Scale Invariant Privacy Preserving Video via Wavelet Decomposition

Chengkai Yu*, Charles Fleming† and Hai-Ning Liang‡
Department of Computer Science and Software Engineering, Xi’an Jiaotong Liverpool University
Suzhou, China
Email: *chengkai.yu14@student.xjtlu.edu.cn, †charles.fleming@xjtlu.edu.cn, ‡haining.liang@xjtlu.edu.cn

Abstract—Video surveillance has become ubiquitous in the modern world. Mobile devices, surveillance cameras, and IoT devices, all can record video that can violate our privacy. One proposed solution for this is privacy-preserving video, which removes identifying information from the video as it is produced. Several algorithms for this have been proposed, but all of them suffer from scale issues: in order to sufficiently anonymize near-camera objects, distant objects become unidentifiable. In this paper, we propose a scale-invariant method, based on wavelet decomposition. This work was originally published as [1]. Please cite the original paper.

Index Terms—Privacy, anonymization, video

I. INTRODUCTION

Cameras and camera-embedded devices have become pervasive in our daily life. Not only wearable devices such as GoPro cameras and Google Glasses but also surveillance systems, IoT devices, and even drones threaten our privacy. First-person videos are especially becoming very popular among YouTubers and video bloggers. Wearable cameras are also widely equipped by the police for security and evidence-gathering purposes. Many such videos are eventually uploaded to the Internet and processing techniques are often used to remove sensitive information such as people’s faces. However, studies have shown that video blurring techniques cannot balance privacy with awareness of risky situations by the person being recorded [2]. As the privacy issue of such videos recorded by wearable cameras is attracting more attention from the public [3], people are paying more attention to the potential threats to their privacy, and methods to preserve privacy in video need to be developed.

The usual video processing technique for privacy protection is to anonymize the video by applying blurring effects on sensitive regions so that the information is not observable to the viewers. However, common methods for anonymization processing often require human selection of sensitive regions. Faces are the only thing that would be blurred out in most videos. The effect might not be actually anonymous due to other information revealed in the videos, the person’s body shape, or from the background and nearby objects. Other methods blur the whole video from, but this has the side effect of making distance too indistinct to separate from the background.

II. RESEARCH AIM AND OBJECTIVES

As minor details could as well threaten people’s privacy, actual anonymity using an existing algorithm would in fact, produce a video that is so anonymous that it destroys most of the visual information, including the objects and background. However, this would generally make the videos themselves unusable for whatever purpose they were recorded for. Therefore, detecting and performing the blurring effect on different information in the video based on the scale could potentially blur out the sensitive information but maintain usability.

III. LITERATURE REVIEW

Privacy issues in wearable cameras have been widely discussed with the growth of the popularity of recording videos by portable devices. Wearable cameras are more portable than conventional video recording devices and have emerged as a popular way to capture a wide variety of experiences that threaten people’s privacy more aggressively and pervasively. Nguyen et al. conducted an extensive study on how individuals perceive and react to being recorded in first-person videos [4]. Findings suggest that most people would like to be asked for permission in case the recordings are shared with others, and most people would mind if they are being recorded without being notified.

A study on addressing privacy concerns from videos taken in first-person point-of-view evaluated the effectiveness of four techniques (face detection, image cropping, location filtering, and motion filtering) at reducing privacy infringing content [5]. Minor information that could be linked back to an individual as a non-obvious threat to privacy was pointed out in the study. All four methods were not particularly effective and could still pose privacy concerns. Glasses-style wearable devices were investigated with respect to recording and privacy and how these devices differ from other classes of cameras [6]. The qualitative study found that for such subtle devices, reactions to recording can be affected by the perception of the recorder and whether or not they could be identified in the recording. It was also pointed out that people frequently change their perceptions with repeated exposure or change their views as they become active users of such devices.

Ethical considerations of wearable cameras were investigated by [7]. Guidelines for all involved and best practices for third parties were proposed to address the ethical considerations of wearable cameras. Considerations in pervasive
recording technologies were assessed by [8] for an insight into how design, technology, and policy can work together for the appropriate usage of such technologies. An interesting finding suggested that a lack of control over recordings could actually make recording more tolerable. In an inescapable situation, everything has been decided, and people could rationalize it better than in controllable situations. Wearable cameras are demonstrated as an important emerging method to provide personalized feedback and support in public health interventions [3]. Ethical approval and privacy concerns are the most significant barriers and require more research in this domain. An important goal is to create interventions that explain, control, and notify people about the technologies.

The issue of privacy protection has been widely discussed in computer vision, especially when it comes to human recognition from sources such as robot [9], wearable cameras [10, 11], first-person video [12], or surveillances videos [13]. Human activity recognition has received a great amount of attention and recognition algorithms for various environments and activities were introduced [14, 15, 16] and [17] which highlight the importance of privacy-preserving videos. However, studies that cover privacy issues were focused on approaches for protecting peoples’ privacy but not on analyzing the actual privacy protection of the current anonymious algorithms. Privacy is a key factor in adopting new technologies [18, 19].

While some attempts to use adversarial attacks such as [20] have been proposed, they do not fully address the issue. Systems to prevent leakage, such as [21], also do not address the problem when the data is willingly uploaded.

IV. ANONYMIZATIONS ALGORITHM

As baseline algorithms, we compare with three commonly used blurring algorithms, including Gaussian blur, downsampling, and superpixel, applying these to our test videos. The three algorithms tend to produce different blurry effects and thus were chosen for determining and assessing their degree of anonymization in surveillance and wearable settings. We compare our algorithm versus this standard algorithm on both up close and distant objects in videos and show that our algorithm outperforms all three.

V. WAVELET TRANSFORMATION

A wavelet transformation decomposes the signal into several bands to capture and separate different characteristics of the original signal. The signal information of an object contains detectable differences, which could be captured by one or more bands during wavelet decomposition. The edges and surfaces are separated by different sets of bands due to the different characteristics of their signal. Different levels tend to capture the changes in color or textures in original images.

The wavelet transformation technique used in the study is the discrete wavelet transformation (DWT). The discrete wavelet transformation of an image signal of a level is calculated by passing it into a filter bank, where a series of filters perform levels of decomposition. The signal is transformed by a high-pass filter which gives the output of the detail coefficients, while the low-pass filter returns an approximation coefficient. As the image signal has been decomposed at the current level, the output of the low-pass filter will then be subsampled by 2 in the next level.

The Wavelet transformation anonymization algorithm (WTAA) demonstrates the potential of balancing anonymity and usage by performing scalable blurring effects based on the scale of the objects. We anonymize the video by decomposing the video using the wavelet transform, selectively destroying certain wavelet coefficients, then reconstructing the image via the inverse transform.

We compare the performance of our algorithm by considering a series of videos with both near and far objects. The wavelet transformation anonymization algorithm shows a great improvement when objects are far away. Gaussian blur has good anonymization but preserves insufficient information for usage. Downsampling has the lowest level of anonymization and does not keep the outline of the object from a distance. Superpixel has a reasonable anonymization level and preserves part of the shape; however, would not be sufficient to be considered useful. Wavelet transformation can keep both the shape and the color at a comparable level to the original video and performs extremely well in preserving distance objects due to the inherent scale in the wavelet decomposition.

A the zoomed-in shot, the person is about 15 meters away from the camera. Gaussian blur does not preserve any shape or color at this distance in order to maintain the level of anonymity. Downsampling preserves a degree of color when the color contrast to the background is large, but the shape is left out. Superpixel merges the person with adjacent superpixels, and the color would be destroyed as well as part of the shape. WTAA preserves both the shape and the color enough for the figure to be recognizable as a person. This effect is more pronounced when viewed as a video.

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Fig. 1. Comparison of anonymization algorithms for distant figures.

Fig. 2. Comparison in the level of anonymity in the last frame.
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