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Reconstruction of Patch Face Reducing Malicious Attack in Secure Computation

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ABSTRACT: Secure Computation of Face Identification (SCiFI) is a recently developed system which combines security with face recognition system and that ensures the list of faces it can identify remains private. A detailed study that shows the outcome of distorted input attacks on the system—from both a security and computer vision standpoint is given. In particular, the following is proposed, 1) a cryptographic attack that allows a fraudulent user to unnoticeably obtain a coded representation of faces on the list, and 2) a visualization approach that turns the lossy recovered codes into human-identifiable face sketches exploiting the breach.

KEYWORDS: SCiFI, Reconstruction, Fragmentation.

I. INTRODUCTION

A large research is going on computer vision is focused around facial recognition and detection. Facial recognition is a form of biometric identification and has great application in security. In identification task to determine if there is a close match between images, a system compares a single with list of images. This identification process is useful especially in surveillance for identifying terrorists, criminals, or missing people from a single shot of their face. For example, this system is useful in screening dangerous personnel from being able to board their planes in Airport authorities. An identification system makes security camera takes images of passengers and cross-examines them with a suspect list stored on the external server. The match of image is known by only the server and hence if any match results then server will notify to airport authorities. The public often believes surveillance cameras or videos are a violation of privacy. Most people do not want their day to day activities to be recorded. A compromised system links social networking faces, an appropriate response would be to implement cryptography in the system and have data encrypted. Even though people are still being recorded, encryption will protect the confidentiality of the individuals. However, by introducing cryptography, scalability and efficiency are an immediate problem. Recent developed system is Secure Computation of Face Identification (SCiFI) [1] which combines security with facial recognition. It provides secure transmissions and facial comparisons performing face identification. SCiFI is an elegant system that allows two mutually untrusting parties to represent and compute whether their two respective input face image matches efficiently and securely. The SCiFI system's protocol performs a cross-examination of faces, providing no any additional information about individual being compared or what are in the database. Hence, the suspect list is confidential and input faces in the system are only used to check for matches.

We explore the outcome of dishonest user that uses distorted inputs to attack the SCiFI protocol. Our contribution has two phases: a cryptographic attack phase and a visualization phase. In first phase we introduce an ill formed input, an attacker knows if the particular feature exists in target image. An entire vector encoding facial parts appearance and layout of a target person can be obtained by repeating this multiple times. Recovering facial vector alone constitutes an attack which is not usable by a human observer, as result is scattered set of patches. In second phase we show reconstruction of underlying face using computer vision technique.

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II. RELATED WORK

There has been a lot of work done involving human faces, such as facial recognition, modeling, and reconstruction. We will discuss some of the relevant work and its application to our work.

2.1 Modeling Human Faces

The fundamental of facial recognition is modeling human faces. We refer to Zhao and Chellappa and references therein for more details [3]. Models class is called holistic, and the entire face representation is utilized by these models. In facial recognition it has been shown that Eigen faces are a holistic approach [4]. Principal Component Analysis (PCA) direct applications are Eigen faces. In face database from covariance matrix using eigenvectors face subspace is created. Vector weights representation is done for face in the database. Now, by projecting an input face image, into the face space we obtain weights for the particular image. An identification task is done by comparing the input face image weights with one in face database .To perform reconstruction using face subspace we use a variation of PCA technique. Our goal is reconstruction of human faces from a SCiFI facial vector by using PCA to estimate regions of missing facial information in contrast to classic Eigen faces technique. Active Shape Models (ASM) [5] and their extensions, Flexible Appearance Models (FSM) [6] and Active Appearance Models (AAM)[7] are more advanced than Eigen faces. ASM introduce idea of analysis through synthesis, they are much more flexible and robust than Eigen faces. In addition to shape both FSM and AAM try to account for textural variations. The idea of splitting into two separate components appearance and spatial is utilized by SCiFI.

3-D Morphable models are powerful in modeling area. The 3-D faces from photographs are generated by these models [8]. We also want reconstruct a very natural human face from our extracted facial vector. However, our face must resemble the true face. The SCiFI system uses a part-based model to form an index-based face representation. A part-based model gives the representation of faces as collection of images or fragments corresponding to different parts of the face. Face can be turned easily into index based models if parts are fixed, because these models split up the representation of the face into different parts. For face recognition using boosting and transduction Li and Wechsler used part-based models [9].To fool an identification system they proposed the idea of an impostor to hide or occlude parts of his/her face. However, certain parts of the face that will remain unchanged, and such parts can be utilized for successful identification. As the SCiFI system is aimed to be used in security, this process helps in motivating the usage of a part-based model. A pictorial structure representations using one form of part-based models have been shown for facial recognition[10].To detect faces and human bodies in novel images pictorial structures can be used [11].However, the facial encoding does not provide the optimal way of combining the appearance and spatial information to form a patch face ,our work appearance and spatial information is encoded inside the facial vectors.

2.2 Secure Facial Recognition

Facial recognition is a large area of study in computer vision and is a very successful area in image analysis. Actually, there are three tasks (1) detection, (2) feature extraction, and (3) identification and/or verification [3]. There are two major problems that arise while combining security with facial recognition is a difficult. The facial recognition systems want to match similar inputs, for no two images of a face are going to be exactly the same is the first problem. Since cryptographic algorithms require two inputs to be exactly the same, this is a problem of cryptography. Thus, some works introduce the idea of “fuzzy" schemes attempting to solve this problem [12, 13]. Now, given similar image inputs, one can map them to the same result.

The current state-of-the-art facial recognition algorithms often employ continuous representations of faces is a problem. This is a problem for cryptographic algorithms that utilize discrete values. Conversion to discrete one from a continuous representation will affect facial recognition accuracy. Utilizing Eigen faces work has been done with secure facial recognition [14,15]. For enabling Cryptography to be applied to facial representations, the Eigen faces are essentially quantized. They require large amounts of computation to query the system for face matches even when these systems have been shown to be effective in securely recognizing faces. The usage of Eigen faces implies that every pixel must be used, and with higher image resolutions, there is a facial recognition accuracy and time complexity trade

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off. In addition, a simple match detection by comparing the Hamming distance of two face vectors is allowed by SCiFi's facial representation. In our work, we reverse engineer face images by utilizing this representation.

2.3 Reconstructing Occluded Regions of Faces

Facial occlusions are one major problem that face recognition systems encounters. The range can vary from glasses, hair, or even some external object blocking a part of a person's face. Thus, how to remove occlusions or work around them is an interesting problem in computer vision. We can treat missing regions of a person's face as being damaged or occluded in our task. A fair amount of work is done dealing with removing occlusions. The work has been done on removing eyeglasses from facial images [16].Firstly they isolate the region and then use recursive PCA to synthesize the eyes of the face based on the surrounding information without glasses. This process is very similar to how we will perform our face reconstruction. PCA on a morphable face model has also been investigated [17]. One drawback with this approach is the lack of precision of the displacement between the input face and the reference face. There are other similar techniques using PCA for reconstruction [18, 19, 20].The previously done reconstruction techniques have been fairly successful. In our case the source is a fragmented reconstruction itself, computed from a fairly course binary face encoding however, whereas in all previous such methods a real image is the true source. In addition, our reconstructions are estimating 60%-80% of missing facial information as opposed to very specific and small occluded regions such as where eyeglasses lie. These two issues make our reconstruction task significantly more challenging. In addition, our task of sketching faces based on a security break is novel, and has compelling practical implications.

III. FRAMEWORK: THE SCiFI SYSTEM

The brief overview of the SCiFI system [1]. The SCiFI system server stores a list of faces and the client inputs a single face into the system. The system goal is to securely test whether the face input by the client is present in the server's list. The typical setting has the server's list comprised of faces of suspects or criminals, while the client inputs a face of a passerby from a surveillance camera. To this end, SCiFI develops a part-based face representation, a robust distance to compare two faces, and a secure client-server protocol to check for a match according to that distance, as we explain next.

Face Representation: In order to perform the secure computation, in SCiFI system each face is deconstructed into a standard set of facial features(nose,mouth,eyes).The system establishes a set of typical examples of that feature based on an unrelated public database Y for each feature. The most similar word to input face feature is selected from the appearance vocabulary $V^i = \{V^i_1,\ldots,V^i_N\}$ and arranging these words in a spatial configuration similar to the input will produce an output similar to the original face.The representation also keeps track of the distance of each input feature from the center of the face to match the spatial configuration called spatial vocabulary $D^i=\{D^i_1,\ldots,D^i_Q\}$. Thus, the final face representation is comprised of the set of features in the vocabulary that are most similar to each feature, and the approximate distance of each feature from the center of the face.

For input face, let the set of its patches be $\{I_1,\ldots,I_p\}$.For each Ii two things are recorded :Appearance component, it contains the indices of n visual words in V_i that are similar to Ii, set $s^a_i\{1\ldots N\}$.Spatial component ,it contains the indices of the z distance words in D_i which are closest to I_i's distance from the center of the face, set s^s_i $\{i\ldots,Q\}$.

Comparing Faces: To compare two faces, SCiFi uses distance metric to decide whether two faces match. The SCiFi system considers faces to be matched if the distance metric is below certain threshold value.
As shown in [20], Hamming distance is set difference if the sets are coded as l=p(N+Q)-bit binary vectors. Each set s^a_i is represented by w^a_i,N-bit binary indicator vector for which n entries are 1(i.e., those n indices that are in s^a_i).Similarly, each set s^s_i is represented by w^s_i,a Q-bit binary indicator vector for which z entries are 1.The full representation for a given face is $w=[w^a_1,\ldots,w^a_p,w^s_1,\ldots,w^s_p]$.

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Secure Protocol: SCiFi protocol input is a list of M face vectors $w_1,\ldots w_M$ thresholds $t_1,\ldots t_M$ from the server, single face vector w from the client. The protocol's output is "match", if H $(w_i,w)<t_i$ for some i,and "no match" otherwise where H is Hamming distance.

IV. CRYPTOGRAPHIC MALFORMED INPUT ATTACK

The proposed attack on SCiFI allows the attacker to obtain a face code (w) that was meant to remain private. The attack relies on the fact that a dishonest adversary is able to input vectors of any form, not just vectors that are properly formatted. The attack learns the client's face code bit-by bit through the output of "match" or "no match".

Suppose the client's vector is w. A dishonest server can add any vector wm to its suspect list, and choose each corresponding threshold value, tm, arbitrarily. First, the server inputs the vector wm = [1, 0, . . . , 0], with a 1 in the first position and zero everywhere else. Next, the protocol comparing w and wm is run as usual.By learning whether a match was detected, the server actually learns information about the first bit, w1, of the client's input. We know that the nonzero entries of the input client vector must sum to exactly p(n+z). This creates two distinct possibilities in the outcome of the protocol:

- w1 = 1: In this case, the two input vectors will not differ in the first position. Therefore, they will only differ in the remaining p(n + z) − 1 positions where w is nonzero. Hence, we know that the Hamming distance between the two vectors is H (w,w_m) = p(n+z)−1.
- w1 = 0: In this case, the two input vectors will differ in the first position. In addition, they will differ in all of the p(n + z) remaining places where w is nonzero. Hence, we know the H (w,w_m) = p(n + z) + 1.

Taking advantage of these two possible outcomes, the dishonest server can fix the threshold tm = p(n+z). Then, if a match is found, it must be the case that H (w,w_m) =p(n + z) – 1 ≤ p(n + z), so w1 = 1. If a match is not found, then H (w,w_m) = p(n + z) + 1 > p(n + z), so w1 = 0. Thus, the dishonest server can learn the first bit of the client's input. Consequently, the attacker can learn the client's entire vector by creating l vectors w^i_m , 1≤ i≤ l, where the i-th bit is set to 1.

V. PROPOSED SYSTEM

Our method consists of two major components. The first is the offline stage that builds the facial vocabulary and face subspace from the public database. The second is the online stage that assembles a human face and is done only after a face vector is obtained.

5.1 Offline Stage: The face images should come from an external database Y, which are used to create the fragment vocabularies which can be completely unrelated to the people registered in the server's list. All faces are normalized to a canonical size, and the positions of landmark features (i.e., corners of the eyes) are assumed to be given. Figure 5.1 gives idea about what is done in offline stage.

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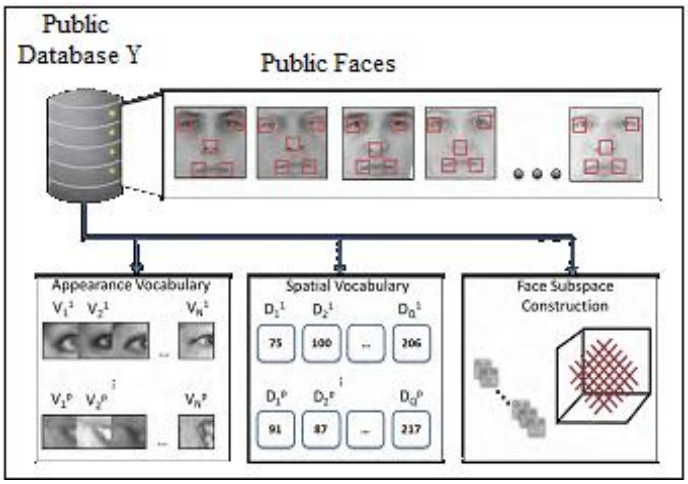

Figure 5.1: The figure shows the three major parts of the Offline Processing stage. At the top of the figure, we build a public face database. Here we show five landmarks indicated by red boxes on each person's face. The red boxes and their centers serve as windows to build the appearance (bottom left) and spatial vocabularies (bottom middle). The whole faces are also used to build the face subspace (bottom right).

Given face images in external database, to form appearance and spatial vocabularies $V_1,\ldots V_p$ and $D_1,..D_p$ use an unsupervised clustering algorithm (k-means) to quantize image patches and distances.We also use the external database Y to construct a generic face subspace. The space of all face images occupies a lower-dimensional subspace within the space of all images, as has been long known in the face recognition community[21,17].To compute low-dimensional image representations this face can be exploited. In order to "hallucinate" the portions of a reconstructed face not covered by any of the p patches we exploit a face subspace.

Formally, face images in external database Y consist of a set of F vectors $y'_{1,\ldots}y'_{F,}$ where each y'_i is concatenating the pixel intensities in each row of the i-th image. By computing mean face $\mu=1/F\ \Sigma^F_{i=1}\ y'_i$, and then center original faces by subtracting the mean from each one.
Let the matrix Y contain those centered face instances, where each column is an instance $Y=[y_1,\ldots y_F]=[y'_{1-}\mu,\ldots y'_F-\mu]$.

Principal component analysis (PCA) identifies the ordered set of F orthonormal vectors $u_1,\ldots u_F$ that describes the data, by capturing the directions with maximal variance. The eigenvectors of $1/F\ \Sigma^F_{i=1}\ y'_i\ y_i^T=YY^T$, sorted by the magnitude of their associated eigenvalues,by the definition the desired vectors are the eigenvectors of the covariance matrix computed on Y.The top K eigenvectors define a K-dimensional face subspace.

5.2 Online stage: The SCiFI protocol can be executed after building appearance and spatial vocabularies. A patch face representing the individual using the indices from the vector will be shown by attackers by reverse engineering. The attacker can estimate the missing regions of the face and return a identifiable human face using our reconstruction technique. Figure 5.2 provides an outline of the second stage of our visual reconstruction.

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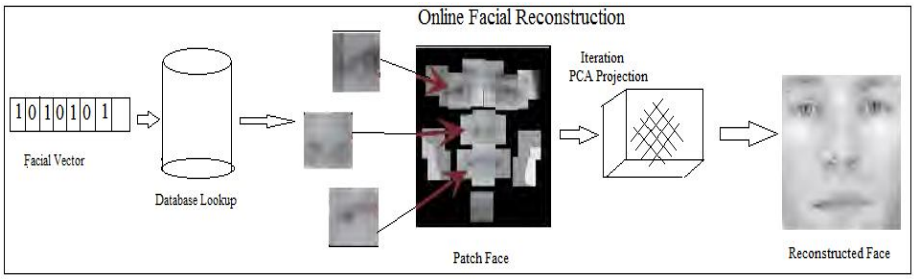
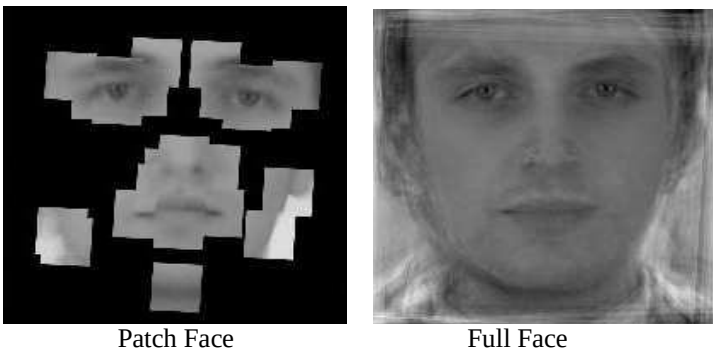


Figure 5.2: The figure is an overview of the online face reconstruction process. Given a facial vector from the system, we look up each of the patches that were representative of this face. We can then construct a patch face. Using the patch face as the initial input, we then iteratively project into the face space to synthesize a complete human face.

Finding a best matching face: Now we can define how to form patch face reconstruction. For each face of p facial parts, the cryptographic attack defined above yields the n selected appearance vocabulary words and z selected distance words. This encoding reveals which prototypical appearance and spatial was most similar to those that occurred in the original face specifying indices into public vocabularies.

Thus, we map retrieved corresponding quantized patches and distance values for each part into an image buffer. we take the n quantized patches and randomly select one of them to reconstruct the appearance of a part i . We average the z distance values for spatial information of part i. We place the patch into the buffer relative to its center, displaced according to the direction oi and the amount given by the recovered quantized distance bin. For example, if n = 4 and s^a_i={1,3,7,19},we look into the patches {v^i_1,v^i_3,v^i_7,v^i_{19}},and compute average then,if say z=2,and he associated distances are s^s_i={4,10},we average patch's center at ½(D^i_4+D^i_{10})o_i, where the buffer's center is at the origin. To get the patch face reconstruction we repeat this for i=1,…, p.Figure5.3 shows an example patch face. To reverse the SCiFi mapping the process uses all information available in encoding.



Patch Face Full Face

Figure 5.3. We first reconstruct the quantized patches based on the binary encoding (left), and then expand the reconstruction to hallucinate the full face given those patches (right).

Principal component analysis: Based on Face Reconstruction

The remainder of the face image based on the constraints given by the initial patch face is estimated by second stage of our reconstruction approach .We can exploit the structure in the generic face subspace to hypothesize or estimate values for the remaining pixels because these regions are outside of the original SCiFI representation. Associated uses of subspace methods have been investigated for dealing with partially occluded images in face recognition for example, to reconstruct a person wearing sunglasses, a hood, or some other strong occlusion before performing recognition [16, 18, 19, 17, 20]. Here we want to reconstruct portions of the face that are missing, with the end goal of creating a better visualization for a human observer or a machine recognition system.

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We adopt a recursive PCA technique presented in [20], which is used to compensate for an occluded eye region within an otherwise complete facial image. Firstly we will initialize the result with our patch face, and then project iteratively into and using public face subspace reconstruction is done each time adjusting the face with our known patches. Comparable to experiments in [20], our process makes substantially greater demands on the hallucination, since about 60%-80% of the total face area has no information and must be estimated. Figure 5.4 gives a sketch of this technique.

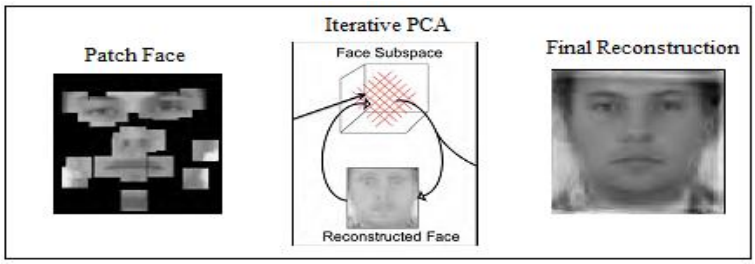

Figure 5.4: The figure illustrates the iterative PCA technique. The input is the patch face and the output is a fully reconstructed face.

Given a novel face x, to obtain its lower-dimensional coordinates in the face space we project face onto the top K eigenvectors (so called eigen faces). Particularly, the i-th Projection coordinate is:

$$w_i=u^T_i(x-\mu),$$

For i=1,…, K.The resulting w= $[w_1,w_2,\ldots,w_k]$ weight vector specifies the linear combination of eigenfaces that best approximates (reconstructs) the original input:

$$x\hat{}=\mu+Uw,$$

Where the i-th column of matrix U is u_i. In our case simply reconstructing once from the lower dimensional coordinates may give a poor hallucination, since many of the pixels have unknown values (and are thus initialized at an arbitrary value of 0).

However, by bootstrapping the full face estimate given by the initial reconstruction with the high-quality patch estimates, we can continually refine the estimate using the face space. This works as follows: Let x^0 denote the original patch face reconstruction. Then, define the projection at iteration t as

$$W^t=U^T(x^t-\mu),$$

the intermediate reconstruction at iteration t + 1 as

$$\tilde{x}^{t+1}=\mu+Uw^t,$$

and the final reconstruction at iteration t + 1 as

$$x^{t+1}=\omega x^t+(1-\omega)\tilde{x}^{t+1},$$

Where the weighting term ω is a binary mask the same size of the image that is 0 in any positions not covered by an estimate from the original patch face reconstruction, and 1 in the rest. We cycle between these steps, stopping once the difference in the successive projection coefficients is less than a threshold: max $(|w_i^{t+1}-w_i^t|) < \varepsilon$.

VI. EXPERIMENTAL RESULTS

This experimental results figure 5.5 shows the triplet from left to right original image, patch face and reconstructed image. When the input image is sent its features are extracted and stored in database .In general all public faces images and their extracted features are stored in SCiFI system if matching features are found to input face image then patch face image is formed and applying PCA algorithm to it we finally get a reconstructed face image which resembles the original face image. We apply PCA iteratively after patch face is to get a reconstructed face. We see that reconstructed faces forms the sketches of true face which are underlying.

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Figure 5.5: The figure shows the results of PCA technique.

VII. CONCLUSION

We present a novel attack on a secure face identification system that control detailed perception from both security as well as computer vision techniques. While the SCiFI system appropriately claims security only under the honest but-curious model, we have demonstrated the dangerous consequences of such a system when exposed to a dishonest adversary. Our vision contributions are to stretch the limits of subspace-based reconstruction algorithms for visualization of severely occluded faces.

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