Combining and Steganography of 3D Face Textures

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Abstract—One of the serious issues in communication between people is hiding information from others, and the best way for this, is deceiving them. Since nowadays face images are mostly used in three dimensional format, in this paper we are going to steganography 3D face images, detecting which by curious people will be impossible. As in detecting face only its texture is important, we separate texture from shape matrices, for eliminating half of the extra information, steeganography is done only for face texture, and for reconstructing 3D face, we can use any other shape. Moreover, we will indicate that, by using two textures, how two 3D faces can be combined. For a complete description of the process, first, 2D faces are used as an input for building 3D faces, and then 3D textures are hidden within other images.

Index Terms—steganography, shape, texture, face image, combining images.

I. INTRODUCTION

In cryptography, encrypted message is at the center of people’s attention, and its security is based on the difficulties on access to the message key. In steeganography, other’s unawareness is used for hiding the message to send it in the safest way. For this reason, first, the essential information of one image which we want to send to others will be embedded in another host image in a way that others cannot understand outward discrepancy of the initial host image and the embedded host image, therefore legal receiver can extract and reconstruct initial embedded image. The most important researches conducted in this area are [1], [2], [7], [10], [15].

Embedding capacity and visual quality are the two essential parameters in the stego or cover images [4]. Embedding capacity refers maximum amount of secretive message which can be embedded in the host image, and visual quality is embedding message in the host image in a way that human eye cannot notice any difference between the new form and the original one. One criteria which is usually used for evaluating visual quality is the peak of signal to noise ratio (PSNR) between stego image and original host image and expressed in dB unit. The bigger the PSNR, the higher visual quality of estego image . In other words, it is more difficult for eye to detect stego image than to do so for host image [5].

In this paper, to construct the 3D image of the intended face for steeganography within other images first, a colored 2D face image will be processed using Basel database as [9] to the 3D model is fitted. 3D face and texture matrices are extracted separately from constructed 3D face. Now, if this 3D texture is used for any other 3D shapes, it is possible to recognize the person as well. For this reason, in steeganography the shape matrix is not too important and we only use texture matrix. A wavelet-based watermarking algorithm is used for enhancing the secrecy. By using singular value decomposition (SVD) and discrete wavelet transform (DWT), the information of an 3D texture of an image will be hidden in a label image. This label image can be any 2D image e.g. a fingerprint, a shape, or a texture of other 3D images. First, label image is converted to frequency domain, and SVD is used on both of the original cover image and 3d texture. In the following, the two obtained singular values will be replaced with each other.

II. MÓRPHABLE MODEL

At first, 3D morphable models had been introduced by Blanz and Vetter [2], [3]. They were applied successfully in computer’s images and graphics. An 3DMM includes separate shape and texture models which by themselves can build each person’s shape and texture’s changes, respectively. An 3DMM is used for one group of 3D scanned images.

Constructing 3D models is very hard and time consuming which Paysan and his colleagues provided their 3DMM for public using; Basel model uses 3D models of 100 men and 100 women who ranged from 8 to 64 [9].

An Iterative Multiresolution Dense 3D Registration which has been introduced by Rodriguez [14] will be studied in this section. Suppose that the ith vertex of registered image be in the \((x_i, y_i, z_i)\) point and its RGB color is \((R_i, G_i, B_i)\). It will be assumed that for any face N 3D points had been registered; Therefore, one registered face in face and texture language can be shown as:

\[
S' = \begin{pmatrix} x_1, \ldots, x_N \\ y_1, \ldots, y_N \\ z_1, \ldots, z_N \end{pmatrix} \quad (1)
\]

\[
T' = \begin{pmatrix} R_1, \ldots, R_N \\ G_1, \ldots, G_N \\ B_1, \ldots, B_N \end{pmatrix} \quad (2)
\]

Also these points can be shown by one row or column vector of 3N length. For example, the vertical vector of shape and texture are:

\[
S' = (x_1, \ldots, x_N, y_1, \ldots, y_N, z_1, \ldots, z_N)^T, \quad (3)
\]

\[
T' = (R_1, \ldots, R_N, G_1, \ldots, G_N, B_1, \ldots, B_N)^T \quad (4)
\]

which N is the number of registered faces. We suppose that this two kinds of point’s display are equivalent, and we will
use any of these tow formats when needed.

Now, for a database which has 200 shape and texture matrices, a linear combination for shapes and textures will be used. These linear combinations can be as follows:

\[
S = \sum_{i=1}^{200} \alpha_i S_i, \quad T = \sum_{i=1}^{200} \beta_i T_i .
\] (5)

It is almost impossible that these combinations, despite the fact that they include all the possible faces, be similar to a real face. If a convex combination \((\sum \alpha_i = 1, \sum \beta_i = 1, \alpha_i, \beta_i \in [0, 1])\) of faces be supposed, a face can also be obtained, but again, it is not possible that the points which are far from convex area form an actual face points. Therefore, for any vector, a coefficient is needed to be allocated to a probability distribution for description of a face. This probability is modeled by a Gaussian distribution, in which shapes and textures are decorrelated, with a diagonal matrix. Suppose a Gaussian distribution allows that subspace of face to be estimated by a smaller set of orthogonal basis vectors which is calculated using principle component analysis (PCA) of the test samples.

Principle component analysis is a statistical tool which transform shape or texture so that covariance matrix will be diagonal (it means data are decorrelated). In this section, using PCA for the shape will be studied. Using it for the texture will be studied as well. PCA is a transform in the vector space which is used mostly for decreasing the dimension of the data sets. At first, principle component analysis had been used by Karl Pearson in 1901 [11]. This analysis includes the decomposition of the eigenvalues of the covariance matrix. The average of the shapes is calculated as:

\[
\bar{S} = \frac{1}{200} \sum_{i=1}^{200} S_i .
\] (6)

By subtracting each sample shape from average shape matrix, the vertical vector \(a_i\) can be calculated as:

\[
a_i = vec(S_i - \bar{S}) .
\] (7)

This vertical vectors are used as the columns of matrix A, and the eigenvalue vectors of a covariance C is calculated by a singular value decomposition [12]. So we have:

\[
A = (a_1, a_2, \cdots, a_{200}) = UWU^T
\] (8)

and

\[
C = \frac{1}{200} AA^T = \frac{1}{200} UW^2U^T ,
\] (9)

\(vec(S)\) will change matrix \(S\) to a column vector by concatenating its columns in a vertical order. 200 columns of orthogonal matrix \(U\) are eigenvectors of covariance matrix \(C\) and \(\lambda_i^2 = \frac{\alpha_i^2}{200}\) is its eigenvalues which \(\lambda_i\)'s are diagonal elements of matrix \(W\) that are arranged in decreasing order. The \(i\)th column of \(U\) is shown by \(U_{0,i}\), and the principle component of \(i\) will be changed to a \(3 \times n\) matrix by \(S^{(i)} = U_i^{(3)}\). The notation \(a_{m \times 1}^{(n)}\), changes the \(m \times 1\) vector a to a \(n \times (m/n)\) matrix [8].

Now, instead of describing a new shape or texture as the linear combination of the samples as equation 5, they can be expressed by the linear combination of \(n_s\) shapes and \(n_t\) textures as principle components:

\[
S = \bar{S} + \sum_{i=1}^{n_s} \alpha_i S^{i}
\] (10)

and,

\[
T = \bar{T} + \sum_{i=1}^{n_t} \beta_i T^{i} .
\] (11)

Therefore, the combination of arbitrary number of shapes and textures for constructing 3D morphable faces is used. The 3DMMs should be so limited that improbable faces could be rarely sampled.

Experiments on the real data shows that supposing Gaussian distribution on the face when sufficient information in the extraction is available, the result will be satisfying. Anyhow, supposing Gaussian distribution is unexpected, so Patel and Smith [10] presented another assumption. They observed that the length of parameters’ vectors has Chebyshev distribution. In other words, the real faces are on the spherical manifolds. In the model, the average model, which its vector length is zero, is improbable, and the faces should have a certain level of distinction.

III. EXTRACTING 3D SHAPE AND TEXTURE FROM 2D FACE IMAGES

Bas [1] used also Basel database for fitting 2D images on the 3D model which fitting \(N\) 2D \(X_i = (x_i, y_i)\) points for \(i = 1, \cdots, N\) to the 3D \(V = (u, v, w)\) vectors on the model for getting the best shape and pose which can minimize the Euclidean distance of the \(N\) \(X_i\) points from scaled orthogonal projection of four components \((V, R, t, s)\) which \(R\) is a 3 by 3 rotation matrix of real numbers, \(t\) is a translation 2-tuple of real numbers, and also \(s\) scale is a real number which is a positive real number, are three pose parameters. By fitting 2D image on a 3D image, the 3D shape \(S\) and texture \(T\) of the 3D face are obtained as equation 1 and 2 which by using shapes and textures, the 3D faces can be constructed. Now suppose that two 2D face images, which can be chosen completely by accident, and their obtained 3D images are as figure 1.

The shape and texture of Obama’s face are \(S_1, T_1\), respectively, and the shape and texture of Trump’s image are \(S_2, T_2\) respectively.

Now, if we use Obama’s texture which is a 3D matrix \(T_1\), and Trump’s 3D shape matrix which is shown by \(S_2\), the
As it can be seen in the figure 2, the 3D shape for detecting a person’s face is not so important, and only the face texture for reconstructing human face is sufficient. For this reason, if we want to steganography a 3D face image, it would be better to ignore half of the information, which is the shape matrix, and only use the texture matrix which will be described in the section IV.

Moreover, if we want to combine the obtained 3D images from the 2D images with each other, an appropriate way is using coefficients of principle components. For a 53490 × 3 dimensional shape matrix $S_1$, by using PCA with Alternating Least Squares (ALS) algorithm [6] we have:

$$[\text{coef } S_1, \text{score } S_1, \mu] = \text{pca} (S_1)$$ (12)

that 3 × 3 dimensional coefficient coef $S_1$ is obtained which its columns are arranged in an increasing order and include any of the 3 principle component coefficients. The 53490 × 3 dimensional score matrix is also shown by score $S_1$. The 1 × 3 dimensional average of any variables $\mu S_1$ matrix is shown by $\mu S_1$. In the same way, by principle component analysis and using ALS algorithm, it can be done on the $S_2, T_1, T_2$. Now, if the new shapes and textures be obtained as equations 13, the 3D face models of figure 3 can be constructed.

$$T_1 = \text{score}_1 \times \text{coef}_2 + \text{repmat}(\mu_2, 53490, 1),$$
$$T_2 = \text{score}_2 \times \text{coef}_2 + \text{repmat}(\mu_2, 53490, 1),$$
$$S_1 = \text{score} S_2 \times \text{coef } S_2 + \text{repmat}(\mu S_2, 53490, 1),$$
$$S_2 = \text{score} S_2 \times \text{coef } S_2 + \text{repmat}(\mu S_2, 53490, 1).$$ (13)

For constructing the left face in figure 3, the new shape and texture matrices $S_1, T_1$ have been used, and for constructing the right face in figure 3, the new shape and texture matrices $S_2, T_2$ have been used.

Now by the transform which has been applied in the equation 13, only by taking a simple average in equation 14, we can see a satisfactory behavior of two politicians as the face in the figure 4.

$$S_m = (S_1 + S_2)/2$$
$$T_m = (T_1 + T_2)/2$$ (14)

IV. 3D Face Image Steganography

As it is shown in the previous section, what is essential in the constructing of a 3D face images and needs to be masked, is half of the face information videlicet, the texture of the 3D face image, and by using any other shape the face can be reconstructed significantly same as the original one.

As it has been said, a texture matrix is a 53490 × 3 dimensional matrix. For hiding this 3D image, we add some zeros to the end of this matrix to obtain an 53824 × 3 dimension matrix which we have $232 \times 232 = 53824$. By using the second dimension of the resulted matrix, we change it to three vertical 53824 × 1 vectors, and after that we reshape each of these vectors to a $232 \times 232$ square matrix as the symbols of red, green, and blue colors, respectively. The values of these matrices which might not be number, will be replaced by zero (also for better results, other techniques could be used by adjacent points to recover the missing texture
points. Now by using singular value decomposition, any of the colors is decomposed to a 3-tuples like \((U_t, S_t, V_t)\), by subindices which are related to their colors.

Also a colored image is used as the cover image which its size will be changed into an \(464 \times 464 \times 3\) dimensional matrix that we show it by \(C\) (the cover matrix can also be any other 3D texture matrix that in this way we do as mentioned above). The matrix \(C\), by using a single-level discrete 2D wavelet transform, is decomposed to a 4-tuple \((CA, CH, CV, CD)\) by same \(232 \times 232 \times 3\) dimensions which \(CA\) is the approximation coefficient matrix which has low frequency, and 3 details coefficient matrices by the names horizontal matrix \(CH\), vertical matrix \(CV\) which has medium frequency, and diagonal matrix \(CD\) which has high frequency. Now, because of the third dimension of the \(CD\), we decompose it to 3 \(CD_r, CD_g, CD_b\) matrices by \(232 \times 232\) dimension for the symbol of red, green, and blue colors, respectively. In the following, by using singular decomposition, each color matrices, like the matrices which were obtained by texture, is decomposed to 3-tuples \((U_c, S_c, V_c)\) by subindices belongs to the colors.

Now, for red, green, and blue colors, the obtained singular value matrix from the cover image is replaced by the Sc of that color, added to the a tenth of St, for example for the red color we can obtain new value of \(CD_{new, r} = U_{Cr} \times (S_{Cr} + 0.1 \times S_{Tr}) \times V_{Cr}^T\). Then by concatenation of these 3 red, green, and blue matrices, the new value of \(D_{new}\) will be obtained and by inverse wavelet decomposition on the 4-tuple \((CA, CH, CV, CD_{new})\) the stego image will be constructed.

For extracting the hidden image we should do as the inverse of abovementioned process, and at first 2D wavelet decomposition for rebuilding 4-tuple \((wA, wH, wV, wD)\) is performed on the stego image. Because of the third dimension of \(wD\), we decompose \(wD\) to the three red, green, and blue color images, and on any color by singular value decomposition, the 3-tuple \((U_e, S_e, V_e)\) by subindices which belong to any color, is obtained which for calculating \(S_e\) we should subtract that value of \(Sc\) from singular value and multiply it to 10 (the inverse of what mentioned before). Next, the new texture column components from the result of \(U_e \times S_e \times V_e^T\) for each color will be calculated. We can implement the resulted texture on any shape to reconstruct the desired 3D face image. As an example, the images for mentioned process are as figure 5 which from left to right are original cover image, 3D used original image, stego image, and desired extracted image, respectively. A known used criteria for measuring image quality is peak of signal to noise ratio \([13]\). The peak of signal to noise ratio of two original cover image and stego image of figure 5 is 81.51 (dB) by equation 15 which MSE is the Mean Square Error and S is the maximum pixel value.

\[
PSNR = -10 \log_{10} \frac{MSE}{S^2}
\]  

V. CONCLUSION

Hiding the secretive information from the enemies’ view in a way that they do not be at all skeptical to the existence of hidden messages helps to the safe communication. In this paper, by using the idea of extracting 3D face texture, this matrix is embedded in other images, and it has been indicated that how by using only half of the face information, which is texture, we can appropriately reconstruct face images. In addition, it has been shown that how by combining two textures and without any stricture on shape matrix, we can combine two faces pleasantly.

REFERENCES

[1] Bas, Anil, et al. "Fitting a 3D morphable model to edges: A comparison between hard and soft correspondences." arXiv preprint arXiv:1602.01125 (2016).
[2] Blanz, Volker, and Thomas Vetter. "A morphable model for the synthesis of 3D faces." Proceedings of the 26th annual conference on Computer graphics and interactive techniques. ACM Press/Addison-Wesley Publishing Co., 1999.
[3] Blanz, Volker, and Thomas Vetter. "Face recognition based on fitting a 3D morphable model." IEEE Transactions on pattern analysis and machine intelligence 25.9 (2003): 1063-1074.
[4] Chang, C. C., T. S. Chen, and K. F. Hwang. "Electronic Image Techniques." Taipei: Unalis (2000).
[5] Johnson, N.F., Jajodia, S., 1998. Exploring steganography: Seeing the unseen. IEEE Comput. (February), 26Â–S64
[6] Kiers, Henk AL. "Setting up alternating least squares and iterative majorization algorithms for solving various matrix optimization problems." Computational statistics and data analysis 41.1 (2002): 157-170.
[7] Kittler, Josef, et al. "3D Morphable Face Models and Their Applications." International Conference on Articulated Motion and Deformable Objects. Springer International Publishing, 2016.
[8] Minka, Thomas P. "Automatic choice of dimensionality for PCA." Nips. Vol. 13. 2000.
[9] P. Paysan, R. Knothe, B. Amberg, S. Romdhani, and T. Vetter, ąÂIA 3D face model for pose and illumination invariant face recognition,ąÂAI in Proc. IEEE Intl. Conf. on Advanced Video and Signal based Surveillance, 2009.
[10] Patel, Ankur, and William AP Smith. "3d morphable face models revisited." Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on. IEEE, 2009.
[11] Pearson, Karl. "Principal components analysis." The London, Edinburgh and Dublin Philosophical Magazine and Journal 6.2 (1901): 566.
[12] Press, William H., et al. "Singular value decomposition." Solution of Linear Algebraic Equation from Numerical Recipes in C (1992): 59-70.
[13] Rafael, C. "Gonzalez, and Richard E. Woods." Digital Image Processing (1992).
[14] Rodríguez, JR Tena. "3D face modelling for 2D+ 3D face recognition." (2007).
[15] Zhu, Xiangxin, and Deva Ramanan. "Face detection, pose estimation, and landmark localization in the wild." Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on. IEEE, 2012.