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Survey on Face Recognition in the Scrambled Dataset by Using Many Kernels

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Abstract

Expressions of face are an important factor in the modern human interacting systems that find the difference between the human expressive states at different times. Scrambling or encryption of data in a captured image gives a solution to an enhanced system. Consider the Internet of Things (IoT) directed distribution of image/video, the encryption of face is considered as a major part for protection of privacy. For this, biometric verification is required to get the encrypted data. After the encryption procedure the face models become chaotic signals. Using various face recognition methods, we can obtain the data, which is a traditional method. This survey paper presents the different techniques which is used to getting the face from the decrypted data by using many kernel methods.

Index Terms: *face scrambling, many kernels, random discriminant analysis, Internet-of-things.*

I. Introduction

By comparing different encryption techniques, face scrambling is used to encipher or hiding the image, not data. By using manual tries it can be easily unscrambled. Face scrambling is simpler than many encryption algorithms and is computationally feasible. Face scrambling can be performed in many ways. Some scrambling technique like masking and cartooning will misplace the facial data. One of the basic step called Arnold transform is use to recover the data from encrypted information.

A face consists of many semantic components like eyes, nose and mouth. An encrypted face appearance is different from the original or correct face of an image. For a normal face we can apply the 3D model, but a scrambled face it is difficult to apply. This survey paper shows a comparison of different face recognition techniques.

II. Related Works

A. Face Scrambling

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Many researches are done in the visual surveillance field; in visual surveillance scrambling is used for protecting the security or privacy in general security. An encrypted image is very different from the original appearance or look of the actual face image. In many business field the scrambling purposes is limited to only privacy protection from unwanted goggling of data. So here full encryption techniques are not needed. Usually a variety of techniques are used to perform the encryption techniques.

From the visual information F.Dufaux [2] proposed a glossy encryption procedure from the whole image we encrypts the sensitive data in a parametric form which helps to protect privacy-sensitive image regions. Using secret key, the encoded data could be enciphered by performing fully or partially decryption we can obtain a protected version of original image. If we know the details of full key, we can decrypt the image in a quality levels. This method complicated and is not efficient to implement in an enciphered domain.

Scrambling helps to adjust the amounts of changes introduced. It proposes a region based transform domain scrambling technique. It helps to preserve privacy in video surveillance system. Similarly in the case of videos the main problem is detecting the regions. People who are assume to be it is privacy sensitive information. Then the region of interest (ROI) is encrypted. This technique can be applied to image transform coding the most important image transform coding are discrete cosine transform (DCT) and discrete wavelet transform (DWT). The encryption process depends on the private key. This process is done with the help of law-enforcement authorities like court or a trusted third party. The trusted third party can unlock and view the whole information or data in clear.

Arnold transform was proposed by V. I. Arnold in the research ergodic theory. Usually Arnold transform is applied in digital image. This technique is called as cat-mapping. Arnold transform is a most important retrievable scrambling technique, and it is the first step in many scrambling algorithms. By many manual tries the scrambled faces can be unscrambled. In this method, we calculate the Arnold transformation of a digital image, it produce a fully different encrypted image. Then we will encrypt the scrambled image using Tent mapping. This algorithm provides high security. Image encryption can be done in various technologies based on first one is pixel scrambled, second is the image encryption technology based on the secret sharing and secret segmentation and finally, encryption technology based on chaos as well as the dynamic systems. This method assist to envelop the faces in a digital image and it also gives high security.

In the Arnold transform, a pixel at point (x, y) is changed to another pixel point (x’, y’) by:

$$\begin{matrix}x'\\y'\end{matrix} \quad \begin{matrix}1&1\\1&2\end{matrix} \quad = \quad \begin{matrix}x\\y\end{matrix} \quad \bmod N$$

It is called a two-dimensional Arnold scrambling. Here, x and y denotes the coordinates of original pixel; N is the height or width of the square image taken; x’ and y’ are the coordinates of the scrambled or replaced pixel.

Arnold transform is an important image encryption technique. This technique cannot encrypt the image having various sizes, which is one of the weaknesses in security. To solve this problem combing the Arnold transform with some random strategies, and then performing the encryption. It is done by dividing image in to different square blocks. After that it will generate in random iterative numbers and random encryption order. Then encryption is performed in image blocks by using Arnold transform.

The proposed encryption scheme is robust and secure, which has no size limitation indicting the application to any size image. The image encryption algorithm can be classified as two types. First one spatial based method and second one frequency based method. The spatial based algorithm is achieved by changing the position of the pixels or swapping the pixels and performs the image encryption. In earlier stages the image is encrypted by applying Arnold transform and exclusive or operation.

In the encrypted image the face components are shows as a disordered or tangled manner. That is the eyes, nose, and mouth becomes chaotic patterns, R. L. Hsu and A. K. Jain [5]. Then semantic face matching approach is applied to the disordered image. This approach is based on semantic characteristics of a face. Then it produces a semantic face graph containing face components like eyes, nose and mouth in the spatial domain. Then it arranges the semantic facial components in the semantic graph in an appropriate way by using various techniques. Aligned facial components are applied for face matching which is spanned by the Fourier descriptors of facial components and is transformed to a feature space. A semantic face graph relives the whole illustration of the face by using its facial components. To identify a specific face semantic facial components are used, because these components are important factors of a facial image and it helps to describe the facial expressions. This technique is applied in statistic face modelling and also it is used for an important study for semantic facial mapping.

In semantic face recognition, it derives the weights of the facial components based on their uniqueness and visibility. It helps to perform face matching based on these components weights.

Linear dimensionality reduction such as principal Component Analysis (PCA), Independent Component Analysis (ICA) and Fishers Linear discriminant analysis (FLD) are developed for face recognition in previous stages. With the help of face recognition system, this paper shows the comparison between PCA and ICA. The relative performance of PCA and ICA architecture, ICA algorithm and the subspace distance metric are described in this paper. By testing two ICA algorithms and two ICA architectures against PCA with four different distance measures explores the space of PCA or ICA comparisons.

Principal Component Analysis (PCA) is an important face recognition technique. This recognition scheme reduces the mean squared error between the original image and the scrambled image which has different compression levels and it more optimal. Analysing the

Independent Component Analysis (ICA) in the basis vectors, it will generate spatial features that are localized. These features are constantly independent (they are not linearly decor related as with PCA). PCA is a most widely used face recognition technique; it works based on the projections of subspace. In the ease of PCA basis vectors are component from a set of training images I. In the first step, the average of the images in the training image I is computed and subtracted from the training images and produces the result as a set of data samples. These data samples area stored in an arrayed matrix X. The main advantage of ICA rather than PCA, it reduces the higher order input dependencies.

M. H. Yang [7] proposed the use of Kernel Discriminant Component Analysis (KDCA) and Kernel Fisher Linear Discriminant Analysis (KFLDA). This technique represents the low dimensional face recognition. This is called Kernel Eigen Face and Kernel Fisher Face methods. Based on the second order correlation of samples Eigen face and Fisher Face methods find the projection directions.

Given a set of m centred zero mean unit variance samples. They are $x_k = (x_{k1}, x_{k2}, \ldots, x_{kn})$ $T \in R$. The main aim of PCA is to find the direction of projections. This projection direction maximizes the variance of a subspace. Also consider the covariance matrix of the image, because this technique finds the Eigen values from the covariance matrix, C, $\lambda w = Cw$. In the case of Eigen face and Fisher face methods the image representation is based on the second order statisticsof the input image. Covariance matrix shows the second order statistics of the image. Relationship between three or more pixels represents a higher order statistical dependency. In these techniques high order statistical dependencies are not used. Comparing with ICA, Kernel Eigen Faces and Kernel Fisher Face method has minimum error rates. Independent component analysis cannot recognizing the faces effectively when the images containing to scale, pose and lighting difference.

Because ICA cannot treat these variations. Such cases the ICA algorithm not properly worked.

In a multiple-view problem the same manifold can have different shapes in different subspaces. C. Hedge [8] proposed multiple projection method. This method is applied in the same manifold. In this technique, a novel method is proposed. Here the novel method performs the linear dimensionality reduction of the multiple data. First, M number of random projections are selected, and then consider the sample points in *R*exp*N*, these sample points positioned in to an unknown k-dimensional Euclidean manifold. This sample set consists of an intrinsic dimension (ID), and it is highly accurate. Second, by using the structure of the manifold prove that the random projections are correct. In the above two cases, the number of random projections K and logarithmic N means that $K \leq M \leq N$. By performing the problem practically using a greedy algorithm and it finds the smallest size of the projection.

Y.X. Lin, T. L. Liu [9] proposed a sequence or a set of data points, which are in the second subspace and is shuffled. Then joining two sub manifolds, it will create a noisy distribution.

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Due to this two sub manifolds cannot merged. Due to this, consider it as a multiple manifold problem. Then also discover the many manifold structures. Many kernel techniques are used for discover the discriminative structures in each subspace. Then we get many kernels representation k_{ik} by applying this representation in the discriminant analysis with the kernel subspace and it also finds the discriminative projection.

R. Jiang and D. Crookes [10] develop the Deep Salience model. This model perceives the semantic feature mapping. Compared with other models like pixel contrast based colour salience, this model gives more importance to the algorithm on the structure salience, so it perceive the semantic components as well as it salient features very easily. Finally in the training data points a Gaussian mixture model is applied, which contains the learned salience maps, then the salience distribution obtained as a Gaussian functions.

$$(p|\lambda) = \sum i w_i g\ (x/\mu_i\,, \sigma_i) \qquad (1)$$

where $g(x|\ \ \mu_i,\sigma_i)$is the normalized Gaussian distribution with mean μ_i and variance σ_i . Here we use a two class GMM function. This function represents the chance of a pixel being salient or non-salient. And performing learning in the GMM mixtures, all the Gaussian distribution parameters in the GMM model are optimized. This optimized GMM model produces a distribution map, S = $(p|\lambda)$. This distribution map is called a semantic importance map. This significant map represents the significance of feature subspace and its association to semantic features.

In a biological neural system, visual salience is a significant factor. Visual salience can be modelled by using various mathematical techniques like different feature contrasts. Feature contrasts can be either locally or globally. But the main problem is that the algorithmic models provide more significance to the structural pattern of the images. It does not consider the problems of biological solutions or results. In the case of visual salience, spawning the appearance of visual stimuli along the visual cortex. This paper proposed a deep salience model. In this model, we check the input image consecutively through the deep belief propagation by using a consecutive Successive Markov Random Fields (SMRF). Due to this method, the background object or irrelevant information is automatically apart from the background image in a fully unsupervised manner.

III. Conclusion

Many techniques are used for encrypted or disordered face recognition for biometric verification. Principle Component Analysis (PCA), Independent Component Analysis (ICA) and Fishers Linear Discriminant Analysis (FLD) widely adopted face recognition techniques. These algorithms have some limitation when it applied in a scrambled image for recognizing the correct faces. To avoid these limitations we propose a newmethod Many Kernel Random Discriminant Analysis (MKRDA) to discover the patterns from scrambled signals. And this method is also combined with a salience-aware model. This salience-aware technique extracts the facial expressions and semantic components. This method is a more efficient and accurate for face recognition.

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