[[1]](#footnote-1)

Face Privacy Protection and Self-decryption Method Based on Humanoid Association Mechanism

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***Abstract*—** **With the large-scale industry application of artificial intelligence and video surveillance, massive video data storage and personal privacy issues are highlighted, which restrict the application expansion. From the perspective of humanoid memory mechanism, we propose a video abstraction encryption and decryption algorithm based on high and low dimensional information association cognitive mechanism, which uses face recognition algorithm to locate human faces and encrypt the original video with mosaic encryption method, and then perform spatio-temporal index encoding, and further use abstract face feature memory to match and decode with the same identity person to construct a de-mosaic decryption key function. The core innovation is the humanoid memory mechanism for parsing and modelling, and combined with specific AI techniques such as YOLO and GAN for initial experimental validation in face encryption and decryption. The algorithm research will be important in the research of video information compression and storage, person re-identification and personal privacy protection.**

***Index Terms*—Enter keywords or phrases in alphabetical order, separated by commas. For a list of suggested keywords, send a blank e-mail to** [keywords@ieee.org](mailto:keywords@ieee.org) **or visit** <http://www.ieee.org/organizations/pubs/ani_prod/keywrd98.txt>

# I. INTRODUCTION

The surveillance cameras distributed in all corners of the city play an indispensable role in the city security management. Surveillance video/image data collection and analysis based on AI and IOT technologies has been an important technical grip for different scenes in smart city development.

The extraction of trust information from surveillance data has attracted the interest of many researchers and has led to the analysis of images from numerous IoT vision sensors [1-3]. However, the large-scale deployment of vision sensors leads to a number of challenges: 1) First, the huge number of camera video images leads to a data disaster. At 30 frames per second and 5MB per image, a single camera generates a data storage requirement of 12,656.25Gb a day, while IHS research indicates that there will be over one billion surveillance cameras worldwide in future. These video stores take up a large amount of hardware resources, and no data center can withstand the daily growth of video data, which must be overwritten on a regular basis [2]. Secondly, information redundancy in massive camera video data leads to key information being overwritten and video-based information retrieval being difficult [3]. In addition, massive video transmission takes up a large amount of communication bandwidth, and communication costs are high, making it difficult to achieve widespread cameras for collaborative use to achieve mega-city governance [4]. Meanwhile surveillance cameras have led to the leakage of residents' biometric privacy, raising ethical and regulatory concerns. How to safeguard the functionality of surveillance cameras while improving the above challenges has become a research direction for a wide range of scholars.

In this paper, we take a humanoid cognitive perspective to carry out theoretical research for exploring new models of large-scale camera urban applications. We humans, from infants to the elderly, perceive a large amount of picture information with both eyes over decades and can have long-term clear memories of the people and things we experienced. However, we are often unable to reproduce all of the image information that occurred, but rather combine it with high-dimensional semantic abstraction to achieve coarse-grained picture recall. We also tend to remember familiar faces not through detailed facial features such as single or double eyelids, but into general impressions of higher-dimensional semantic information. In addition, the high-dimensional abstract semantics in our human brain memory plays an important role in blurring human decryption recognition. Humans can recognize acquaintances through blurred or partially blurred facial images, but not strangers. The process of humanoid perceptual memory mechanism to handle the massive amounts of video data is difficult to have a theoretical explanation. But the association between low-dimensional fine-grained information and higher-dimensional coarse-grained information for humanoid perceptual data compression and decryption has theoretical significance and practical value, which are worth using for processing massive surveillance vidio data. In this paper, we try to propose an autonomous face degradation encryption and decryption algorithm based on the above humanoid association memory mechanism.

The main contributions are summarized as follows.

1. 加解密算法流程
2. 加密算法
3. 解密算法

# II. RELATED WORK.

## A. face recognition of video surveillance

In the perspective of recent advances in the field of AI-driven face recognition of video surveillance, the human face object tracing for video surveillance has gained widespread adoption in urban security and community management. A lot of scholars are committed to the research of computer vision technique with promising accuracies and efficiencies for face recognition and object detection [5-7]. The face recognition methods mainly include 1) traditional methods, which rely on hand-crafted feature extraction techniques and a pre-trained classifier along with fusion, and 2) deep learning methods, which automatically learn features and classifiers together utilizing enormous quantities of data[10,13, 14]. With the development of deep learning technology, the application boundary of face recognition will be gradually opened. The majority of face recognition in video surveillance today is "closed-set," which only recognizes the identity of previously registered objects. However, "open-set" has gained popularity as a result of the differences between the source and target domains, which make it less effective when transferring face recognition systems from controlled environments to uncontrolled scenes. Suandi proposed fuzzy ARTMAP neural networks to solve the open-set single-sample face recognition problem and an automatic pose normalization technique without model fitting and human intervention, which greatly improves the performance of open-set single-sample face recognition methods in surveillance environments [9,11]. The "open-set" face recognition prone to increase the human privacy exposure degree in the ubiquitous city surveillance network.

The low resolution of urban monitoring picture and the difficulty of small face feature extraction are being changed. Even though the surveillance cameras are usually placed far away from the objects and the resolution of the captured face images is low due to distance, extensive research has been carried out for recognizing acceptable recognition features at low quality video frames. Zhao et al. took an end-to-end approach to match high-resolution (HR) images with low-resolution (LR) images in surveillance videos[8]. Singh et al. improved the number of descriptors in the image and mitigates the effects of noise based on super-resolution faces[12]. Dharrao et al. used the Viola-Jones algorithm to detect the face part in the video sequential frames and improved the quality of the face part by applying a super-resolution scheme based on bicubic interpolation[15]. In addition, the multi-resolution convolutional neural networks (MRCNN) and anti-aliasing techniques were adopted to solve the low-resolution problems[16].

The development trend of face recognition technologies shows that the challenge of citizen's face privacy feature under the ubiquitous cameras is more and more serious. How to explore a new paradigm for large-scale camera urban applications from the perspective of humanoid cognition by performing face reduction encryption on the recognized video images are meaningful.

## B. Face encryption and decryption algorithm

The problem of privacy leakage has aroused widespread concern. Face recognition of video surveillance have become ubiquitous in daily lives, but it is difficult to balance between intelligent vision applications and personal privacy protection. In addition to improving relevant laws and regulations to regulate the acquisition, storage and use of videos, corresponding technical measures are needed to protect personal privacy. The cryptography-based face privacy protection scheme selectively encrypts the face region in the video that shows the identity and can be decrypted to recover the original video in case of future legitimate demand. How to integrate the autonomous face degradation encryption and decryption algorithm of humanoid association memory mechanism into AI face recognition algorithm is an urgent breakthrough direction.

Most of the existing face encryption schemes are homomorphic-based[18-26]. There are three different types of homomorphic encryption schemes: (1) partially homomorphic encryption, (2) somewhat homomorphic encryption and (3) fully homomorphic encryption (FHE).Tamiya et al. proposed a successful homomorphic encryption-based face template protection scheme by computing the squared Euclidean distance between facial features with a single homomorphic multiplication method[20]. Román et al. suggested using the Kyber and Saber public key encryption (PKE) algorithms along with homomorphic encryption (HE) in facial recognition systems to achieve smaller protected template and key sizes and faster execution times than other HE schemes that use lattices[21]. The use of fully homomorphic encryption algorithms provides a higher level of privacy authentication for the queried face. Huang offered a successful, privacy-preserving face verification method based on a corrupted circuit and fully homomorphic encryption[22]. Some researchers used CKKS fully homomorphic encryption to encrypt the normalised facial feature vector [18,23].

Due to the low computational efficiency of using homomorphic encryption, other studies tried to find lightweight algorithms to encrypt faces. Tan et al. proposed a novel approach to implement video-based ring-learning (ring-LWE) cryptography for face encryption and decryption on a graphics processing unit (GPU)[29].Duong-Ngoc et al. proposed a novel method to comprehensively protect facial images extracted from videos based on NewHope cryptography for post-quantum cryptosystems, greatly reducing the time for encryption and decryption [27]. Zhao et al. proposed and implemented a simple and efficient speckle-based optical cryptosystem to encrypt face images by seemingly random optical speckles at the speed of light, by training an cryptographic neural network to decrypt face images from random speckles [28]. A fast block scrambling method was used to scramble the detected faces [31,32]. In addition, an encryption technique using face biometrics to generate random phase masks [33]. A THM (Tent-Henon Map) chaotic encryption of faces was proposed in combined with the properties of tent chaos and Henon chaos[34]. Liu proposed a RGB image encryption algorithm based on DNA encoding and chaos map [35]. Wu proposed a Generative Adversarial Network (GAN)-based method to encrypt facial features using Wasserstein Generative Adversarial Network Encryption (WGAN-E) [36]. Ashiba used a graph theory-based graph first decomposition mask (GFH) coding algorithm[37]. There are still room for improvements in terms of computational communication efficiency and privacy-preserving effects. Active perception of key privacy features for target encryption based on humanoid cognitive mechanism provides a preliminary exploration in this direction.

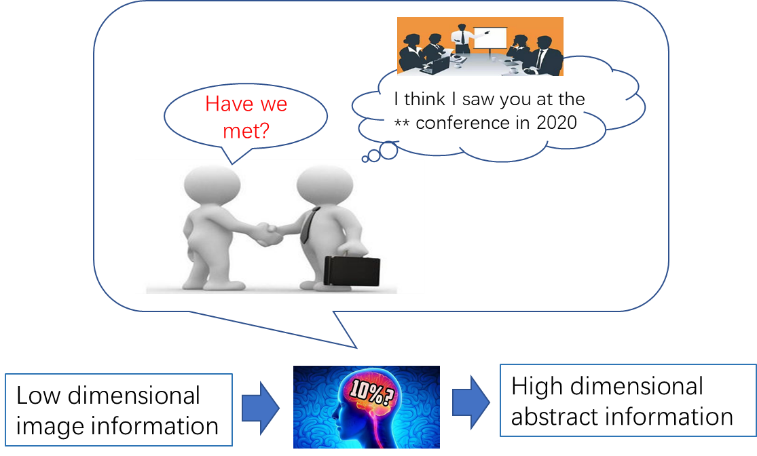
C.Humanoid memory cognition

Human brain is a typical encryption and decryption processing device with low energy consumption and high efficiency. The brain can store learned concepts in memory and recall them when it sees partial or broken patterns. Franklin et al. proposed a structured event memory model (SEM) of event cognition, illustrating human abilities in event segmentation, memory and generalization. SEM can be extended to a high-dimensional input space to produce humanoid event segmentation for natural video data, and illustrates a wide range of memory phenomena [38]. Sun et al. proposed a new model humanoid visual cognitive and language-memory network for visual dialog (HVLM) to simulate global and local dual-view cognition in the human visual system to comprehensively understand images [39]. Inspired by humanoid perception and memory we explored a new model of face privacy protection for urban large-scale camera monitoring with . The research of this algorithm is of great significance to the research of video information compression and storage, character recognition and personal privacy protection.

# III. PROPOSED APPROACH

## A. Problem description.

The process of human face perception and identity recognition based on fuzzy impression memory association is highly complex. Each of us sees many faces in daily life scenarios, however, not all the information about faces are remembered. As shown in figure 1 for example, when some people meet with each other unintentionally, their mind will unconsciously recall that they have seen such a face at a certain time, place and event. Moreover, they can recall the memory of more detailed scene and clearer features. The process can actually be simplified as the human brain perceives the concrete face image information seen by the eyes to extract high-dimensional abstract semantic features. The high-dimensional abstract semantic features are retrieved and matched with the high-dimensional semantic information indexed in memory combining person, event, time and place, and the past feature-blurred memory scene is clearly reproduced in combination with the current perceived face image.

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**Fig. 1. Case: Humanoid abstract associations triggered by perceptual features.**

The general expression of the Humanoid Association is as follows.

(1)

where *I is the image, Ai* is the set of low-dimensional full-dimensional information about the *ith* people’s face perceived by the brain in the first stage, *Bi* is the set of high-dimensional abstract semantic features of *ith* people’s face formed by the brain in the mind based on *Ai*, is the encrypted data set of , *A'ip* is the decryption set partially from and , is the set of low-dimensional full-dimensional information about the face perceived by the brain in the second stage, and is the set of high-dimensional abstract semantic features formed by the brain in the mind based on . The algorithm for solving the above expression is as follows.

|  |
| --- |
| **Algorithm: encryption and decryption** |
| Input: *, Bi, A'i,*  Output: *A'ip*  For *Ai* in Brain Do encryption Key matching  Using cerebral neural network for high dimensional semantic abstraction  *f1(Ai) →AiP,* where*AiP* ⊊*Ai, i*=*1, 2,* ……  For *Bi* in Brain Do decryption  *f1(A'i) →B'i*  Find matching key *B'i* to *Bi*， where is the maximum face similarity  *P*(*A'ip | Aip*)= *f2*(*B'i* ∩ *Bi*)→1  For *AiP* in Brain Do encryption  *f3*(*AiP, Bi*) →*A'ip*  return *A'ip* |

This paper combines the above humanoid perceptual associative memory algorithm with the face encryption and decryption requirements of surveillance video to solve the following problems.

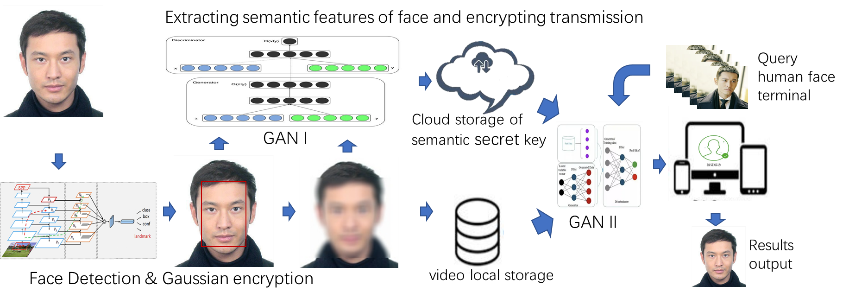
1) To modeling the humanoid cognitive mechanism, the high-dimensional abstract memory and compressed perception process f1 function need to be solved. and propose an artificial intelligence algorithm for solving Aip and Bi to identify and locate faces in videos, extract high-dimensional semantic features while encrypting video faces with reduced resolution.

2) Drawing on humanoid associative memory mechanism, the algorithm models the memory storage of high-dimensional semantic features and associative matching f2, and proposes a recall-triggered matching index mechanism to achieve associative memory matching based on B1 and B2.

3) Drawing on the humanoid perception-triggered recall mechanism, the associative recall of high-dimensional semantic features A1 and B2 low-resolution video is modelled to solve f3 for indexing location as well as high-resolution decryption.

## B. AI Methodologies

Inspired by humanoid perception, compressed memory, and associative recall, we propose an algorithmic framework that can be used to encrypt/decrypt surveillance video faces as shown in the figure below.

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**Fig. 2. Framework of personal self-decryption.**

**1) Encryption method**

For the video frame input *V*, the YOLO5-face deep learning model *ф* is used to achieve the recognition and localisation of faces by the surveillance cameras at the edge end, into obtaining *A1* = ф(*V*), YOLO5-face is chosen because the model targets the face recognition segmentation needs, adds landmark branches in YOLOV5, and improves the accuracy of face detection and localisation by regressing the wing loss function through five facial key points. The wing-loss function and the overall loss function are as follows.

(2)

(3)

After completing face target detection, the face in the recognition frame is subjected to Gaussian blurring, i.e. a Gaussian convolution budget is applied to the face image with the probability density distribution function shown below.

(4)

After the above face localization + Gaussian blurring, a video will be obtained in which part of the face is displayed by encrypted blurring and the rest is displayed normally, this video corresponds to in Eq. 1) above and is stored locally. The solving process of *f1(Ai)* is thus completed.

2) Key storage and matching

Unlike traditional video surveillance systems, this method no longer stores the original video, but chooses to locally store the encrypted video, while uploading the high-dimensional abstract semantics to the cloud for subsequent processing and analysis. For example, for the face retrieval service of post-surveillance, as the local storage of encrypted faces loses a large amount of face feature information, the video cannot be retrieved for review, but needs to be indexed for the high-dimensional semantic B for query service, which is similar to the human perceptual memory.

In order to equip AI systems with human-like high-dimensional abstract computational capabilities, we use the pixel2style2pixel (pSp) model to generate latent codes to obtain high-dimensional abstract semantics . The model expression is as follows:

)

(5)

Taking the previous original video A1 as input, L(\*) denotes the latent code of obtaining A1 to get the abstract semantic feature B1.E(\*) denotes the Encoder of the pSp model.The potential vector obtained from is summed with the average potential vector w ̅ in the network model to obtain the final potential vector. This step usually helps to balance the quality and diversity of the generated images.

After extracting the high-dimensional abstract semantic feature from the original video using the above model, the temporal sequence of the video frames, the latitude, longitude and pixel coordinates of the edge camera itself are fused as the symbolic bit encoding of the high-dimensional abstract semantic feature, and the mapping relationship between the high-dimensional abstract semantic feature and the encrypted face image frames is associated with the above symbolic bit encoding to facilitate subsequent video decryption work. These together serve as the key for decrypting the and are stored in the cloud key pool.

The high-dimensional abstract semantic features learned by the above model are often not interpretable, so it is necessary to conduct an in-depth study of the abstract semantics and to investigate how to match face retrieval by both. At present, in the field of face recognition, the technology of matching face features by deep neural networks to determine the identity of faces is relatively mature, while using abstract semantics B1 and B2 as the identity key to determine the identity of faces becomes more challenging.

The identity recognition of a face is divided into two parts, one part is to determine the identity by matching the specific features of the face, not simply by comparing the specific features; the other part belongs to the impression abstract semantics, just like the general impression given by the face, and the identity is determined by matching the specific features of the face. When a face needs to be decrypted, the same model is first used to extract features from the face, and then certain dimensions are taken to match with the features in the human cloud keystore, and the accuracy of the matching is calculated. Thus the recall triggered call function *f2*(*B'i* ∩ *Bi*) is implemented.

3) Decryption process

The previous section implements the original video encryption and the process of key storage and query matching. This section discusses how to output the the decrypted videoby the encrypted video , high-dimensional abstract semantics and the facein the second video that matches the identity of a person in the first video.

This process is equivalent to associative memory, where we can associate images from the past with the current image, and the blurred features of a face can often be made clear again.

To this end, we build an open-set face re-recognition and decryption model based on styleGAN generators. Firstly, through the method described in the previous section, the high-dimensional abstract semantics is extracted from . Then, the similarity is calculated between and all the high-dimensional abstract semanticsin the key pool corresponding to the encrypted video , and the with the highest similarity is taken. If the similarity is lower than a certain threshold, the face is judged to be strange and further decryption is rejected; if the similarity exceeds a certain threshold, the high-dimensional abstract semantics is added to the generator with as input as a constraint, and the decrypted video *A'ip* is output. Then the solution of the decryption *f3*(*AiP, Bi*) in the human-like memory mechanism is obtained.

# IV. EXPERIMENTS AND RESULTS

## A. Dataset

数据集部分暂时不知道怎么改

数据集使用的是generated\_yellow-stylegan2

老化的图像是怎么生成的

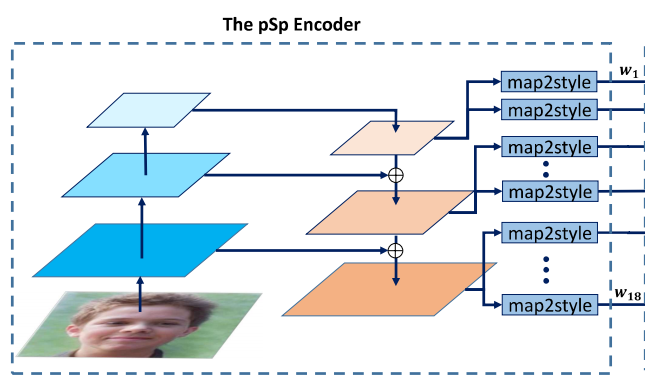
We acquired face images based on temporal head pose changes of experimental subjects of different genders and ages, and obtained a dataset with Gaussian encryption paired with the original images using a method based on YOLO5-face with Gaussian encryption. 1000 images were acquired for each person, for a total of 20 people with a total of 20,000 images, in order to exclude other background features in the images from the subsequent GAN network high-dimensional semantic abstraction In order to exclude other background features in the images from the subsequent GAN network high-dimensional semantic abstraction, all faces were collected in the same background for the face collection process. The figure below shows a portion of the extracted paired dataset. This data encryption process also validates the feasibility of the video encryption method.



**Fig. 3. Encryption method test**

## B. GANI Training and Encryption Process

We use the pixel2style2pixel (pSp) model to complete the training of the above dataset,which uses the standard feature pyramid on top of ResNet to extract the feature mapping.For each of the 18 target styles, a small mapping net is trained to extract the learned styles from the corresponding feature maps.0-2 styles are generated from small feature mappings, 3-6 styles are generated from medium feature mappings,and 7-18 styles are generated from large feature mappings. Corresponding to the high-dimensional abstract memory and compressed perception processes of the human brain in humanoid cognitive mechanisms, high-dimensional feature information is generated from smaller feature mappings.



**Fig. 4.此图是网上的，需要修改**

We first extract the original face P1 from the training set, use psp encoder to train P1, extract multi-dimensional face features from low-dimensional to high-dimensional, and integrate and encrypt this information to form a key, which is bound to the processed face identity ID, added to the face key pool, and stored in existing\_faces.pkl.

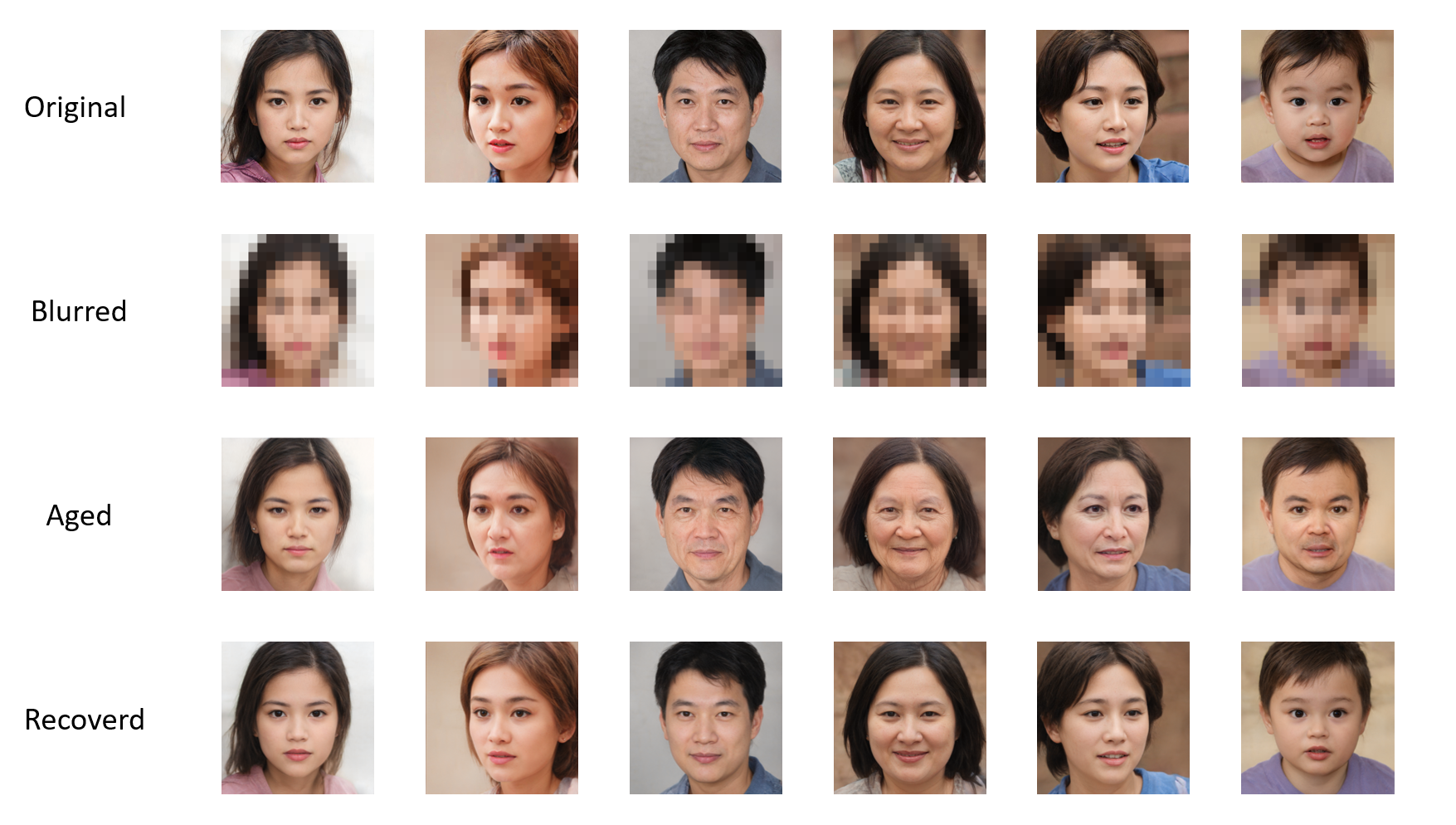
## C. GANI Decryption Process

For decryption, a newly captured face is input. The newly captured face P2 is encoded using the same coding model to extract features, and the extracted features are taken in certain dimensions and matched with the features in the face feature key pool. Based on the similarity of the face features determine whether it has appeared in the dataset. If it has not appeared, the decryption is rejected. If it has appeared, then confirm its identity ID and input it into the generator of styleGAN with the previously stored feature key, decrypt the face with the mosaic of the specified ID, and then output the decrypted face. styleGAN uses an unsupervised image super-resolution method to transform low-resolution images into high-quality, high-resolution images, thus reproducing the detailed features of the image such as skin color, eyes, lips, and so on.

## D. Results Discussion

**a) Encryption and decryption effects**

The encryption and decryption effects are shown below.Original denotes the original face P1.Blurred denotes the encrypted face.Aged denotes the photo of Original after face aging treatment, most of the photos are set to be aged to 50 years old as the newly captured face P2 in this experiment, and Recoverd denotes the face after decryption under the guidance of the previously stored face feature key.



**Fig. 5.**

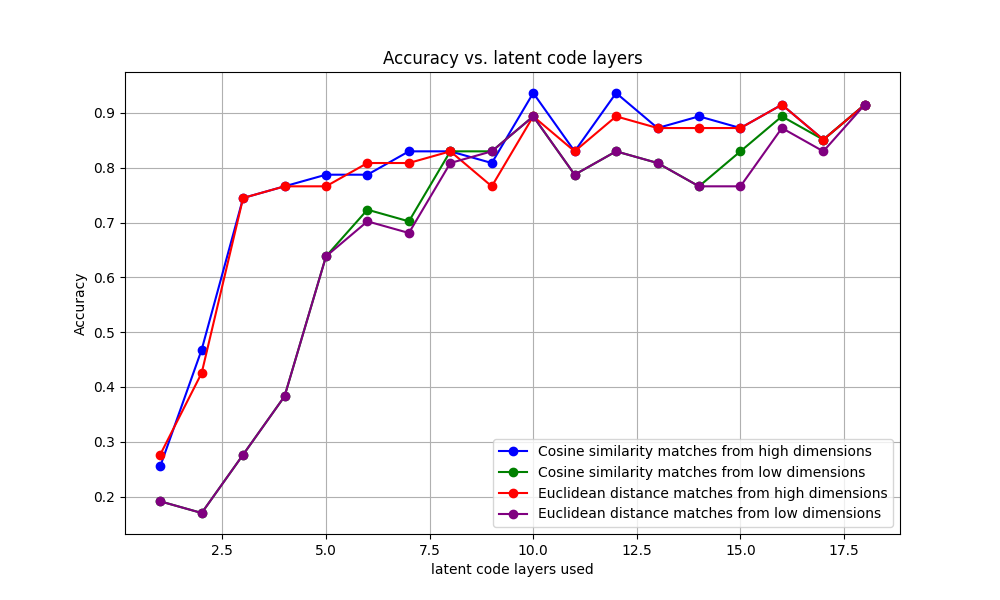
b) Feature Matching Methods

In the experiment, there are 47 photos that have been processed by face aging, and after extracting the features with the same model, certain dimensions are taken to match with the features in the face feature key pool, and the accuracy of matching is calculated.

Different dimension selections and different matching criteria are chosen in the experiment to fully explore the impact of different matching methods. The dimension selection combinations used are matching from high dimension:1, 1-2, 1-3, ... , 1-18; and from lower dimensions: 18, 17-18, 16-18, ... ,1-18.The matching criteria used are cosine similarity (taking the highest similarity) and Euler distance (taking the smallest distance). The matching accuracies of different matching methods are shown in the following table.

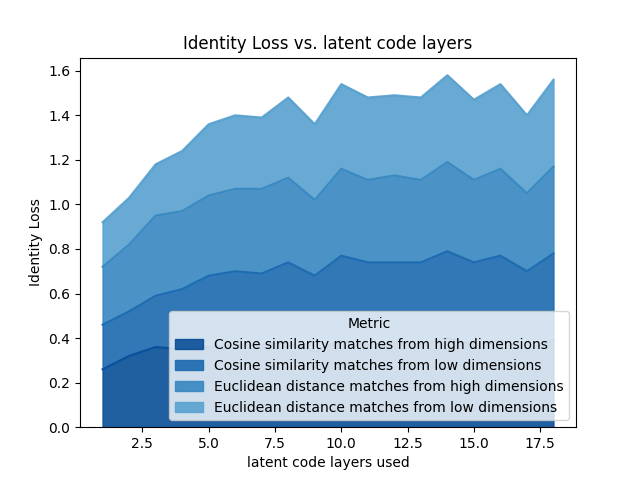
|  |  |  |
| --- | --- | --- |
| Table 1. Matching from high dimensions | | |
| latent code layers used | Accuracy | |
| Cosine similarity | Euclidean distance |
| 1-1 | 0.2553 | 0.2766 |
| 1-2 | 0.4681 | 0.4255 |
| 1-3 | 0.7447 | 0.7447 |
| 1-4 | 0.7660 | 0.7660 |
| 1-5 | 0.7872 | 0.7660 |
| 1-6 | 0.7872 | 0.8085 |
| 1-7 | 0.8298 | 0.8085 |
| 1-8 | 0.8298 | 0.8298 |
| 1-9 | 0.8085 | 0.7660 |
| 1-10 | 0.9362 | 0.8936 |
| 1-11 | 0.8298 | 0.8298 |
| 1-12 | 0.9362 | 0.8936 |
| 1-13 | 0.8723 | 0.8723 |
| 1-14 | 0.8936 | 0.8723 |
| 1-15 | 0.8723 | 0.8723 |
| 1-16 | 0.9149 | 0.9149 |
| 1-17 | 0.8511 | 0.8511 |
| 1-18 | 0.9149 | 0.9149 |

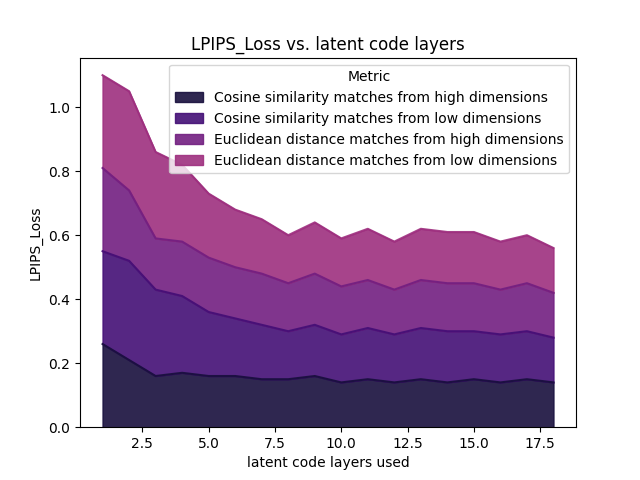
|  |  |  |
| --- | --- | --- |
| Table 2. Matching from low dimensions | | |
| latent code layers used | Accuracy | |
| Cosine similarity | Euclidean distance |
| 18-18 | 0.1915 | 0.1915 |
| 18-17 | 0.1702 | 0.1702 |
| 18-16 | 0.2766 | 0.2766 |
| 18-15 | 0.3830 | 0.3830 |
| 18-14 | 0.6383 | 0.6383 |
| 18-13 | 0.7234 | 0.7021 |
| 18-12 | 0.7021 | 0.6809 |
| 18-11 | 0.8298 | 0.8085 |
| 18-10 | 0.8298 | 0.8298 |
| 18-9 | 0.8936 | 0.8936 |
| 18-8 | 0.7872 | 0.7872 |
| 18-7 | 0.8298 | 0.8298 |
| 18-6 | 0.8085 | 0.8085 |
| 18-5 | 0.7660 | 0.7660 |
| 18-4 | 0.8298 | 0.7660 |
| 18-3 | 0.8936 | 0.8723 |
| 18-2 | 0.8511 | 0.8298 |
| 18-1 | 0.9149 | 0.9149 |

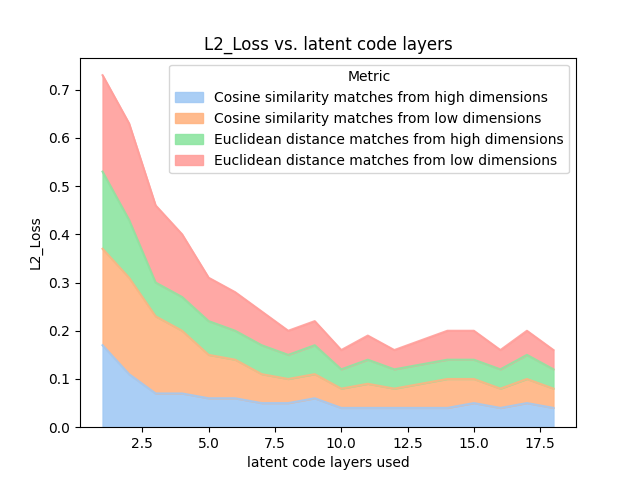


From the above figure, it can be seen that selecting the cosine similarity (taking the highest similarity) as the matching criterion and selecting some high-dimensional features as the basis of matching is more effective.

3) Multiple loss functions







# V. Conclusion

## In this paper, we propose a video abstraction encryption and decryption algorithm based on high and low dimensional information association cognitive mechanism for massive video data disaster and personal privacy problems. When storing the video, the YOLO-based face recognition and face encryption algorithm is used to encrypt the video, while the high and low dimensional semantic information of the face is extracted to form a feature key, and index association is established with the face in the video and stored in the key pool corresponding to the video. When decrypting, the features extracted from the specified new faces are used to search in the key pool, and the matched faces are reduced to clear faces using the GAN model. We initially validate the feasibility of this video encryption and decryption algorithm on a self-built dataset. Our research has important implications in terms of how to strike a balance between privacy protection and machine vision research. In the future, this algorithm is promising to play an important role in privacy protection and big data storage, face re-identification, and other fields.

Appendix

Appendixes, if needed, appear before the acknowledgment.

Acknowledgment

The preferred here.

# 

# IEEE Guidelines and Policies

A full.

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1. 有一个年轻时候的人脸，先经过高斯加密，得到一个模糊的人脸，存储在本地
2. 将这个年轻的人脸，上传到云端通过psp的encoder抽取密钥，形成人脸密钥特征池，存储在云端
3. 当需要调取某一个人的监控，获得了他当前的人脸照片，相当于就是年老以后的人脸，
4. 对当前的年老以后的人脸同样经过psp的encoder抽取密钥
5. 拿着这个密钥去跟云端密钥池中的密钥进行匹配，找到了匹配的密钥
6. 这个密钥附带有时空索引等，所以只要知道是哪个密钥就知道要解密的部分是哪里，然后将这个密钥放到了styleGAN的生成器中生成解密以后的人脸，并用这个人脸将视频对应区域进行还原，就可以得到解密之后的视频了。
7. 本地存储的是高斯模糊以后的视频，这个视频是没有办法直接解密的，所以必须通过GAN来生成解密之后的人脸，从而才能够进行人脸的恢复.
8. （这个地方稍微改了一下，感觉本地不做复杂度很高的训练过程也可以，可以把原始视频中的人脸上传到云端以后再做提取密钥的过程）

对于人脸和视频没有做下标区分，现在写的还有一点不清晰

**TABLE I**

|  |  |  |
| --- | --- | --- |
| MATCHING FROM HIGH DIMENSIONS. | | |
| latent code layers used | **Accuracy** | |
| Cosine similarity | Euclidean distance |
| 1-1 | 0.2553 | 0.2766 |
| 1-2 | 0.4681 | 0.4255 |
| 1-3 | 0.7447 | 0.7447 |
| 1-4 | 0.7660 | 0.7660 |
| 1-5 | 0.7872 | 0.7660 |
| 1-6 | 0.7872 | 0.8085 |
| 1-7 | 0.8298 | 0.8085 |
| 1-8 | 0.8298 | 0.8298 |
| 1-9 | 0.8085 | 0.7660 |
| 1-10 | 0.9362 | 0.8936 |
| 1-11 | 0.8298 | 0.8298 |
| 1-12 | 0.9362 | 0.8936 |
| 1-13 | 0.8723 | 0.8723 |
| 1-14 | 0.8936 | 0.8723 |
| 1-15 | 0.8723 | 0.8723 |
| 1-16 | 0.9149 | 0.9149 |
| 1-17 | 0.8511 | 0.8511 |
| 1-18 | 0.9149 | 0.9149 |

**TABLE Ⅱ**

**MATCHING FROM LOW DIMENSIONS.**

|  |  |  |
| --- | --- | --- |
|  | | |
| latent code layers used | **Accuracy** | |
| Cosine similarity | Euclidean distance |
| 18-18 | 0.1915 | 0.1915 |
| 18-17 | 0.1702 | 0.1702 |
| 18-16 | 0.2766 | 0.2766 |
| 18-15 | 0.3830 | 0.3830 |
| 18-14 | 0.6383 | 0.6383 |
| 18-13 | 0.7234 | 0.7021 |
| 18-12 | 0.7021 | 0.6809 |
| 18-11 | 0.8298 | 0.8085 |
| 18-10 | 0.8298 | 0.8298 |
| 18-9 | 0.8936 | 0.8936 |
| 18-8 | 0.7872 | 0.7872 |
| 18-7 | 0.8298 | 0.8298 |
| 18-6 | 0.8085 | 0.8085 |
| 18-5 | 0.7660 | 0.7660 |
| 18-4 | 0.8298 | 0.7660 |
| 18-3 | 0.8936 | 0.8723 |
| 18-2 | 0.8511 | 0.8298 |
| 18-1 | 0.9149 | 0.9149 |

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