Exploring Remote Cardiac Signals for Biometric Verification: A Study Using Eulerian Video Magnification

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***Abstract*—With technological advancements enhancing the capabilities of mobile devices to capture physiological data, new human characteristics are increasingly being explored for the development of biometric systems. The remote cardiac signal, obtained through the Eulerian Video Magnification (EVM) technique from image sequences, emerges as a promising physiological trait in this evolving landscape. This study aims to assess the viability of the remote cardiac signal as a biometric modality for verification tasks. The methodology includes data collection in a controlled environment, transforming video sequences into one-dimensional signals using the EVM technique, filtering unwanted frequencies from the signal, and employing a simple convolutional neural network for data representation. A one-against-all protocol for biometric verification evaluation complements this approach. Experiments on a dataset containing videos of 56 individuals yielded an Equal Error Rate (EER) of 13%.**

***Index Terms*—Eulerian Video Magnification, EVM, Biometrics, Remote Cardiac Signal.**

I. Introduction

Biomedical signals play an important role in healthcare, providing crucial insights into the physiological and pathological conditions of humans. These signals encompass a variety of data, including, but not limited to, ECG (electrocardiogram), EEG (electroencephalogram), and EMG (electromyography). They are essential for diagnosing, monitoring, and treating a broad spectrum of medical disorders [1]. The significance of processing and analyzing these signals has increased exponentially, stimulated by technological advancements that have facilitated real-time data collection and the implementation of advanced computational analysis methods.

Integrating these technological advances into everyday use, particularly in mobile devices and wearables, has revolutionized the continuous monitoring of various physiological signals, such as body temperature, heart rate, and blood pressure. This evolution represents a paradigmatic shift in monitoring and managing individual health, highlighting the fusion between technology and health. In this landscape, biometric systems emerge as a logical extension of the deepened analytical exploration of biomedical signals, establishing themselves as an additional possibility for individual authentication [2], [3].

Biometrics is a field that utilizes an individual's unique physical or behavioral characteristics for authentication in electronic systems [4]. Beyond traditional modalities such as fingerprint, iris, and facial recognition, research has shifted towards new biometric modalities, such as ECG signals [2], EEG signals [3], and blood flow via photoplethysmography (PPG) [5]. Among these innovations, the extraction of cardiac signals from video using Eulerian Video Magnification [1] (EVM) [6] represents a novel approach whose feasibility for biometric applications is yet to be established. This work hypothesizes that cardiac signals obtained through video and EVM can be applied to biometric verification systems. To test this hypothesis, a dataset named *Dataset-RCS* was created using a conventional cell phone camera. A convolutional neural network model was employed for the latent representation of the data, drawing inspiration from prior studies focused on ECG and EEG signals [2], [3], and the analysis of biometric verification was conducted [7]. The findings indicate that the cardiac signal captured via EVM is viable for biometric verification, demonstrating an Equal Error Rate (EER) of 13.53%.

II. Related Works

Beyond conventional biometric approaches such as fingerprint analysis, iris, and facial recognition, more research has been dedicated to studying physiological signals as unique and reliable biomarkers for identity verification and identification.

In the work of [8], a detailed investigation into the applicability of electrocardiogram (ECG) signals in biometric contexts is presented, discussing recent advancements and challenges encountered in using ECG signals for biometric authentication. The study addresses the reliability and efficiency of this biometric modality, exploring its potential and identifying areas requiring further investigation. Complementarily, the research in [9] explores the feasibility of using sub-sampled ECG signals at lower frequencies for individual identification. The authors investigate the properties of the ECG signal at low frequencies and their validity as a biometric measure. Additionally, in [2], latent representations of ECG signals through deep learning techniques (CNNs) are explored. The results achieve significant advancements compared to the state-of-the-art on two off-the-person ECG datasets, recording an Equal Error Rate (EER) of 14.27% for the UofTDB [10] and 13.93% for the CYBHi [11] in multi-session evaluations.

The study presented in [5] represents the first bibliographic survey on biometric systems based on photoplethysmographic (PPG) signals. The authors conducted a literature review

[1]https://people.csail.mit.edu/mrub/evm/

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examining this technology's recent advancements, techniques, and applications. The study explored various methods and techniques for collecting and analyzing PPG data for biometric identification, addressing the advantages, limitations, and challenges in implementing these systems. The paper highlights the viability and effectiveness of PPG biometrics in various applications, such as biometric authentication and health monitoring. The authors identified areas of ongoing research and technical challenges to be addressed, such as the development of robust algorithms to handle variations in measurement conditions and improvements in the accuracy and reliability of PPG systems.

The work presented in [12] proposes using dual photoplethysmographic (PPG) signals for active authentication and vitality detection in biometric systems. The authors introduce "Ppg2live," a system that utilizes two PPG sensors on different parts of the body to verify the authenticity of the user and detect vital signs in real time. Experiments were conducted to validate the system's efficacy under different scenarios and conditions, and the results suggest that the proposed approach is promising for providing an additional layer of security in biometric systems, ensuring the authenticity of the user and detecting vital activity. Challenges remain regarding the accuracy of detection in adverse conditions, such as variations in lighting or rapid movements of the user, and future work may focus on enhancing the robustness and reliability of the "Ppg2live" system in various environments and situations.

Regarding signals extracted from video images, in the work of [13], the Eulerian Video Magnification (EVM) technique is proposed for measuring pulse transit time. The study explores EVM to amplify small color and motion variations in video, enabling the visualization of signals imperceptible to the naked eye, such as subtle changes in blood flow. EVM was applied to measure pulse transit time, which is the time difference between the arterial pulse wave generated by the heart and its detection at a distant body point, such as the finger or face. The results suggest that the EVM technique can effectively measure pulse transit time in a non-invasive and low-cost manner. The authors highlighted challenges regarding the accuracy and robustness of the technique under different lighting conditions and individual variations. Future work may enhance the EVM technique for more precise and reliable pulse transit time measurement across various clinical and health monitoring scenarios.

[14] presents an innovative method for remote heart rate monitoring based on remote photoplethysmography (rPPG). The study proposes using ambient light to measure blood volume changes in the skin, thereby estimating heart rate non-invasively. The technique employs non-intrusive optical sensors to detect changes in light intensity reflected by the skin, allowing for the acquisition of accurate physiological information without the need for direct contact with the individual. The results demonstrate the viability and effectiveness of this method as a promising alternative for remotely monitoring heart rate in various applications, including health monitoring and vital signs detection. The authors identified areas of open research and challenges to be addressed, such as improving accuracy and reliability, exploring new applications, clinical validation, and the development of robust devices and technologies.

Despite various approaches using Eulerian Video Magnification (EVM) to extract the cardiac signal from video images—here referred to as the remote cardiac signal—this signal has not yet been explored as a potential biometric modality. This gap in research represents the focal point of this investigation, aiming to explore the potential of the remote cardiac signal as an effective biometric modality for authentication. By integrating existing advancements and identifying gaps in the literature, this study seeks to contribute to the advancement of the biometric field.

III. Materials and Methods

This section outlines the application of the Eulerian Video Magnification technique to extract cardiac signals, followed by the presentation of the dataset constructed to investigate this study's hypothesis. The fundamental hypothesis examines the feasibility of employing cardiac signals captured through video cameras as a biometric modality. Additionally, the methodology for conducting biometric verification is described.

A. Eulerian Video Magnification for Cardiac Signal Extraction in Video

The Eulerian Video Magnification (EVM) technique aims to enhance temporal variations in videos that are not perceptible to the naked eye. To achieve this, EVM operates on a sequence of video frames, initially applying a spatial decomposition followed by temporal filtering on each frame. The resultant signal is then amplified to highlight hidden information. This process allows for the visualization of, for example, blood flow in the face and the amplification of small movements, revealing details that would normally go unnoticed [6].

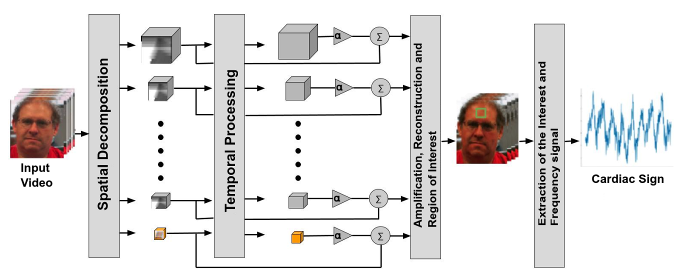


Figure 1. EVM sequential flow.

The technique of *Eulerian Video Magnification*, as depicted in Figure 1, involves several computational steps, which are described as follows:

a) Spatial Decomposition:: The spatial decomposition of a video can be represented by the pyramidal Laplace transform [15], [16] or another multiscale decomposition method. For the i-th spatial frequency band, the decomposition can be represented as:

$$L_i(t) = \text{Decomposition}(V(t), i), \tag{1}$$

where $L_i(t)$ is the representation of the i-th band at time t, and $V(t)$ is the input video.

b) Temporal Processing:: Temporal processing involves the application of a temporal filter to each spatial frequency band. The filter may be a band-pass filter that isolates the frequencies of interest. The filtering can be represented as:

$$\hat{L}_i(t) = \text{TemporalFilter}(L_i(t)), \quad (2)$$

where $\hat{L}_i(t)$ is the i-th band after temporal processing.

c) Amplification:: Amplification is applied to each filtered band with an amplification factor α_i, which may vary for each frequency band:

$$A_i(t) = \alpha_i \cdot \hat{L}_i(t) \quad (3)$$

where $A_i(t)$ is the amplified band.

d) Reconstruction:: Finally, the amplified video is reconstructed by combining all the amplified spatial frequency bands. The reconstruction can be represented by a weighted sum of all the amplified bands:

$$V_{\text{out}}(t) = \sum_i A_i(t) + V_{\text{original}}, \quad (4)$$

where $V_{\text{out}}(t)$ is the magnified output video and V_{original} is the original input video.

e) Region of Interest (ROI) Detection:: Following the previous step, the detection of the ROI can be formalized as:

$$R(t) = \text{ROI}(V_{\text{out}}(t)), \quad (5)$$

where $R(t)$ is the region of interest at time t.

f) Intensity Signal Extraction:: In this study, the intensity signal, also referred to here as the remote cardiac signal, is extracted by calculating the mean pixel intensity within the Region of Interest (ROI) over time:

$$I(t) = \frac{1}{|R(t)|} \sum_{p \in R(t)} V_{\text{out}}(p, t), \quad (6)$$

where $I(t)$ is the average intensity at time t, and $V_{\text{out}}(p, t)$ is the pixel value of p in frame t.

g) Fourier Transform:: The Discrete Fourier Transform (DFT) is applied to the intensity signal in this study to convert it from the time domain to the frequency domain:

$$F(k) = \text{DFT}(I(t)) = \sum_{t=0}^{T-1} I(t) e^{-\frac{2\pi i}{T} kt}, \quad (7)$$

where $F(k)$ is the Fourier transform value at frequency k, T is the total number of frames, and i is the imaginary unit.

h) Heart Rate Identification:: The heart rate is identified by finding the most prominent peak within the frequency spectrum, limited to the band from 0 to 30 Hz. According to the Nyquist theorem, this limit is determined as half the frame rate per second (FPS) of the video, which dictates the highest frequency accurately representable in the digital signal:

$$f_{\text{cardiac}} = \text{argmax}_{k \in [0,K]} |F(k)|^2, \quad (8)$$

where $|F(k)|^2$ represents the power spectrum of the frequency signal k, and K is the index corresponding to the 30 Hz frequency in the DFT.

i) Conversion of Frequency Index to Hz:: The heart rate in Hz is obtained by converting the index k to the actual frequency in Hz, based on the frame rate per second (FPS) of the video:

$$f_{\text{Hz}} = \frac{k \times FPS}{T}, \quad (9)$$

where f_{Hz} is the heart rate in Hz, and T represents the total number of frames derived from the duration of the video and the FPS.

The index k for the heart rate should be chosen considering the typical range of human heart rates at rest or during activity, which generally spans from about 0.5 Hz (30 beats per minute) to 3 Hz (180 beats per minute). This range should be adjusted based on the context of the application, such as rest or exercise scenarios.

The EVM technique facilitates visual observation of blood flow in the facial region, enabling the extraction of a waveform correlated with blood pressure.

B. Dataset Remote Cardiac Signal (Dataset-RCS)

A dataset was specifically developed for this study following a rigorously defined acquisition protocol to assess the applicability of the Eulerian Video Magnification (EVM) technique for extracting cardiac signals in biometric contexts. Criteria such as camera height, lighting conditions, and recording distance were controlled, as detailed in Figure 2. The camera, set to Full HD (FHD) resolution, was positioned at a distance of 55 cm in front of the subject, capturing continuous images over a period of 60 seconds.

The process for data acquisition was approved by the Ethical Review Board of the first author's institution. The authors confirm that the data acquisition and storage comply with the ethical guidelines. The processed data, namely the cardiac remote signals, will be made available to the public.

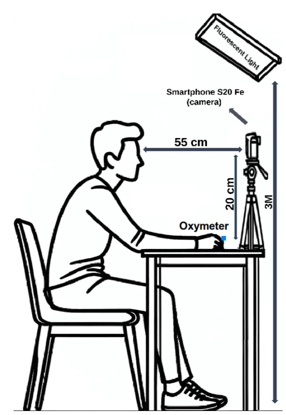


Figure 2. Data collection setup.

Videos were captured in a controlled environment using the rear camera of a Samsung Galaxy S20 FE 5G, which was set to 60 frames per second (fps). Participants were instructed to remain motionless during the video capture. The study involved 56 individuals, each providing two videos recorded in separate sessions at least 14 days apart. Consequently, 112 videos, each lasting 60 seconds, were generated, amounting to 3600 samples per video. For each session, lighting conditions were meticulously controlled. Although the conditions within each session were consistent, the ambiance and noise levels varied. Illumination was provided by a fluorescent lamp and natural light, ensuring diverse visual and auditory environments across the recordings. A pulse oximeter was utilized as the ground truth to ascertain the calculation of heart rate from remote cardiac signals.

C. Proposed Methodology

The proposed methodology for constructing the remote cardiac signal and subsequent biometric verification can be divided into four main stages: (i) preprocessing; (ii) detection of the area of interest; (iii) extraction of the cardiac signal; (iv) training and evaluation of the model.

1) Preprocessing and Detection of the ROI: Preprocessing involves resizing all videos to a resolution of 640×480 to reduce computational cost. Once the videos have been preprocessed, the region of interest is identified following the method in [17]. For this study, the forehead area was defined as the region of interest (ROI).

2) Extraction of the Cardiac Signal: The Region of Interest (ROI) of the preprocessed frames was subjected to the Eulerian Video Magnification (EVM) technique to extract the cardiac signal from each video. Initially, the frames of a video undergo spatial-frequency decomposition through an image pyramid, where each layer represents a scaled-down version of the original image. This reduction allows for analysis at different scales, which is useful for detecting subtle variations in skin coloration caused by blood flow [6]. Each frame generates a sample (a point) of the cardiac signal at that moment.

Considering that each recorded video lasts 60 seconds and is captured at 60 frames per second, this results in 60 samples per second. Therefore, each video session produces a remote cardiac signal of 3,600 samples per individual. To evaluate the feasibility of these generated signals as biometric identifiers, deep learning methods—specifically, Convolutional Neural Networks (CNNs)—were employed for latent space representation. The rationale for this choice is supported by literature within a related domain, specifically biometrics derived from electrocardiograms [2].

3) Training and Evaluation of the Model: In this study, a CNN architecture considered state-of-the-art for latent space representation of ECG signals for biometric purposes is investigated [2]. The methodology for representing ECG signals in latent space adheres to the workflow depicted in Figure 3.

a) Filtering Process: Physiological signals are subject to various noises [2], which can interfere with the neural network's learning process. Therefore, applying a band-pass filter was proposed for each cardiac signal generated through EVM, aiming to improve the quality of the signals and the data derived from them. A 0-30Hz band-pass filter, consisting of a 12th-order FIR-type Butterworth filter, was applied. Subsequently, the dataset should undergo Min-Max normalization [18].

b) Data Splitting: With the signals derived from the feature extraction (section III-C2), 90% of these data were used for training, and the remaining 10% were allocated for testing. For analysis, the data were segmented into 5-second windows, each containing 300 samples suitable for input into the neural network. A data augmentation technique was adopted to expand the training dataset using a sliding window with a 30-sample offset between windows. Combining the sessions and applying data augmentation generated 12,320 training instances, evenly distributed across 110 instances for each of the 112 videos. As a result, the *Dataset-RCS* was formed. It is important to note that data augmentation was applied only to the training set. Also, it is highlighted that the data from the two sessions were shuffled before the division.

c) CNN Architecture and Biometric Verification: The methodology used for feature extraction or signal representation was developed based on a review of existing literature and the specificities of the problem under study. Subsequently, the training phase of this network was initiated, utilizing data augmentation techniques to perform classification in a supervised context.

During training, the network underwent supervised learning, in which the neuron weights were adjusted to minimize a loss function specific to the classification task, where each individual in the dataset was considered a distinct class. At the end of this phase, the focus of the neural network's application shifted: the last layer was removed, adapting it to function as a data representation tool. The network's output dimensionality was adjusted to a feature set size of 256.

With the last layer discarded, the convolutional neural network model began to act as a feature extractor or representation of the cardiac signal in latent space. The features extracted in this new context were duly stored and applied in evaluating the biometric verification system. This approach allowed for addressing the challenge of an open gallery or open world, resulting in a more compact and meaningful representation of the data, facilitating the comparison and identification of patterns relevant to biometric verification.

The evaluation is conducted in biometric verification mode, which can be formalized as follows:

Let $I = i_1, i_2, \ldots, i_N$ be the set of individuals, where N is the total number of individuals. Each i_j can have several instances in a set (here we can call it a gallery), denoted by $G_{i_j} = g^1_{i_j}, g^2_{i_j}, \ldots, g^K_{i_j}$, where K is the number of instances for the individual i_j.

The instances are representations of the cardiac signal obtained via EVM and transformed into a latent space by a pre-trained CNN. Thus, each instance $g^k_{i_j}$ is represented by a vector in the latent space $L^k_{i_j}$.

For a pair of instances $(L^a_{i_x}, L^b_{i_y})$, the distance $d(L^a_{i_x}, L^b_{i_y})$ is calculated using a similarity metric. In this work, the simple Euclidean distance is used. We define two types of pairs:

- **Genuine Pairs:** when $i_x = i_y$, indicating that both instances belong to the same individual. The ideal distance for genuine pairs, in the context of this work, is close to zero, $d(L^a_{i_x}, L^b_{i_y}) \approx 0$.
- **Impostor Pairs:** when $i_x \neq i_y$, indicating that the instances belong to different individuals. The ideal distance

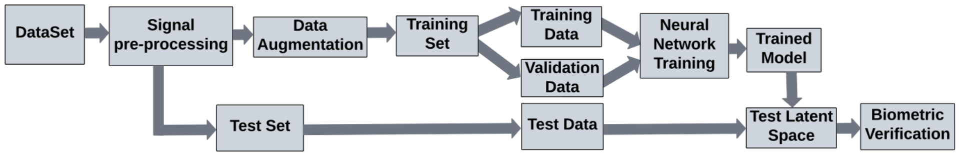


Figure 3. Methodology workflow developed for the proposed work.

for impostor pairs should be close to one, $d(L^a_{i_x}, L^b_{i_y}) \approx 1$.

To evaluate the performance of the biometric verification system, the frequency of the distances for both types of pairs is computed, generating two histograms: one for genuine pairs and another for impostor pairs. A threshold is defined based on the histogram curves, allowing the calculation of the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). From these rates, the main metric of the work, the Equal Error Rate (EER), is computed. In the context of biometrics, the Detection Error Tradeoff (DET) curve is a graphical representation that illustrates the tradeoff between the False Acceptance Rate (FAR) and the False Rejection Rate (FRR).

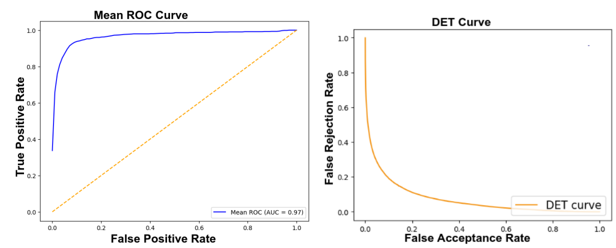
IV. Experiments and Results

This study investigates the potential of the remote cardiac signal as a new biometric modality, using a convolutional neural network model to represent these signals in latent space. Additionally, an experiment was conducted using the raw cardiac signal without feature extraction techniques to assess its effectiveness directly. Subsequently, a detailed analysis was conducted through an evaluation of biometric verification. The experiments were carried out using a machine with the following technical specifications: a 24-core AMD Ryzen Threadripper 3960X processor, 128 GB DDR4 RAM, and an NVIDIA RTX 3090 graphics card equipped with 24 GB of GDDR6X memory.

The implemented architecture is based on [2]. The input to the first layer of the CNN is dimensioned at 300×1, tailored to the size of the segmented signal window. The CNN comprises four sequences of convolutional layers, followed by batch normalization and max pooling, two dense layers (512 and 256 neurons), a dropout layer (with a 40% rate), and finally, another dense layer that utilizes the softmax activation function for the classification of individuals. The activation function used in the convolutional layers and dense layers is the Rectified Linear Unit (ReLU).

The neural network was trained using the Stochastic Gradient Descent (SGD) algorithm for optimization, with a momentum coefficient of 0.9, and the filter weights were initialized according to [19]. The training was conducted over more than 300 epochs, during which the neural network employed three different learning rates, initially set at 0.1 for the first two epochs, adjusted to 0.01 from the beginning until epoch 245, and finally reduced to 0.001 for subsequent epochs. Additionally, 90% of the data were reserved for training and the remaining 10% for testing.

The results of training the CNN model are depicted in Figure 4(a), where a score of 0.97 suggests that the model achieves a high true positive rate (TPR) and a low false positive rate (FPR). While the CNN demonstrates promising outcomes in feature extraction and classification, employing a conventional CNN architecture yielded an Equal Error Rate (EER) of 13.53% in verification mode on the test set. The EER is defined as the point at which the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR), with these rates being calculated from the comparison of intra-class (genuine) and inter-class (impostor) pairs. Figure 4(b) presents the Detection Error Tradeoff (DET) curve, illustrating the relationship between FAR, FRR, and EER as the decision threshold varies.



(a) (b)

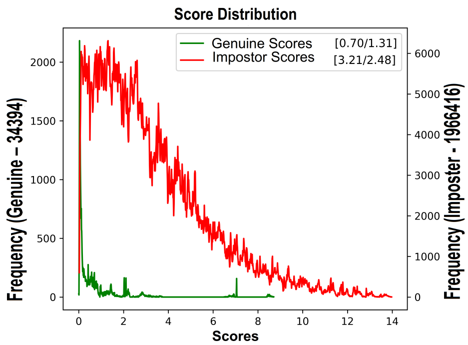
Figure 4. ROC curve generated by the average of CNN classes on the test set (a) and DET curve for the test set (b).

For the experiment conducted using raw data without feature extraction, Figure 5 (a) displays a significant overlap between the genuine and impostor curves, underscoring the enhanced representation achieved by the CNN (see Figure 5 (b)). In total, 34,394 genuine pairs and 1,966,416 impostor pairs were analyzed.

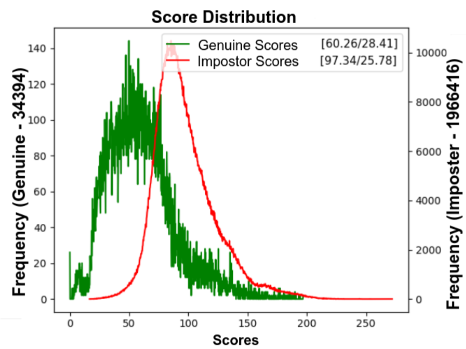
These results demonstrate that the raw signal cannot be directly utilized for biometric verification and highlight the convolution network's capability to represent these signals effectively. This study did not explore other CNN architectures and preprocessing techniques, which could significantly influence the outcomes. However, the primary objective of this preliminary work is to investigate the viability of the remote cardiac signal as a biometric modality for verifying or identifying an individual based on a segment of the signal and to explore the criticality of impostor attacks. From the histogram in Figure 5 (b), it can be observed that the individual was correctly verified in several instances, and impostors were successfully rejected.

V. Conclusion

This preliminary study explored the feasibility of using remote cardiac signals captured through the Eulerian Video Magnification (EVM) technique for biometric verification applications. The analysis, conducted using a simple convolutional



(a) raw data



(b) CNN feature extraction

Figure 5. Distribution of impostors and genuine data: (a) for raw data and (b) with CNN feature extraction.

neural network (CNN) to achieve latent data representation from a dataset of 56 individuals, demonstrated potential, as evidenced by an Equal Error Rate (EER) of 13%. However, the study encountered limitations due to the dataset used, which was characterized by a limited number of participants and a restricted data collection period. As a result, the generalization capability and scalability of the proposed biometric modality were not fully assessed.

Further exploration of the methodology with larger samples/instances and individuals is crucial to determine how the approach would scale to extensive galleries of individuals. It is recommended that additional research be conducted to expand and diversify the dataset, focusing on increasing the number of individuals (classes) to more adequately evaluate the potential applicability of the proposal in real-world environments. Another path for future investigation could involve exploring alternative methods for representing the remote cardiac signal beyond EVM and employing other networks for the latent representation of data to enhance robustness, especially in uncontrolled environments.

We posit that the remote cardiac signal, as a biometric modality, holds significant potential to function in conjunction with other modalities. For example, it could complement facial recognition systems to enhance biometric re-identification in surveillance scenarios, particularly in cases where facial recognition is insufficient or compromised. Additionally, we believe that this remote cardiac signal can also assist with liveness detection in conjunction with face recognition.

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