A REVIEW ON VISUAL PRIVACY PRESERVATION TECHNIQUES FOR ACTIVE AND ASSISTED LIVING

Siddharth Ravi
Department of Computing Technology
University of Alicante,
Alicante, 03690, Valencian Community, Spain
siddharth.ravi@ua.es

Pau Climent-Pérez
Department of Computing Technology
University of Alicante,
Alicante, 03690, Valencian Community, Spain
pcliment@dtic.ua.es

Francisco Florez-Revuelta
Department of Computing Technology
University of Alicante,
Alicante, 03690, Valencian Community, Spain
francisco.florez@gcloud.ua.es

December 20, 2021

ABSTRACT

This paper reviews the state of the art in visual privacy protection techniques, with particular attention paid to techniques applicable to the field of active and assisted living (AAL). A novel taxonomy with which state-of-the-art visual privacy protection methods can be classified is introduced. Perceptual obfuscation methods, a category in the taxonomy, is highlighted. These are a category of visual privacy preservation techniques particularly relevant when considering scenarios that come under video-based AAL monitoring. Obfuscation against machine learning models is also explored. A high-level classification scheme of the different levels of privacy by design is connected to the proposed taxonomy of visual privacy preservation techniques. Finally, we note open questions that exist in the field and introduce the reader to some exciting avenues for future research in the area of visual privacy.

Keywords Visual privacy preservation · active and assisted living · privacy by design · survey.

1 Introduction

There are two major reasons for visual privacy to be preserved. One is identity protection, where the identity of the person in a visual is to be hidden from entities who might analyse the feed without the necessary access privileges. Following convention, these entities will be addressed as adversaries in this review. Adversaries can either be machine learning models that train on data collected without user consent, or persons who view sensitive visuals without being provided with the necessary consent. The second reason for visual privacy is the preservation of trust for persons who require monitoring.

Active and Assisted Living (AAL) is considered as the primary area of interest while choosing the methods surveyed. In active and assisted living scenarios, computer vision systems provide support to the older section of society, assisting them in their everyday tasks within a care home or a nursing home, a living community, or in their private homes. A typical AAL care home might be equipped with RGB cameras, the feeds of which are monitored and analysed to provide support to the residents in time of need. In these cases, the identity of the resident is of relatively less interest, as that is usually of a more public nature. A typical AAL care home resident, for example, could have given consent
for them to be monitored by the home’s personnel and their family for safety reasons. But a level of trust needs to be preserved for cameras to be deployed in privacy-sensitive settings in the home, such as toilets and bedrooms. Borrowing the categorisation of privacy provided by Clarke [1999][2006], what is crucial, however, is the need to preserve the resident’s bodily privacy in various sensitive scenarios. Bodily privacy refers to the privacy regarding images of the body. More precisely, it considers the activities that are carried out, and the loss of privacy given the nature of some of these activities (e.g., nudity during showering, etc.). What is also of interest is to preserve the privacy of sensitive personal behaviour, such as a person’s political activities, sexual habits, religious practices, and with the personal space required to facilitate such behaviour. To obtain and preserve this element of trust, visual privacy needs to be preserved at every stage of a system used for monitoring.

With this idea in focus, this document surveys the state of the art in visual privacy protection methods, with special attention paid to the concept of visual obfuscation. The dichotomy between identity protection and bodily privacy can also be observed in the classification scheme this paper proposes for visual privacy preservation techniques. Perceptual obfuscation methods (explained in Section 4.1) aim to preserve trust through the protection of bodily privacy. Machine obfuscation methods (explained in Section 4.2) are mainly aimed at the protection of identity from machine learning models.

The issue of privacy preservation goes hand in hand with the creation of trusted pipelines, which help in increasing the adoption of monitoring technology in places like AAL care homes, where the use of such technology can be highly beneficial. This review introduces a framework with which visual privacy protection methods can be classified under, and introduces terminology that can be used to categorise methods developed to provide visual privacy. It attempts to capture the field in a broad sense, while also connecting the state-of-the-art in the field to the framework of privacy by design [Cavoukian et al., 2009]. This is important, since privacy is a societal problem, as opposed to being a challenge that is purely technical in nature. Solutions that are deployed need to provide privacy from the ground up, while providing users with enough knowledge and options to control the flow of data which is obtained from their actions.

The central contributions of this review are as follows:

1. With emphasis on visual obfuscation methods, this paper reviews the state of the art in visual privacy protection methods.
2. It connects low-level concepts in the field of visual privacy to high-level concepts encountered when discussing privacy by design.
3. This paper proposes a novel classification scheme to make sense of visual obfuscation methods.

The rest of the review is structured as follows. Section 2 looks at prior reviews. Section 3 explores the state of the art in visual privacy protection methods. A novel classification scheme for the methods in this category is also introduced. Here, the review expands on those methods that are classified by the scheme under the categories of intervention methods, blind vision, secure processing and data hiding [Padilla-López et al., 2015].

Section 4 explores in greater detail the state of the art in visual obfuscation methods, another subcategory of visual privacy protection methods that is essential to this review. In this section, the review also ties privacy preservation methods to the concept of pipelines and systems that ensure visual privacy, and to the idea of broadcasting different visualisations based on access privileges.

Section 5 explains the concept of privacy by design, a high-level concept in systems design essential to the creation of truly end-to-end private systems. In this section, the paper links together a categorisation scheme proposed for ensuring privacy by design to the scheme proposed in this review for categorising visual privacy protection methods. This is done to link both high and low-level concepts encountered when discussing visual privacy.

Section 6 introduces the reader to performance evaluation setups used when measuring the efficacy of privacy preservation techniques. Important technical privacy metrics which are frequently employed are explored. It also introduces the reader to datasets that are commonly used to train models that work to impart visual privacy. Meta-studies are also explored which evaluate the real-life effectiveness of performance evaluation frameworks employed for privacy preservation techniques, through the use of user acceptance studies. Finally, Section 7 concludes the survey by introducing the reader to important future work to be conducted to advance the field.

This work is meant to serve as more than merely a survey of the state-of-the-art. It seeks to provide the connection between high-level concepts defined in the area of privacy by design to the lower level taxonomy of methods proposed in this review. This is meant to introduce the reader to the idea of end-to-end privacy preserving systems to be used in areas like care homes. This is to highlight the practical relevance of privacy preserving technologies developed, and to push the field towards a place where more of the techniques developed through research is deployed in real-world scenarios. This is especially important when considering the ageing demographics in most developed nations, a trend
that is expected to continue in the future. Considering this, there is the urgent need for more privacy to be imparted to the part of the population which is going to be residing and monitored in private settings or in care homes.

2 Prior Reviews

Prior work has attempted to systematise knowledge in the field of visual privacy preservation, notable examples being reviews by Padilla-López et al. [2015], Ribaric et al. [2016], and Meden et al. [2021]. Padilla-López et al. [2015] introduces the reader to a taxonomy of visual privacy preservation techniques seen in the literature. These are grouped under five major categories based on the manner in which they impart privacy, these being Intervention Methods, Blind Vision, Secure Processing, Data Hiding, and Redaction methods. Redaction methods are further subdivided into image filtering, encryption, $k$-same family of algorithms, object / people removal, and visual abstraction. The authors also provide a survey of privacy-aware intelligent monitoring systems as part of their review.

Another more recent work is by Meden et al. [2021], which provides a taxonomy of methods for the area of biometric privacy enhancing technologies, paying particular attention to facial biometrics. The survey also introduces a taxonomy of biometric privacy enhancing techniques. The taxonomy of methods is grouped based on 6 criteria, namely — the target biometric attributes, biometric utility, referring to the usefulness of data for automatic extraction of various attributes like health indicators and identity information, guarantees of reconstruction from privacy-enhanced data, biometric attributes targeted, type of mapping used, and type of data the method is applied to. The classification scheme introduced along with the grouping criteria can be seen in Figure 1.

The survey by Ribaric et al. [2016] is a broader survey of the field of privacy preservation, touching on both visual and non-visual (e.g. audio) aspects of privacy. The survey provides an overview of de-identification approaches for non-biometric identifiers (e.g. text, hairstyle, dressing style, licence plates), physiological identifiers (e.g. face, fingerprint, iris, ear), behavioural (e.g. voice, gait, gesture) and soft-biometric (e.g. body silhouette, gender, age, race, tattoo) identifiers in a multimedia context (see figure [here]). The authors then present examples of methods used to provide privacy to users based on these classifiers.

In contrast to the prior reviews in the field, this work seeks to present privacy preservation techniques that are meaningful in AAL applications. Therefore, the focus is on protecting bodily privacy, and is not concerned with whether the identity...
of the person is protected, as that is something commonly of a public nature. A broader exploration of the state of the art is presented, tying together concepts from the privacy by design literature to ideas coming from computer vision.

As the focus of this review is on biometric identifiers that affect bodily privacy in the scenario of visuals from private settings or care home environments supporting AAL, some identifiers of direct importance here are behavioural identifiers (e.g., gait, gestures, actions, or activities), dressing styles, and body silhouettes. It might also be the case that wearable cameras are used to provide an AAL service. In this case, when the resident moves out of the private environment, they might encounter other persons who might not have consented to being monitored. Hence, there is a need for stricter measures of privacy to be implemented through the obfuscation of other biometric identifiers. These are faces (in still and video images); gait, and gesture; scars, marks, and tattoos; and the hair, and dressing style. These have the potential to reveal the identity of passers-by to observers of the visual feed.

Obfuscation of some of these above-mentioned identifiers: scars, marks, and tattoos, and the hairstyle or dressing style have not been explored in the literature to the best of the authors’ knowledge. Anonymisation techniques targeting other identifiers are explored in some depth in the next sections of this review, namely those concerning body silhouettes (using full-body de-identification), gait, and faces.

Papers in the field of visual obfuscation reviewed in this work are listed in Table 1. Importance is given to research published in the field of perceptual obfuscation, as it is especially relevant for AAL. This work also puts more emphasis on work published after 2016, as it reviews the state of the art in the field. Since the rise of deep learning, the field of computer vision has also undergone a revolutionary change. Arguably, most state-of-the-art methods proposed to impart visual privacy attempt to do so through the use of deep learning. This is also reflected in the methods surveyed as part of this review.

3 Visual Privacy Preservation Methods

Building on the taxonomy for visual privacy preservation methods introduced by Padilla-López et al. [2015], this review categorises visual privacy preservation methods into 5 categories: intervention methods, blind vision, secure processing, data hiding, and visual obfuscation. The taxonomy can be seen visualised in Figure 2.

3.1 Intervention Methods

Intervention methods are those techniques that interfere during the data collection phase, preventing private visual data from being collected from the environment. Perez et al. [2017] classify these methods under three categories — sensor saturation, broadcasting commands, and context-based approaches.

Sensor saturation methods impart privacy by feeding the input device’s sensor a signal that is far more in amplitude than the maximum that the device can handle. Physical interventions that prevent the capture of private images under sensor saturation schemes are also present under this category. One of the most commonly used intervention methods of this type are commercial webcam covers, also known as privacy stickers for laptops and phone cameras. These are stickers that can be stuck onto the camera, and some can be closed and opened at will. The nature of the adhesive and
the construction of the blocking mechanism differs between methods [Jonsson and Berghorsdottir, 2016] [Barangan et al., 2015] [Haddad, 2017] [Miller, 2020] [Mitskog and Ralston, 2012] [Rolle, 2018].

The Blindspot system developed by Patel et al. [2009] is an example of another intervention of this kind. Blindspot consists of a camera lens tracking system that locates retro-reflective CCD or CMOS cameras in the vicinity, along with directing a pulsing light at the camera’s lens that distorts recorded visuals. Anti-paparazzi devices have also been devised that qualify as intervention methods [Harvey and Knight, 2009] describe anti-paparazzi devices that are cloaked as fashionable clutch bags. These detect camera flashes with the use of light sensors along with IR sensors to detect autofocus lights. The intervention device then uses an array of LEDs to produce pulses of light bright enough to overexpose photos taken by the photographers.

Zhu et al. [2017] created the concept of LiShield, which protects a physical scene against photographing. This is achieved through the use of smart LEDs, which emit specially constructed waveforms to illuminate a scene. The LEDs emit intensity modulated waveforms that are imperceptible to the human eye, but their waveforms are constructed in such a way as to interfere with the image sensors of mobile camera devices. Mobile phones have also started to be shipped with inbuilt mechanisms for sensor saturation-based intervention. Examples include the PinePhone [Pine64, 2021a] which comes with physical ‘kill switches’ for configuring its hardware. These can be individually configured to disable both its front and rear cameras, among other peripherals [Pine64, 2021b].

Broadcasting commands are another category of intervention methods, where devices broadcast commands using various communication protocols to disable input devices present around the subject. One example is Hewlett-Packard’s concept of a paparazzi-proof camera. This includes cameras with inbuilt facial recognition, which upon receiving a remote command, selectively blurs sensitive parts of images that includes faces [Pilu, 2007]. Broadcasting commands are considered less effective than their physical counterparts. This is because user consent is required for these methods to work. Broadcasting commands are also arguably less popular as intervention methods than sensor saturation methods.

Context-based approaches are used by devices that use various methods of context recognition to understand the scene of data collection. Once recognised, the context is used to dictate whether data is to be collected or not by triggering software actions at the sensor level. One example of this is the Virtual Walls framework described by Kapadia et al. [2007], where devices use contextual information such as GPS data to trigger software action like the disabling of sensors in the device. This allows users to control their digital footprint. To the best of the authors’ knowledge, this has not been implemented in commercial devices. Context-based approaches are also arguably less popular than intervention methods.

3.2 Blind Vision

Blind vision [Avidan and Butman, 2006] refers to the methods by which the processing of images and videos is done in an anonymous way. The authors describe the example of two operators, Bob and Alice, to illustrate an example of blind vision. Bob possesses a face detection algorithm that he does not want compromised. Alice, on the other hand, possesses private data on which a face detection algorithm is required to be run. Blind vision methods allow commonly used computer vision tasks to be executed without compromising on privacy of neither the algorithm used for computing, nor the data itself. In this case, both Alice and Bob can operate without compromising on the privacy requirements of either side. Blind vision works through the use of secure multi-party computation (SMC) techniques, a subfield of cryptography that allow computations to be performed privately. This allows algorithms to be executed privately, but at the same time leads to the slowdown of computation due to the overhead involved.

Some notable techniques belonging to the category of blind vision include schemes by Avidan et al. [2009], Erkin et al. [2009], and Sadeghi et al. [2010]. To the best of the authors’ knowledge, blind vision is not a field that is actively researched.

3.3 Secure Processing

Those privacy preservation methods that are not based on SMC, but which still can process visual information in a privacy respectful way, are classified in this review under secure processing. These refer to algorithms and queries where privacy is required in a unidirectional sense: the databases on which the queries are performed are usually public, but the query and its results are to be kept private. The image matching algorithm for private content-based image retrieval (PCBIR) by Shashank et al. [2008] is one example. Algorithms that reject visual information that is not necessary for processing are also considered by the authors to be under the framework of secure processing. As an example, consider the concept of using depth or thermal cameras as the sensor device in conducting privacy preserving machine learning. These devices allow the observer to glean some information from the visual feed (e.g., number

---

2 In this case the photographer’s as they are the users of the camera.
of people in the room, the activity being performed etc) while hiding the most commonly utilised privacy-sensitive information (facial identity, location information, etc) [Heitzinger and Kampel, 2021].

There are also secret sharing schemes that can be classified under secure processing, wherein inference is not done on the original data, but on privacy preserving derived data obtained from the original. One example is the scheme proposed by Upmanyu et al. [2009], in which images are split into multiple privacy preserving parts, which can then be distributed across nodes. Algorithms can then be applied on these image parts privately. Homomorphic encryption schemes also figure into the space of secure processing. These allow data to be encrypted in such a way that algorithms can still be run with utility on the resulting encrypted data, thereby protecting privacy. Homomorphic encryption has been successfully applied in computer vision applications as well [Yonetani et al., 2017, Bian et al., 2020].

3.4 Data Hiding

Data hiding methods refer to privacy preservation methods that, in addition to modifying privacy-sensitive regions in images, aim to embed the original information inside the modified image so that the original can be retrieved if its need arises. Petitcolas et al. [1999] provide a useful classification of data hiding methods. Under the process, embedded data (secret message) is hidden within another message (cover message) which in this case is a video frame. Thus, a marked message is obtained as a result of this hiding process. Data hiding techniques include steganography, digital watermarking, and fingerprinting. Steganography uses a key to allow the recovery of the secret message. Digital watermarking encodes the information about the ownership of an object by a visible pattern, such as a logo. Fingerprinting, conversely, hides serial numbers that uniquely identify an object inside an image, such that the owner of the copyright can detect violations of licence agreements. In the context of visual privacy protection, watermarking can be used to hide the sensitive attributes in an original video inside an obfuscated version. As an example, for facial privacy preservation, Yu and Babaguchi [2007] hide real faces inside frames of a video where the real face has been replaced by a generated one. Quantisation index modulation [Chen and Wornell, 2001] is used for the process of data hiding, and the original information can be retrieved using a secret key. This method, however, has limitation such as the artificial nature of the generated faces, and a lack of control for the generated expressions.

Depending on whether the method is fully reversible or not, data hiding techniques allow recovery of the original video to various extents. Fully reversible data hiding methods allow the original to be restored without information loss [Ni et al., 2006]. With non-reversible methods, the original image cannot be fully restored, but this usually means an increase in hiding capacity [Yabuta et al., 2005, Zhang et al., 2005].

PECAM [Wu et al., 2021] is a method that uses elements of data hiding for creating reversible privacy-preserving transformations of images. This is, however, a method which can be used in two different modalities where the system can either be producing reversible image transformations or be irreversible. For this reason, in this review, PECAM has been categorised as a visual obfuscation method and is explained in more detail in Section 4.

4 Visual Obfuscation

This work classifies methods that seek to hide sensitive visual information directly from adversaries under visual obfuscation methods. They are divided into two major categories, perceptual obfuscation and machine obfuscation, based on their intention and the type of adversary from whom the private data in an image is to be obfuscated. The landscape of visual obfuscation methods analysed in this review can be seen in Table 1.

The following sections deal with the state of the art in each of the major subcategories of perceptual obfuscation methods.

4.1 Perceptual Obfuscation: Targetting Human Observers

In the case where obfuscation targets human observers, methods aim to impart visual privacy for users who wish to keep private from humans without the necessary access privileges, i.e. perceptually (therefore, ‘perceptual obfuscation’). The primary objective of this category of methods is to create images in which the privacy-sensitive elements are perceptually different from the original. Although the lines are blurred between some methods, these types of techniques can broadly be split into five subcategories of methods based on the result — Image filtering, facial de-identification, total body abstraction, gait anonymisation, and environment replacement. The latter, being an under-researched subject, is discussed in Section 7.1.1 in this review.

Perceptual obfuscation methods can also be either reversible in nature, where the original image can be retrieved after modification, or conversely be irreversible. A broad treatment of the classical literature in perceptual obfuscation can be seen in Padilla-Lopez et al. [2015].
| Category          | Sub-category                        | Approach                                           | Reference(s)                      |
|-------------------|-------------------------------------|---------------------------------------------------|-----------------------------------|
|                   | Perceptual Obfuscation              |                                                   |                                   |
|                   | Image Filtering                     | Morphing                                          | Korshunov and Ebrahimi [2013a]   |
|                   |                                    | Warping                                           | Korshunov and Ebrahimi [2013b]   |
|                   |                                    | Cartooning - mean shift / adaptive filter         | Erdélyi et al. [2013a], Erdélyi et al. [2014] |
|                   |                                    | Cartooning - using convolutional neural networks  | Hassani et al. [2017]            |
|                   |                                    | False Coloring                                    |Street et al. [2015]              |
|                   |                                    | PELAM                                             |Wu et al. [2016]                  |
|                   |                                    | Adaptive Blurring                                  |Sun et al. [2018]                 |
|                   |                                    | Head Equating                                     |Wang et al. [2019]                |
|                   | Facial De-Identification            |                                                   |                                   |
|                   |                                    | Live Facial de-Identification                      |Saitier et al. [2019a]            |
|                   | Gait Anonymisation                  |                                                   |                                   |
|                   |                                    | AnonymousNet                                      |Li and Liu [2019]                 |
|                   |                                    | Gait anonymisation using deep learning            |Tieu et al. [2019]                |
|                   |                                    | STGAN                                             |Tieu et al. [2019b]               |
|                   | Total Body Abstraction              |                                                   |                                   |
|                   |                                    | Generative Full Body and Face De-Identification   |Bhasin et al. [2019]              |
|                   | Machine Obfuscation                 |                                                   |                                   |
|                   | Evasion Attacks                     | Spectacles                                        |Shafahi et al. [2018]             |
|                   |                                    | Adversarial stickers and patches                  |Komkov and Petrushko [2021], Brown et al. [2016], Wu et al. [2020], Tuyys et al. [2019] |
|                   | Poisoning Attacks                   | Clean label attacks                               |Shahabi et al. [2017], Zhu et al. [2017], Shafahi et al. [2018] |
|                   |                                    | Model Corruption                                  |Shen et al. [2019]                |

**Table 1:** Categorisation of visual obfuscation approaches reviewed.
4.1.1 Image Filters

Image filtering is a class of perceptual obfuscation techniques that relies on the alteration/redaction of images in a way that imparts privacy to an image. Image filters can be applied globally to entire images, or to sensitive parts of images where privacy is required. The simplest forms of these filters are blurring and pixelation.

Blurring filters slide a Gaussian kernel over an image, thereby using neighbourhood pixels to influence the values of a central pixel. The resulting image is one that has reduced resolution in the areas where the blurring filter has been applied (Figure 6f). Although widely used in applications as large as Google Maps, blurring has been shown to be ineffective for protecting identity against various deep learning-based attacks, even while appearing de-identified to human observers [McPherson et al., 2016; Oh et al., 2016]. For pixelation, a grid of a certain size is chosen for the sensitive pixels in an image. For each box in the grid, an average colour over all the pixels within the box is calculated and assigned to each pixel within the box (Figure 6e). Pixelation has been widely used in the media, especially to obscure the identity of subjects who want to remain anonymous. These simple techniques have, however, been shown in various studies to not be robust in providing privacy [Newton et al., 2005; Korshunov and Ooi, 2011; McPherson et al., 2016; Menon et al., 2020]. Deblurring techniques have also been researched in literature [Rozumnyi et al., 2021; Kupyn et al., 2019; Zhang et al., 2020]. It could be posited that these techniques can also be repurposed as attacks against images obfuscated using blurring filters. Commercial tools for deblurring have also been developed [Knight, 2021].

Morphing and warping are filtering techniques primarily used for facial anonymisation. In morphing [Korshunov and Ebrahimi, 2013a], the input face is morphed into a target face (see figure here). This is done using interpolation and intensity parameters, which are used to steer the positions of the keypoints in the input face towards the target. In warping [Korshunov and Ebrahimi, 2013b], a set of keypoint parameters are determined using face detection techniques. These keypoints are then shifted according to a ‘warping strength’ parameter. The new intensity values are determined using interpolation.

Çiftçi et al. [2018] devise false colours as a filter to impart visual privacy to images. For this method, RGB images are first converted into greyscale. Several colour palettes are devised for this step, and depending on the colour palette chosen, the pixel intensity is mapped into a pre-defined set of RGB pixel values. This false colour filter scheme also allows for reversible transformations from which the original image can be retrieved, through the storage of a difference image and a sign image. The authors also devise a secure pipeline for this purpose. Being a fairly generic method, the false colour scheme can be applied to nearly any RGB image, regardless of whether any pre-processing has been done on the image. This is also a lightweight scheme that can be used on entire images instead of on pre-specified areas of interest. The main downside of this approach, however, is that it is reversible if an attacker figures out the relationship between the false colour pixels and the real object’s colours. A possible attack strategy that can be theorised is through the use of a neural network which is trained to learn these relationships. This introduces a serious threat to the security of the pipeline using the method, as there is no guarantee of protection of privacy (see figure here).

Adaptive blurring [Zhang et al., 2021] is an algorithm that relies on semantic segmentation masks to guide the process of blurring on videos. The model relies on two steps. The authors use DeepLab [Chen et al., 2018] to create segmentation masks for the privacy-sensitive parts of the video. A scale dependent Gaussian blur is devised for blurring those parts delineated by the mask. A custom strategy based on symmetry is used to guide the application of the Gaussian blur on the edges of the objects in question. After a bounding box is estimated for the object in question, the filter radius and standard deviation for the Gaussian blur kernel are set relative to the lengths of the two sides of the bounding box.

One major downside of this approach is that the blurring parameters are determined simply by the estimated bounding box size. It does not consider factors like camera distortion and depth uncertainty. This leads to the algorithm miscalculating the amount of blurring necessary for some objects, leading to under-blurring or over-blurring of parts of images. Another downside of the approach is that commercial tools have devised attacks specifically to deblur obfuscated images [Knight, 2021]. This significantly reduces the security of the pipeline when the method is used, as it provides no guarantees for the protection of private information.

Cartooning has been proposed multiple times in literature as a method for filtering images for privacy reasons. Erdélyi et al. [2013], for example, introduce a Meanshift-based method for cartooning. With this, they reduce the total number of colours and simplify the texture based on a neighbourhood pixel’s property, and use edge recovery to preserve the sharpness of edges in the image. They also blur faces as part of the algorithm, and recolour parts of the image by shifting the hue as part of the final algorithm. Erdélyi et al. [2014] also improve the previous work with the introduction of an adaptive filter, allowing users to determine the level of obfuscation. Hassan et al. [2017] introduce a deep learning scheme for cartooning videos by which privacy-sensitive objects in videos are replaced by abstract cartoon clip art. For this, a region convolutional neural network (R-CNN) Girshick et al. [2014] is used to get bounding boxes for the privacy-sensitive personal objects in the video. After selecting the right clip art and correcting for pose (the algorithm
utilises the histogram of oriented gradients method of Dalal and Triggs [2005], the clip art is inserted into the frame creating privacy-preserving cartooning effects (see figure here).

Encryption methods for images exist which can also be thought of as image filtering, the results of which can be reversed by using a key. Naive encryption schemes treat the feed as textual data, thereby encrypting the entire stream. This leads to the algorithms not being effective in real-time scenarios. To solve this problem, various selective encryption schemes have been put forward. These work by only operating on a specific part of the image in question, thereby decreasing the total computation cost. Much of the classical literature in encryption is summarised in Padilla-López et al. [2015].

Devised by Wu et al. [2021], PECAM is a system that allows for reversible filtering transformations through the use of data hiding. The PECAM system is built for streaming, and allows for the creation of filtered images that can then be reconstructed if such a need arises. In this scheme, depending on whether the model is aiming to reconstruct the images after transformation, different directions in the pipeline are followed. A generator (referred to as a transformer in the paper) neural network and discriminator (termed reconstructors) network are trained using the cycle-consistent GAN approach. The transformer is used to generate filtered images, and the reconstructor is used to regenerate the originals if need be.

In the pipeline that requires reconstruction, a secret key is generated that is used by the transformer and the reconstructor to guide the transformations. This is embedded into the image using data hiding (steganography) as an alpha channel. This RGBA image is then fed to the generator network, which after compression produces a filtered image that preserves privacy. This filtered image can then be broadcast to viewers. This image can then be fed to the reconstructor to create a reconstruction of the original image. In the cases where reconstruction is not necessary, a lightweight network is used as the generator, which is created through model distillation of the original network. After compression, this student network outputs the filtered image that is broadcasted to viewers. One disadvantage of the PECAM network is that the network could cause privacy leakage, as it might not work well when the privacy-sensitive objects are close to the camera.

4.1.2 Facial De-identification

Facial de-identification methods generate artificial faces through various means for protecting facial features from being identified. For this, it is necessary to blend the artificial faces into the original image. Traditional methods have relied on the use of the $k$-same family of algorithms for the task [Newton et al., 2005, Gross et al., 2006a,b].

State-of-the-art methods for facial de-identification have mostly relied on the generative power of GANs. One notable attempt is by Sun et al. [2018a], which uses keypoint generation to condition an adversarial autoencoder (deep convolutional GANs). This scheme has two stages. The first stage uses as input either a feature-redacted blacked out or blurred image, or the original image itself. If a blacked out or blurred image is provided as input, a landmark generator is adversarially trained to accept this and generate estimates of facial landmarks in the form of a landmark heatmap. If
the original image is provided, a landmark detector is used to extract the landmark heatmap required for the subsequent stage. Stage 2 accepts as input the landmark heatmap from the previous stage concatenated with the blacked out original. This is then fed to another adversarial DCGAN autoencoder that generates images in which realistic looking generated faces have been inpainted. The de-identification framework used can be seen in Figure 3.

Gafni et al. [2019a] create a live facial de-identification method for use in videos. The system works by trying to distance the facial descriptors of a person from a target image of the person already provided to the system. This target image can be any image of the person and need not be from the same video stream. For this method, facial bounding boxes are first extracted from the video frame, and facial keypoints are extracted from this setup. A transformation matrix is obtained from this using a similarity transformation to an averaged face. This is used to then transform the input face and passed through the network to obtain an output facial image and a mask. An adversarial autoencoder network is devised for this task, and it provides a recreation of the input image, along with providing an output mask that can be used to guide the network’s output. The inverse of the similarity transformation is used to transform back this output face image and a mask. A linear per-pixel mixing of the input image and the output image is done, weighted by the transformed mask. This is then merged into the original frame using the convex hull of facial keypoints, to get the final generated facial output. The framework used for de-identification can be seen in Figure 4.

The approach by Li and Lin [2019] is interesting for the way it straddles the worlds of both perceptual obfuscation and machine obfuscation (explored in Section 4.2). This method, named AnonymousNet, creates perceptually altered images based on knowledge of both the facial attributes of persons observed and the distribution of those attributes in the real world (approximated by the dataset in the image). The method aligns and crops faces using a neural net referred to by the authors as a deep alignment network, after which it does facial feature extraction using GoogleNet [Szegedy et al., 2015] and random forest models [Breiman, 2001]. This is then used as input to a custom privacy preserving attribute selection algorithm, which obfuscates the features of the face and lets the outputs resemble the features of the real world in terms of their distribution. A de-identified face is then generated by a starGAN [Choi et al., 2018] model, conditioned by the features selected by the algorithm in the previous step. Finally, to obfuscate the outputs from machines, adversarial perturbation is done on the output image, using a universal perturbation vector defined by the DeepFool algorithm [Moosavi-Dezfooli et al., 2016].

4.1.3 Total Body Abstraction

Total body abstraction methods aim to impart privacy by replacing the entire body of the subject in a visual with another generated one. Most methods under this category arguably use semantic segmentation methods to segment out humans from frames, and then subsequently replace these with abstractions such as avatars. Other visual abstractions include silhouettes, where a binary mask of the person is obtained (and sometimes modified for various purposes); invisibility, where inpainting techniques are used to replace the person with the environment/background [Climent-Pérez and Florez-Revelueta, 2021]; and background subtraction, where a background image is generated and subtracted from the current frame to obtain a mask of the foreground object (here a person) of interest [Mondejar-Guerra et al., 2019; Rezaei et al., 2020].
A REVIEW ON VISUAL PRIVACY PRESERVATION TECHNIQUES FOR ACTIVE AND ASSISTED LIVING

One particularly interesting total body abstraction method relied on the use of generative adversarial models to generate full-body replacements. The approach by Brkic et al. [2017] use conditional GANs (DCGANs) to synthesise entire bodies of subjects, while the faces are generated using deep convolutional GAN models. The conditional GAN was trained on pairs of segmentation masks and images, and is trained to operate on segmentations with different levels of detail, from simple silhouette blobs to full-body segmentations with detailed tags for individual garments (see figure here).

State-of-the-art motion capture methods relying on the fitting of 3D avatars to humans in frames can also serve to impart visual privacy. These mostly build on the Skinned Multi-Person Linear (SMPL) model [Loper et al., 2015]. SMPL is created to be fast and to operate with standard rendering engines, producing realistic looking avatars that do not produce the unnatural joint deformation effects commonly seen in other avatar fitting schemes. Blend shapes are represented in the scheme as a vector of concatenated vertex offsets. An artist created mesh of 6890 vertices and 23 joints is obtained. The mesh used for the rendering uses the same topology for men and women. The model also comes with other options such as a spatially variant resolution and a skeletal rig. SMPL is, however, a function solely of joint angles and face parameters. It does not consider other bodily actions such as breathing, facial motions or actions, muscle tension, or changes independent of skeletal joint angles and overall shape. SMPL also does not generalise well to account for all the variations found in people’s body shapes, and produces unnatural deformations of blend shapes.

A recent example of a method devised using SMPL is Frankmocap [Rong et al., 2020], capable of both hand and body capture and replacement in real time. Since hands are harder to motion capture than most parts of the body as they are small, the authors also built a custom 3D monocular hand capture method that uses the hand part of the SMPL model to achieve this task. One drawback of this scheme is that garments are not modelled for the avatar.

Most advancements in avatar fitting have focussed solely on returning the SMPL parameters which stand in for the 3D body meshes, ignoring the garments worn. Some advances over the standard SMPL model have focused on modelling garments worn by the person. One such recent model is the SMPLicit [Corona et al., 2021]. This approach specifically models garment topologies on top of the SMPL model. Garments are predicted through the use of a semantically interpretable latent vector. The objective is to then be able to influence the looks of garments by manipulating this interpretable vector. SMPL-X [Pavlakos et al., 2019] is another extension of the SMPL model, which generates avatars with fully articulated hands and facial expressions. The Sparse Trained Articulated Human Body Regressor (STAR, Osman et al., 2020) improves the SMPL by producing more realistic deformations, and with only 20% of the model parameters required for the SMPL. The model also generalises better to account for the variations in the body shapes of the human population.

The creation of a dense correspondence between images and surface-based representations is another active area of research. Some works have utilised depth images [Taylor et al., 2012; Wei et al., 2016; Pons-Moll et al., 2015], and others have employed RGB images to correspond to objects [Bristow et al., 2015; Zhou et al., 2016; Gaur and Manjunath, 2017].

One noteworthy example using RGB images is the DensePose [Neverova et al., 2018] framework. The authors set about annotating persons appearing in the COCO dataset [Lin et al., 2014] through the use of human annotators utilising a novel annotation pipeline, thereby creating a ‘DensePose-COCO’ dataset. They then set about training deep neural networks to learn the associations between RGB image pixels and the surface points of human bodies. The authors use a Mask-RCNN segmentation model [He et al., 2017] and couple it with a Dense regression system (DenseReg) [Alp Guler et al., 2017] for the task. DensePose has also been successfully employed in protecting visual privacy in AAL settings. Clement-Perez and Florez-Revuelta [2021] create various privacy preserving visualisations using a union of masks obtained from DensePose and a Mask-RCNN model, along with the original RGB image used as input for the models (See Figures 5 and 6).

Object/People Removal — There exists several algorithms which modify frames in a way that privacy-sensitive objects and persons in the frames are removed. These also fall under total body substitution methods. The object or person of interest inside frames, once removed, leaves a gap in the frame. This is then substituted with a generated background to create a coherent image. Inpainting methods are utilised to perform this substitution. Although methods vary, information from surrounding areas is mostly used in filling in the missing areas in the case of image inpainting methods. Considering video inpainting, information from previous frames can be utilised to perform inpainting in a subsequent frame, but temporal consistency between frames has to be ensured. This is also commonly referred to in literature as background modelling or background subtraction.

There are various techniques that have been created for image inpainting. Paunwala [2018] classifies these into partial differential equation-based methods, exemplar-based methods, and hybrid methods. The review introduces a category of deep learning based inpainting schemes, which have been increasingly used since the creation of generative adversarial networks.
Deep Learning-based methods — With the rise of generative adversarial models capable of state-of-the-art generative capabilities, newer literature has also focussed on leveraging their power to produce anonymised gaits. Tieu et al. [2019a] create spatio-temporal generative models that can obfuscate gaits present in videos, creating natural-looking sequences. This architecture makes use of one generator and two discriminators. The generator accepts the original gait and random noise to generate anonymised gaits. The first discriminator is a spatial discriminator which accepts a contour vector extracted from frames of the gait, and tries to distinguish the shape of real gaits from generated gaits at each frame. The results improve the naturalness of the shape of the generated gait. The second discriminator is a temporal discriminator, which distinguishes between the temporal continuity of the real gait and a generated gait. This determines whether the generated gait moves smoothly. A contour sequence is fed through a long short-term memory network [Hochreiter and Schmidhuber, 1997], the outputs of nodes of which are concatenated to form one input vector for the network. A binary anonymised gait is obtained through the generation process, which is then colourised to merge into the original background.

This process is known to work only on high-quality silhouette inputs, and fails notably with low-quality silhouettes. Tieu et al. [2019b] expand on this work by creating a colourisation network, in addition to a different STGAN-based generator-discriminator architecture defined in Tieu et al. [2019a]. Through this approach, the authors were able to provide gait anonymisation for low-quality silhouettes as well (see figure here).

4.2 Machine Obfuscation: Targetting Algorithms

This review classifies those algorithms that seek to protect the privacy of users from machine learning algorithms, under the category of machine obfuscation techniques. This is currently a highly active field of research, and a large amount of work has gone towards creating machine obfuscation models. These type of algorithms, commonly categorised as attack because they seek to attack the validity of deep learning models used for automated analysis

PDE-inspired algorithms — Algorithms in this category utilise geometric information to do inpainting of the gaps, by looking at the image inpainting process as one of heat diffusion. Several types of PDE-inspired algorithms exist, notably anisotropic diffusion [Perona and Malik, 1990], diffusion-based image inpainting [Bertalmio et al., 2000], and total variational inpainting [Rudin et al., 1992].

Exemplar-based methods — Initially created by [Criminisi et al., 2004], algorithms under this category gather information from nearby regions of the same image or from a database of images for inpainting. Texture synthesis methods can be regarded as a subsection of exemplar-based methods. In this scheme, synthetic textures derived from one portion of the image are used to fill the missing regions in another portion of the image. Texture synthesis algorithms are, however, slower than other patch-based exemplar-based methods since they do inpainting on a pixel-by-pixel basis.

Hybrid Approaches — Hybrid approaches combine the advantages of both PDE-based methods and exemplar-based methods to create better inpainting results. Examples include the approach by [Bertalmio et al., 2003], and the wavelet decomposition-based methods by Zhang and Dai [2012] and Cho and Bui [2008].

‘Deep Learning’-based methods — Although their use in the scenario of object removal is scarce, deep learning models have increasingly been used for image inpainting tasks. These typically make use of generative adversarial networks, to create realistic looking inpainted results [Yeh et al., 2017, Yu et al., 2018]. Similar approaches which have also utilised deep learning to do video inpainting include [Kim et al., 2019, Chang et al., 2019, Lee et al., 2019, Zhang et al. [2019], Oh et al. [2019].

4.1.4 Gait Anonymisation

Research has pointed to the notion that gait is an important biomarker that can be used to identify individuals, as it is individually unique [Wang et al., 2003, Bashir et al., 2010, Liu and Sarkar, 2006, Zhang et al., 2004, Makihara et al., 2006, Bobick and Johnson, 2001]. A deeper treatment of the subject of gait recognition can be seen in the work by Wan et al. [2018]. Gait anonymisation is, however, a relatively newer area of research. Typically, video surveillance anonymisation tools use filters such as pixelation and blurring, and then assume the gait to be anonymised in the process [Agrawal and Narayanan, 2011]. These approaches typically result in the video looking artificial and thus increase its chances of being detected as a fake. The apparent non-robust nature of classical obfuscation approaches like blurring and pixelation through targeted attacks also leave the obfuscated footage in a vulnerable position.

Work done by [Tieu et al., 2017] proposes the use of deep neural networks to generate an anonymising gait. This gait is generated by using the original gait from the frames of the visual feed along with a specially created ‘noise gait’ as inputs to a convolutional neural network. This network then outputs an anonymising contour vector, which after processing produces the anonymised gait. This is then placed back into the original scene.

With the rise of generative adversarial models capable of state-of-the-art generative capabilities, newer literature has focussed on leveraging their power to produce anonymised gaits. Tieu et al. [2019a] create spatio-temporal generative models that can obfuscate gaits present in videos, creating natural-looking sequences. This architecture makes use of one generator and two discriminators. The generator accepts the original gait and random noise to generate anonymised gaits. The first discriminator is a spatial discriminator which accepts a contour vector extracted from frames of the gait, and tries to distinguish the shape of real gaits from generated gaits at each frame. The results improve the naturalness of the shape of the generated gait. The second discriminator is a temporal discriminator, which distinguishes between the temporal continuity of the real gait and a generated gait. This determines whether the generated gait moves smoothly. A contour sequence is fed through a long short-term memory network [Hochreiter and Schmidhuber, 1997], the outputs of nodes of which are concatenated to form one input vector for the network. A binary anonymised gait is obtained through the generation process, which is then colourised to merge into the original background.

This process is known to work only on high-quality silhouette inputs, and fails notably with low-quality silhouettes. Tieu et al. [2019b] expand on this work by creating a colourisation network, in addition to a different STGAN-based generator-discriminator architecture defined in Tieu et al. [2019a]. Through this approach, the authors were able to provide gait anonymisation for low-quality silhouettes as well (see figure here).
Machine obfuscation attacks can be split into two different types — Poisoning attacks and Evasion attacks [Shan et al., 2020]. The objective of machine obfuscation attacks are to create changes in images that cause misclassification in machine recognition models. These changes are also most often imperceptible, to evade humans from detecting their presence, and also to be perceptually pleasing as to be useful for sharing on popular photo sharing applications.

### 4.2.1 Poisoning Attacks

A subcategory of machine obfuscation attacks, termed as poisoning attacks, aims to disrupt the training of machine learning models through the introduction of specific ‘poisoned’ images. After the introduction of such images to the set, models trained on these images behave in unexpected ways. Poisoning attacks can be further split into ‘clean label’ attacks and ‘model corruption’ attacks.

**Clean Label Attacks** — In clean label attacks, adversarial noise is created so that models trained on the data learn to misclassify a specific image, or a set of images containing the person [Shafahi et al., 2018, Zhu et al., 2019]. This is done by creating the adversarial noise in a very specific way as to alter the feature space that is used by machine learning models for recognition. In the test phase, after encountering an unaltered image, a model classifies the image incorrectly due to it seeing a different feature vector than what was seen during training.

Most clean label attacks work on the possible misclassification of a single preselected image that is introduced, although exceptions do exist. Shan et al. [2020] developed Fawkes, which is one such approach through which users can produce ‘cloaked’ images of themselves through the addition of imperceptible adversarial noise. These then cause machine learning models trained on the cloaked images to misclassify normal images of the user.

**Model Corruption Attacks** — A model corruption attack aims to distort the feature space of images in such a way that upon using the altered images, it reduces the overall accuracy of the trained model [Shen et al., 2019]. The objective of model corruption attacks are to prevent unauthorised data collection and model training. One disadvantage of these types of attacks is that they are more easily detectable because the presence of such an attack would be readily reflected in the drop in overall model accuracy seen.

### 4.2.2 Evasion Attacks

Evasion attacks create images that are difficult for image recognition systems to identify. These commonly rely on the creation of adversarial examples through the use of real-life artefacts, which upon being shown to cameras during capture increases the chances of the subject being misidentified. Prominent examples of this sort include wearables like a specially crafted pair of spectacles [Sharif et al., 2016], adversarial stickers [Komkov and Petiushko, 2021] (see figure here), or adversarial patches [Brown et al., 2017, Wu et al., 2020, Thys et al., 2019] that increase the chances of misidentification. The downside of these types of attacks is that these are obvious to a human observer of the footage. Techniques that use adversarial models to alter faces to avoid detection can also be classified under evasion attacks, while in this survey, these are moved to perceptual obfuscation techniques as they alter the appearance of the person in obvious ways, and are usually primarily aimed at human adversaries. The lines are blurred, however, as they can be created to fool machine recognition systems as well.

Evasion attacks are not to be confused with intervention methods. While evasion attacks prevent machine learning algorithms from recognition through the use of hardware, these do not prevent the collection of the data itself. Intervention methods, on the other hand, use specialised hardware to interfere during the data collection stage, preventing private data from ever being sent to the subsequent stages of the pipeline.

### 4.3 Privacy Protecting Pipelines

Research has also been conducted to create end-to-end pipelines that aim to preserve visual privacy through the combination of various techniques in visual privacy preservation. One notable example is by Climent-Pérez and Florez-Revuelta [2021] (see Figure 5). Here, the authors accept an RGB image as input, creating with it a Densepose [Neverova et al., 2018] and Mask R-CNN [He et al., 2017] masks. Using these representations along with a background model created after using a union of the two masks as input, the authors produce five privacy preserving representations, namely the avatar, blurring, invisibility, embossing, and pixelation. These preserve privacy to differing extents, and the footage can be broadcast to users depending on access privileges. The results from the application of the pipeline on a frame from the Toyota Smarthomes dataset [Das et al., 2019] can be seen in Figure 6.
Privacy by Design

Privacy by Design is a systems design concept defined by Cavoukian et al. [2009], which advances the view that privacy cannot be ensured through compliance with regulatory frameworks, and must instead stem from an organisation’s default mode of operation. The concept is accomplished through adhering to the following 7 principles:

1. Proactive not Reactive; Preventative not Remedial — Systems ought to be created that prevent privacy invasive events before they occur.
2. Privacy as the Default Setting — In any business practice or IT system, an individual’s privacy is automatically protected even if they perform no actions.
3. Privacy Embedded into Design — Privacy is embedded into the core design and architecture of IT systems, and into the surrounding business practices.
4. Full Functionality (Positive-Sum, not Zero-Sum) — False dichotomies, such as that of privacy vs security, is avoided. The system seeks to accommodate legitimate interests of both the user and service provider in a win-win fashion.
5. End-to-End Security (Full Lifecycle Protection) — The system architecture ensures that strong security measures which are essential to ensuring privacy are established, extending through the entire lifecycle of the data.
6. Visibility and Transparency (Keep it Open) — Components of the system are created in a way as to be visible and transparent to users and data providers. This ensures verification of the objective that the business is operating according to its stated promises.
7. Respect for User Privacy (Keep it User-Centric) — The system is architected in such a way that the interests of the individual is upheld. This is done through providing strong privacy defaults, appropriate notice, and user-friendly options.

Based on different design elements present in lifelogging technologies, [Mihailidis and Colonna, 2020] created a classification schema that separates privacy by design into levels. According to the schema, components in a pipeline acting at each level must be compliant with existing data protection rules for the system to adhere to the notion of privacy by design.
The most basic of these is at the sensor level. Moving upwards in scope, they can be specified as model level, system level, user interface level, and at the most abstract, privacy at the user level. For clarity, this is connected to the taxonomy of visual privacy preservation methods presented in Section 3. The correspondence between both taxonomies can be seen in Figure 7 and is further explained in subsequent subsections.

5.1 Sensor level

Sensor level privacy preservation techniques prevent the capture of sensitive data in visual feeds using various software and hardware implements. These mechanisms can prevent the capture of sensitive content in the first place by the camera. This can also be implemented at the software level, as a filter to clear the captured images of protected content before the images are stored to disk. Intervention methods (Section 3.1) can be grouped under the umbrella of intervention methods, as these intervene during the data collection phase to protect the privacy of users and environments.

5.2 Model Level

To observe model level privacy, methods are created that preserve privacy for users while at the same time enabling models to infer information from data. Also termed as privacy-preserving data mining (PPDM), these techniques aim to create privacy in such a way that unintended third parties cannot make sense out of protected attributes in data, while also removing sensitive knowledge that has been mined from the data.
Since blind vision methods (see Section 3.2) help in processing the data securely, these schemes can be considered under model level methods, as they contribute to the model level privacy of the pipeline. Since blind vision techniques also allow inferring from data while preserving privacy, it could also be noted as contributing to the system level privacy of a pipeline. Another example of a technique that contributes to the model level privacy of a pipeline is federated learning [Konecný et al., 2016], a technique used for the private training of machine learning models.

### 5.2.1 Federated Learning

Machine learning, being data hungry, requires large amounts of training data. Distributing the training of models aims to speed up the process. Common distributed training schemes revolve around a central model, which is then fed with data that is kept across several nodes. This requires the transporting of data to a central location such as a data centre where the model is located, which gives rise to numerous privacy concerns.

Federated learning is a model training framework that alleviates this issue. Instead of bringing the data to the model, federated learning distributes copies of the central model to where the distributed data stores are located. These are most often user’s mobile devices, as mobile computing is where federated learning is commonly used. Model training is done on the devices, and the gradients are then transferred to the main model, which is then updated. Thus, data does not leave the user’s device, alleviating privacy concerns.

The ideal use cases for federated learning is when data is privacy-sensitive, and not representative of public datasets available for model training. For example, predictive keyboards need to adapt according to specific user preferences. Training on a public dataset like Wikipedia articles would lead to bad predictions. This also facilitates better training because users can correct predictions, which then yield better targets for model training. This is beneficial feedback, which is required for federated learning. This also allows models to evolve with the evolution of language. Poor use cases for federated learning are such as when the ideal dataset for training is already inside the data centre.

Privacy leakages can happen while the gradients are being sent back up to the central model. For this reason, federated learning is often coupled with database privacy preservation techniques for preventing attacks, such as the addition of differentially private noise [Dwork, 2006]. Strong encryption schemes are also commonly employed in the federated learning pipeline.

Federated learning has been researched specifically in computer vision settings as well. [Liu et al., 2020a] created Fedvision, a platform to specifically support the use of federated learning in computer vision settings, such as for object detection. It has also prominently been used in medical imaging settings, medical images being highly privacy-sensitive in nature [Yan et al., 2021, Silva et al., 2019].
5.3 System Level

For system level privacy preservation, techniques need to be developed so that the data used in the pipeline becomes secure, and that user consent for the use of the data in the pipeline is traceable. Traceability requires two components [Mihailidis and Colonna, 2020]. The first is that personal data can be traced to when user consent for its usage was recorded. Secondly, the flow of the data to various sources should also be traceable. This is essential because withdrawal of consent is an important facet of privacy laws like the GDPR [Council of the European Union, European Parliament, 2018]; upon withdrawal of consent, actions have to be taken by the authorised administrator to comply with the request. For this reason, system level privacy is not only an essential concept, but also an arguably overlooked one that is critical to managing the legal requirements surrounding the use of data in machine learning projects.

Additionally, an important facet to system level privacy is the creation of secure databases that protect against information breaches. State-of-the-art techniques like homomorphic encryption allow for machine learning models to infer from the data privately. Boulemtafes et al. [2020] provide a more in-depth treatment on the subject of privacy preserving deep learning. Techniques under secure processing (see Section 3.3) can be considered as contributing to the system level privacy in a system that enforces privacy by design, as for system level privacy, it is required that the data remains secure inside the pipeline. Secure processing techniques assist the pipeline in this regard. It is, however, unclear whether techniques categorised as secure processing also fall under model level privacy preservation schemes as they do allow models to infer information from the data, while also preserving user privacy.

5.4 User Interface Level

Privacy provided at the user interface level, prevents the exposure of privacy-sensitive images or parts of images in various scenarios. Under the classification of privacy preservation methods proposed in this review, techniques under the category of visual obfuscation (Section 4) can be mentioned as adding to user interface level privacy of pipelines. Data hiding methods also contribute to the user interface level privacy of a pipeline because, according to definition, these act to restrict the exposure of private visual information within the image, differing from the former category by the strategy with which the hiding of sensitive information is performed.

5.5 User Level

User level privacy measures empower users by helping them manage their data. These also help users understand the privacy risks involved with the sharing of their data, and also give them mechanisms through which they can control the disclosure of their data. User level privacy is ensured through various educative measures, such as through the use of clear and easy to understand privacy disclosures and agreements. The creation of transparent dashboards through which users can control their data usage is another measure. The regular collection, analysis, and incorporation of user feedback into the pipeline is also a measure to incorporate user level privacy into the pipeline.

6 Performance Evaluation

For the case of visual obfuscation techniques, the type of performance evaluation used depends on the adversary. In systems to perform machine obfuscation, image quality metrics [Pedersen and Hardeberg, 2012] are popularly used. Since the objective of machine obfuscation techniques is to create images that are perceptually similar to the original, image quality metrics are employed to ascertain the (dis)-similarity of the two images. As for perceptual obfuscation, where the adversary is a human observer, a more empirical evaluation is often used. Human feedback is commonly sought for this purpose through the deployment of targeted surveys. Machine recognition systems are also often employed in the case of facial de-identification tasks.

The following subsections deal with the most commonly used metrics in the literature. Popular datasets used during evaluation are also explained.

6.1 Technical Privacy Metrics

There are different types of privacy metrics that have been employed for measuring the performance of privacy preservation methods. Wagner and Eckhoff [2018] refer to 8 categories of metrics used to measure privacy in various contexts. We classify technical privacy metrics into two strains: those which measure an adversary’s estimates to gauge how private a dataset is, and those metrics which gauge privacy according to a variable independent of adversarial estimates.
6.1.1 Indistinguishability Metrics

Indistinguishability metrics measure whether an adversary can distinguish between two outcomes of a privacy mechanism, and gather information about the dataset’s composition from the differences between the outcomes. One commonly used indistinguishability metric is differential privacy [Dwork et al., 2014], which is nowadays extensively used in the securing of databases.

Dwork et al. [2014] define differential privacy as a promise made by a data holder/curator to a data subject. The promise is defined as follows:

You will not be affected, adversely or otherwise, by allowing your data to be used in any study or analysis, regardless of what other studies, datasets or information sources are available.

When differential privacy is implemented for a specific database, it ensures protection against differencing attacks that can reveal information about a specific user in the database. By assuring differential privacy, the designer is ensuring that upon removal of a record containing a specific user’s information, queries executed against the database do not produce a different output from when the same query was executed on the version of the database with the user’s record present.

In obfuscation tasks, a commonly used metric is the accuracy of machine recognition systems, which Wagner and Eckhoff [2018] classify into error-based metrics. This looks at how often a machine recognition system like Amazon Rekognition engine [Amazon Web Services, 2021] can identify subjects in images that have been visually obfuscated. It is usually the case that a simple tally is used as the metric, counting the number of times the subject of interest is detected.

Of particular interest to the concept of perceptual obfuscation are metrics that are independent of adversary. These are solely dependent on observable or measurable differences between two data points or sets of data.

6.1.2 Data Similarity Metrics

One such category proposed by Wagner and Eckhoff [2018] is data similarity. These include metrics that measure the similarity within a dataset through the formation of equivalence classes, or between two sets of data. Some common types include $k$-anonymity [Sweeney, 2002] and its variants, namely $l$-diversity [Machanavajjhala et al., 2007] and $t$-closeness [Li et al., 2007].

$k$-Anonymity — $k$-anonymity is one of the most widely used metrics to evaluate privacy and defines itself regarding quasi-identifiers inside a database. Quasi-identifiers are attributes that can be taken together to identify an individual. Examples of this include the postcode or the birthdate in a personal database. In the case of a facial features database, this can refer to features like glasses, shapes of facial features like noses and the face itself. The metric is defined as follows -

A database is private if each record, $k$, in the database is indistinguishable from at least $k - 1$ records in the database with quasi-identifiers.

Upon satisfaction of $k$-anonymity, a person’s record can only be chosen from a database with a probability of $1/k$.

$l$-Diversity — Proposed to address the limitations of $k$-anonymity, $l$-diversity is defined as follows -

For the equivalence class representing a set of records with the same values for quasi-identifiers, it should have at least $l$ ‘well-represented’ values for the sensitive attribute.

‘Well represented’ values are commonly defined as whether an equivalence class has $l$ distinct values for the sensitive attribute, without considering the frequency of values. A stronger version of the metric is called entropy $l$-diversity, defined as follows

$$\text{Entropy}(E) \geq \log l$$
$$\text{Entropy}(E) = - \sum_{s \in S} p(E,s) \log p(E,s)$$

with $E$ being the equivalence class, $S$ being the value set of the sensitive attribute, and $p(E,s)$ is the fraction of records in $E$ that have sensitive value $s$. 

t-Closeness - To prevent attacks on privacy by adversaries with knowledge of global distribution of sensitive attributes inside a database, Li et al. [2007] devised the measure of t-closeness. This measure updates k-anonymity as follows.

The distribution of sensitive values, \( S_E \), in an equivalence class \( E \) shall be close to its distribution, \( S \) inside the entire database.

\[
\forall E : d(S, S_E) \leq t
\]  

(1)

with \( d(S, S_E) \) being the distance between distributions \( S \) and \( S_E \) measured by the Earth mover distance [Andoni et al., 2008], and \( t \) is a privacy threshold that should not be exceeded.

### 6.1.3 Machine Recognition Scores

Particularly in the context of facial de-identification, machine recognition is commonly employed as a metric to gauge the effectiveness of obfuscation methods. Machine recognition algorithms work by scoring how often a trained recognition algorithm can identify a de-identified subject. In the context of facial recognition, the most commonly used API services are the Google Vision API [Google, 2008], Microsoft Azure Face API [Microsoft Azure, 2021], Amazon Rekognition [Amazon Web Services, 2021] and Face++ [Megvii, 2021]. Simple scoring systems are mostly used for these metrics, often a simple tally of the recognised attribute in the case of attribute recognition, or the recognised activity category in the case of an activity recognition task on obfuscated frames.

For gait obfuscation, custom metrics are usually employed. [Tieu et al., 2019b] craft custom automatic evaluation strategies that seek to measure the difference between a standard gait and a generated one. They employ a frame score and a video score to measure the differences. The frame score measures the degree to which the shape of the object in the frame looks human. For this, they employed a pretrained YOLO model [Redmon and Farhadi, 2018] that detects and classifies objects in an image. The authors compute the probability that a person in a frame belongs to the ‘person’ class. The video score measures the degree to which the gait in the video looks like a humanoid walking. A pretrained ResNeXt-101 [Xie et al., 2017] was used for this purpose, which classifies actions in the video. The probability that the action in the video corresponds to the ‘video’ class is measured and reported for this score.

### 6.1.4 Human Recognition Scores

Humans are also often employed to gather user feedback about the efficacy of privacy preservation methods. Targeted questionnaires are often employed for this purpose. These are mostly composed of questions that allow the respondents to select from an available set of options. Some questionnaires featuring a free form-filling section where the respondents can fill in their responses. As an alternative to in-person surveys, various services have also sprung up over the years that helps researchers solicit responses from targeted audiences. Arguably the most popular ones seen in literature are the Mechanical Turk [Amazon Inc., 2021] and Prolific [Prolific, 2021]. Çiftçi et al. [2018] created an interface through which the authors solicit responses from participants who are tasked with recognizing faces after image filtering (using the ‘false colors’ method) is done. They also asked participants to do activity recognition on filtered videos. Padilla-López et al. [2015] employed targeted questionnaires to quantify the degree of privacy provided by various perceptual privacy preservation methods. The methods that were chosen were, in no order: blurring, pixelation, embossing, silhouette, skeleton, and an avatar. Visuals after applying these methods were shown to participants. The participants were then tasked to answer questions that delved into perceptual attributes such as the colour of the obfuscated subject’s hair, skin colour, and whether subjects are smiling in the frames presented.

### 6.2 User Acceptance Studies

Another important concept is the acceptance of the privacy preservation technology in use. The work done by Wilkowska et al. [2021] is one such example, where the authors create a user survey to understand preferences of German and Turkish participants of lifelogging studies. The study examines and compares perspectives of users from the two countries to understand whether cultural influences affect perceptions of lifelogging technologies and the visual obfuscation techniques that are commonly used on these feeds. As part of the study, the researchers created visualisations of various privacy preservation techniques, selecting representative images that were obfuscated in 5 different ways. In order from low to high levels of privacy protection, these are: real image, Pixelation, Solid Silhouette, Avatar, and Skeleton. They invited a diverse set of users to then provide feedback on the images to answer, among others, the following question: “Do German and Turkish participants choose similar or different visualisation modes of information representation for their use, be it in the context of the accepted location or regarding the data access for the
others?” It also addresses the question of which visualisation mode being the most preferred one for the participants of the survey.

6.3 Datasets

The research community has employed several datasets for the task of measuring visual privacy. The most commonly used datasets consist of RGB images or video streams. It is also popular to curate subsets of these datasets for various targetted experiments. In this section, various datasets that are used for validating the efficacy of privacy preservation methods are listed, along with details of their composition and the papers that use these sets for experimentation.

For the case of facial anonymisation, some popular datasets used are the following:

**Facial Recognition Technology (FERET)** dataset [Phillips et al., 1998] — Containing 14,126 facial stills of 1,199 people, FERET is a publicly available dataset from the US Army. For every facial image, the coordinates for the centres of the eyes and tip of the nose are provided. Examples of privacy preservation methods using FERET for validation include Çiftçi et al. [2018].

**People in photo albums (PIPA)** dataset [Zhang et al., 2015] — is a dataset consisting of over 6,000 images of around 2,000 persons, with only half of the images being of persons from a frontal frame of reference. This creates a challenging task, as recognition systems are mostly trained on frontal imagery. The dataset contains people in a good variety of poses, activities, and scenery. One example of a method validated using PIPA is the method proposed by Sun et al. [2018a].

**AT&T Database of Faces** [AT&T Laboratories Cambridge, 2002] — The AT&T database of faces contains 400 grayscale images of 40 individuals of resolution 92×112. The dataset contains 10 images of each individual, taken under a variety of conditions including varied lighting, different expressions, and different facial details. One example privacy protection scheme that uses this dataset for testing is that by Fan [2018].

**Facescrub** [Ng and Winkler, 2014] is a large dataset consisting of slightly more than 65,000 facial images of 530 celebrities collecting from online publications. Only URLs are distributed for copyright reasons. Li and Lin [2019] proposes a scheme that makes use of this dataset while testing.

**PubFig images dataset** [Kumar et al., 2009] — This is a dataset of images of public figures (celebrities and politicians) obtained from the internet. The dataset consists of around 60,000 images, with around 300 images per individual. Shan et al. [2020] and Sharif et al. [2016] are notable examples of papers using the PubFig images dataset.

**CelebFaces Attributes (CelebA)** dataset [Liu et al., 2015] — Used for facial attribute estimation in the process of training facial de-identification methods, this dataset contains 202,599 images and 10,177 identities of celebrities. Each image has around 40 boolean attribute labels. Li and Lin [2019] is notable for making use of the CelebA dataset for testing.

**Labeled Faces in the Wild (LFW)** dataset [Huang et al., 2008] is another dataset containing ≈13,000 images of faces collected from the web. 1,680 individuals in the set have two or more distinct images of themselves represented in the dataset. Several alternative datasets of faces in the wild have also been proposed, some notable ones being Fine-grained LFW [Deng et al., 2017], LFWGender [Jalal and Tariq, 2017], and LFW3D. Zhang et al. [2021] proposes a method that is notable for using the LFW dataset during testing.

Generic image recognition and object detection datasets are often used in validating the efficacy of privacy preservation schemes, mostly in the case of machine obfuscation schemes. Some commonly used ones are the following:

**Modified NIST (MNIST)** [LeCun, 1998] — MNIST is an extremely popular dataset consisting of images of handwritten digits collected from census bureau employees and high school students in the USA. The entire dataset consists of 70,000 images in total. Abadi et al. [2016] proposes a scheme that is benchmarked using the MNIST dataset.

**CIFAR-10** [Krizhevsky, 2009] — Another popular dataset is CIFAR-10, consisting of a total of 60,000 images of size 32×32. Labels of the dataset consists of either animals (e.g., cats, dogs etc.), or vehicles (e.g., planes, cars, etc.). Abadi et al. [2016] proposes a scheme that uses the CIFAR-10 dataset for validation.

**YouTube 8M video dataset** [Abu-El-Haija et al., 2016] — The YouTube 8M dataset is a video dataset composed of around 8 million videos, approximately 300,000 hours of content, annotated in a multi-label format with 4,800 distinct labels. These labels are machine generated and human curated, with 1.9 billion video frame-level annotations. The entities in videos are also categorised, with some categories represented in the dataset being ‘Arts & Entertainment’,

---

5 It is to be noted that a number of these datasets presented are aimed at measuring the efficacy of machine obfuscation methods

6 The original dataset contains URLs to 100000 images, with a number of URLs broken due to missing media.
'Games', 'People & Society', and 'Books & Literature'. Wong et al. [2020] proposed a privacy preservation scheme that notably uses the YouTube 8M video dataset for testing.

In the context of gait anonymisation, the CASIA-B gait dataset [Yu et al., 2006] is one that is arguably most popular. This dataset contains 124 individuals in total, with 110 sequences (10 sequences each for each of 11 viewing angles from 0° to 180°). Tieu et al. [2017] create a gait anonymisation scheme that uses the CASIA-B dataset for validation.

In the context of full-body de-identification, the following datasets are commonly used —

**Clothing Co-Parsing dataset** [Yang et al., 2014] — This dataset consists of 2,098 high resolution, street fashion images. Pixel-level segmentations of individual garments and skin are available for ~1000 of the images. 59 segmentation tags defining various garment types, e.g., blazer, cardigan, sweatshirt etc., are used in this dataset. Brkic et al. [2017] makes use of the clothing co-parsing dataset to test their full-body privacy preservation scheme.

**Human3.6M dataset** [Ionescu et al., 2014] — This dataset consists of 3.6 million video frames of actors performing actions in a controlled setting. 3D joint positions, the laser scans of the actors, and their corresponding 3D poses are available as annotations. The dataset utilises a static camera angle for the recordings. Brkic et al. [2017] proposed a privacy protection scheme that utilised this dataset for testing purposes.

**Toyota Smarthomes dataset** [Das et al., 2019] — This is a dataset of slightly more than 16,000 video clips, of 31 activity classes performed by 18 seniors in a smarthome setting. The dataset is labelled with both coarse and fine-grained labels and contains heavy class imbalances, high intra-class variation, simple as well as composite activities, and activities with similar motion and of variable duration. Climent-Pérez and Florez-Revuelta [2021] use the Toyota Smarthomes dataset to validate their privacy preservation scheme.

**NTU RGB+D dataset** [Shahroudy et al., 2016] - Containing 60 different action classes including daily, interaction-based, and health-related actions, this is a large-scale dataset for RGB+D human action recognition, containing greater than 56,000 samples and 4,000,000 frames, collected from 40 distinct subjects. Wang et al. [2019] use this dataset to test the efficacy of their privacy preserving action recognition method. An extended version of this dataset was published by Liu et al. [2020b].

### 7 Conclusion and Future Directions

This work reviews the state of the art in visual privacy preservation methods. A low-level taxonomy of visual privacy preservation methods is introduced, and the categories under the taxonomies were subsequently explored. Special attention was given to visual obfuscation methods, these being of most relevance to AAL applications. The taxonomy is then connected to a high-level classification scheme of the levels of privacy by design.

Visual obfuscation methods are categorised into two categories in this review based on the targets from whom the algorithms are seeking to hide private information: perceptual obfuscation and machine obfuscation methods. Perceptual obfuscation seeks to perceptually alter images in ways that unauthorised human observers who view the visual feed are thwarted. By contrast, machine obfuscation methods try to hide privacy-sensitive elements from machine learning algorithms. These seek to alter the feature space of images in ways that machine recognition systems are thwarted, while also perceptually changing the visuals to the least possible extent.

As these are two different directions of research, algorithms can also be built such that they perform both machine and perceptual obfuscation. The capability of performing reversible transformations through secure pipelines is another promising direction for research. This is useful in the case when reversibility is required, such as for an arbiter (a judge, a doctor, etc.) to view unedited footage to obtain full information about a specific scenario.

#### 7.1 Technical Questions

In the context of visual privacy preservation, numerous technical challenges remain to be addressed. One major challenge is to create real-time pipelines that impart privacy. Most of the existing state-of-the-art methods rely on computationally intensive pipelines. To create real-time privacy protection, methods have to be made more lightweight.

There are also some widely used cameras that are arguable not sufficiently researched in literature from the perspective of privacy preservation. Egocentric/wearable cameras have been touted as a method to protect identity, but this poses problems if the environment contains objects (e.g. mirrors) that reveals one’s personal attributes. This also introduces issues when bystanders come into the visual field; bystanders would typically not have given permissions for them to be captured on camera. This poses ethical and legal challenges, in addition to technical ones when egocentric cameras are utilised [Gurrin et al., 2013].
Omnidirectional cameras have fisheye lenses that provide the user with a mostly non-occluded view of an entire room based on its placement (usually on the ceiling). However, object detection algorithms have not typically been trained to detect on images from distorted lenses. Privacy preservation algorithms that rely on detection as part of the pipeline are therefore summarily excluded from use on these streams. Other non-standard cameras (thermal, infrared) also face similar problems. Therefore, the authors call for more research to create privacy preserving algorithms that work on non-standard cameras.

Some identifiers have also been arguably addressed less in the literature. Gait is one such example, and to the authors’ knowledge, only a few papers have attempted to create gait anonymisation algorithms. Environmental identifiers are also another.

### 7.1.1 Environmental Privacy

Although included in this review as a sub-category of perceptual obfuscation, literature searches show that environmental privacy is an under-researched area, but arguably one that is critical to the ensuring of visual privacy. Most of the existing methods that impart privacy target people and their visible attributes. However, objects in the environment are also required to be obfuscated if the identity of the person is to be protected. Objects like credit cards and address labels create privacy risks if not obfuscated. Some methods do, however, provide environmental privacy as a side effect upon their use. As an example, consider a blurring filter. When a blurring filter is applied to an image as a whole, textural information is lost, which might lead to smaller privacy-sensitive objects such as credit cards (and specifically the numbers printed on them) being obfuscated. Depending on the parameters used for the blurring, however, larger objects in the environment might still contribute to privacy leakages.

### 7.2 Social Scientific and Legal Aspects of Privacy

There is also the urgent need to understand the methods from social scientific and legal perspectives. There needs to be studies to ascertain the level of acceptance of different perceptual obfuscation methods among the monitored subjects. It is also unclear as to the extent of the acceptability of reversible transformations for the subjects being monitored. Although there are several methods that reconstruct obfuscated images, the acceptability of reconstructed images through a reverse transformation pipeline that contains embedded stochasticity is an especially interesting one to study. In a setting such as that of a court or in forensics, as reconstruction is an imperfect process, there is always the possibility of information loss. It is unclear if such images are viable for presentation in such circumstances. There also needs to be more studies that detail the relationship between human perception and the metrics that are used to measure perceptual obfuscation. Although there are some studies that do this, there is a distinct need for more wide-ranging targeted studies to be performed.

The concept of a ‘privacy paradox’ also needs to be investigated. It is a known phenomenon that people act in contrast to what they believe their privacy preferences are, especially when it comes to their online behaviour [Barth and de Jong [2017]]. Users claim to be concerned about their online privacy, but they do little to protect their personal data. If this is also the case for visual data like that used in AAL applications, then the gathering of subjective data about user preferences through a medium such as questionnaires should be called into question. It could mean that better ways of gauging preferences should be created and deployed. It could also mean that existing studies that gauge privacy preferences ought to be re-evaluated.

### Data Availability

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

### Acknowledgements

This work is part of the visuAAL project on Privacy-Aware and Acceptable Video-Based Technologies and Services for Active and Assisted Living ([https://www.visuaal-itn.eu/](https://www.visuaal-itn.eu/)). This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 861091. The authors would also like to acknowledge the contribution of COST Action CA19121 - GoodBrother, Network on Privacy-Aware Audio- and Video-Based Applications for Active and Assisted Living ([https://goodbrother.eu/](https://goodbrother.eu/)), supported by COST (European Cooperation in Science and Technology) ([https://www.cost.eu/](https://www.cost.eu/)).
References

Roger Clarke. Internet Privacy Concerns Confirm the Case for Intervention. *Commun. ACM*, 42(2):60–67, Feb 1999. ISSN 0001-0782. doi: 10.1145/293411.293475.

Roger Clarke. What’s ‘Privacy’. In *Proc. of the Workshop at the Australian Law Reform Commission*, 2006.

Ann Cavoukian et al. Privacy by Design: The 7 Foundational Principles. *Information and Privacy Commissioner of Ontario, Canada*, 5:12, 2009.

José Ramón Padilla-López, Alexandros Andre Chaaraoui, and Francisco Flórez-Revuelta. Visual Privacy Protection Methods: A Survey. *Expert Systems with Applications*, 42(9):4177–4195, 2015. ISSN 0957-4174. doi: https://doi.org/10.1016/j.eswa.2015.01.041. URL https://www.sciencedirect.com/science/article/pii/S0957417415000561

Slobodan Ribaric, Aladdin Ariyaeenia, and Nikola Pavesic. De-identification For Privacy Protection in Multimedia Content: A Survey. *Signal Processing: Image Communication*, 47:131–151, 2016. ISSN 0923-5965. doi: https://doi.org/10.1016/j.image.2016.05.020. URL https://www.sciencedirect.com/science/article/pii/S0923596516300856

Blaz Meden, Peter Rot, Philipp Terhörst, Naser Damer, Arjan Kuijper, Walter J. Scheirer, Arun Ross, Peter Peer, and Vitomir Štruc. Privacy–Enhancing Face Biometrics: A Comprehensive Survey. *IEEE Transactions on Information Forensics and Security*, 16:4147–4183, 2021. doi: 10.1109/TIFS.2021.3096024.

Alfredo J. Perez, Sherali Zeadally, and Scott Griffith. Bystanders’ Privacy. *IT Professional*, 19(3):61–65, 2017. doi: 10.1109/MITP.2017.42.

Karl S Jonsson and Sigurbjorg Hlin Berghorsdottir. Webcam Privacy Shield, October 11 2016. US Patent 9,465,276.

Alexander Paul Barangan, Victor E Cocchia, Michael Stephen Fiske, and Waleed Sami Haddad. Microphone and Camera Disruption Apparatus and Method, September 1 2015. US Patent 9,124,792.

Waleed Sami Haddad. Detachable Lens Shuttering Apparatus For Use With a Portable Communication Device, February 14 2017. US Patent 9,571,708.

Kameron Miller. Electronic Device Privacy Cover, October 27 2020. US Patent 10,816,878.

Thor FR Mitskog and Richard AnthonyRalston. Camera Blocker For a Device With an Integrated Camera That Uses a Thin Film Organic Polymer, November 29 2012. US Patent App. 13/477,485.

Ryan Rolle. Camera-Covering Accessory For a Computer, September 4 2018. US Patent 10,070,021.

Shwetak N. Patel, Jay W. Summet, and Khai N. Truong. *BlindSpot: Creating Capture-Resistant Spaces*, pages 185–201. Springer London, London, 2009. ISBN 978-1-84882-301-3. doi: [10.1007/978-1-84882-301-3_11].

Adam Harvey and Heather Knight. Anti-Paparazzi Fashion. www.marilynmonrobot.com, 2009. Accessed: 2021-06-30.

Shilin Zhu, Chi Zhang, and Xinyu Zhang. Automating Visual Privacy Protection Using a Smart LED. In *Proceedings of the 23rd Annual International Conference on Mobile Computing and Networking*, MobiCom ’17, page 329–342, New York, NY, USA, 2017. Association for Computing Machinery. ISBN 9781450349161. doi: 10.1145/3117811.3117820.

Pine64. Pinephone. https://www.pine64.org/pinephone/, 2021a. Accessed: 2021-05-05.

Pine64. Pinephone Killswitches. https://wiki.pine64.org/index.php?title=PinePhone#Killswitch_configuration, 2021b. Accessed: 2021-05-05.

Maurizio Pilu. Detector For Use With Data Encoding Pattern, April 19 2007. US Patent App. 11/491,174.

Apu Kapadia, Tristan Henderson, Jeffrey J. Fielding, and David Kotz. Virtual Walls: Protecting Digital Privacy in Pervasive Environments. In Anthony LaMarca, Marc Langheinrich, and Khai N. Truong, editors, *Pervasive Computing*, pages 162–179. Berlin, Heidelberg, 2007. Springer Berlin Heidelberg. ISBN 978-3-540-72037-9.

Shai Avidan and Moshe Butman. Blind vision. In Aleš Leonardis, Horst Bischof, and Axel Pinz, editors, *Computer Vision – ECCV 2006*, pages 1–13. Berlin, Heidelberg, 2006. Springer Berlin Heidelberg. ISBN 978-3-540-33837-6.

Shai Avidan, Ariel Elbaz, Tal Malkin, and Ryan Moriarty. *Oblivious Image Matching*, pages 49–64. Springer London, London, 2009. ISBN 978-1-84882-301-3. doi: [10.1007/978-1-84882-301-3_4].

Zekeriya Erkin, Martin Franz, Jorge Guajardo, Stefan Katzenbeisser, Inald Lagendijk, and Tomas Toft. Privacy-Preserving Face Recognition. In Ian Goldberg and Mikhail J. Atallah, editors, *Privacy Enhancing Technologies*, pages 235–253. Berlin, Heidelberg, 2009. Springer Berlin Heidelberg. ISBN 978-3-642-03168-7.
Ahmad-Reza Sadeghi, Thomas Schneider, and Immo Wehrenberg. Efficient Privacy-Preserving Face Recognition. In Donghoon Lee and Seokhie Hong, editors, Information, Security and Cryptology – ICISC 2009, pages 229–244, Berlin, Heidelberg, 2010. Springer Berlin Heidelberg. ISBN 978-3-642-14423-3.

J. Shashank, P. Kowshik, Kannan Srinathan, and C.V. Jawahar. Private Content Based Image Retrieval. In 2008 IEEE Conference on Computer Vision and Pattern Recognition, pages 1–8, 2008. doi: 10.1109/CVPR.2008.4587388.

Thomas Heitzinger and Martin Kampel. IPT: A Dataset for Identity Preserved Tracking in Closed Domains. In 2020 25th International Conference on Pattern Recognition (ICPR), pages 8228–8234, 2021. doi: 10.1109/ICPR48806.2021.9412979.

Maneesh Upmanyu, Anoop M. Namboodiri, Kannan Srinathan, and C.V. Jawahar. Efficient Privacy Preserving Video Surveillance. In 2009 IEEE 12th International Conference on Computer Vision, pages 1639–1646, 2009. doi: 10.1109/ICCV.2009.5459370.

Ryo Yonetani, Vishnu Naresh Boddeti, Kris M. Kitani, and Yoichi Sato. Privacy-Preserving Visual Learning Using Doubly Permutated Homomorphic Encryption. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), Oct 2017.

Song Bian, Tianchen Wang, Masayuki Hiromoto, Yiyu Shi, and Takashi Sato. ENSEI: Efficient Secure Inference via Frequency-Domain Homomorphic Convolution for Privacy-Preserving Visual Recognition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020.

F.A.P. Petitcolas, R.J. Anderson, and M.G. Kuhn. Information Hiding—a Survey. Proceedings of the IEEE, 87(7): 1062–1078, 1999. doi: 10.1109/5.771065.

Xiaoyi Yu and Noboru Babaguchi. Privacy Preserving: Hiding a Face in a Face. In Asian Conference on Computer Vision, pages 651–661. Springer, 2007.

Brian Chen and Gregory W Wornell. Quantization Index Modulation Methods for Digital Watermarking and Information Embedding of Multimedia. Journal of VLSI Signal Processing Systems for Signal, Image and Video Technology, 27(1):7–33, 2001.

Zhicheng Ni, Yun-Qing Shi, Nirwan Ansari, and Wei Su. Reversible Data Hiding. IEEE Transactions on Circuits and Systems for Video Technology, 16(3):354–362, 2006.

Kenichi Yabuta, Hitoshi Kitazawa, and Toshihisa Tanaka. A New Concept of Security Camera Monitoring with Privacy Protection by Masking Moving Objects. In Pacific-Rim Conference on Multimedia, pages 831–842. Springer, 2005.

Wei Zhang, Sen-Ching S Cheung, and Minghua Chen. Hiding Privacy Information in Video Surveillance System. In IEEE International Conference on Image Processing 2005, volume 3, pages II–868. IEEE, 2005.

Hao Wu, Xuejin Tian, Minghao Li, Yunxin Liu, Ganesh Anantharayanan, Fengyuan Xu, and Sheng Zhong. PECAM: Privacy-Enhanced Video Streaming and Analytics via Securely-Reversible Transformation. In Proceedings of the 27th Annual International Conference on Mobile Computing and Networking, MobiCom ’21, page 229–241, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 9781450383342. doi: 10.1145/3447993.3448618.

Pavel Korshunov and Touradj Ebrahimi. Using Face Morphing To Protect Privacy. In 2013 10th IEEE International Conference on Advanced Video and Signal Based Surveillance, pages 208–213, 2013a. doi: 10.1109/AVSS.2013.6636641.

Pavel Korshunov and Touradj Ebrahimi. Using Warping For Privacy Protection in Video Surveillance. In 2013 18th International Conference on Digital Signal Processing (DSP), pages 1–6, 2013b. doi: 10.1109/ICDSP.2013.6622791.

Ádám Erdélyi, Thomas Winkler, and Bernhard Rinner. Serious Fun: Cartooning for Privacy Protection. In MediaEval, 2013.

Ádám Erdélyi, Tibor Barát, Patrick Valet, Thomas Winkler, and Bernhard Rinner. Adaptive Cartooning For Privacy Protection in Camera Networks. In 2014 11th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pages 44–49, 2014. doi: 10.1109/AVSS.2014.6918642.

Eman T. Hassan, Rakibul Hasan, Patrick Shaffer, David Crandall, and Apu Kapadia. Cartooning for Enhanced Privacy in Lifelogging and Streaming Videos. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, July 2017.

Serdar Çiftçi, Ahmet Oğuz Akyüz, and Touradj Ebrahimi. A Reliable and Reversible Image Privacy Protection Based on False Colors. IEEE Transactions on Multimedia, 20(1):68–81, 2018. doi: 10.1109/TMM.2017.2728479.

Zhiyong Zhang, Thomas Cilloni, Charles Walter, and Charles Fleming. Multi-Scale, Class-Generic, Privacy-Preserving Video. Electronics, 10(10), 2021. ISSN 2079-9292. doi: 10.3390/electronics10101172. URL https://www.mdpi.com/2079-9292/10/10/1172.
A Review on Visual Privacy Preservation Techniques for Active and Assisted Living

Qianru Sun, Liqian Ma, Seong Joon Oh, Luc Van Gool, Bernt Schiele, and Mario Fritz. Natural and Effective Obfuscation by Head Inpainting. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2018a.

Oran Gafni, Lior Wolf, and Yaniv Taigman. Live Face De-identification in Video. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), pages 9378–9387, October 2019a.

Tao Li and Lei Lin. AnonymousNet: Natural Face De-identification With Measurable Privacy. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, June 2019.

Ngoc-Dung T. Tieu, Huy H. Nguyen, Hoang-Quoc Nguyen-Son, Junichi Yamagishi, and Isao Echizen. An Approach For Gait Anonymization Using Deep Learning. In 2017 IEEE Workshop on Information Forensics and Security (WIFS), pages 1–6, 2017. doi: 10.1109/WIFS.2017.8267657.

Ngoc-Dung T. Tieu, Huy H. Nguyen, Hoang-Quoc Nguyen-Son, Junichi Yamagishi, and Isao Echizen. Spatio-Temporal Generative Adversarial Network For Gait Anonymization. Journal of Information Security and Applications, 46:307–319, 2019a. ISSN 2214-2126. doi: https://doi.org/10.1016/j.jisa.2019.03.002. URL https://www.sciencedirect.com/science/article/pii/S2214212618304629.

Ngoc-Dung T. Tieu, Huy H. Nguyen, Fuming Fang, Junichi Yamagishi, and Isao Echizen. An RGB Gait Anonymization Model for Low-Quality Silhouettes. In 2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), pages 1686–1693, 2019b. doi: 10.1109/APSIPAASC47483.2019.9023188.

Karla Brkic, Ivan Sikiric, Tomislav Hrkac, and Zoran Kalafatic. I Know That Person: Generative Full Body and Face De-identification of People in Images. In 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pages 1319–1328, 2017. doi: 10.1109/CVPRW.2017.173.

Enric Corona, Albert Pumarola, Guillem Alenyà, Gerard Pons-Moll, and Francesc Moreno-Noguer. SMPLicit: Topology-Aware Generative Model for Clothed People. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 11875–11885, June 2021.

Yu Rong, Takaaki Shiratori, and Hanbyul Joo. FrankMocap: Fast monocular 3D hand and body motion capture by regression and integration. arXiv preprint arXiv:2008.08324, 2020.

Natalia Neverova, Riza Alp Guler, and Iasonas Kokkinos. Dense Pose Transfer. In Proceedings of the European Conference on Computer Vision (ECCV), September 2018.

Jonathan Taylor, Jamie Shotton, Toby Sharp, and Andrew Fitzgibbon. The Vitruvian Manifold: Inferring Dense Correspondences For One-Shot Human Pose Estimation. In 2012 IEEE Conference on Computer Vision and Pattern Recognition, pages 103–110, 2012. doi: 10.1109/CVPR.2012.6247664.

Lingyu Wei, Qixing Huang, Duygu Ceylan, Etienne Vouga, and Hao Li. Dense Human Body Correspondences Using Convolutional Networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

Gerard Pons-Moll, Jonathan Taylor, Jamie Shotton, Aaron Hertzmann, and Andrew Fitzgibbon. Metric Regression Forests For Correspondence Estimation. International Journal of Computer Vision, 113(3):163–175, 2015. doi: 10.1007/s11263-015-0818-9.

Hilton Bristow, Jack Valmadre, and Simon Lucey. Dense Semantic Correspondence Where Every Pixel is a Classifier. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), December 2015.

Tinghui Zhou, Philipp Krahenbuhl, Mathieu Aubry, Qixing Huang, and Alexei A. Efros. Learning Dense Correspondence via 3D-Guided Cycle Consistency. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

Utkarsh Gaur and B. S. Manjunath. Weakly Supervised Manifold Learning for Dense Semantic Object Correspondence. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), Oct 2017.

P. Perona and J. Malik. Scale-Space and Edge Detection Using Anisotropic Diffusion. IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(7):629–639, 1990. doi: 10.1109/34.56205.

Marcelo Bertalmio, Guillermo Sapiro, Vincent Caselles, and Coloma Ballester. Image Inpainting. In Proceedings of the 27th Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH ’00, page 417–424, USA, 2000. ACM Press/Addison-Wesley Publishing Co. ISBN 1581132085. doi: 10.1145/344779.344972.

Leonid I. Rudin, Stanley Osher, and Emad Fatemi. Nonlinear total variation based noise removal algorithms. Physica D: Nonlinear Phenomena, 60(1):259–268, 1992. ISSN 0167-2789. doi: https://doi.org/10.1016/0167-2789(92)90242-F. URL https://www.sciencedirect.com/science/article/pii/016727899290242F.

A. Criminisi, P. Perez, and K. Toyama. Region Filling and Object Removal by Exemplar-Based Image Inpainting. IEEE Transactions on Image Processing, 13(9):1200–1212, 2004. doi: 10.1109/TIP.2004.833105.
M. Bertalmio, L. Vese, G. Sapiro, and S. Osher. Simultaneous Structure and Texture Image Inpainting. *IEEE Transactions on Image Processing*, 12(8):882–889, 2003. doi: 10.1109/TIP.2003.815261.

Hongying Zhang and Shimei Dai. Image Inpainting Based on Wavelet Decomposition. *Procedia Engineering*, 29:3674–3678, 2012. ISSN 1877-7058. doi: https://doi.org/10.1016/j.proeng.2012.01.551. URL [https://www.sciencedirect.com/science/article/pii/S1877705812005619](https://www.sciencedirect.com/science/article/pii/S1877705812005619). 2012 International Workshop on Information and Electronics Engineering.

Dongwook Cho and Tien D. Bui. Image Inpainting Using Wavelet-Based Inter- and Intra-Scale Dependency. In 2008 19th International Conference on Pattern Recognition, pages 1–4, 2008. doi: 10.1109/ICPR.2008.4761110.

Raymond A. Yeh, Chen Chen, Teck Yan Lim, Alexander G. Schwing, Mark Hasegawa-Johnson, and Minh N. Do. Semantic Image Inpainting With Deep Generative Models. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

Jiahui Yu, Zhe Lin, Jimei Yang, Xiaohui Shen, Xin Lu, and Thomas S. Huang. Generative Image Inpainting With Contextual Attention. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

Dahun Kim, Sanghyun Woo, Joon-Young Lee, and In So Kweon. Deep video inpainting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.

Ya-Liang Chang, Zhe Yu Liu, Kuan-Ying Lee, and Winston Hsu. Free-Form Video Inpainting With 3D Gated Convolution and Temporal PatchGAN. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.

Sungho Lee, Seoung Wug Oh, DaeYeun Won, and Seon Joo Kim. Copy-and-Paste Networks for Deep Video Inpainting. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.

Haotian Zhang, Long Mai, Ning Xu, Zhaowen Wang, John Collomosse, and Hailin Jin. An Internal Learning Approach to Video Inpainting. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.

Seoung Wug Oh, Sungho Lee, Joon-Young Lee, and Seon Joo Kim. Onion-Peel Networks for Deep Video Completion. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.

Mahmood Sharif, Sruti Bhagavatula, Lujo Bauer, and Michael K. Reiter. Accessorize to a Crime: Real and Stealthy Attacks on State-of-the-Art Face Recognition. In *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, CCS ’16, page 1528–1540, New York, NY, USA, 2016. Association for Computing Machinery. ISBN 9781450341394. doi: 10.1145/2976749.2978392.

Stepan Komkov and Aleksandr Petiushko. AdvHat: Real-World Adversarial Attack on ArcFace Face ID System. In 2020 25th International Conference on Pattern Recognition (ICPR), pages 819–826, 2021. doi: 10.1109/ICPR48806.2021.9412236.

Tom B Brown, Dandelion Mané, Aurko Roy, Martín Abadi, and Justin Gilmer. Adversarial patch. *arXiv preprint arXiv:1712.09665*, 2017. URL [https://arxiv.org/pdf/1712.09665.pdf](https://arxiv.org/pdf/1712.09665.pdf).

Zuxuan Wu, Ser-Nam Lim, Larry S. Davis, and Tom Goldstein. Making an Invisibility Cloak: Real World Adversarial Attacks on Object Detectors. In Andrea Vedaldi, Horst Bischof, Thomas Brox, and Jan-Michael Frahm, editors, *Computer Vision – ECCV 2020*, pages 1–17, Cham, 2020. Springer International Publishing. ISBN 978-3-030-58548-8.

Simen Thys, Wiebe Van Ranst, and Toon Goedeme. Fooling Automated Surveillance Cameras: Adversarial Patches to Attack Person Detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, June 2019.

Ali Shafahi, W. Ronny Huang, Mahyar Najibi, Octavian Suciu, Christoph Studer, Tudor Dumitras, and Tom Goldstein. Poison Frogs! Targeted Clean-Label Poisoning Attacks on Neural Networks. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, NIPS’18, page 6106–6116, Red Hook, NY, USA, 2018. Curran Associates Inc.

Chen Zhu, W. Ronny Huang, Hengduo Li, Gavin Taylor, Christoph Studer, and Tom Goldstein. Transferable Clean-Label Poisoning Attacks on Deep Neural Nets. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 7614–7623. PMLR, 09–15 Jun 2019. URL [https://proceedings.mlr.press/v97/zhu19a.html](https://proceedings.mlr.press/v97/zhu19a.html).

Shawn Shan, Emily Wenger, Jiayun Zhang, Huiying Li, Haitao Zheng, and Ben Y. Zhao. Fawkes: Protecting Privacy against Unauthorized Deep Learning Models. In 29th *USENIX Security Symposium* (*USENIX Security 20*), pages 1589–1604. *USENIX Association*, August 2020. ISBN 978-1-939133-17-5. URL [https://www.usenix.org/conference/usenixsecurity20/presentation/shan](https://www.usenix.org/conference/usenixsecurity20/presentation/shan).
A REVIEW ON VISUAL PRIVACY PRESERVATION TECHNIQUES FOR ACTIVE AND ASSISTED LIVING

Juncheng Shen, Xiaolei Zhu, and De Ma. TensorClog: An Imperceptible Poisoning Attack on Deep Neural Network Applications. IEEE Access, 7:4149-41506, 2019. doi: 10.1109/ACCESS.2019.2905915.

Richard McPherson, Reza Shokri, and Vitaly Shmatikov. Defeating Image Obfuscation With Deep Learning. arXiv preprint arXiv:1609.00408, 2016.

Seong Joon Oh, Rodrigo Benenson, Mario Fritz, and Bernt Schiele. Faceless Person Recognition: Privacy Implications in Social Media. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, Computer Vision – ECCV 2016, pages 19–35, Cham, 2016. Springer International Publishing. ISBN 978-3-319-46487-9.

E.M. Newton, L. Sweeney, and B. Malin. Preserving Privacy by De-identifying Face Images. IEEE Transactions on Knowledge and Data Engineering, 17(2):232–243, 2005. doi: 10.1109/TKDE.2005.32.

Pavel Korshunov and Wei Tsang Ooi. Video Quality for Face Detection, Recognition, and Tracking. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 7(3), sep 2011. ISSN 1551-6857. doi: 10.1145/2000486.2000488.

Sachit Menon, Alexandru Damian, Shijia Hu, Nikhil Ravi, and Cynthia Rudin. Pulse: Self-supervised photo upsampling via latent space exploration of generative models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020.

Denys Rozumnyi, Martin R. Oswald, Vittorio Ferrari, Jiri Matas, and Marc Pollefeys. DeFMO: Deblurring and Shape Recovery of Fast Moving Objects. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 3456–3465, June 2021.

Orest Kupyn, Tetiana Martyniuk, Junru Wu, and Zhangyang Wang. Deblurgan-v2: Deblurring (orders-of-magnitude) faster and better. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), October 2019.

Kaihao Zhang, Wenhan Luo, Yiran Zhong, Lin Ma, Bjorn Stenger, Wei Liu, and Hongdong Li. Deblurring by realistic blurring. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2737–2746, 2020.

Will Knight. Clearview AI Has New Tools to Identify You in Photos. https://www.wired.com/story/clearview-ai-new-tools-identify-you-photos/, Oct 2021. Accessed: 2021-11-03.

Li-Cheng Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L. Yuille. DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4):834–848, 2018. doi: 10.1109/TPAMI.2017.2699184.

Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2014.

N. Dalal and B. Triggs. Histograms of Oriented Gradients For Human Detection. In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), volume 1, pages 886–893 vol. 1, 2005. doi: 10.1109/CVPR.2005.177.

R. Gross, L. Sweeney, F. de la Torre, and S. Baker. Model-Based Face De-Identification. In 2006 Conference on Computer Vision and Pattern Recognition Workshop (CVPRW’06), pages 161–161, 2006a. doi: 10.1109/CVPRW.2006.125.

Ralph Gross, Edoardio Airoldi, Bradley Malin, and Latanya Sweeney. Integrating Utility into Face De-identification. In George Danezis and David Martin, editors, Privacy Enhancing Technologies, pages 227–242, Berlin, Heidelberg, 2006b. Springer Berlin Heidelberg. ISBN 978-3-540-34746-0.

Qianru Sun, Liqian Ma, Seong Joon Oh, Luc Van Gool, Bernt Schiele, and Mario Fritz. Natural and effective obfuscation by head inpainting, 2018b.

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going Deeper With Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2015.

Leo Breiman. Random Forests. Machine Learning, 45(1):5–32, 2001.

Yunjey Choi, Minje Choi, Munyoung Kim, Jung-Woo Ha, Sung hun Kim, and Jaegul Choo. StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2018.
A REVIEW ON VISUAL PRIVACY PRESERVATION TECHNIQUES FOR ACTIVE AND ASSISTED LIVING

Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, and Pascal Frossard. DeepFool: A Simple and Accurate Method to Fool Deep Neural Networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

Pau Climent-Pérez and Francisco Florez-Revuelta. Protection of Visual Privacy in Videos Acquired With RGB Cameras For Active and Assisted Living Applications. Multimedia Tools and Applications, pages 1–16, 2021. doi: 10.1007/s11024-019-10249-1.

Víctor Manuel Mondéjar-Guerra, José Rouco, Jorge Novo, and Marcos Ortega. An End-to-End Deep Learning Approach For Simultaneous Background Modeling and Subtraction. In BMVC, page 266, 2019.

Behnaz Rezaei, Amirreza Farroosh, and Sarah Ostadabbas. G-LBM: Generative Low-dimensional Background Model Estimation from Video Sequences. In ECCV, 2020.

Oran Gafni, Lior Wolf, and Yaniv Taigman. Live face de-identification in video, 2019b.

Matthew Loper, Naureen Mahmood, Javier Romero, Gerard Pons-Moll, and Michael J. Black. SMPL: A Skinned Multi-Person Linear Model. ACM Trans. Graph., 34(6), oct 2015. ISSN 0730-0301. doi: 10.1145/2816795.2818013.

Georgios Pavlakos, Vasileios Choutas, Nima Ghorbani, Timo Bolkart, Ahmed A. A. Osman, Dimitrios Tzionas, and Michael J. Black. Expressive Body Capture: 3D Hands, Face, and Body From a Single Image. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2019.

Ahmed A A Osman, Timo Bolkart, and Michael J. Black. STAR: A sparse trained articulated human body regressor. In European Conference on Computer Vision (ECCV), pages 598–613, 2020. URL https://star.is.tue.mpg.de.

Tsung-Yi Lin, Michael Maire, Javier Romero, Gerard Pons-Moll, and Piotr Dollár, C. Lawrence Zitnick. Microsoft COCO: Common Objects in Context. In David Fleet, Tomas Pajdla, Bernt Schiele, and Tinne Tuytelaars, editors, Computer Vision – ECCV 2014, pages 740–755, Cham, 2014. Springer International Publishing. ISBN 978-3-319-10602-1.

Kaiming He, Georgia Gkioxari, Piotr Dollar, and Ross Girshick. Mask R-CNN. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), Oct 2017.

Riza Alp Guler, George Trigeorgis, Epameinondas Antonakos, Patrick Snape, Stefanos Zafeiriou, and Iasonas Kokkinos. DenseReg: Fully Convolutional Dense Shape Regression In-The-Wild. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), July 2017.

Chirag N Paunwala. Image Inpainting Evolution: A Survey. Encyclopedia of Image Processing, page 293, 2018.

Liang Wang, Tieniu Tan, Huazhong Ning, and Weiming Hu. Silhouette Analysis-Based Gait Recognition for Human Identification. IEEE Transactions on Pattern Analysis and Machine Intelligence, 25(12):1505–1518, 2003. doi: 10.1109/TPAMI.2003.1251144.

Khalid Bashir, Tao Xiang, and Shaogang Gong. Gait Recognition Without Subject Cooperation. Pattern Recognition Letters, 31(13):2052–2060, 2010. ISSN 0167-8655. doi: https://doi.org/10.1016/j.patrec.2010.05.027. URL https://www.sciencedirect.com/science/article/pii/S0167865510001844.

Zongyi Liu and S. Sarkar. Improved Gait Recognition by Gait Dynamics Normalization. IEEE Transactions on Pattern Analysis and Machine Intelligence, 28(6):863–876, 2006. doi: 10.1109/TPAMI.2006.122.

Rong Zhang, C. Vogler, and D. Metaxas. Human Gait Recognition. In 2004 Conference on Computer Vision and Pattern Recognition Workshop, pages 18–18, 2004. doi: 10.1109/CVPR.2004.361.

Changsheng Wan, Li Wang, and Vir V. Phoha. A Survey on Gait Recognition. ACM Comput. Surv., 51(5), aug 2018. ISSN 0360-0300. doi: 10.1145/3230633.

Prachi Agrawal and P. J. Narayanan. Person De-identification in Videos. IEEE Transactions on Circuits and Systems for Video Technology, 21(3):299–310, 2011. doi: 10.1109/TCSVT.2011.2105551.

Sepp Hochreiter and Jürgen Schmidhuber. Long Short-Term Memory. Neural Computation, 9(8):1735–1780, 1997. doi: 10.1162/neco.1997.9.8.1735.
A REVIEW ON VISUAL PRIVACY PRESERVATION TECHNIQUES FOR ACTIVE AND ASSISTED LIVING

Srijan Das, Rui Dai, Michal Koperski, Luca Minciullo, Lorenzo Garattoni, Francois Bremond, and Gianpiero Francesca. Toyota Smarthome: Real-World Activities of Daily Living. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), October 2019.

Alex Mihailidis and Liane Colonna. A Methodological Approach to Privacy by Design Within the Context of Lifelogging Technologies. Rutgers Computer & Tech. LJ, 46:1, 2020.

Jakub Koncny, H. Brendan McMahan, Felix X. Yu, Peter Richtaria, Ananda Theertha Suresh, and Dave Bacon. Federated Learning: Strategies for Improving Communication Efficiency. CoRR, abs/1610.05492, 2016.

Cynthia Dwork. Differential privacy. In Michele Bugliesi, Bart Preneel, Vladimiro Sassone, and Ingo Wegener, editors, Automata, Languages and Programming, pages 1–12, Berlin, Heidelberg, 2006. Springer Berlin Heidelberg. ISBN 978-3-540-35908-1.

Yang Liu, Anbu Huang, Yun Luo, He Huang, Youzhi Liu, Yuanyuan Chen, Lican Feng, Tianjian Chen, Han Yu, and Qiang Yang. FedVision: An Online Visual Object Detection Platform Powered by Federated Learning. Proceedings of the AAAI Conference on Artificial Intelligence, 34(08):13172–13179, Apr. 2020a. doi: 10.1109/IBHI.2020.3040015.

Zengqiang Yan, Jeffry Wicaksana, Zhiwei Wang, Xin Yang, and Kwang-Ting Cheng. Variation-Aware Federated Learning With Multi-Source Decentralized Medical Image Data. IEEE Journal of Biomedical and Health Informatics, 25(7):2615–2628, 2021. doi: 10.1109/JBHI.2019.8759317.

Santiago Silva, Boris A. Gutman, Eduardo Romero, Paul M. Thompson, Andre Altmann, and Marco Lorenzi. Federated Learning in Distributed Medical Databases: Meta-Analysis of Large-Scale Subcortical Brain Data. In 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), pages 270–274, 2019. doi: 10.1109/ISBI.2019.8759317.

Amazon Web Services. Amazon Rekognition API. https://aws.amazon.com/rekognition/ 2021. Accessed: 2021-06-30.

Microsoft Azure. Facial Recognition — Microsoft Azure. https://azure.microsoft.com/en-us/services/cognitive-services/face/ 2021. Accessed: 2021-06-30.

Megvii. Face++ Cognitive Services. https://www.faceplusplus.com/ 2021. Accessed: 2021-06-30.

Joseph Redmon and Ali Farhadi. YOLOv3: An Incremental Improvement. arXiv preprint arXiv:1804.02767, 2018.
A REVIEW ON VISUAL PRIVACY PRESERVATION TECHNIQUES FOR ACTIVE AND ASSISTED LIVING

Saining Xie, Ross Girshick, Piotr Dollar, Zhuowen Tu, and Kaiming He. Aggregated Residual Transformations for Deep Neural Networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), July 2017.

Amazon Inc. Amazon Mechanical Turk. https://www.mturk.com/, 2021. Accessed: 2021-06-30.

José Ramón Padilla-López, Alexandros Andre Charaouei, Feng Gu, and Francisco Flórez-Revuelta. Visual Privacy by Context: Proposal and Evaluation of a Level-Based Visualisation Scheme. Sensors, 15(6):12959–12982, 2015.

Wiktoria Wilkowska, Julia Offermann van Heek, Francisco Florez-Revuelta, and Martina Zießle. Video Cameras for Lifelogging at Home: Preferred Visualization Modes, Acceptance, and Privacy Perceptions among German and Turkish Participants. International Journal of Human–Computer Interaction, 37(15):1436–1454, 2021. doi: 10.1080/10447318.2021.1888487.

P.Jonathon Phillips, Harry Wechsler, Jeffery Huang, and Patrick J. Rauss. The FERET Database and Evaluation Procedure For Face-Recognition Algorithms. Image and Vision Computing, 16(5):295–306, 1998. ISSN 0262-8856. doi: https://doi.org/10.1016/S0262-8856(97)00070-X. URL https://www.sciencedirect.com/science/article/pii/S026288569700070X

Ning Zhang, Manohar Paluri, Yaniv Taigman, Rob Fergus, and Lubomir Bourdev. Beyond Frontal Faces: Improving Person Recognition Using Multiple Cues. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2015.

AT&T Laboratories Cambridge, 2002. URL https://git-disl.github.io/GTDLBench/datasets/att_face_dataset/.

Liyue Fan. Image Pixelization with Differential Privacy. In Florian Kerschbaum and Stefano Paraboschi, editors, Data and Applications Security and Privacy XXXII, pages 148–162, Cham, 2018. Springer International Publishing. ISBN 978-3-319-95729-6.

Hong-Wei Ng and Stefan Winkler. A Data-Driven Approach To Cleaning Large Face Datasets. In 2014 IEEE International Conference on Image Processing (ICIP), pages 343–347, 2014. doi: 10.1109/ICIP.2014.7025068.

Neeraj Kumar, Alexander C. Berg, Peter N. Belhumeur, and Shree K. Nayar. Attribute and Simile Classifiers For Face Verification. In 2009 IEEE 12th International Conference on Computer Vision, pages 365–372, 2009. doi: 10.1109/ICCV.2009.5459250.

Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep Learning Face Attributes in the Wild. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), December 2015.

Gary B. Huang, Marwan Mattar, Tamara Berg, and Eric Learned-Miller. Labeled Faces in the Wild: A Database for Studying Face Recognition in Unconstrained Environments. In Workshop on Faces in ’Real-Life’ Images: Detection, Alignment, and Recognition, Marseille, France, October 2008. Erik Learned-Miller and Andras Ferencz and Frédéric Jurie. URL https://hal.inria.fr/inria-00321923

Weihong Deng, Jiani Hu, Nanhai Zhang, Binghui Chen, and Jun Guo. Fine-Grained Face Verification: FGLFW Database, Baselines, and Human-DCMN Partnership. Pattern Recognition, 66:63–73, 2017. ISSN 0031-3203. doi: https://doi.org/10.1016/j.patcog.2016.11.023. URL https://www.sciencedirect.com/science/article/pii/S003132031630382X

Ahsan Jalal and Usman Tariq. The LFW-Gender Dataset. In Chu-Song Chen, Jiwen Lu, and Kai-Kuang Ma, editors, Computer Vision – ACCV 2016 Workshops, pages 531–540, Cham, 2017. Springer International Publishing. ISBN 978-3-319-54526-4.

Yann LeCun. The MNIST Database of Handwritten Digits. http://yann.lecun.com/exdb/mnist/, 1998. Accessed: 2021-09-13.

Martin Abadi, Andy Chu, Ian Goodfellow, H. Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep Learning with Differential Privacy. In Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security, CCS ’16, page 308–318, New York, NY, USA, 2016. Association for Computing Machinery. ISBN 9781450341394. doi: 10.1145/2976749.2978318.

Alex Krizhevsky. Learning Multiple Layers of Features from Tiny Images. Master’s thesis, University of Toronto, 2009.

Sami Abu-El-Haija, Nisarg Kothari, Joonseok Lee, Apostol (Paul) Natsev, George Toderici, Balakrishnan Varadarajan, and Sudheendra Vijayanarasimhan. YouTube-8M: A Large-Scale Video Classification Benchmark. In arXiv:1609.08075, 2016. URL https://arxiv.org/pdf/1609.08075v1.pdf
Kok-Seng Wong, Nguyen Anh Tu, Anuar Maratkhan, and M.Fatih Demirci. A Privacy-Preserving Framework for Surveillance Systems. In 2020 the 10th International Conference on Communication and Network Security, ICCNS 2020, page 91–98, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 9781450389037. doi: 10.1145/3442520.3442524.

Shiqi Yu, Daoliang Tan, and Tieniu Tan. A Framework for Evaluating the Effect of View Angle, Clothing and Carrying Condition on Gait Recognition. In 18th International Conference on Pattern Recognition (ICPR’06), volume 4, pages 441–444, 2006. doi: 10.1109/ICPR.2006.67.

Wei Yang, Ping Luo, and Liang Lin. Clothing Co-Parsing by Joint Image Segmentation and Labeling. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2014.

Catalin Ionescu, Dragos Papava, Vlad Olaru, and Cristian Sminchisescu. Human3.6M: Large Scale Datasets and Predictive Methods for 3D Human Sensing in Natural Environments. IEEE Transactions on Pattern Analysis and Machine Intelligence, 36(7):1325–1339, 2014. doi: 10.1109/TPAMI.2013.248.

Karla Brkić, Tomislav Hrkač, and Zoran Kalafatić. Protecting the privacy of humans in video sequences using a computer vision-based De-identification pipeline. Expert Systems with Applications, 87:41–55, 2017. ISSN 0957-4174. doi: https://doi.org/10.1016/j.eswa.2017.05.067. URL https://www.sciencedirect.com/science/article/pii/S0957417417303986.

Amir Shahroudy, Jun Liu, Tian-Tsong Ng, and Gang Wang. Ntu rgb+d: A large scale dataset for 3d human activity analysis. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

Zihao W. Wang, Vibhav Vineet, Francesco Pittaluga, Sudipta N. Sinha, Oliver Cossairt, and Sing Bing Kang. Privacy-preserving action recognition using coded aperture videos. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, June 2019.

Jun Liu, Amir Shahroudy, Mauricio Perez, Gang Wang, Ling-Yu Duan, and Alex C. Kot. NTU RGB+D 120: A Large-Scale Benchmark for 3D Human Activity Understanding. IEEE Transactions on Pattern Analysis and Machine Intelligence, 42(10):2684–2701, 2020b. doi: 10.1109/TPAMI.2019.2916873.

Cathal Gurrin, Rami Albatal, Hideo Joho, and Kaori Ishii. A Privacy by Design Approach to Lifelogging. In Digital Enlightenment Yearbook 2014, pages 49–73. IOS Press, 2014.

Susanne Barth and Menno D.T. de Jong. The Privacy Paradox – Investigating Discrepancies Between Expressed Privacy Concerns and Actual Online Behavior – A Systematic Literature Review. Telematics and Informatics, 34(7):1038–1058, 2017. ISSN 0736-5853. doi: https://doi.org/10.1016/j.tele.2017.04.013. URL https://www.sciencedirect.com/science/article/pii/S0736585317302022