Video is All You Need: Attacking PPG-based Biometric Authentication

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Abstract

Unobservable physiological signals enhance biometric authentication systems. Photoplethysmography (PPG) signals are convenient owning to its ease of measurement and are usually well protected against remote adversaries in authentication. Any leaked PPG signals help adversaries compromise the biometric authentication systems, and the advent of remote PPG (rPPG) enables adversaries to acquire PPG signals through restoration. While potentially dangerous, rPPG-based attacks are overlooked because existing methods require the victim’s PPG signals. This paper proposes a novel spoofing attack approach that uses the waveforms of rPPG signals extracted from video clips to fool the PPG-based biometric authentication. We develop a new PPG restoration model that does not require leaked PPG signals for adversarial attacks. Test results on state-of-art PPG-based biometric authentication show that the signals recovered through rPPG pose a severe threat to PPG-based biometric authentication.

1. Introduction

The security of biometric systems is enhanced with the adoption of physiological signals (like Electrocardiogram [17], Electroencephalogram [41], Photoplethysmography [19]), assuming that attackers cannot easily obtain the victim’s physiological signals [36]. Photoplethysmography (PPG) signals are commonly measured by wearable devices integrated with cost-effective PPG signal sensors. For example, Apple Watch and Samsung Galaxy Fit2 use PPG sensors to monitor the heart health status. PPG signal satisfies the basic properties (Universality, Distinctiveness, Permanence, Collectability [20]) of the biometrics. PPG signals collected from wearable devices are invisible to the naked eye, which facilitates unnoticeable authentication or even continuous authentication.

There are various studies on PPG-based user authentication relying on temporal features [48], spectrum features [9], automated feature extraction through CNN-LSTM models [19], or many alike. Moreover, industry vendors are investigating new PPG-based biometric authentication. Such authentication is designed to improve the security of existing authentication systems. Some well-known patents are filed by Samsung [21] and Nymi [33]. These proposals use physiological signals, especially PPG, as unique user identifiers. PPG-based biometric authentication is an emerging and promising research topic.

Nevertheless, the unobservable characteristics of PPG signals are challenged by remote acquisition. The remote acquisition allows PPG signals to be obtained beyond the close contact physical distance, implying that the PPG-based biometric system loses its unobservable advantage. Several remote PPG (rPPG) methods are proposed to infer biometric signals, including discerning facial video sequences [16], detecting arterial blood [32], and monitoring heart rate information [3, 38]. Though some studies are provided for exploiting PPG signals [3, 22, 38], there is no attack targeting biometric authentication systems using rPPG. One reason is the overlook of signal features, for instance, the morphological features of the signal waveform are disregarded [3, 38]. The second reason is the narrow view of the features of a single cardiac cycle used as a unique identifier for PPG-based biometric systems [18, 49]. The third reason is the requirement of close physical contact between the attacker and the victim to obtain the high-quality PPG signals [22]. Exploring the potentials of rPPG-based attacks is essential to assess the security of PPG-based biometric systems, which motivates this work.

In this paper, we propose a spoofing attack with video clips against PPG-based biometric authentication. Our spoofing attack directly uses the rPPG signals extracted from a human face presented in videos. The technical challenge is the differences between the rPPG signal and PPG.
rPPG is used to estimate the Inter-Pulse Interval (IPI) and attack the IPI-based key distribution scheme.

A malicious sensor is installed to steal the victim's PPG signal.

The leaked PPG signal can be used to attack PPG-based authentication.

The rPPG signal extracted from the victim's video clips is restored to perform spoofing attacks on PPG-based authentication.

Figure 1. An evolving timeline for attacks against PPG-based biometric authentication.

signal in the timing of signal attainment. To mitigate the signal difference, our method uses a generative model to restore the rPPG signal to the PPG signal. The PPG signal is collected from the subject’s fingertip using an FDA-approved oximeter. As shown in Fig. 1, generalizing attacks with fewer assumptions, this work successfully attacks PPG-based biometric authentication with nothing except an HD video clip of the victim’s face. To the best of our knowledge, this is the first work to exploit the morphological features of rPPG to spoof PPG-based authentication. The major contributions of this paper are:

• We are the first to conduct a spoofing attack on PPG-based biometric authentication using video clips. We propose a novel signal restoration method called SigR to accurately restore rPPG signals to PPG signals.
• We model and measure the effectiveness of restoring PPG signals from rPPG signals extracted from video clips in the UBFC-PHYS [31] dataset, where human subjects are in different states (‘resting’, ‘talking’, or ‘calculating’).
• We conduct experiments on the impact of various video quality factors (frame size, frame rate, bit-rate, and beauty filter) by comparing the results obtained on the spoofing attack.

2. Related Work

2.1. PPG-based Biometric Authentication

The PPG signal corresponds to a wealth of heart-related information distinct to the individual. Features from the PPG signal can be used for biometric applications [6]. Early studies extracted temporal features from the fiducial points of the PPG waveform, such as peak number, time interval, and upward/downward slope [11]. The first and second-order derivative of the PPG signal serves as a useful feature for biometric authentication [24]. Some features that are commonly used for biometric authentication are shown in Fig. 2. Temporal features of the PPG signals are sensitive to noises, including baseline wander, motion artifact, and respiration [23]. To improve the robustness against noise, frequency-based features are obtained by applying transform methods to the PPG signal like Fourier transform [10] and wavelet transform [44]. Recent state-of-the-art PPG-based biometric authentication uses deep learning to learn features automatically from the raw data [1, 19].

2.2. Existing Attacks

The emergence of rPPG has exposed PPG-based security systems to an unprecedented threat. Up to 70% of the inter-pulse interval (IPI) information obtained by contact-based PPG methods can be leaked by rPPG signals [3]. IPI measures the time difference between two consecutive systolic peaks. The IPI information is used as a random sequence in a key distribution scheme [46]. An attacker can use rPPG to mimic PPG for generating IPI-based biometric identifiers before compromising an IPI-based key distribution [38].

Karimian et al. [22] use leaked signals to present spoofing attacks against PPG-based biometric authentication systems. Three differential equations are used to synthesize a PPG signal for spoofing attacks. Then, two Gaussian functions are applied to convert the model parameters of an arbitrary PPG signal to the victim’s to spoof the authentication system. Since PPG signals can be easily acquired from many measurement points on the human body, malicious PPG sensors attached to the body covertly help steal the victim’s PPG signals. Subsequently, the attacker can reproduce the victim’s PPG signal based on the malicious sensor’s recorded signal through a waveform generator [15].
However, these attacks require the victim’s PPG signal that is challenging to acquire through close physical contact without the victim’s awareness. The assumption of the victim’s PPG signals strongly limits the power of existing attacks. This limitation motivates this work to establish novel attacks with easily acquired videos. To our best knowledge, no existing attacks target PPG-based authentication systems by using video clips.

2.3. Remote Photoplethysmography (rPPG)

To obtain rPPG signals from a video clip, anyone can calculate differences among the facial color channels. The green channel has the strongest plethysmographic signal, corresponding to the absorption peak of hemoglobin [40]. Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are used to separate the pulse signal from the RGB channels [26, 35]. CHROM [8] projects the normalized RGB values to two orthogonal chromaticity vectors before calculating their difference to extract the PPG signal. The rotation angle between the skin pixel subspaces in the video frame is used to recover the rPPG signal [42]. As a mature deep learning technique, CNN has been proposed for end-to-end video-based heart rate measurement [5]. To acquire a reliable rPPG feature representation, rPPGNet combines the skin segmentation task with the rPPG recovery task through a spatial-temporal convolutional network along with a skin-based attention module [45]. GAN has been used in [29, 39] to improve the quality of continuous waveforms of rPPG signals. However, most existing works extract the heart rate without emphasizing the waveform’s accuracy.

3. Our Spoofing Attack

We aim to design a spoofing attack on PPG-based biometric authentication only by video clips. Fig. 3 presents the workflow of our attack. Sec. 3.1 introduces the threat model of our attack. Initially, we obtain the region of interest in a video clip through face detection. To acquire a suitable rPPG signal, we adopt CHROM (Sec. 3.2). Finally, we elaborate on how to restore a rPPG signal to the PPG signal (Sec. 3.3).

3.1. Threat Model

We outline the adversary’s capabilities to understand the requirements of executing an attack against PPG-based biometric authentication systems. In this paper, we assume that the attacker has access to videos containing the victim’s face. Our assumption is practical and realistic because the rPPG signal from video extraction is free of physical contact with the victim. An active attacker may install a hidden HD camera to record the victim’s face video to steal rPPG signals. Conversely, passive attackers can retrieve videos shared by the victims through online social media platforms like YouTube, Facebook, and TikTok. It makes the attack more stealthy and unnoticeable to the victim than any other existing method. In previous work, attacks against PPG-based authentication almost always require the availability of the victim’s leaked PPG signals. Our attack method does not require any leaked PPG signals, resulting in realistic attacks.

3.2. rPPG Acquisition

Our rPPG acquisition method consists of two steps. In Step one, we mark the region of interest (ROI) in the video by segmenting the face skin area. In Step two, we use the CHROM tool to extract the rPPG signal from the skin region of the human faces in the continuous video frames.

First, we detect the ROI in the video by using MTCNN [47] to separate human faces from video frames. By using MTCNN, we obtain the face positions at different granularity levels with accurate ROIs. Having obtained the position of the face, we filter the ROI by the adaptive skin detection algorithm [25]. By setting an appropriate threshold value, we exclude the pixels from non-skin sections, like background and hair, to mitigate the impact of background noise. Now, we capture the skin region from the video clip.
Next, we use the chrominance-based method CHROM to extract the rPPG signal from the skin region. As CHROM is based on a skin optical reflection model, we can quickly acquire the signal with good robustness to motion artifacts. And CHROM works well on high-resolution face images alone. Currently, there are limited publicly available data samples that include the face video and corresponding PPG signals. Hence, we choose the CHROM method to extract the rPPG signal from the isolated ROIs.

### 3.3. SigR: Our Restoration Model

After obtaining the rPPG signal, we construct a restoration model SigR to restore the rPPG signal to the PPG signal. The PPG signals reflect changes in blood flow from facial skin and fingers. However, we observe that the collected PPG and rPPG signals significantly differ because they emit at different distances from the heart and tissues. For instance, the difference in the signal’s arrival time causes differences in the signal phase. The difference in human tissues results in a variation in the magnitude of the waveform. Traditional methods struggle with modeling this relationship due to the human body’s complex nature and the overwhelming noise in the external environment.

In this work, we propose a signal restoration model \((R: \text{rPPG} \rightarrow \text{PPG})\). It aims to learn the distribution of differences between signals from a small amount of data. It adapts GAN’s network structure for signal processing. Specifically, our generator \(G\) takes the rPPG signal as the input to learn the latent space, approximating the generated signal close to the victim’s PPG signal that spoofs the discriminator. As illustrated in Fig. 4, our generator \(G\) has four Conv1D layers to capture the signal differences between one-dimensional signals. LeakyReLU is used as the activation function. The discriminator consists of two layers of Conv1D and MaxPooling1D layers, respectively. The discriminator checks the reference PPG signal and determines whether the restored signal output by the generator is acceptable or not. We apply Wasserstein distance and gradient penalties to stabilize the training process [12].

To remain consistent with existing work, the PPG signal of one cardiac cycle is used as a unique identifier for each user. We use one cardiac cycle of PPG signal and rPPG signal to train the GAN network. To isolate individual cardiac cycle, the heartbeat segmentation is performed on the continuous signal with the beat separation algorithm in [28]. Segmented rPPG signals are fed into the generator for supervised latent space learning.

Through adversarial learning between the generator and the discriminator, the generator’s output signal yields a distribution similar to the PPG signal. As shown in Fig. 4, our restoration model combines the trained generator and the subsequent filter. We apply the Savitzky-Golay filter [37] to smooth the signal. After restoring the single cardiac cycle rPPG signal to the PPG signal, we average the multiple restored signals to reduce the bias.

### 4. Experiment

In this section, we evaluate the effectiveness of the proposed spoofing attack method. We conduct a series of experiments on the UBFC-PHYS [31] dataset, including the use of rPPG signals in three different states (‘resting’, ‘talking’, or ‘calculating’). We also evaluate the attack success rate at different video qualities, including frame rate, frame size, bit-rate, and use of beauty filter.

#### 4.1. Datasets

UBFC-PHYS [31]: It includes facial videos of 56 participants and their PPG signals. Each participant has a three-minute video with different states. The video resolution is 1024 \times 1024 with a frame rate of 35 FPS and 227,474 Kbps bit-rate. The sampling rate of the PPG sig-
4.2. Experimental Settings

The data was collected under three different states — ‘resting’, ‘talking’, or ‘calculating’. The ‘resting’ state requires the participants to remain relaxed and silent; the ‘talking’ state demands the participants to talk with a facilitator. Moreover, the ‘calculating’ state challenges the participants with mathematical tasks and requires them to read their answers aloud. These conditions simulate environments with different pressure levels of a human. Due to the participants’ physical movement, faces are not recognizable in some video frames, resulting in signal interruptions. Therefore, we exclude the videos with signal interruptions. In the end, we acquire 51 video data in the ‘resting’ state, 40 videos in the ‘talking’ state, and 47 videos in the ‘calculating’ state.

In our experiments, each user is treated as a victim separately, while the other users are considered non-victims. For each video clip, we extract the rPPG signals in a range between 150 and 287 cardiac cycles, which corresponds to a video clip of 3 minutes long. All non-victim users have PPG signals embedded in approximately 11,800 cardiac cycles.

4.2. Experimental Settings

We use Keras\(^1\) to simulate a state-of-the-art biometric authentication system with a CNN/LSTM network [19]. We adjust the average equal error rate (EER) of the biometric authentication component to approximately 14%, consistent with the EER used in [19]. Our model’s architecture resembles a state-of-the-art PPG-based biometric authentication’s architecture [19]. We use the open-source framework pyVHR [2] to extract the rPPG signals from video clips.

We label the victim’s signal as category 1 and other users’ signal as category 0. For each user in the dataset, we use all the contact data of the victim and one-tenth of other users’ as the training data. The other users’ data is used as a control group to evaluate our spoofing attacks. For the restoration model, we use the rPPG signal as the input to the generative model and the PPG signal as the discriminator’s reference. To prevent the model from learning the variations between the victim’s rPPG and PPG, we exclude the victim’s data when training the restoration model for each victim.

In our experiments, EER is used to evaluate the performance of the biometric system. EER is the error rate where the false acceptance rate (FAR) and the false rejection rate (FRR) are equal. FAR and FRR are the most commonly used indicators in biometric systems. FAR indicates the possibility that the system incorrectly accepts access by an unauthorized user. FRR represents the possibility of the system denying access to an authorized user. For evaluating the spoofing attack, we use FAR as an indicator. Because we need to evaluate whether the system incorrectly accepts restored PPG signals injected by the attacker, the higher FAR indicates that the restored PPG signals are more threatening to the authentication system. While SigR is proposed for signal restoration using GAN, the component of signal restoration in the new spoofing attack can be implemented by other machine learning/deep learning models. As a comparison, we use the Gaussian process (GP) and Gaussian mixture model (GMM) as baseline models. We use the Stochastic Variational Gaussian Process [13] in GPflow [30] as the GP implementation, and GaussianMixture from scikit-learn [34] as the GMM implementation.

4.3. Experimental Results

4.3.1 PPG Restoration Performance

In our attacking process, the more similar the restored signal is to the PPG signal, the higher the signal quality is. Since the Kolmogorov-Smirnov test (KS) is sensitive to the probability distributions’ location and shape, we use it to measure the similarity of two signals. The smaller the value of the KS test, the more similar the distributions of the signals are. Tab. 1 shows the results of KS tests between rPPG, GMM, GP, SigR (our method), and PPG waveform features. These features are considered to be associated with individuals [28]. The KS distribution of specific features is listed in Fig. 5. We observe that most of the feature distributions from SigR are closer than other methods to PPG.

Herein, we compare the correlation between the signals. As shown in Fig. 6, blue squares show the Pearson correlation coefficient between the PPG signal restored by SigR and the reference PPG signal. Red dots show the Pearson correlation coefficient between the original rPPG signal harvested from the video and the reference PPG signal. We find that the coefficient between the rPPG signal harvested from the video and the reference PPG signal is drastically unstable. Conversely, the coefficient of the PPG signal restored by SigR and the reference PPG signal is steady between 0.96 and 1.00. Most of the signals restored by SigR have higher coefficients than directly harvested rPPG signals, indicating that the PPG signals restored by SigR are positively correlated with the reference PPG signal. Our restoration model successfully makes the restored PPG signal significantly closer to the reference PPG signal than the original rPPG signal harvested from the video. The average increase in the correlation coefficient is 3.3%, with a maximum increase of 7.7%.

These results show that SigR well learns the relationship information between rPPG and PPG signals from the training data. SigR can use the learned information to restore a PPG signal from the corresponding rPPG signal that is the distorted or noise contaminated version of the PPG signal.

\(^1\)https://www.tensorflow.org/
Table 1. Average Kolmogorov-Smirnov test of features between the restored PPG signal and the reference PPG signal collected in the 'resting' state. SP: systolic peak index, DN: dicrotic notch index, DP: diastolic peak index.

| Method | SP   | DN   | DP   | A2_area | A1_area | A2_A1_ratio | a1   | b1   | ta1   | delta_t |
|--------|------|------|------|---------|---------|-------------|------|------|-------|---------|
| rPPG   | 0.3107 | 0.3264 | 0.2817 | 0.3233 | 0.2802 | 0.3654 | 0.2623 | 0.3592 | **0.3084** | 0.2347 |
| GMM    | 0.5019 | 0.4180 | 0.4866 | 0.4290 | 0.4786 | 0.3929 | 0.6251 | 0.4649 | 0.6051 | 0.4027 |
| GP     | 0.2849 | 0.3068 | 0.2564 | 0.3178 | 0.2525 | 0.3770 | **0.2525** | 0.2882 | 0.3892 | 0.2802 |
| SigR   | **0.2370** | **0.2498** | **0.2145** | **0.2549** | **0.2164** | **0.3141** | 0.3849 | 0.2627 | 0.3319 | **0.2217** |

4.3.2 Attack Success Rates in Different States

The victim in the video clip may be in an arbitrary state ('resting', 'talking', or 'calculating'). Tab. 2 lists the FAR results of our method on the UBFC-Phys dataset. Since PPG signals have distinct patterns related to human individuals, the quality of randomly generated data is insufficient to compromise the authentication system. Our random attacks use PPG signals collected from non-victim users as

| Status                       | T1   | T2   | T3   |
|------------------------------|------|------|------|
| Random Attack                | 0.14 | 0.15 | 0.15 |
| MTTS-CAN                     | 0.09 | -    | -    |
| Victim rPPG Signal Attack    | 0.25 | 0.19 | 0.21 |
| Victim GMM Signal Attack     | 0.34 | 0.27 | 0.26 |
| Victim GP Signal Attack      | 0.34 | 0.27 | 0.28 |
| Victim SigR Signal Attack    | 0.40 | 0.27 | 0.29 |
| Mean MTTS-CAN                | 0.13 | -    | -    |
| Mean rPPG Signal Attack      | 0.34 | 0.35 | 0.35 |
| Mean GMM Signal Attack       | 0.53 | 0.46 | 0.48 |
| Mean GP Signal Attack        | 0.43 | 0.44 | 0.40 |
| Mean SigR Signal Attack      | **0.61** | **0.49** | **0.57** |

Table 2. Spoofing attack FAR results of UBFC-Phys. T1: resting, T2: talking, T3: calculating. Random attack indicates the non-victim’s PPG signal captured by the fingertip. Victim means a single cardiac cycle from the victim signal. rPPG, GMM, GP, SigR indicate methods of acquiring signals. The mean signal is the mean value of multiple signals. We use the mean value to maximize the FAR results for each victim.
the input. We observe that FAR of the random attack is 14%, while it is 25% of rPPG signal attack, which indicates that it is easier to directly apply the victim’s PPG signal than random attack in the ‘resting’ state to mislead the biometric authentication system. Attacking the system using SigR’s generated signal has a 15% increase in FAR over the original rPPG signal, suggesting that our approach significantly increases the possibility of spoofing the authentication system. A recently published rPPG extraction method named MTTS-CAN [27] only achieved 0.09 FAR result and 0.13 mean-treated FAR in the resting state. It performs even worse than random attacks. In addition, attacking using the mean-treated SigR signal performs the best (61% in terms of FAR), increasing over 30% in FAR compared to the original rPPG signal. It indicates that every two attempts will succeed in breaking through the authentication system. It makes our attack more realistic than the existing works as a real-world authentication system usually allows three attempts [43]. We also find almost no difference in the FARs of the mean-treated rPPG signal for the three states, indicating that the mean-treatment reduces the influence of noise on the signal.

Compared to the rPPG signal in the ‘resting’ state, the FARs in both ‘talking’ and ‘calculating’ states are reduced. ‘Talking’ is usually accompanied by visible body movement, increasing the signal’s noise. The ‘calculating’ state simulates the person under pressure when the Autonomic Nervous System mediates the pressure. Since the Autonomic Nervous System controls cardiac activity, it changes the PPG signals [4]. Meanwhile, the restored PPG signals are also affected.

### 4.3.3 Attack Success Rates in Different Video Qualities

To evaluate our attack FAR with different video qualities, we choose the video with the highest quality of the extracted rPPG signal from UBFC-PHYS as the benchmark. Through FFmpeg\(^2\), we convert each original video clip into multiple video clips with different settings — resolution (1024 × 1024, 512 × 512, 256 × 256), frame rate (35, 14, 30, 20 FPS), bit-rate (227474, 113865, 255 Kbps). Videos with human faces are abundant on social networks. These videos are usually processed with beauty filters to achieve a nice visual effect. We use FFmpeg’s ‘smartblur’ filter to blur the facial area in input video without affecting the facial outline, which works similarly to the beauty filters.

Tab. 3 shows the authentication system’s FAR results for the rPPG and restored signals at different video qualities. FAR drops significantly when the video’s frame rate, frame size, or bit-rate decreases. Among all the parameters, the frame rate has the most significant influence on the rPPG signal result because the signal is extracted from each frame’s color channel. A lower frame rate infers a lower sampling rate. A low sampling rate increases the difference between rPPG signal and PPG signal. The smartblur filter also significantly impacts the quality of the extracted rPPG signal. As smartblur uses a Gaussian filter to smooth the image and simultaneously alter the pixel differences between video frames. We note that bit-rate slightly affects FAR, e.g., FAR is 0.62 when the bit-rate drops to 255 Kbps. When the bit-rate exceeds the threshold, the quality of the video image will be reduced. Meanwhile, the FAR results for SigR signals are significantly less influenced by the video quality than the rPPG signal. When the video quality decreases from 35 FPS to 30 FPS, the average FAR of SigR’s PPG drops by 5%, but the FAR of the rPPG signal drops by 12%. Regarding the frame rate that has the most significant impact on the rPPG signal, SigR shows good robustness as the FAR does not vary substantially. SigR learns a good representation of the latent space, making it insensitive to the rPPG signal sampling rate changes. Resolution is the most influential of all factors on the FAR of SigR. The lower resolution increases the contribution of each pixel in the video, which causes the random noise occurring in the signal we acquire to be more pronounced. Regarding the bit-rate and smartblur filter, although SigR is affected, the impact is significantly smaller than that on rPPG.

| Video Quality          | rPPG  | SigR  |
|------------------------|-------|-------|
| Original Video (FR: 35 FPS) | 0.75  | 0.96  |
| FR: 30 FPS             | 0.63  | 0.91  |
| FR: 20 FPS             | 0.54  | 0.92  |
| FS: 512 × 512          | 0.63  | 0.88  |
| FS: 256 × 256          | 0.60  | 0.81  |
| BR: 113,865 Kbps       | 0.71  | 0.93  |
| BR: 255 Kbps           | 0.62  | 0.92  |
| Filter: smartblur      | 0.64  | 0.92  |

\(^2\)FFmpeg is an open-source video transcoding tool used by many video transcoding software tools. It is available at [https://www.ffmpeg.org/](https://www.ffmpeg.org/).
Table 4. Comparisons of the KS test results with rPPG signal and PPG signal features captured at the different video quality. FR: frame rate, FS: frame size, BR: bit-rate. The bold values indicate that the rPPG signal captured with the video parameter has the most significant difference from the PPG signal regarding this feature. SP: systolic peak index, DN: dicrotic notch index, DP: diastolic peak index.

| Video Quality | SP  | DN  | DP  | delta_t | A1_area | A2_area | A2_A1_ratio | a1  | b1  | ta1 |
|---------------|-----|-----|-----|---------|---------|---------|-------------|-----|-----|-----|
| Original Video| 0.13| 0.10| 0.09| 0.14    | 0.18    | 0.16    | 0.47        | 0.28| 0.44| 0.28|
| FR: 30 FPS    | 0.16| 0.13| 0.15| 0.10    | 0.21    | 0.16    | **0.61**    | 0.19| 0.24| 0.15|
| FR: 20 FPS    | 0.12| 0.12| 0.20| 0.11    | **0.37**| **0.36**| 0.37        | 0.15| 0.25| 0.11|
| FS: 512 × 512 | 0.26| 0.34| 0.21| 0.12    | 0.36    | 0.33    | 0.22        | 0.26| 0.13| 0.17|
| FS: 256 × 256 | 0.26| 0.29| 0.23| 0.12    | 0.23    | 0.21    | 0.46        | 0.17| 0.38| 0.23|
| BR: 113,865 Kbps| 0.18| 0.14| 0.17| 0.10    | 0.26    | 0.25    | 0.51        | 0.15| 0.32| 0.14|
| BR: 255 Kbps  | 0.22| 0.22| 0.14| 0.12    | 0.32    | 0.26    | 0.45        | 0.20| 0.29| 0.09|

4.4. Discussion

Our experimental results demonstrate the threat of rPPG to PPG-based biometric authentication, and our restoration model can significantly amplify the threat. Our proposed method restores rPPG to PPG signals that mislead the PPG-based biometric authentication setups. Our restoration model will strengthen with more high-quality datasets by eliminating the variances across datasets caused by different camera parameters, shooting distances, and lighting conditions. Though our results are derived from the UBFC-PHYS dataset, our method has huge potentials for accurate PPG signal acquisition in telemedical scenarios. Due to this paper’s scope, we will experiment with more videos captured under different conditions to improve the restoration model as future work.

Defensive Strategies: A common defense strategy against spoofing attacks may add an authentication component before activating the facial authentication system [7]. The restriction of accessing high-quality video may decrease the success rate of our spoofing attack since the rPPG signal is affected by the video quality. Furthermore, protecting the HD video of the potential victim is a key for defense because our method requires a high-quality video clip of the victim to isolate the rPPG signals for a single heartbeat cycle before performing the restoration. We conduct further experiments on the COHFACE dataset [14]. All rPPG signals recovered from COHFACE are insufficient to compromise the biometric authentication setup. As shown in Fig. 7, the quality of the waveform obtained by the rPPG signal is low in the COHFACE dataset. Even the rPPG signal from one heartbeat cycle of the same individual varies drastically. The frame rate of COHFACE videos is 20 FPS, the resolution is 640 × 480, and the bit-rate is 255 Kbps. These parameters are significantly lower than the parameters in the UBFC-PHYS dataset. In the worst-case scenario, when the high-quality video needs to be released to the public, anyone may use some easily accessible means like beauty filters to mitigate leaking rPPG signals.

5. Conclusion

As the shortcomings of traditional authentication solutions have become increasingly apparent, researchers have turned to explore new solutions like PPG-based authentication. However, we find that PPG-based biometric methods are vulnerable to spoofing attacks. To gain insights on the security of the PPG-based biometric authentication
techniques, we propose a new spoofing attack requiring videos only. The challenge lies in the subtle differences in the phase and shape between the face’s rPPG signal and the actual PPG signal. In this paper, we propose a signal restoration model to restore rPPG to PPG signals. For the PPG-based biometric authentication, our results confirm the severity of the attack. We experimented with rPPG signals from videos in different states, and the results were consistently and significantly higher than random attacks. Our generative model restores the rPPG signals well in different states. Our empirical studies achieved the highest average success rate of 0.62, indicating that rPPG poses a severe threat to PPG-based biometric authentication. We also find that the quality of the video significantly affects the threat of the rPPG signal to the authentication system. Our spoofing attack is still practical in real world scenarios. For example, popular social networking applications like Facebook (Meta), Youtube and Tiktok, host millions of videos in HD quality. Today, most smartphones are capable of shooting HD quality video. Our empirical study shows that high-quality rPPG signals can be extracted from such videos. To mitigate such spoof attacks, we recommend alleviating rPPG signal leakage by adding a beauty filter before releasing HD videos.

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