG-based method can be found in [17]. Similar to the ECG-based methods, the common drawback of PCG-based methods for authentication is also the requirement of using obtrusive PCG sensor for the acquisition of ECG signal from a subject. In another words, for obtaining heart signals using ECG and PCG the required sensors need to be

directly installed on subject's body, which is obviously not always possible, especially when subject is not cooperative.

A recent study at Massachusetts Institute of Technology (MIT) showed that circulating the blood through blood-vessels causes periodic change to facial skin color [18]. This periodic change of facial color is associated with the periodic heartbeat signal and can be traced in a facial video. Takano et al. first utilized this fact in order to generate heartbeat signal from a facial video and, in turns, calculated Heartbeat Rate (HR) from that signal [19]. A number of other methods also utilized heartbeat signal obtained from facial video for measuring different physiological parameters such as HR [20], respiratory rate and blood pressure [21], and muscle fatigue [20].

This paper introduces Heartbeat Signal from Facial Video (HSFV) for biometric recognition. The proposed system uses a simple webcam for video acquisition, and employs signal processing methods for tracing changes in the color of facial images that are caused by the heart pulses. Unlike ECG and PCG based heartbeat biometric, the proposed biometric does not require any obtrusive sensor such as ECG electrode or PCG microphone. Thus, the proposed HSFV biometric has some advantages over the previously proposed biometrics. It is universal and permanent, obviously because every living human being has an active heart. It can be more secure than its traditional counterparts as it is difficult to be artificially generated, and can be easily combined with state-of-the-art face biometric without requiring any additional sensor. This paper proposes a method for employing this new biometric for person's identity recognition by employing a set of signal processing methods along with a decision tree based classification approach.

The rest of this paper is organized as follows. Section 2 describes the proposed biometric system and Section 3 presents the experimental results. Section 4 concludes the paper and discusses the possible future directions.

2 The HSFV based Biometric Identification System

The block diagram of the proposed HSFV biometric for human identification is shown in Fig. 2. Each of the blocks of this diagram is discussed in the following subsections.

2.1 Facial Video Acquisition and Face Detection

The proposed HSFV biometric first requires capturing facial video using a RGB camera, which was thoroughly investigated in the literature [21]–[23]. As recent methods of facial video based heartbeat signal analysis utilized simple webcam for video capturing, we select a webcam based video capturing procedure. After video capturing, the face is detected in each video frame by the face detection algorithm of [22].

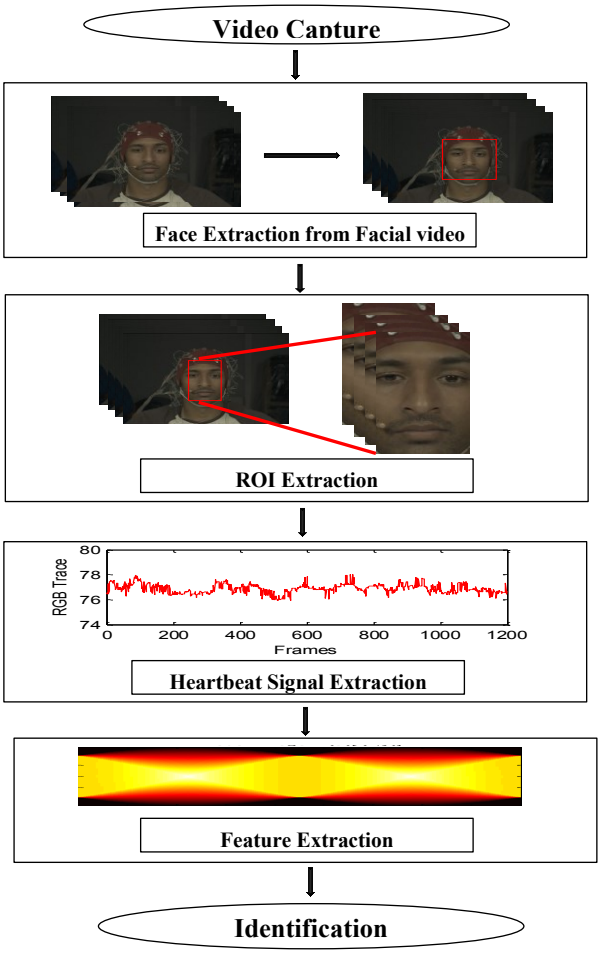


Fig. 2. The block diagram of the proposed HSFV biometric for human identification

2.2 ROI Detection and Heartbeat Signal Extraction

The heartbeat signal is extracted from the facial video by tracing color changes in RGB channels in the consecutive video frames using the method explained in [21]. This is accomplished by obtaining a Region of Interest (ROI) from the face by selecting 60% width of the face area detected by the automatic face detection method. The average of the red, green and blue components of the whole ROI is recorded as the RGB traces of that frame. In order to obtain a heartbeat signal from a facial video, the statistical mean of these three RGB traces of each frame is calculated and recoded for each frame of the video.

The heartbeat signal obtained from such a video looks noisy and imprecise compared to the heartbeat signal obtained by ECG, for example that in Fig. 1. This is due

to the effect of external lighting, voluntary head-motion, and the act of blood as a damper to the heart pumping pressure to be transferred from the middle of the chest (where the heart is located) to the face. Thus, we employ a denoising filter by detecting the peak in the extracted heart signal and discarding the outlying RGB traces. The effect of the denoising operation on a noisy heartbeat signal obtained from RGB traces is depicted in Fig. 3. The signal is then transferred to the feature extraction module.

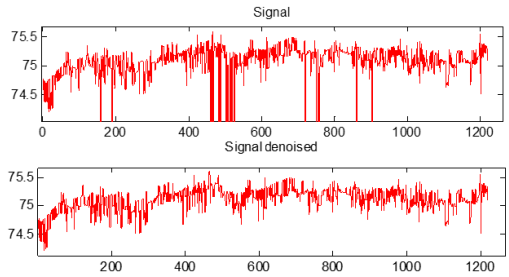


Fig. 3. A heartbeat signal containing outliers (top) and its corresponding signal obtained after employing a denoising filter (bottom).

2.3 Feature Extraction

We have extracted our features from radon images, as these images are shown in the ECG based system of [7] to produce proper results. To generate such images we need a waterfall diagram which can be generated by replicating the heartbeat signal obtained from a facial video. The number of the replication equals to the number of the frames in the video. Fig. 4 depicts an example of a waterfall diagram obtained from the heartbeat signal of Fig. 3. From the figure, it can be seen that the heartbeat signal is replicated and concatenated in the second dimension of the signal in order to generate the waterfall diagram for a 20 seconds long video captured in a 60 frames per second setting. In order to facilitate the depiction on the figure we employ only 64 times replication of the heartbeat signal in Fig. 4. The diagram acts as an input to a transformation module in order to extract the features.

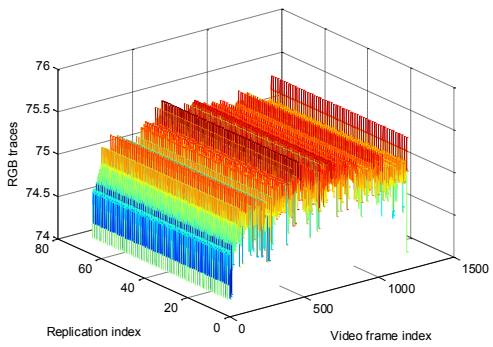


Fig. 4. Waterfall diagram obtained from an extracted heartbeat signal of a given video.

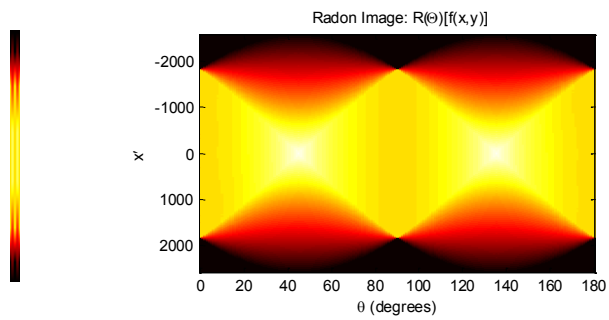
The features used in the proposed system are obtained by applying a method called Radon transform [24] to the generated waterfall diagram. Radon transform is an integral transform computing projections of an image matrix along specified directions and widely used to reconstruct images from medical CT scan. A projection of a two-dimensional image is a set of line integrals. Assume $f(x, y)$ is a two-dimensional image expressing image intensity in the (x, y) coordinates. The Radon transform (R) of the image, $R(\theta)[f(x, y)]$, can be defined as follows:

$$R(\theta)[f(x,y)] = \int_{-\infty}^{\infty} f(\acute{x}\cos\theta - \acute{y}\sin\theta, \acute{x}\sin\theta - \acute{y}\cos\theta)\, d\acute{y} \tag{1}$$

where θ is the angle formed by the distance vector of a line from the line integral with the relevant axis in the Radon space, and

$$\begin{bmatrix} \acute{x} \\ \acute{y} \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{2}$$

When we apply Radon transform on the waterfall diagram of HSFV a two-dimensional Radon image is obtained, which contains the Radon coefficients for each angle (θ) given in an experimental setting. An example Radon image obtained by employing Radon transform on the waterfall diagram of Fig. 4 is shown in Fig. 5.



(a) (b)

Fig. 5. Radon image obtained from the waterfall diagram of HSFV: (a) without magnification, and (b) with magnification.

In order to extract features for authentication, we employ a pairwise distance method between every possible pairs of pixels in the transformed image. We use the well-known distance metric of Minkowski to measure the pairwise distance for a $m \times n$-pixels of the Radon image R by:

$$\mathrm{d}_{st} = \sqrt[p]{\sum_{i=1}^{n} |R_{si} - R_{ti}|^p} \tag{3}$$

where R_s and R_t are the row vectors representing each of the $m(1 \times n)$ row vectors of R, and p is a scalar parameter with $p = 2$. The matrix obtained by employing the pairwise distance method produces the feature vector for authentication.

2.4 Identification

We utilize the decision tree based method of [25] for the identification. This is a flowchart-like structure including three types of components: i) Internal node- represents a test on a feature, ii) Branch- represents the outcome of the test, and iii) Leaf node- represents a class label coming as a decision after comparing all the features in the internal nodes. Before using the tree (the testing phase), it needs to be trained. At the training phase, the feature vectors of the training data are utilized to split nodes and setup the decision tree. At the testing phase, the feature vector of a testing data passes through the tests in the nodes and finally gets a group label, where a group stands for a subject to be recognized. The training/testing split of the data is explained in the experimental results.

3 Experimental Results and Discussions

3.1 Experimental Environment

The proposed system has been implemented in MATLAB 2013a. To test the performance of the system we've used the publicly available database of MAHNOB-HCI. This database has been collected by Soleymani et al. [26] and contains facial videos captured by a simple video camera (similar to a webcam) connected to a PC. The videos of the database are recorded in realistic Human-Computer Interaction (HCI) scenarios. The database includes data in two categories: 'Emotion Elicitation Experiment (EEE)' and 'Implicit Tagging Experiment (ITE)'. Among these, the video clips from EEE are frontal face video data and suitable for our experiment [20], [27]. Thus, we select the EEE video clips from MAHNOB-HCI database as the captured facial videos for our biometric identification system. Snapshots of some video clips from MAHNOB-HCI database are shown in Fig. 6. The database composes of 3810 facial videos from 30 subjects. However, not all of these videos are suitable for our experiment. This is because of short duration, data file missing, small number of samples for some subjects to divide these into training and testing set, occluded face (forehead) in some videos, and lack of subject's consent. Thus, we selected 351 videos suitable for our experiment. These videos are captured from 18 subjects (16-20 videos for each subject). We used the first 20 seconds of each video for testing and 80 percent of the total data for training in a single-fold experiment.

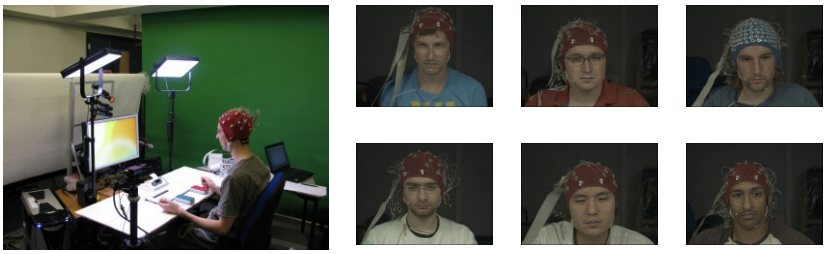


Fig. 6. Snapshots of some facial video clips from MAHNOB-HCI EEE database [26].

3.2 Performance Evaluation

After developing the decision tree from the training data, we generated the authentication results from the testing data. The features of each test subject obtained from the HSFV were compared in the decision tree to find the best match from the training set. The authentication results of 18 subjects (denoted with the prefix 'S-') from the experimental database are shown in a confusion matrix (row matrix) at Table 1. The true positive detections are shown in the first diagonal of the matrix, false positive detections are in the columns, and false negative detections are in the rows. From the results it is observed that a good number of true positive identifications were achieved for most of the subjects.

Table 1. Confusion matrix for identification of 351 samples of 18 subjects using the proposed HSFV biometric.

Subjects	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*	*S11*	*S12*	*S13*	*S14*	*S15*	*S16*	*S17*	*S18*
S1	**16**	2	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
S2	0	**17**	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0
S3	1	1	**16**	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
S4	0	0	0	**18**	0	0	0	1	0	0	0	0	0	0	1	0	0	0
S5	0	0	0	0	**19**	0	1	0	0	0	0	0	0	0	0	0	0	0
S6	4	1	0	0	0	**15**	0	0	0	0	0	0	0	0	0	0	0	0
S7	0	0	0	0	0	0	**18**	0	0	0	0	0	0	2	0	0	0	0
S8	1	0	0	0	0	0	0	**10**	0	0	1	0	1	0	2	1	0	0
S9	0	0	0	0	0	0	0	0	**20**	0	0	0	0	0	0	0	0	0
S10	0	0	0	0	0	0	0	0	0	**18**	0	1	0	1	0	0	0	0
S11	2	2	0	0	0	1	0	1	0	0	**13**	0	0	0	0	0	0	0
S12	0	0	0	0	0	0	2	0	0	0	0	**16**	0	0	0	0	0	0
S13	1	2	0	0	0	0	1	2	0	0	0	0	**12**	0	2	0	0	0
S14	0	0	0	0	0	0	0	0	0	3	0	0	0	**17**	0	0	0	0
S15	0	1	2	0	0	0	0	1	0	0	0	0	1	0	**15**	0	0	0
S16	3	2	0	0	0	0	0	0	0	0	1	0	2	0	1	**11**	0	0
S17	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	**16**	0
S18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	**16**

The performance of the proposed HSFV biometric was evaluated by the parameters defined by Jain et al. in [28], which are False Positive Identification Rate (FPIR) and False Negative Identification Rate (FNIR). The FPIR refers to the probability of a test sample falsely identified as a subject. If *TP* = True Positive, *TN* = True Negative, *FP* = False Positive, and *FN* = False Negative identifications among *N* number of trials in an experiment, then the FPIR is defined as:

$$FPIR = \frac{1}{N}\sum_{n=1}^{N}\frac{FP}{TP+TN+FP+FN} \tag{4}$$

The FNIR is the probability of a test sample falsely identified as different subject which is defined as follows:

$$FNIR = \frac{1}{N}\sum_{n=1}^{N}\frac{FN}{TP+TN+FP+FN} \tag{5}$$

From FNIR we can calculate another metric called True Positive Identification Rate (TPIR) that represents the overall identification performance of the proposed biometric as:

$$TPIR = 1 - FNIR \tag{6}$$

Besides the aforementioned metrics, we also calculated the system performance over four other metrics from [29]: precision, recall, sensitivity and accuracy. Precision and recall metrics present the ratio of correctly identified positive samples with total number of identification and total number of positive samples in the experiment, respectively. The formulations of these two metrics are:

$$Precision = \frac{1}{N}\sum_{n=1}^{N}\frac{TP}{TP+FP} \tag{7}$$

$$Recall = \frac{1}{N}\sum_{n=1}^{N}\frac{TP}{TP+FN} \tag{8}$$

Specificity presents the ratio of correctly identified negative samples with total number of negative samples and sensitivity presents the ratio of correctly identified positive and negative samples with total number of positive and negative samples. The mathematical formulations of these two metrics are:

$$Specificity = \frac{1}{N}\sum_{n=1}^{N}\frac{TN}{TN+FP} \tag{9}$$

$$Sensitivity = \frac{1}{N}\sum_{n=1}^{N}\frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

Table 2 summarized the overall system performance in the standard terms mentioned above. From the results it is observed that the proposed HSFV biometric can effectively identify the subjects with a high accuracy.

Table 2. Performance of the proposed HSFV biometric based authentication system

Parameters	Results
FPIR	*1.28%*
FNIR	*1.30%*
TPIR	*98.70%*
Precision rate	*80.86%*
Recall rate	*80.63%*
Specificity	*98.63%*
Sensitivity	*97.42%*

One significant point can be noted from the results that the TPIR and precision rate have a big difference in values. This is because the true positive and true negative trials and successes are significantly different in numbers and the system achieved high rate of true negative authentication as indicated by specificity and sensitivity metrics. This implies that the proposed biometric, though is of high potential may need improvement in both the feature extraction and the matching score calculation.

To the best of our knowledge, this paper is the first to use HSFV as a biometric, thus, there is not any other similar systems in the literature to compare the proposed system against. Though touch based ECG [12] and PCG [14] biometrics obtained more than 90% accuracy on some local databases, we think their direct comparison against our system is biased towards their favor, as they use obtrusive touch-based sensors, which provide precise measurement of heartbeat signals, while we, using our touch-free sensor (webcam), get only estimations of those heartbeat signals that are obtained by touch based sensors. This means that it makes sense if our touch-free system, at least in this initial step of its development, does not outperform those touch-based systems.

The observed results of the touch-free HSFV definitely showed the potential of the proposed system in human identification and it clearly paves the way for developing identification systems based on heartbeat rate without a need for touch based sensors. Reporting the results on a publicly available standard database is expected to make the future studies comparable to this work.

4 Conclusions and Future Directions

This paper proposed heartbeat signal measured from facial video as a new biometric trait for person authentication for the first time. Feature extraction from the HSFV was accomplished by employing Radon transform on a waterfall model of the replicated HSFV. The pairwise Minkowski distances were obtained from the Radon image as the features. The authentication was accomplished by a decision tree based supervised approach. The proposed biometric along with its authentication system demonstrated its potential in biometric recognition. However, a number of issues need to be studied and addressed before utilizing this biometric in practical systems. For example, it is necessary to determine the effective length of a facial video viable to be captured for authentication in a practical scenario. Fusing face and HSFV together for authentication may produce interesting results by handling the face spoofing. Processing time, feature optimization to reduce the difference between precision and acceptance rate, and investigating different metrics for calculating the matching score are also necessary to be investigated. The potential of the HSFV as a soft biometric can also be studied. Furthermore, it is interesting to study the performance of this biometric under different emotional status when heartbeat signals are expected to change. These could be future directions for extending the current work.

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