Sanitization of Visual Multimedia Content: A Survey of Techniques, Attacks, and Future Directions

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The exploding rate of multimedia publishing in our networked society has magnified the risk of sensitive information leakage and misuse, pushing the need to secure data against possible exposure. Data sanitization—the process of obfuscating or removing sensitive content related to the data—helps to mitigate the severe impact of potential security and privacy risks.

This paper presents a review of the mechanisms designed for protecting digital visual contents (i.e., images and videos), the attacks against the cited mechanisms, and possible countermeasures. The provided thorough systematization, alongside the discussed challenges and research directions, can pave the way to new research.

1 INTRODUCTION

Over the recent years, the volume of images and videos generated, shared, and stored by social media platforms, sensor and IoT networks, and video surveillance systems, to cite a few, has drastically increased. However, the exploding amount of available data has increased the risk of privacy breaches. This risk is exacerbated by the availability of affordable hand-held electronic devices (e.g., smartphones, cameras) and high-speed 5G networks, that have made it much easier for the average user to create and globally share video and image files. Such visual content is often uploaded to untrusted third parties or cloud providers for storage and further processing. Therefore, the need for privacy-preserving technologies is more critical now than ever.

Privacy is a serious concern in our networked societies, and thus several data protection laws and international standards were enacted worldwide. Similarly, most social media networks enforce policies to combat the dire consequences of privacy violations on users, such as social impact (e.g., damaged reputation, identity theft), financial losses, and even physical harm. For over two decades, considerable research was directed towards privacy-enhancing approaches for digital media. The proposed solutions can be categorized into two branches [76]: (a) access restriction; and, (b) controlling media content by modifying the sensitive parts (i.e., multimedia data sanitization).

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In this survey, we consider only the second approach. That is, we do not include works based on hardware-oriented solutions (including intervention and blind vision [91]), access control (e.g., user authentication and roles management), secure processing (e.g., secure multiparty computation and naïve encryption), and data hiding (e.g., steganography and digital watermarking).

Data sanitization includes the obfuscation or removal of sensitive information such as personally identifiable information (PII) to preserve the user's privacy. In some use-cases, some information leakage is needed in the obfuscated media content to maintain its usability and intelligibility; hence, a degree of privacy loss is always inevitable. Throughout the paper, this concept is highlighted as the *privacy-utility trade-off*. Nowadays, research efforts are focused on attaining provable security guarantees that precisely characterize the degree of information leakage about the sanitized multimedia. In the past, the sanitization process was performed manually by trained experts. However, in recent years, with the advent of Machine Learning (ML)-based techniques, there is a widespread trend to semi or fully automate the cumbersome and costly process. However, sanitization is not the only process being automated; attacks against it are also automated using state-of-the-art techniques, such as neural networks, face recognition [119], etc.. Consequently, in this survey, we additionally review the countermeasures devised to thwart such automated attacks.

Data sanitization technologies are a double-edged sword. Indeed, we note that many of the to-be-discussed obfuscation techniques can also have malicious use cases. For example, adversaries may utilize obfuscation methods to evade being recognized by biometric verification and video surveillance systems. However, since obfuscation methods should withstand conventional recognition and identification algorithms that the adversary may use, we do not differentiate obfuscation based on its intent. Typically, in data sanitization, the region hosting sensitive information is either distorted, replaced, or removed. On the one hand, distortion modifies the original object to render it unintelligible, while replacement substitutes the element with a visually similar one. Object removal ensures complete protection; however, the utility is severely compromised. On the other hand, distortion and replacement methods may leak information about the obfuscated content while achieving higher utility than removal. Fig. 1 depicts the privacy-utility trade-off between the obfuscation categories. The figure also illustrates the possibility of combining the different methods, a technique called *multimodal obfuscation*.
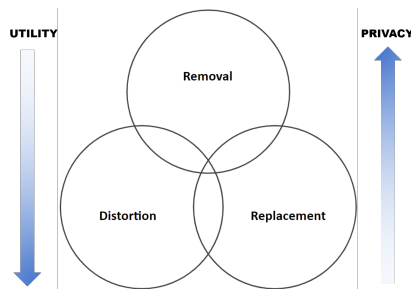
Fig. 1. The Utility-Privacy Trade-off of Obfuscation Methods

As it will be shown later in the paper, there is no single best approach to sanitization; each redaction solution comes with its benefits and drawbacks. Therefore, one of the objectives of this contribution is to help practitioners, in industry and academia, in devising the optimal combination of techniques to reach a certain degree of privacy, while maintaining an acceptable value of the utility function.

Over the past years, not many attempts were made to survey the literature on sensitive information protection using obfuscation methods. In one of the first surveys in the area, Padilla-López et al. (2015) summarized hardware and software solutions for image and video redaction in the context of privacy-aware intelligent monitoring systems [76]. The authors classified protection methods into five large categories: intervention, blind vision, secure processing, redaction, and data hiding. Intervention and blind vision are mainly hardware-based solutions. In contrast, in our survey, we limit our focus to methods concerning direct modification of the multimedia's regions of interest (ROI) to obscure information (i.e., redaction). A comprehensive survey of de-identification in multimedia content for protecting privacy is given in [88]. Ribaric et al. (2016) [88] presented de-identification of non-biometric, physiological, and behavioral biometric identifiers and soft-biometric identifiers found in images and video. In [91], Sah et al. (2017) focused on video redaction, including the problem of object detection and tracking. In [85], Rakhmawati et al. (2018) presented a very brief survey about the techniques of image privacy protection in a five-page conference paper. Their paper describes the characteristics, evaluation methods, and privacy protection methods that apply to images. The surveys in [106] and [61] address two specific applications of image privacy protection in visual sensor networks and image sharing on online social networks, respectively. In comparison to the cited surveys, we include a more detailed discussion of the observed current research trends and possible future research directions. We also provide a general discussion in each multimedia obfuscation section reviewing the provided methods, reference applications, key properties, and challenges. Additionally, our survey is the first comprehensive survey that addresses attacks and countermeasures concerns of visual media obfuscation in one paper.

Table 1 compares the main existing surveys in the literature (including our contribution) in terms of the addressed media type (images and video) and whether attacks and countermeasures are explored. As it can be seen from the table, other surveys go back in time and are not as comprehensive as ours.

Table 1. Comparison of Main Surveys on Multimedia Security and Privacy

| Survey & Year | Digital Media | | Attacks & Solutions | Future Directions |
	Images	Video		
2014 [106]	✓	✗	✗	✗
2015 [76]	✓	✓	✗	✗
2016 [88]	✓	✓	✗	✗
2017 [91]	✓	✓	✗	✗
2018 [85]	✓	✗	✗	✗
2020 [61]	✓	✗	✗	✗
Our survey	✓	✓	✓	✓

Contributions. In this paper, we provide several contributions: We start with a thorough systematization of sanitization techniques for images and video; we later review the attacks that these techniques are subject to; in addition, we discuss current countermeasures; and, finally, we highlight further research directions. In detail, our main contributions are summarized as follows:

- Categorization of the obfuscation methods according to their underlying mechanism (distortion, replacement, or removal) and highlighting of the properties expected to be preserved after obfuscation.
- Summary of the most recent and relevant contributions in the literature about the obfuscation techniques for each media type and their known attacks and possible countermeasures.
- Provisioning of an in-depth discussion for each media type exploring topics such as obfuscation challenges, current trends, and future research directions.
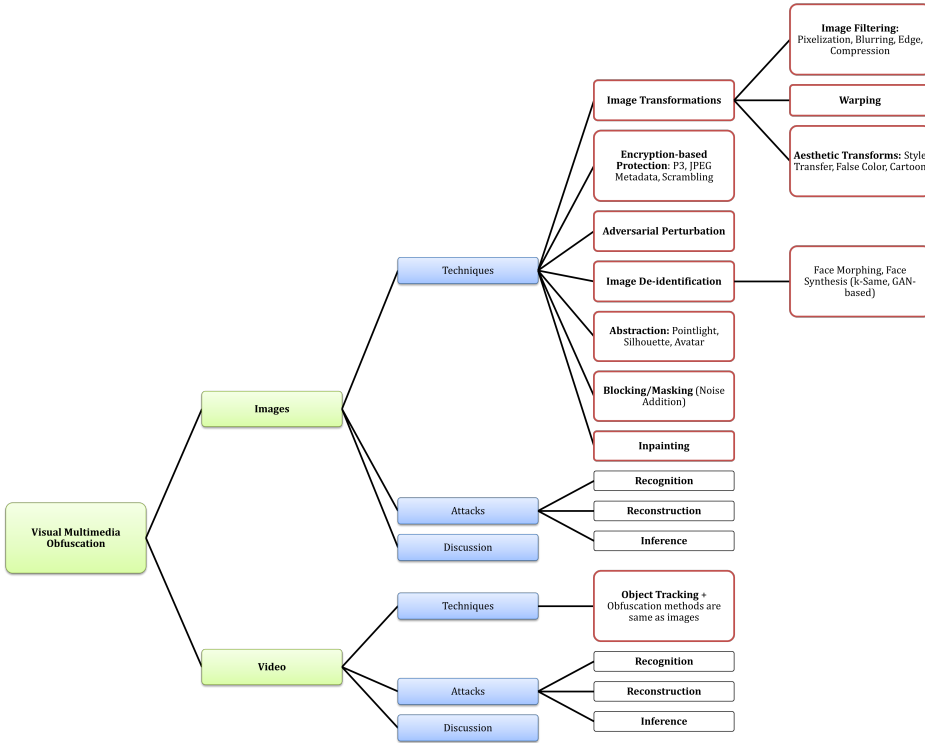
Fig. 2. Overview of the surveyed domains, techniques, attacks, and provided discussion.

Roadmap. The remainder of the paper (see paper overview in Fig. 2) is organized as follows. We detail the sanitization techniques used for images (Section 2) and video (Section 3), where each section also provides a comprehensive discussion about the described techniques in terms of their key properties, the attacks they are subjected to, and possible research directions. We establish our conclusions in Section 4.

2 IMAGE OBFUSCATION

The number of images captured daily is rapidly increasing due to the availability and affordability of high-quality cameras embedded in personal devices and surveillance systems, among others. A vast percentage of these images are uploaded to online social networks or cloud-based platforms for processing and storage. To put numbers into perspective, in November 2020, Google Photos announced that it had stored more than 4 trillion images [1]. Every day, approximately 300 million photos are uploaded to Facebook and 95 million to Instagram [2]. Thus, the critical regions in the images must be identified then removed or replaced to minimize the risk of disclosing sensitive or personal information.

An automated sanitization system typically involves multiple steps. The desired security level must be clearly defined in the pre-processing stage, including which sensitive objects must be identified and protected. The second stage involves two further steps: the identification step and

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[1]Google Blog: https://blog.google/products/photos/storage-changes/
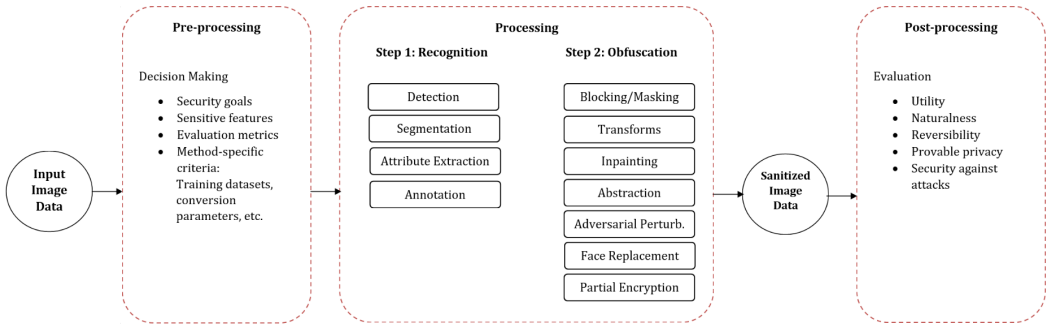[2]https://dustinstout.com/social-media-statistics/

Fig. 3. Major Steps and Components of an Image Obfuscation System

the obfuscation step. In the identification step, the region of interest (ROI) is detected using well-established *image recognition* techniques (e.g., face recognition). The boundaries of the ROI are then localized (i.e., *image segmentation*) and annotated. An obfuscated image is produced by applying an obfuscation algorithm on the annotated ROI. In the post-processing stage, the output image is evaluated for its security based on the pre-defined security goals, i.e., whether it should withstand human recognition, machine recognition, or both. Fig. 3 depicts the main integral components and steps of an image sanitization system.

The authors in [88] categorized sensitive image attributes as biometric, non-biometric, and soft-biometric. This paper follows the same taxonomy; however, we extend it to include confidential and censored categories to incorporate attributes that are not personal but must be secured. The types and examples of sensitive content in images are listed in Table 2. Most images have multiple types of objects that need to be identified and protected, known as the *multimodal identification* problem. For instance, even if the face is obfuscated in an image, soft biometrics such as body silhouette, clothing style, and skin color can be strong leads to a person's identity. Even after the obfuscation process, some residual visual features will remain. They are either left intentionally to maintain the utility and intelligibility of the image or missed unintentionally due to detection errors. This is repeatedly referred to as the *privacy-utility trade-off* in the literature. According to the application scenario, the obfuscated image may be required to retain specific characteristics: (a) reversibility, (b) utility, and (c) naturalness. *Reversibility* is a property achieved by the provision of additional translational variables. These variables are expected to remain secret or partially unknown to an attacker; otherwise, the obfuscation security is compromised. The *utility* and *naturalness* of images are highly desirable when images are intended for public use or model training for automatic recognition and classification algorithms. Also, maintaining a natural appearance helps conceal the fact that some identifiers were obfuscated, which can be a security goal on its own. Besides the usability and intelligibility trade-off, another common challenge is providing provable and quantifiable privacy or security guarantees. This section explores the different obfuscation techniques and the possible attacks an adversary may perform to infer the hidden content. Furthermore, we suggest some countermeasures and insights regarding current trends in the research and potential areas of improvement.

2.1 Techniques

We propose the following classification of image obfuscation techniques based on the primary mechanism of obfuscation (distortion, replacement, or removal of image features). The list of seven categories is presented in Table 3. The categories are *image transformation*, *encryption-based*

Table 2. Types of Sensitive Content in Images

Type	Description	Examples
Biometric	Unique, measurable and permanent personal identifiers [88].	Face, iris, ear, fingerprint
Soft biometric	Vague physical, behavioral or adhered personal characteristics that are not necessarily unique or permanent [88].	Height, eye color, body shape, age, gender, skin color, tattoos, birthmarks, scars
Non-biometric	Personal identifiers that provide non-physical and non-behavioral contextual information about the individual. Such attributes are either temporary and changeable.	Clothing, hairstyle, location, license plate, identification cards (e.g. health card, driver's license), credit cards
Confidential	Non-personal attributes that should be withheld from public for security and privacy reasons.	QR codes, cheques, keys, classified images (e.g., high-security buildings)
Censored	Visual censorship of content due to laws and regulations.	Branded products, pornography, gruesome content

protection, *adversarial perturbation*, *image de-identification*, *abstraction*, *masking* and *blocking*, and *inpainting* methods. In the following subsections, we provide explanations and further discussions about each technique. In Table 3, we rate the main obfuscation techniques based on the protection level against human and machine attackers separately, the utility of the obfuscated image, and the ability to reverse the obfuscation. A low utility rating indicates severe quality degradation and an absence of naturalness and intelligibility. A medium rating indicates a general lack of naturalness or intelligibility. A high rating indicates that naturalness, usability, and quality are preserved. In terms of security, a low rating indicates that the obfuscated image is easily detectable and recognizable either with the naked eye or using image detection and recognition algorithms. A medium rating indicates the existence of known attacks that can leak information; however, the attacks do not have high success guarantees. A high rating indicates that the obfuscated image has a low risk of information disclosure.

2.1.1 Image Transformations. Image transformation is an image editing method that refers to mapping an input image to a processed output image using a function. Early attempts at redacting photos relied on image transforms to hide sensitive regions. Image transformation techniques, specifically pixelization and blurring, are typically used for censorship in television and online news [85]. Here we consider *image filtering*, *image warping*, and *aesthetic transforms* as types of image transformations used for distorting the appearance of the original image (see Table 4 for examples). In image filtering and image warping, the obfuscated image is a degraded version, characterized by its information and utility loss. Since the image transforms are based on a parameterized model, this category of obfuscation is highly vulnerable to ML-assisted attacks [65, 98]. Such attacks are trained to reconstruct an approximated (i.e., lossy) original from the redacted image or deduce the image's original using evident correlations from within a set of unobscured images. As per aesthetic transformations, they modify the input image to produce an abstract or a cartoon equivalent which may thwart weak recognition systems. Overall, these methods are ineffective against human and machine attackers.

Image filtering: Image filtering has many applications in image processing, including edge detection, smoothing, sharpening, and noise reduction. The image is treated as an M x N matrix.

Table 3. Main Image Protection Techniques in the Literature (L: Low, M: Medium, H:High)

Category	Main Techniques	Subtype	Sub-Subtype	Security Level Human	Security Level Machine	Utility	Reversibility
Distortion	Image Transformations	Image filtering	Pixelization Blurring Edge Compression	L	L	L	✓ (lossy)
		Image warping	-	L	L	L	✓ (lossy)
		Aesthetic transforms	Cartooning False color Style transfer	L	L	M	✓ (lossy)
	Encryption-based Protection	Partial Encryption Scrambling	P3, TPE -	H	H	L	✓ (lossless)
	Adversarial Perturbation	-	-	L	M	H	×
Replacement	Image De-identification	Face synthesis	k-Same ML-based	H	H	H	×
		Face morphing	-	H	M	M	×
	Abstraction	-	-	H	H	M	×
Removal	Blocking/Masking	-	-	H	H	L	×
	Inpainting	-	-	H	H	M	×

Each cell in the matrix contains an integer from 0 to 255 (0 is black and 255 is white). An image can also have multiple channels such as RGB (red-green-blue), HSV (hue-saturation-value) and YUV [110]. Filtering is a mathematical operation where a matrix (aka, kernel) is convoluted with each pixel value and its neighbors within an image.

Pixelization. Pixelization (aka, mosaicing) is a widely adopted technique where the region of interest (ROI) is divided into a square grid (e.g., 8×8, 16×16) or a rectangular grid. The average color value of the pixels within each box is computed. Then, the value of each pixel within the box is replaced with the computed average. Pixelization can be considered a reduction in the resolution of the obfuscated region [65]. For a pixel box of size $n \times n$, the resolution is effectively reduced by a factor of n^2 [65]. Increasing the size of the pixel box increases the level of security as more pixels are averaged together. As can be seen in Fig. 4, pixelated images of smaller pixel boxes, e.g., 5×5, are still human-recognizable.

(a) Original   (b) 5×5   (c) 10×10   (d) 20×20   (e) 30×30
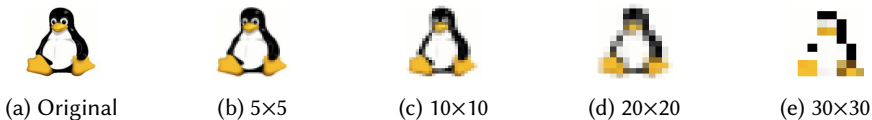
Fig. 4. Pixelization: 5×5, 10×10, 20×20, and 30×30 grids.

In [28], Liyue Fan (2018) presented an image pixelization method that extends the notion of differential privacy, providing rigorous privacy guarantees. Differential privacy [25] (aka, statistical disclosure control) is the state-of-the-art privacy paradigm for statistical database sanitization. It defines a parameter ϵ that corresponds to the degree of privacy, where the smaller the value of ϵ, the stronger the privacy. The algorithm first performs pixelization on an input image and applies Laplace perturbation to the pixelized image. The Laplace perturbation uses the notion of m-neighborhood, which protects up to m pixels. The output image would closely resemble a normally pixelized image except for m grid cells. The algorithm guarantees the indistinguishability of the output of two neighboring images having the same dimensions and differing by at most m pixels. As m increases, the privacy is increased, but the utility is lowered as the Laplace perturbation

Table 4. Main Image Transformation (Editing) Techniques in the Literature

Category	Technique	Example	Reference & Year
Image filtering	Pixelization		2018 [28], 2019 [29]
	Blurring		2016 [28]
	Edge Detection		2019 [36]
Image warping	e.g. Twirl effect		2013 [50]
Aesthetic Transforms	False Color		2017 [19]
	Cartooning		2014 [27], 2017 [37], 2018 [54]

noise increases. Fig. 5 shows a pixelized image (left) and its differentially private (DP) alternative (right), where the pixel box size is 16×16, $m = 16$, and $\epsilon = 0.5$. The noise added after pixelization protects the image from machine-based recognizers and provides provable and quantifiable privacy guarantees. The author also extended the concept of differential privacy to blurring. The algorithm first adds Laplace noise to each pixel and then applies Gaussian blur to smoothen the output.
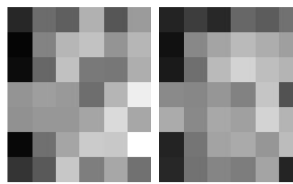
Fig. 5. Pixelized (left) and DP-pixelized (right) images for 16×16 pixel grid, $m = 16$, $\epsilon = 0.5$ [28].

In [29], the same author (2019) expanded on DP pixelization to yield higher utility. The output of this method exhibits more resemblance to the original image. Compared to standard pixelization, the accuracy of re-identification using CNN-based attacks is lowered from 96.25% to 82.5% for $\epsilon = 0.5$ and 17.5% for $\epsilon = 0.1$. The author used a generalized notion of DP known as *metric privacy*. Metric

privacy guarantees a level of indistinguishability proportional to the distance between two inputs. Meaning, the mechanism's output is roughly the same for all visually similar images in a set, and an adversary cannot infer the exact input image by observing the obfuscated image. The obfuscation algorithm involves two major steps: transformation and random sampling. The first step transforms a sensitive ROI into a k-dimensional feature vector using Singular Value Decomposition (SVD). SVD is used as a (invertible) perceptual image hashing method that captures geometric features and characteristics of the image data. The higher the value of k, the higher the resemblance between the input and obfuscated ROI. Next, the vector is randomly sampled according to a certain probability distribution, satisfying metric privacy. The sampled vector is processed with an inverse transform to produce the obfuscated ROI. The technique was evaluated using Mean Square Error (MSE) and Structural Similarity (SSIM) metrics between the obfuscated ROI and the original ROI. SSIM is a value between 0 and 1 representing the holistic similarity between two images, where 1 indicates identical images [98].

Blurring. Blurring is another image quality degradation technique. There are several types of blur filters. A *Gaussian blur* is where pixels within the ROI are convoluted with a Gaussian kernel to achieve a "smoothing" effect. The blurriness level is controlled by the standard deviation σ parameter. Another type of blurring is motion blur. The *motion blur* alters the details of an image by replicating the effect of a synthetic camera's motion. The degree of blurriness is affected by the length and the angle of the synthesized motion. *Box blur*, also known as a linear box filter, is a form of a low-pass filter where each pixel is replaced with the average value of its neighboring pixels.

Edge Detection. In image processing and computer vision, edge detection is a fundamental technique for feature detection and feature extraction. It includes various mathematical methods that identify the points at which the image brightness discontinues or changes sharply. Image edges preserve the shape and some internal details of the ROI [35]. Unlike pixelization and blurring, edge detection is not a typical obfuscation method and it is considered a form of abstraction. Nonetheless, there were a few mentions of edge detection as an obfuscation method in [106, 36, 35]. The level of obfuscation is controlled by an "edge filter" parameter which affects the strength and visibility of the edges and the inner details of the image.

Discussion. The methods detailed in this section are regarded as naïve and conventional methods that are no longer secure against machine detectors and that can still leak information to human observers. In [65], pixelated images of objects belonging to 1 out of 10 classes and smaller pixel boxes, e.g., 4×4, were easily recoverable using neural networks with an identification accuracy of over 70%. With 16×16 box size, the accuracy of recovery is about 31%. In [60] and [102], the authors investigated the effectiveness of pixelization and blurring against human recognition as well and explored its impact on user satisfaction. The evaluation proved that both methods are ineffective against human recognition. However, considering user satisfaction, they performed better than blocking or masking methods but still were not favorable.

There are other image processing techniques that are sparsely cited as forms of visual privacy protection such as scaling, stretching, rotation, modifying saturation and brightness, grayscaling, and lossy compression [78]. However, they are no longer viable due to the robustness of image fingerprinting and image recognition methods that can easily identify matching images even after severe quality degradation. *Lossy compression* (aka, *high compression* or *downsampling*) is an irreversible data encoding that significantly decreases the peak signal-to-noise ratio (PSNR) [78, 45] of the image and produces inexact approximation or partial discarding of the image data. It is commonly used to reduce data size during storage and transmission. The most widely used lossy compression scheme applies discrete cosine transform (DCT) on the images. Existing compression standards are JPEG and JPEG-2000 for images, and M-JPEG, M-JPEG 2000, MPEG-4, or AVC/H.264 for videos [45]. Similar to pixelization and blurring, the utility of the image is lowered

after compression; however, it can remain easily recognizable by the end-user. Research has shown that compression is also vulnerable to super-resolution ML-trained models [79, 104, 3].

Image warping: Image warping is a geometric transformation of an image such that any depicted object is significantly distorted. Warping destroys the details and relationship between neighboring pixels while retaining the general shapes of the image. It is commonly used for animation and artistic purposes. In [50], Korshunov et al. (2013) proposed an algorithm that uses warping techniques to obfuscate faces. The algorithm works as follows: the face region is detected using face recognition algorithms. Then, a set of key pixels in the image are selected from the eyes, nose, mouth, and sides of the face. These pixels are shifted (i.e., their coordinates changed) by a random shifting distance that is decided using a pseudo-random algorithm. The next step is to estimate the transformation matrix based on the original and destination coordinates of the shifted pixels. The transformation is applied to the remaining pixels using the estimated matrix, while any gaps are interpolated using a bicubic algorithm. The discussed process is reversible if the inverse transformation matrix can be re-estimated [13]. However, due to the interpolation of some pixels, an unwarped image is only an approximation of the original. The strength of the warping effect, and thus the privacy, is based on the shifting distance. Ideally, a warped face would be detectable by face detection algorithms but unidentifiable by face recognition algorithms. Security is enforced by using a secret key for seeding the pseudo-random algorithm and encrypting the selected key pixels.

Aesthetic Transforms: Artistic transformations on images are mainly intended for improving the utility of obscured images. It can be beneficial for online social networks, where sensitive information can be hidden without degrading the user experience. In [36] and [35], the authors conducted an objective evaluation to study aesthetic transforms as a visual obfuscation method and their impact on viewer satisfaction. The study applied cartooning and false colors to conventional obfuscation methods (pixelization, edge detection, and masking) known for their high utility loss and low visual perception. Despite the applied beautifications, the results show that user satisfaction did not significantly increase.

False Color. False colors (see examples in Fig. 6) are typically used as a visualization aid in image processing. They are used to depict invisible features that our eyes cannot normally see (e.g., invisible spectral emissions and sensitivities, line of sight analysis). An RGB input image is first transformed into grayscale. Then, the grayscale value is mapped to an RGB value based on a predefined color palette. The mapped RGB value then replaces the original pixel value. The primary advantages of this technique are that the intelligibility of the image is not compromised, the selection of an ROI is not required, and it can be used in conjunction with other obfuscation techniques [19]. However, false colorization is partially reversible (i.e., lossy) because: (a) the color palette may not be one-to-one; and, (b) the initial RGB to grayscale conversion is a lossy operation—the color information is not retained. Çiftçi et al. (2017) [19] presented a reversible false color-based obfuscation for the JPEG standard, where the entire image is colorized, and the restorative information is encrypted and embedded in the file's metadata. The output of the system is the false-color image (FI), whose JPEG APP Markers contain the encrypted and compressed values of the difference image (DI), sign image (SI), the histograms of the original image, and the color palette. To ensure the reversibility of the scheme, instead of using direct RGB-to-gray conversion, a false-color value is computed for each color value in the original image. Since most color palettes are not one-to-one, a pseudo-inverse image is computed using the inverse table lookup. The resulting FI is then encoded to the JPEG standard. DI is obtained by subtracting FI from the pseudo-inverse of the original image. SI is included since the difference can be negative.

Cartooning. Cartooning achieves an effect similar to watercolor painting, where an ROI is converted into an aesthetically pleasing abstracted frame. For images containing faces, cartooning maintains a high utility since it preserves general properties like behavioral information, gender,
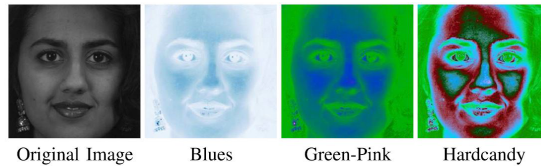
Fig. 6. False color-based protection using three different palettes [19].

emotion, and at the same time obscures facial identity [27, 37]. In [27], Erdelyi et al. (2014) proposed an adaptive mechanism where the intensity of the cartooning filter can be changed according to the level of protection and utility required for specific scenes. The method uses two key techniques: color filtering and edge enhancements, i.e., smoothing the areas with moderate color variations to single-colored areas [27]. Their evaluation metrics were the structural similarity (SSIM) index and peak signal-to-noise ratio (PSNR). The results show that cartooning achieves higher privacy and utility than blurring and pixelization.

Hasan et al. (2017) in [37] proposed a cartooning algorithm having two major components: the first is cartooning the entire scene, and the second is using computer vision to detect the sensitive objects and replace them with visually similar and randomly selected clip-art images of the same class. Their method is intended to preserve semantic scene information while obfuscating fine-grained details. The authors note several challenges in the accuracy of identification and localization of objects, mainly: the selection of suitable clip-art, and the alignment of the clip art with the removed object in terms of scale, position, and orientation in an aesthetically pleasing manner. The results showed a general acceptance by the participants of the images' semantics, aesthetics, and privacy. However, the major downside is that the replacing clip-art is selected randomly from a dataset and, therefore, some participants were not pleased with the quality of the clip arts.

ML-based algorithms are being utilized for cartooning and aesthetic *style transfers*. For example, in [54], Larson et al. (2018) applied to the entire image a cartooning model based on Generative Adversarial Network (GAN). They intended to confuse image classifiers not to predict the correct category of the image while maintaining its visual aesthetics. Aesthetic style transfer (illustrated in Fig. 7) can be achieved using Convolutional Neural Networks (CNN), where a model is trained to generate an output combining the content of an image with the style of another [58].

Fig. 7. Examples of aesthetic CNN-based style transfer for face obfuscation [58].

2.1.2 Encryption-based Protection. A proper encryption of the photos (e.g., using AES in CBC mode) provides complete security. Still, it destroys the information that is not privacy-breaching, therefore, hindering the ability to perform any image processing task without the secret key. Several technologies solve this problem by providing what is referred to as *conditional access* [76] and significantly distorting only the sensitive region of interest in the image while leaving the rest as is. The main advantage of this type of protection is that the original data can be perfectly

recovered using the secret key. The drawbacks are that a secure channel to exchange the key and high computing power are needed, making it inefficient for real-time applications. Encryption and scrambling can be performed in different image domains: pixels, bitstream, or Discrete Cosine Transform (DCT) coefficients [113].

P3. Ra et al. (2013) [83] proposed P3 encryption for JPEG-compliant images, which splits the image, based on an AC coefficient threshold, into a JPEG public part and a private part. The two parts are shared independently, and a secret key is needed to uncover the private part. Their combined size does not significantly exceed the size of the original image. P3 assumes that most information about an image is carried in the 0th DC coefficient and the remaining 63 AC coefficients. Therefore, P3 encrypts the most significant bits of the significant DCT coefficients in the private part; the remaining coefficients and least significant bits are left in the public part. The image can be reconstructed by decrypting the private parts and positioning them back in the public part. According to the authors, P3 was explicitly designed to protect against automated recognition technologies since the public image does not resemble the original image [83]. Later on, it was uncovered that P3 is not effective in privacy preservation against artificial neural networks [65, 28]. When the splitting threshold is not small enough, some visual information could be leaked from the public image. For a threshold of 1, the highest privacy setting of P3, Mcpherson et al. (2016) [65] achieved an 83% re-identification accuracy of obfuscated faces using a simple neural network, and 97% for a threshold of 20.

JPEG Metadata Embedding. Several works in the literature leveraged the metadata (application segments or APPn marker) in the JPEG standard to fully reverse the obfuscation. In [114], an JPEG sub-image is constructed from the DCT coefficients of the original image, where the coefficients outside of the identified ROI are set to zero. A mask matrix is built from the shape, size, and position parameters of the obfuscated ROI. The sub-image is encrypted using symmetric encryption. The mask matrix and other metadata are also encrypted and embedded in the image file. A similar approach in [30] proposed a two-level reversible watermarking scheme, used in conjunction with any obfuscation process, where the residual information needed to reverse the obfuscation process is compressed, authenticated, encrypted, and finally embedded within the obfuscated image. The authors implemented their scheme with k-same face replacement, where the reversing information is the difference between the original and obfuscated image. Other JPEG-specific partial encryption methods include *Cryptagram* [100] and *Thumbnail Preserving Encryption (TPE)* [107]. TPE scheme allows the reconstruction of a low-resolution thumbnail from an encrypted image while preventing the extraction of any further data.

Scrambling. Image scrambling (or image *permutation*) is the process of rearranging pixel tiles randomly in the spatial domain to break the correlation between the neighboring pixels and make the image unintelligible [78, 115, 68]. It can also be performed in DCT domain or codestream domain depending on the media format [85]. For a useful and comparative review of the various scrambling techniques proposed in the literature, refer to the survey given in [69] by Mondal et al. (2017).

Permuting DCT coefficients or image tiles is insufficient to achieve secure scrambling. Scrambling can be solved through a brute force attack whose complexity is $t!$ for t tiles [95]. An adversary can further reduce the attack's complexity by analyzing the boundary, color, shape of the content, and texture of neighboring blocks in the image. Additionally, scrambling is impacted by lossy compression [50, 78]. When scrambling a compressed image, a blurring effect appears at the borders of the permuted pixel grids. Fig. 8 shows an example of a spatial-domain permutation and de-permutation on a compressed JPEG image. In [78], Poller et al. (2012) proposed a secure jigsaw scrambling method that works with compressed JPEG images. The border blurring effect is

reduced by replacing the pixel values at each grid's margins with the pixel values at the border during de-scrambling. To achieve higher security, the authors increased the number of possible permutations by shifting, rotating, and mirroring pixel grids randomly based on a secret key, and then by pseudo-randomly modulating the pixels' channel intensity [78]. The authors suggested salting the encryption key for additional security and decreasing the grid size to increase the number of permutations. Sharma et al. (2018) [95] applied block-wise Randomized Multidimensional Transformations (RMT) to the pixel matrix of the image. Acting like the encryption key, a random orthogonal (i.e., rotation) or a projection matrix multiples the image's matrix. Then, random additive noise uniformly selected from a known range is added to the multiplication output.

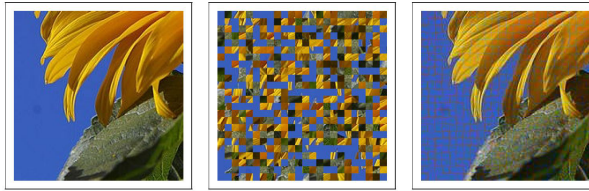
Fig. 8. Conventional Spatial-Domain Permutations [78]: (left: original, center: permuted, right: de-permuted with blurred grid borders).

2.1.3 Image De-identification. De-identification is the process of hiding, eliminating, or substituting personal identifiers (aka, personally identifiable information or PII) with surrogate identifiers to prevent the disclosure and use of private data for unintended and potentially harmful purposes. It aims to hide personal information from human recognizers, automatic recognition techniques, or both. The terms anonymization and de-identification are often used interchangeably in the literature. Nonetheless, the terms can be differentiated based on whether the obfuscation process is reversible (de-identification) or irreversible (anonymization) [88]. Table 5 lists the main attributes and features (biometric, soft-biometric, and non-biometric) that can be extracted from facial and body landmarks in images. The required level of protection and utility determines which of the listed features to obfuscate and which ones to preserve. In Table 5, we refer to works in the literature investigating recognition and de-identification (and, in some cases, the preservation) of the listed features.

The human face is the most prevalent biometric identifier in photos [89, 66]. A trivial solution to de-identifying faces involves blacking out the eyes, mouth, or the entire face, where the first two fail to thwart currently robust face recognition solutions [72]. Nowadays, most research focuses on achieving face obfuscation that is photo-realistic while maintaining standard facial characteristics. In this section, we look at image de-identification from the perspective of face de-identification. Nonetheless, image de-identification also includes the obfuscation of non-biometric identifiers such as license plates [65], QR codes [118], etc..

Face De-identification: Table 6 shows a breakdown of the reviewed solutions for face de-identification: face morphing and face synthesis using *k*-same and adversarial learning methods.

Face Morphing. Face morphing (illustrated in Fig. 9) is a geometrical transformation involving two face images to create a manipulated image that maintains a likeness to each of the original identities. In [50], Korshunov et al. (2013) proposed a partial and randomized face morphing method that works by interpolating the position and intensity of selected key pixels in the input face to match a target face [85, 50]. The interpolation of the key pixels is achieved somewhere in-between the input and target images, and the pixel intensities are weighted. First, a face landmark localization

Table 5. Image De-Identification: Balancing Privacy-Utility in Facial & Body Features

	Feature	Type	Reference
Body	Fingerprint	Biometric	[109, 62]
	Skin tone	Semi-biometric	[23, 82, 44]
	Tattoos, Scars, Birthmarks	Semi-biometric	[64, 40]
	Clothing style	Non-biometric	[8, 10, 80]
	Body Pose, Activity	Semi-biometric	[87, 71]
Face	Iris, eyes	Biometric	[99, 117]
	Ear	Biometric	[26, 43]
	Gender	Semi-biometric	[23, 32, 75]
	Age	Semi-biometric	[23]
	Hair style, hair color	Non-biometric	[82, 8, 81]
	Facial Expression	Semi-biometric	[32]

Table 6. The Main Methods of Face De-identification in the Literature

Main Methods	References & Year	Description
Face Morphing	2013 [50], 2015 [70], 2017 [63], 2019 [59]	Synthesizing a face that maintains a likeness to an input and a target face using various techniques.
Face Synthesis	2005 [72], 2018 [96], 2019 [44, 58], 2020 [55]	Synthesizing realistic faces that preserve generic facial characteristics using k-same algorithms that compute an averaged face representing a cluster of k similar faces or using DL-based synthesis.

algorithm automatically selects pixels around the detected eyes, nose, and mouth from both images. The original and target images are divided into triangles using Delaunay triangulation, with the selected points being the vertices of the triangles. For corresponding pixels in both images, the final pixel coordinate is determined using a given level of interpolation value. For an interpolation level and intensity strength equal to 0, the original pixels are generated, and for a level of 1, the target image is produced. Recovery of the original image is possible by applying the inverse morphing transformation, given knowledge of the target image, selected key points, interpolation values, and intensity values. Security can be ensured by using a secret key for seeding the pseudo-randomization of the interpolation and intensity weights and encrypting the key points used for the triangulation.

The previous method lacked naturalness due to partial morphing. To achieve a higher utility, Nakashima et al. (2015) in [70] proposed a method to preserve facial expression based on image-melding. Compared to the previous method, this technique leverages only a smaller number of corresponding points, specified manually by the user, in target and source images of similar orientation. The corresponding points in the source image are roughly matched to the target's by a transformation process, applying a weighted mask. The mask adjusts the scale, orientation, and position of the source image's facial features. Mahajan et al. (2017) [63] developed a system for *face swapping*. The system works by directly fitting a secondary image over the input image by rotating and scaling it. Color balance adjustment and blending of the facial landmarks from the second image onto the input are made to achieve a more natural appearance. In [59], Li et al. (2019) created a Facial Attribute Transfer Model (FATM) using autoencoders. The DNNs blend the target's facial attributes to those of the original faces.
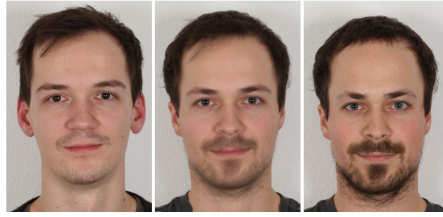
Fig. 9. Face Morphing [94]: (left, right: original faces, center: morphed face).

Face Synthesis: Here, we discuss k-same and GAN-based methods. Both methods rely on different mechanisms to effectively produce a new face image, unlike face morphing that modifies an input face to match a target face.

k-same Family. The basis of k-same algorithms is *k-anonymity*, an extension from differential privacy for micro-aggregated data. Other data anonymization techniques exist for categorical data; the two most popular among those are l-diversity and t-closeness [55]. k-same algorithms compute an averaged face to represent a cluster of k similar faces. The first work to introduce this concept was by Newton et al. (2005) [72] to enable secure sharing of image data with provable guarantees. The algorithm first determines the similarity between faces and clusters them based on a distance metric. The authors proposed pixel-wise averaging (k-Same-Pixel) or eigenvectors averaging (k-Same-Eigen) [72]. Images produced by k-Same-Eigen have a blurred effect because only a minimal number of important facial characteristics is retained. Even though the averaged face may appear similar to one image than another, because the same averaged face replaces all images in the cluster, the method guarantees that the correlation success rate of the k faces is $\frac{1}{k}$ at most. The main challenges are determining the appropriate value for k to achieve the highest privacy and finding the optimal groups of closest faces, which is an NP-hard problem [72]. The main limitation of [72]'s method is its lack of naturalness and information loss during the de-identification process.

Many additions to the k-same family have been proposed to overcome some of the previously mentioned limitations. Gross et al. (2005) [32] presented k-Same-Select, which guarantees the utility of the data by preserving facial expressions or gender. However, k-Same-Select works in the pixel domain and sometimes suffers from alignment mismatch in the de-identified face. k-Same-M by the same authors [33] addressed this limitation by using statistical models instead. Meng et al. (2014) [67] proposed k-Same-furthest, which aims to achieve perfect privacy for any source face regardless of the value of k. Sun et al. (2015) proposed k-Diff-furthest [97] to solve the tracking problem of individuals in k-Same de-identified videos, where k similar faces are replaced with the same averaged face. More recently, two studies incorporated the concept of k-Same algorithms in neural networks and GAN-based face synthesis in [66] and [77], respectively.

GAN-based Methods. Images produced by the early solutions of k-Same may exhibit poor visual quality and ghosting artifacts due to inexact alignment of facial features [55, 21, 12]. Generative Adversarial Networks (GANs) are more successful in producing natural-looking face images [46] that preserve many facial characteristics and cannot be reliably linked to the original identity. However, face detection is problematic when the subjects appear in varied backgrounds, positions, and activities. Most generative face models are suited for frontal and strictly aligned faces. To tackle this problem, Sun et al. (2018) [96] devised a two-stages solution. Depending on the visibility of the face pixels, facial landmarks are either detected or generated. They are detected when the original face image is clear, but hypothetical realistic facial structures and poses are generated when the face has been obfuscated. An advantage of the second scenario is that it allows upgrading weak

obfuscations, including blocking and blurring, to use realistic synthetic faces that blend naturally into the context.

Le et al. (2020) [55] designed a system based on StyleGAN (style-based GAN) [44] and k-same algorithms to achieve provable privacy, which synthesizes a face for a given dataset while simultaneously and iteratively tuning its privacy-utility trade-off. The system uses a two-steps cluster analysis component for feature vector extraction and clustering all input images into fixed-sized sets. The authors report that low-dimensional feature vectors produce better clustering and ensure high naturalness. The synthesized faces preserve properties such as age, gender, skin tone, and emotional expressions. Finally, the authors used a measure of the average Euclidean distances between images in a cluster and the corresponding synthesized image (i.e., measuring total information loss). StyleGAN [44] architecture is superior to traditional GAN in terms of the established quality metrics and the unsupervised separated learning of high-level attributes (e.g., pose, freckles, hair). Another noteworthy work is AnonymousNet (2019) [58] which uses GANs to produce realistic synthetic faces but notably adds adversarial perturbations to reduce the recognition accuracy and provides provable privacy metrics through a k-anonymity-based attribute selection.

2.1.4 Adversarial Perturbation. Studies have shown that advanced ML systems can, in partially obfuscated images, make correct malicious inferences about the person, such as religion, age, and occupation, thus deeming visual obfuscation methods insufficient when adopted in isolation [73]. Adversarial perturbation mechanisms were developed to change the prediction of deep neural networks, so the adversary draws incorrect or specific intended inferences from the image data without making perceptible changes to the input image. Another advantage of this technique is that it can be applied to an already obfuscated image to strengthen the obfuscation further. Recent works have developed the concept of Universal Adversarial Perturbations, which can be added to any image and cause the target ML model to misclassify it. Universal perturbations are more practical to deploy than per-instance perturbations since minimal computation and knowledge (black-box attack) are needed [14].

Some approaches to crafting adversarial face images lack quality and take an unreasonable amount of time to be generated. Deb et al. (2019) [22] proposed, AdvFaces, an automated adversarial face synthesis method that learns to generate minimal perturbations in the facial regions via GANs. AdvFaces produces imperceptible perturbations that evade recognition with high success rates up to 97.22% for obfuscation attacks (falsely rejecting a genuine subject) and 24.30% for impersonation attacks (falsely accepting an imposter) [94, 93]. To contrast image classification tasks, Li et al. (2019) [57] proposed an algorithm that generates adversarial noise using a novel adaptation of Fast Gradient Sign Method (FGSM) [92], which limits the probability of inferring the true class of a distorted image successfully. Different variations of FGSM such as iterative FGSM, private FGSM, random FGSM, and least-likely FGSM may select the true class as the target class. The authors designed the new FGSM approach to pick the target class from an adaptive subset of classes that most likely does not include the class to be protected. A recent survey by Chaubey et al. (2020) in [14] provides a comprehensive summary of the existing adversarial models and defense mechanisms against them. Other examples of works based on image adversarial methods are referred in [41, 86, 74, 84].

2.1.5 Abstraction. Abstraction removes an object of interest and replaces it with a graphical representation that somewhat resembles the removed content. Fig. 10 shows three examples of object abstraction found in the literature: *silhouette*, *point-light* (or *skeleton*), and *avatar*. Since abstraction is a utility-and-privacy-preserving method, it is widely used in online social networks. An abstraction algorithm applies image inpainting methods to remove the segmented object of

interest, renders a visually similar object, and places the abstracted form over the exact pixel locations of the removed ROI.

The effectiveness of the following abstraction methods was investigated by Li et al. (2017) in [60]. The point-light or skeleton method replaces an ROI with points and lines corresponding to the ROI's shape outline. A human point-light can only illustrate a person's activity and height, but completely hides his identity. The silhouette method is where an ROI is replaced with a (monochrome) object that mirrors its shape. A human silhouette can preserve the subject's body pose, activity, clothing style, gender, health condition, or hair style, but still completely removes biometric identifiers. A human avatar can preserve, in addition to all previously listed features, finer details about the person such as facial expressions and age, and still protect the identity from disclosure. The privacy-utility balance is vividly exhibited in the previous examples. Unlike face replacement methods, abstraction does not aim to preserve naturalness; however, it seeks to generate realistic representations of the removed sensitive region. Nonetheless, abstraction is still considered one of the most effective methods for visual obfuscation today.
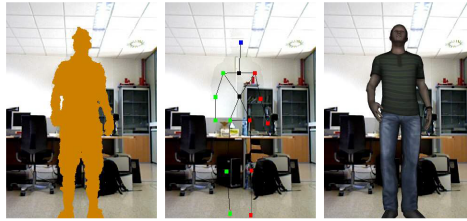

Fig. 10. Abstraction techniques [76]: (left: solid silhouette, center: point-light, right: avatar).

2.1.6 Blocking / Masking. *Blocking* or *blacking* (see Fig. 11-b) is where the sensitive bounding box is detected and replaced with a shape (e.g., square, rectangle, ellipses) in a solid color, typically black. Whereas the term *masking* is similar to blocking and is frequently used interchangeably in the literature. However, we find that it commonly refers to less intrusive covering of the sensitive regions, e.g., the bar mask in Fig. 11-c, where the eyes are determined as the sensitive area of interest. It may also refer to covering the sensitive regions with other objects, e.g., covering a face area with a clip-art [114]. *Noise addition* can be considered a subtype of image masking [72]. In noise addition, random image pixels are replaced by black and/or white pixels (referred to as *salt-and-pepper noise* [94]) as seen in Fig. 11-e. Black/white images are modified by flipping random pixels, and in gray-scale images (see Fig. 11-d), a random value between 0 and 255 replaces random pixels. However, additive random noise does not thwart automated recognition except when roughly 50% of the pixel values have been flipped in black/white images or 75% of the pixels are changed in gray-scale images [72]. Moreover, the black bar mask around the eyes is ineffective against image inpainting attacks, e.g. [5, 108, 120]. Blocking and masking are the most utility-reducing among all other ad-hoc obfuscation methods [102]. Nonetheless, blocking offers high protection against human and automated object recognition [98].

2.1.7 Inpainting. Inpainting methods are generally used to repair damaged or missing parts of photos. However, inpainting as an obfuscation method (see example in Fig. 12) refers to completely removing sensitive content (e.g., full-body region) of an image. The cleared space is then filled to blend naturally in a visually consistent manner, appearing as part of the background [60]. Based on the study conducted in [60], inpainting is the most effective technique for achieving true privacy. In the cited study, it produced the smallest percentage of identification success rate amongst 13
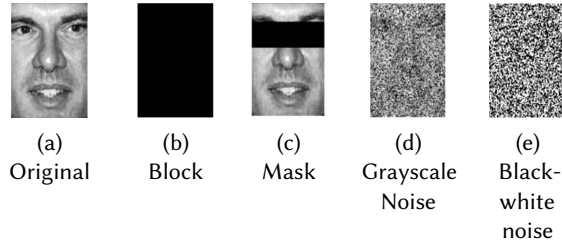
Fig. 11. Examples of Blocking/Masking [72]

other obfuscation methods. The output of inpainting algorithms is becoming more seamless and photo-realistic with the use of deep learning and adversarial training approaches. Once the image is inpainted, a visual abstraction of the removed sensitive information (e.g., [76, 6]) or synthetic faces (e.g., [96]) can be added to prevent complete information loss. A major limitation of inpainting algorithms is their computational complexity [85].

Fig. 12. Image Inpainting [76]: original image (left) and inpainted image (right).

2.2   Attacks and Countermeasures

Image obfuscation alters or removes features from the images to hide sensitive information and retains some visual features to keep the image intelligible and suitable for processing. However, these visual features can still be used to identify or reconstruct the protected objects through different attack styles. The attacks against image obfuscation can be classified as human-based, machine-based, recognition-based, reconstruction-based, or inference-based. In this section, we focus separately on recognition (or re-identification) attacks, reconstruction (or restoration) attacks, and inference attacks.

Recognition-based Attacks. Recognition-based attacks are where an attacker attempts to re-identify obfuscated objects or the person(s) from their obfuscated faces. Human-based recognition is based on the degree of information loss in the obfuscated image and the attacker's familiarity with the scenes and objects before the obfuscation. Removal methods such as blocking, masking, and inpainting may completely prevent human recognition [60, 102]. Conversely, image distortion methods (e.g., image filters, warping, false colors, cartooning) preserve the general shape and intensities of the objects, and therefore, are not very resilient to human detectors [60]. There are several ways to qualitatively measure an identity disclosure risk. A definitive privacy leak is when an image can be correctly linked to an individual with high certainty. Potential privacy risks exist when private information is linked to several individuals. The highest level of privacy is when an image cannot be related to any individual.

In terms of machine-based recognition, an attacker would use machine learning algorithms for image recognition. Three different kinds of automated attacks involve the matching of input

and output images in various arrangements: (a) original to obfuscated; (b) obfuscated to original; and, (c) obfuscated to obfuscated [72]. In the first type of attack, the obfuscated images are run directly through the image recognition software. In this context, the recognition algorithm uses a training set (aka, gallery images) composed of the original images, while the obfuscated images (aka, probe images) are used as input. The second type is the dual of the first; the training set comprises obfuscated images, and the original images are used as input. This attack assumes that the attacker has the complete collection of original images. According to [72], the trained model is expected to have decomposed and dispersed the alterations on the obfuscated images. The work in [34] serves as an example of this attack, where input transformations on perturbed images counteract the effect of adversarial perturbations. In the third attack, the attacker invokes the same obfuscation technique on a set of probe images. The recognition is done by matching an obfuscated probe to an obfuscated gallery. This attack assumes that the adversary has access to the training set obfuscated by a given method. This is also called *parrot attack* or *imitation attack*; a process of comparison and elimination to recognize the obfuscated image. In [76], pixelization and blurring were found to be vulnerable to parrot recognition which can achieve recognition rates close to 100%, despite looking somewhat de-identified to human recognizers [76]. It is shown that parrot attacks drastically reduce the level of privacy protection and improve the recognition rate [88, 89].

To counter image recognition attacks, adversarial perturbations can be added to alter the machine-learning based prediction, while having the introduced perturbation not detectable by the human eye. However, there are some defense mechanisms suggested in the literature for detecting and rectifying such perturbations. Two of such defenses are considered: the first one is to pre-process images at the inference time [34], and the second one relies on increasing the robustness of the model against adversarial training (i.e., training with perturbed images) [14]. In [2], Akhtar et al. (2018) presented a rectification method called Perturbation Rectifying Network (PRN) that pre-processes the images to be classified before passing them to the target recognition model. The output of PRN is a rectified image minus the perturbation. A detector network, separately trained on the DCT of the input-output difference of the PRN, performs a binary classification to decide if an adversarial perturbation is present. If perturbed, a rectified image is passed to the target model instead of the probe image. PRN is shown to have a success rate up to 97.5% against adversarial perturbations. Another possible countermeasure to recognition attacks is pseudo-randomization (based on a secret key) in the de-identification algorithm. The randomization will impede an attacker's ability to replicate the de-identification process exactly. When attaining high privacy is the main concern, we recommend not to use standard image transformations (such as pixelization, blurring, masking, lossy compression, and other transforms), even though they have lower computational complexity, since they are ineffective against ML attacks.

Reconstruction-based Attacks. Reconstruction-based attacks aim to recover the original image before its transformation. Today, with the advent of deep neural networks, this task has become much less challenging. Several studies have shown that conventional image transformations, namely pixelization, blurring, masking, and compression, are ineffective against bicubic interpolation, statistical modeling, and DL-assisted attacks [65, 98, 39].

For pixelized and compressed artifacts, a study in [56] used neural networks to achieve image super-resolution [104, 3], upscaling images up to a factor of 4. In further works, GAN-based models were used to solve super-resolution problems [103], and the study in [112] achieved ultra-resolution for images of lower resolution (e.g., 16×16). Similarly, for canceling the impact of blurring and restoration of sharper images, several image-deblurring methods were proposed in the literature using neural networks [47], and GANs [53].

Image inpainting can be used to infer missing pixels for blacked-out sections in an image. Yeh et al. (2017) [108] trained a deep generative (GAN-based) model to find an encoding in the latent

space that is closest to the corrupted image. The generator then uses the encoding to reconstruct the missing parts. The major advantage of their method is that it works with arbitrarily structured and large masked regions. Another method in the literature was also successful in recovering blacked image regions, however, relying on the presence of similar patches and structures in the remaining parts of the input image [5]. Other solutions used statistical modeling such as total variation and low rank and machine learning such as nearest neighbor (NN) and autoencoders [108]. In comparison, semantic image inpainting produced much more realistic images with sharper edges, having higher PSNR and SSIM in randomized masks, even when 80% of the pixels were missing. Prediction of the missing pixels can be done using external data (e.g., guidance images [120]) or internet-based inpainting [105].

Inference Attacks. As the name suggests, an adversary can infer hidden attributes or information about the obfuscated image in an inference attack. Inference includes determining that an image itself has been manipulated or synthesized. This is specifically valid for naturalness-preserving obfuscation technologies, such as face morphing and face synthesis. In face de-identification, indistinguishability is an important property where the synthetic face should look realistic and not be easily differentiated from a natural one. Examples of works dealing with image forgery exist; detection through analysis of reflections and shadows or binary statistical features, detection of adversarial images [38], or detection of deep fake images [101].

2.3 Discussion

Applications. The need for image obfuscation is urgent and evident, given the amount of images that are circulated and shared daily on the Internet or over Online Social Networks (OSNs). Due to the privacy-intrusive nature of the Internet, the community was driven to advance the research in privacy-preserving and privacy-aware systems and their applications. Examples of such systems and applications are: (a) image processing, search, and retrieval on the cloud; (b) image capture in video camera surveillance, health monitoring applications, IoT sensor networks, Internet of Multimedia Things (IoMT), and commercial applications such as Google Street View; (c) image sharing and publication on OSNs; and, (d) image classification and recognition for automated tasks, such as autonomous driving and supply chain optimization [98].

Challenges and Open Research. Undesirable visual exposure and malicious inference of high-level sensitive information are standard image privacy problems [61]. According to previous studies, implicit information such as health conditions, social class, and relationship status can be deduced from images using ML models, leading to privacy infringement. However, protecting against malicious inference remains challenging due to the multi-modality of the underlying features, which are typically tricky to recognize using conventional image recognition. The field of multimodal attribute detection and obfuscation in images is still in its infancy; only a few studies addressed the perturbation of hairstyle, clothing, race, and gender in images. In image de-identification, face and body detection significantly impact the achieved protection; that is, failure to locate several soft-biometric identifiers results in a high re-identification risk. Face detection challenges include partial visibility of the face regions due to occlusions, accessories, sunglasses, and variations in head pose, lighting, and backgrounds, which can obstruct the detection algorithm's ability to recognize face regions correctly. Current studies still try to mitigate those recognition challenges. In addition, other studies aim to generate realistic faces that maintain a high degree of similarity in terms of facial expressions and head pose and mimic body poses to relay an accurate representation of the human activity being performed [55]. There is also a need for quantifying privacy and utility through objective evaluation.

Key Properties. The key properties to consider when selecting an optimal obfuscation method for protection against information leakage are [57]: (a) *naturalness and utility*: the distortion

should be unnoticeable; (b) *(ir)reversibility*: (in)ability to undo the transformation; (c) *robustness and security*: thwarting most human and machine-based attacks; (d) *adjustable/adaptable*: protection with different degrees of strength; (e) *provably secure*: provides measurable security metrics based on differential privacy or distance metrics; and, (f) *computational complexity*: it should be easy to implement in terms of resource usage. The study field of image obfuscation has reached a mature level, where the latest techniques are based on adversarial learning. Therefore, rather than developing new obfuscation methods, most research is now focused on improving the utility of the adversarial training output while keeping security/privacy a priority. When one refers to the "utility" of an obfuscated image, they are typically concerned with three things: its naturalness (i.e., Does it look realistic?), its intelligibility (i.e., Does the distortion impact the ability to infer important attributes?), and other context-specific properties (e.g., generated obfuscations for images with faces belonging to different people should be distinguishable). The first three properties introduced at the beginning of this paragraph (naturalness, reversibility, and security) are addressed in most image obfuscation methods. However, the remaining ones are selectively implemented based on the user requirement. In terms of provable privacy guarantees, the main way to achieve it is by applying statistical and aggregated data protection methods derived from differential privacy such as k-anonymity. However, most existing protection solutions do not provide measurable privacy guarantees. Moreover, selective obfuscation (i.e., applying the obfuscation on a per-feature basis), adjustable privacy filters, and automatic evaluation of image privacy and utility, are still ongoing research topics.

Review of Methods. In Table 3, we have given low, medium, and high ratings for the main categories of image obfuscation in terms of their utility, the ability to reverse the obfuscation and protection level against human and machine attackers. We further explain the rating choice here. Simple ad-hoc image transformation methods (blurring, pixelization, lossy compression, edge, warping, style transfer, false color, cartooning) distort sensitive ROIs in a way that results in a high degree of information loss. Still, at the same time, their output maintains a strong resemblance to the original general shapes of the image. However, aesthetic transforms (false colors, style transfer, and cartooning) provide a better visual experience than the others. These methods are no longer viable due to robust ML recognition [72] that can deduce the original input before its transformation.

On the one hand, encryption and scrambling completely hide the ROI and, therefore, adversely impact the image's utility. On the other hand, they allow full recoverability of the original content using a secret key. The security of the encryption-based protection depends on the key strength and the permutations' strength. Possible solutions to break the protection are based on brute force and are computationally complex.

Suppression methods such as masking, blocking, and inpainting altogether remove the sensitive ROIs, resulting in the highest degree of information loss. Although, inpainting is less visually intrusive and produces a more natural effect. These methods are robust against human and machine recognition. Studies have shown that image inpainting methods can be used to fill in missing (masked) areas.

Abstraction entirely replaces an ROI, thus protecting its identity with a visually similar representation. The utility of the replacement depends on the replacing object, its quality, and its resemblance to the removed ROI. Overall, inpainting and abstraction may be most useful as obfuscation methods because they are both effective at increasing privacy for elements of an image and providing a good viewer experience [60]. This shows that to achieve a higher privacy-utility balance, more processing time and computations are needed. Machine learning can provide efficient obfuscation models; however, their accuracy depends on how extensive the training set is.

In terms of advanced obfuscation, the solutions are mainly based on face synthesis and adversarial perturbation. Adversarial perturbations are not perceivable by humans; they add little visual

distortion to the image. Their purpose is to deceive automated machine recognition. However, some studies in the literature have shown that adversarial perturbations are detectable and can be countered using ML methods. Though, the cited countermeasures assume an attacker with access to the perturbed training set, which is not always possible in real-world scenarios. Face synthesis is a non-reversible method of generating new faces by averaging a cluster of similar faces (k-same family algorithms) or adversarial learning. The method effectively reduces the re-identification risk and typically generates natural-looking faces that preserve gender, facial expressions, age, or race while protecting the identity.

3 VIDEO OBFUSCATION

Video surveillance systems are today's most ubiquitous source for video capturing people and their activities [91, 89]. As expected, the public use of video surveillance (including CCTV and drone surveillance) introduces the need for privacy protection, specifically for law-abiding citizens, while providing the authorities the ability to retrieve the original video for specific purposes, e.g., crime investigation. When releasing the video, portions of the footage exposing sensitive information are redacted. Such information include but is not limited to faces, license plates, tattoos, clothing, computer screens, and house numbers [91]. Videos are a series of time-related image frames; hence, the expectation is that image de-identification techniques are applicable to videos. However, the process is inherently more complex, since neighboring image frames in a video sequence are closely related.

Object detection and tracking accuracy play a significant role in identifying and obfuscating sensitive regions correctly. Any incorrect detection of sensitive areas in a single frame can destroy the protection for the entire video sequence [91, 48]. Object detection and tracking in video sequences also face further challenges, such as: variation in the object's localization and size throughout the scenes; bad lighting conditions; variable illumination; cluttered scenes; and, partial occlusions due to obstructing components (e.g., sunglasses, accessories, and facial hair on face regions) [88, 89]. Additionally, some video surveillance systems require real-time detection and de-identification of moving objects. For that reason, the selection of the obfuscation method is critical since real-time processing should be fast and effective. In general, for most video surveillance systems, the requirements to be satisfied are: (a) real-time processing; (b) efficiency and low cost; (c) utility-preserving obfuscation (preserving gait, physical actions, and facial gestures); (d) reversible obfuscation; (e) adaptive obfuscation (adjustable levels of privacy filters parameters, or selective obfuscation based on preset rules); and, (f) format compliance (decodable by commercial video players).

3.1 Techniques

Various approaches have been proposed for privacy protection in videos. The most common solution is applying visual transformations on sensitive image regions. Other approaches, which are out of scope but are defined briefly hereafter, include physical intervention, software intervention, and secure multiparty computation [76]. Physical intervention creates capture-resistant regions using specialized hardware (e.g., adhesive camera blockers, pulsating LEDs directed at camera lenses). In contrast, software intervention is achieved through modifying the firmware of a capturing device to prevent capturing specific scenes [76]. Secure multiparty computation allows image processing tasks (e.g., face detection, object tracking, image segmentation) to be computed anonymously. The traditional approach for visually transforming sensitive regions in videos is manually identifying, annotating, and masking ROIs in each video frame. However, considering a typical surveillance video of 30 frames per second, manual redaction is unpractical being extremely time- and labor-intensive [89]. Automatic obfuscation can target specific objects or the entire image frame (aka,

general/global obfuscation). The latter assures higher protection yet it removes the contextual information necessary for monitoring people and their behavior. Even though our main focus in this subsection is object obfuscation, we still give a brief overview of the state-of-the-art object detection and object tracking, focusing on face objects, since they are closely related to the obfuscation process. Next, we review image obfuscation methods in terms of how suitable they are for real-time surveillance.

3.1.1 Object Detection. This step is needed for the automatic localization of relevant objects in a frame. The detection algorithm identifies the object's bounding box, and segmentation obtains the precise pixels outlining the object within the bounding box. There are four main approaches to object detection: sliding search window, region proposals, DL-based, and pixels-based [91]. The sliding window approach sweeps a detection template across an image, computes a function with respect to the template, and classifies the image region. It is a computationally demanding method and, therefore, it is not typically used for video redaction. Region proposal methods use classifiers (e.g., SVM, k-nearest neighbor) that obtain a confidence score for each candidate image region using its extracted low-level features (e.g., SIFT, histogram of oriented gradient (HOG), Harris Corners, etc.). The frequently used deep learning models for object detection include Regional CNN (RCNN), Fast RCNN, Mask RCNN, Multibox, and YOLO (You Only Look Once) [91, 4]. YOLO uses regression models to predict the coordinates of the bounding box and its class confidence by applying a single-pass CNN [91]. Pixel-based methods achieve semantic segmentation and assign a class label to each pixel in a frame. Some approaches use fully convolutional neural networks (FCN) and Conditional Random Field (CRF) to achieve per-pixel classification [91, 82].

In terms of face objects, face detection algorithms [116] are based on feature-level or image-level methods. The feature-based approach uses low-level analysis (edges, skin color, motion, gray-scale), active shape models (snakes, deformable templates, PDM), or facial feature searching and extraction (constellations, Viola-Jones, Gabor Feature). The image-based approach is a learning process where a trained model classifies images as face or non-face, e.g., using linear subspace methods (Eigenfaces), statistical methods (GMM, PCA, SVM), and neural networks [89, 17]. A recent survey providing a comprehensive overview of face detection techniques is referred in [52].

The majority of automated face detection algorithms are limited by head poses, occlusions, image resolution, and so on. To mitigate the inaccuracy of some face detection software in suboptimal conditions, Chen et al. (2018) [16] proposed ReSPonSe—a system that uses human trace tracking instead of face detection to identify the pixels representing facial information in a more robust way. Human trace tracking gives higher assurance that the face and the body regions are still identifiable by color-based skin detection when faces are not detected. The system architecture has two main stages, the encapsulation stage, and the decapsulation stage. In encapsulation, the video sequence is processed in real-time to remove private information using human trace tracking and image encryption. Human trace tracking consists of: face block extraction to accelerate face detection; in-block face detection to detect faces in the extracted blocks; and, detection rectification. This step also utilizes the distribution of skin regions in image tiles surrounding selected key blocks. The extracted detections are then encrypted. In decapsulation, decryption is performed on the redacted video to selectively recover the original faces based on the viewer's certificate. Human trace tracking does not work well when non-face objects (e.g., walls or cars) possess a color similar to skin colors; it results in the unnecessary redaction of the background, thus reducing the utility of the video. Therefore, Chen et al. (2019) [15] proposed the Facial Information Segmentation (FIS) algorithm, which combines color information, Harris Corner, and face detection algorithms to identify the pixels associated with the face region. The authors rely on the observation that the

density of Harris Corners is lower on non-face objects than other face objects with skin color; non-face objects tend to be smoother and have fewer features.

3.1.2 Object Tracking. The purpose of object tracking is to estimate and predict the size and location of a detected (and tagged) object over time in subsequent video frames. Tracking algorithms are susceptible to noise factors due to variations in illumination, object scale, occlusions, pose or camera relative perspective, and motion blur. There are four main approaches to object tracking: motion-based; appearance-based; tracking by detection; and, deep learning methods [91]. Motion-based modeling computes an estimation of the stationary scene background and subtracts the estimated background from each frame having a moving object. The differences calculated from the background subtraction between consecutive scenes indicate the presence of objects in motion. Appearance-based matching of hand-crafted or machine-learned image features includes color histogram matching, shape matching, or texture matching. Again, it is limited by dramatic changes in camera perspective, heavy shadows, etc.. Tracking by detection extends the use of object detection algorithms to enable tracking frame by frame (e.g., using adaptive search windows). However, this method has a high computational overhead and may not be suitable for real-time processing. Lastly, more advanced techniques such as recurrent neural networks exploit the history of an object's location to learn temporal dependencies between frames.

In the case of face tracking, to preserve naturalness for de-identified videos, deep learning methods for face landmark localization (locating facial key points around the eyes, corners of the mouth, and nose) and motion and pose estimation are considered [88, 4]. Additionally, the algorithm should discriminate and predict the location of all moving faces in the video sequence. Although using temporal information for tracking increases robustness, it is ill-suited for real-time tracking. In some solutions, markers or RFID tags worn by the individuals were used to enhance tracking accuracy [91, 18].

3.1.3 Obfuscation Methods. Video surveillance systems follow the same protection techniques used in still images. Masking, pixelization, and blurring are standard methods for video redaction since they do not require an excessive processing power and can be done in real-time. Korshunov et al. (2012) [48] performed a subjective evaluation to assess the detection accuracy of abnormal behavior in video surveillance scenes when the previous methods were applied to body silhouettes and faces. The results showed that the recognition of the obfuscated people was still possible to a certain degree, specifically the gender attribute from the shape of the body image in the video, even when the masking filter is applied. Pixelization was found to offer higher utility in terms of action recognition than blurring in this context, and masking overall provides the highest privacy protection because it can reduce recognition accuracy to near-zero [48, 51]. In [42], Ivasic et al. (2014) studied the impact of Gaussian Blur filters on human activity recognition and de-identification. The results show that specific activities (e.g., jump in place and wave one hand) reveal more discriminant information that can be used for subject identification than others (e.g., walking and running). The authors suggested increasing the variance of the Gaussian blur for such activities.

There are other methods that are also not as demanding for processing power, while being more utility-preserving. For instance, cartooning [27], edge detection [17], style transfer [9, 11], false colors [20], warping [50], and morphing [49]. In the following, we introduce some examples from the literature. In [17], Chen et al. (2008) applied edge motion history image (EMHI) to obscure body images while still capturing the structure of the bodies and their motion using edges. Korshunov et al. (2014) [51] evaluated morphing and warping against blurring, pixelization, and masking. Warping is the least suitable filter because it affects recognition only at very high distortion levels, whereas it is also more complex than the other simple filters. The authors concluded that the morphing filter seems to be the best choice among the evaluated privacy filters for video surveillance since

it is reversible, and recognition accuracy can be varied linearly by varying the pixels' intensity weight. False-colorization is a general obfuscation method applicable to video surveillance since it is reversible. It may also hide identity information without impacting surveillance-related information, such as the count of people in an area.

Lightweight partial encryption (i.e., ROI-based) and scrambling [24, 90] are other applicable methods to real-time processing, even though they are less secure than naïve encryption [76]. The videos are obfuscated in a way that they remain format-compliant and viewable in the distorted form. Other advanced methods such as object replacement (e.g., avatars [6]) or face replacement can be used; however, both require precise position and pose tracking [18]. Blavezvic et al. (2015) in [6] proposed a reversible real-time de-identification pipeline that obfuscates all biometric identifiers in video footage. The system relies on computer vision algorithms, namely human body image detection, segmentation, and tracking of the detections. The detected human body in the original image is replaced with a 3D avatar. The 3D model is rendered precisely on top of the original body with the help of human pose estimation (joint modeling) algorithms. The detection and pose estimation strongly depends on the viewing angle, body shape, clothing, etc.. The de-identified region is encoded and embedded in the carrier image using steganography to enable reversing the concealment. The authors identified some limitations in their 3D modeling; specific body movements are not supported, such as jumping or rotating. In addition, sudden movements are not always accurately tracked. The likelihood of erroneous output and incorrect localization of some joints (and therefore incorrect positioning of the 3D avatar) due to the tracking system is relatively high. To countermeasure the tracking inaccuracies, the authors pixelized and blurred the body sections visible behind the avatar in the original frame. Further works included developing more natural-looking avatars.

3.2 Attacks and Countermeasures

Since the same protection methods used for images are used for videos, the same attacks described in Section 2-B apply. In the following, we explain the major differences in the recognition-based and reconstruction-based attack styles for videos.

Recognition-based Attacks. Recognition-based attacks (or re-identification attacks) are also a significant concern about de-identified videos. Full-body images are more commonly seen in surveillance videos, and even when face masking is used, a person's identity can be exposed using *pairwise constraints* attack [91, 17], also known as, faceless recognition [73]. A pair-wise constraint is when two masked faces can be determined to belong to the same person by using the variations of clothing, body shape, or other cues, across images of the same person, even though the faces are still hidden. Other soft-biometric features in full-body photos, such as age, gender, race, ethnicity, birthmarks, and tattoos, provide further hints for re-identification [73]; however, such features are more complex to detect. In the same direction, obstructing the entire body provides better protection than face-masking alone; however, this way still results in higher unfavorable utility loss. For instance, facial expressions and body actions become imperceivable in the surveillance footage. The body silhouette and the gait can leak information, therefore, Agrawal et al. (2011) [1] proposed slightly dilating or expanding the silhouette area to be obfuscated to hide the gait information and further increase the privacy.

Reconstruction-based Attacks. The same attacks applied to obfuscated images apply to redacted videos. However, there is another attack type applicable to videos, utilizing temporal dependencies between adjacent frames in the video sequences. Cavedon et al. (2011) [13] developed a technique that completely recovers the identity of a pixelized face in video streams under certain conditions. When pixelization is applied to video sequences depicting the same subject, there is a high probability that the pixelization squares will change position with respect to the image

background, hence averaging different pixels at different times. Unlike super-resolution methods, the technique aims to recover the image with its original quality. The authors used a *Maximum Posteriori* to find an image such that, if shifted and pixelized in multiple frames, it will produce a video sequence as close as possible to the input video. Their method assumes that the same image can be tracked in different frames at different positions. A similar attack described in [76] uses image inpainting for interpolating masked parts in a given frame using information from adjacent video frames.

The primary solution to this type of attack is to utilize more precise detection mechanisms, perhaps by combining object detection, segmentation, and tracking algorithms. Chen et al. (2008) [17] proposed a bi-directional tracking algorithm that combines background subtraction, face detection, and face tracking. Manual or automatic screening of the redacted video frames can reduce missed face detections. Once a face is detected, it is simultaneously tracked in both previous and subsequent frames to locate any missed (usually non-frontal) faces. Background subtraction is used to segment the foreground, containing people or other moving objects, from the background. Furthermore, for face images, color-based detection can be combined with other forms of detection to achieve better results [16]. Another countermeasure includes applying general obfuscation (i.e., full-frame obfuscation), but it is not favorable since it degrades the utility of the video.

3.3 Discussion

Applications. Video de-identification is required in scenarios such as public video publishing to protect, among others, the privacy of the individuals who appear involuntarily in the videos. Furthermore, in public surveillance videos, bypassers are captured mainly to record any behavioral anomalies; their actions are relevant but not their identities in real-time. The need for low-cost surveillance has driven the concept of privacy by design into smart camera devices, so specific objects are never stored or transmitted, and complex processing (such as natural face replacement) is moving towards edge computing [91]. Also, drones are now used for surveillance since they can stealthily access a broader range of locations and closely track the object of interest [88, 7].

Challenges and Open Research. Face de-identification in videos is more challenging than in still images. The challenges are related to the complexity of facial detection and localization in video streams. Although face detection in varying poses and profiles, illumination conditions, and occlusions have been studied, the problem remains a known challenge. Similar to still images, for an identity to be protected, multimodal de-identification must be considered. Sensitive personal identifiers are of many diverse forms (e.g., skin, logos, location information such as house numbers, storefront signs, street signs, and graffiti); therefore, fully automating the redaction process still requires further research. Skin color-based segmentation still faces limitations since skin occurs in many tones. Optical character recognition in outdoor scenes is also limited by suboptimal conditions, such as poor lighting and geometric perspective.

Key Properties. There are a few more considerations when selecting an obfuscation method: real-time processing, low computational overhead, reversibility, and utility-privacy trade-off in hiding identity information while preserving behavior-related information (gait, actions, facial gestures). Surveillance and monitoring systems that require real-time de-identification should not use heavy processing methods such as inpainting, encryption, and face replacement. Ad-hoc and simple transformations such as blocking, masking, pixelization, and blurring techniques are more commonly used in real-time scenarios, even though they provide lower protection. Nonetheless, they are also not reversible and severely reduce the utility of the video such that user actions and gait are not readily perceivable [42]. Some works recommend using other simple but utility-preserving filters such as cartooning, edge detection, style transfer, false colors, warping and morphing, where only the last three can be reversed if the transformation parameters are known. When secure

Table 7. Examples of Real-time Video Obfuscation in the Literature

Method	Example	Time	Reversibility
Pixelization			
Blurring (Body)	[1, 111]	Fast	No
Masking			
Cartooning	[27]	Fast	No
Edge	[17]	Fast	No
Style transfer	[9, 11]	Slow	No
False colors	[20]	Fast	Yes
Warping	[50]	Fast	No
Face morphing	[49]	Slow	No
Face replacement	[111, 31]	Slow	No
Scrambling	[24, 90]	Fast	Yes
Avatars (Body)	[6]	Slow	No

processing is required, the more advanced transformations discussed previously should be used, with the caveat that only encryption and scrambling are reversible.

Review of Methods. In Table 7, we list examples of real-time obfuscation methods applicable to video surveillance scenarios. We also compare the reversibility and the computational complexity of the methods—this latter feature expressed in a qualitative appreciation of the required time. As shown, video obfuscation follows the same protection techniques used in still images. The exception is that the obfuscation systems would be slightly modified to ensure the efficiency and speed of object detection, tracking, and object denaturing.

4 CONCLUSION

In this paper, we have provided an up-to-date and thorough review of the major solutions for visual multimedia sanitization—the process of distorting, replacing, or removing specific sensitive content in images and video. In particular, we discuss current applications and constraints of existing visual obfuscation methods, identify present challenges, and highlight possible research directions. We have also shown that the discussed obfuscation methods could be subject to various recognition, reconstruction, and inference attacks—pointing to related trends and research directions to address the cited challenges.

In conclusion, the quest that characterizes this research domain is to find an optimal privacy-utility balance for each obfuscation method although, as shown in this paper, there is not yet a common framework for evaluating the utility and privacy of multimedia sanitization systems. Our contribution provides a systematization of the filed, a highlight on the current trend and technologies, as well as a few research directions to have sanitization techniques meet the objective of providing the desired level of security and privacy, while preserving the needed level of utility.

ACKNOWLEDGMENTS

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