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FACIAL IMAGE RECONSTRUCTION FROM A CORRUPTED IMAGE BY SUPPORT VECTOR DATA DESCRIPTION

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Abstract. This paper proposes a method of automatic facial reconstruction from a facial image partially corrupted by noise or occlusion. There are two key features of this method; the one is the automatic extraction of the correspondences

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between the corrupted input face and reference face without additional manual tasks; the other is the reconstruction of the complete facial information from corrupted facial information based on these correspondences. In this paper, we propose a non-iterative approach that can match multiple feature points in order to obtain the correspondences between the input image and the reference face. Furthermore, shape and texture of the whole face are reconstructed by SVDD (Support Vector Data Description) from the partial correspondences obtained by matching. The experimental results of facial image reconstructions show that the proposed SVDD-based reconstruction method gives smaller reconstruction errors for a facial image corrupted by Gaussian noise and occlusion than the existing linear projection reconstruction method with a regulation factor. The proposed method also reduces the mean intensity error per pixel by an average of 35 %, especially in the reconstruction of a facial image corrupted by Gaussian noise.

Keywords: Face reconstruction, morphable model, SVDD, multiple example image matching

1 INTRODUCTION

The application of facial identification and recognition technology has increased in entrance/exit security, immigration control using electronic passports, criminal search etc. This technology has become more robust to various changes in illumination, expression, viewing angle and so on. On the other hand, in addition to its robustness, it can realize significantly enhanced performance if it can efficiently reconstruct facial images that have been corrupted by camera sensor noise, glasses, hand, occlusion or by tampering or by contamination from external substances.

Recently, an object-based reconstruction method, which models the object in the image and applies it to the reconstruction, has been studied. This method can be used even when the image has been corrupted by object occlusions as well as camera noise and thermal degradation. The most representative of this reconstruction method is the one that uses the morphable face model [2, 3, 8, 9, 11]. This morphable reconstruction method consists of the input image-to-reference face correspondences extraction and data reconstruction that reconstructs the complete shape and texture from partial shape and texture based on the extracted correspondences.

The extraction of the correspondences between the reference face and the input image is based on manual setting of assumed or pre-set feature points in 2-D or 3-D space. However, this process requires the user to spend much time and effort in defining many feature points or in extracting correspondences for many images. Furthermore, stable extraction of correspondences in various environments has been a very difficult task, especially for corrupted input images.

To obtain the correspondences between the input facial image and the reference facial image without human intervention, an algorithm for stably and effectively extracting feature points as well as the descriptive information of the features points is needed. Furthermore, feature matching should be robust to illumination changes, noise, or facial deformation. Therefore, Lowe's Scale Invariant Feature Transform (SIFT) algorithm, which is invariant to image translation, scale and rotation and robust to noise and affine distortions, can be considered [15]. Sampling and descriptive information of features points obtained from SIFT has been widely used in computer vision and pattern recognition fields such as object recognition and extraction [13, 14, 15], 3-D scene modeling, object tracking [7], panorama generation [4] etc.; but they are usually taken from the same object or captured from a converted viewpoint in a small range within a scene. This is because the number of corresponding feature points greatly decreases in images of different objects that belong to the same object category or in images with a large variation of viewpoint. Especially, the SIFT algorithm can extract the correspondences between the facial images of two persons from 10 or fewer feature points even after identifying the image angle, illumination, expression between the two faces. However, the correspondences extracted from such a low number of feature points is insufficient for use in reconstruction.

Everson and Sirovich [6], and Jones and Poggio et al. [11] applied the statistical gradient descent method iteratively to obtain the correspondences of a corrupted input image to reconstruct the whole shape and whole texture from the partial shape and partial texture based on the correspondences extracted from the manual or automatic method. Furthermore, the linear projection in such optimization iterations reconstructed the corrupted region [2, 11]. Hwang et al. [8] used the linear projection method to reconstruct full mesh information from the feature points without iterations. To avoid divergence due to noise or limited amount of information [8], the linear projection method with regularization was used in reconstruction [3, 10]. Luthi and Vetter not only reconstructed full information from partial information using probabilistic modeling but also proposed a method for determining reconstruction uncertainty [16]. All these methods used the Principal Component Analysis (PCA) model, which has linear characteristics, or its evolved model, the Probabilistic PCA (PPCA) model.

This paper proposes a method for finding the accurate global correspondences between a reference image and a corrupted input image based on a morphable model. The correspondences of the feature points between the input facial image and the reference face is determined from multiple example images that are generated by the morphable model. SVDD method, which uses a hyperball to directly approximate the training data domain from correspondence of whole face region interpolated by that of the feature points, estimates the whole shape and full texture without iteration. By combining the estimated whole shape and texture, we can reconstruct an image similar to original one from a facial image corrupted by Gaussian noise or object occlusion.

This paper is structured as follows. Section 2 provides an overview of this paper, describing the entire process of facial reconstruction and the morphable facial model. Section 3 describes the preparation process: the generation of example images and descriptors used to find the corresponding feature points of the input facial image and the reference image; the automatic extraction of the correspondences of the corrupted image; and the method for reconstructing the whole shape and texture from the features points using the SVDD method. Section 4 describes the experimental database, presents the reconstruction results and compares and analyzes the experimental results. Section 5 presents a brief summary of this research and future research plans.

2 OVERVIEW

2.1 Face Reconstruction Procedure

Because the input facial image is very different from the reference face, very few or no matching feature points will be found by the existing feature points matching method. We can prepare multiple example images from a morphable face model within a specific domain. All the example images have dense correspondence the reference face image. Based on this idea, we aim to provide a solution for generating the correspondences between a reference face and an arbitrary input image. In this procedure, the input image is matched to various example images whose correspondences with the reference face are known. Then, the correspondences between the input image and the example images are integrated to obtain the final correspondences between the input image and the reference face.

The facial reconstruction procedure consists of the off-line preparation process and the on-line reconstruction process. As shown in Figure 1, the preparation process consists of the multiple example images generation step (0-a) and the feature descriptor generation step (0-b). The reconstruction process consists of 1–7 steps. The multiple example images generation step and the feature descriptors generation step are described below.

0-a stage: Multiple example images generation

- Develop a morphable face model from a face database of facial images, shape, and texture (refer to [11, 20] for more details on facial model development).
- Based on the morphable facial model, generate shape and texture from the random coefficients with a multivariate normal distribution, and generate multiple example images by forward warping the generated texture image using the shape.

0-b stage: Feature descriptor generation

- Extract feature points from the multiple example images and generate descriptors for these points by the SIFT algorithm.
- Calculate the correspondences of the feature points with the reference face by using the shape.

Facial reconstruction process consists of 7 steps: feature descriptor matching, partial shape generation, complete shape generation based on linear interpolation,

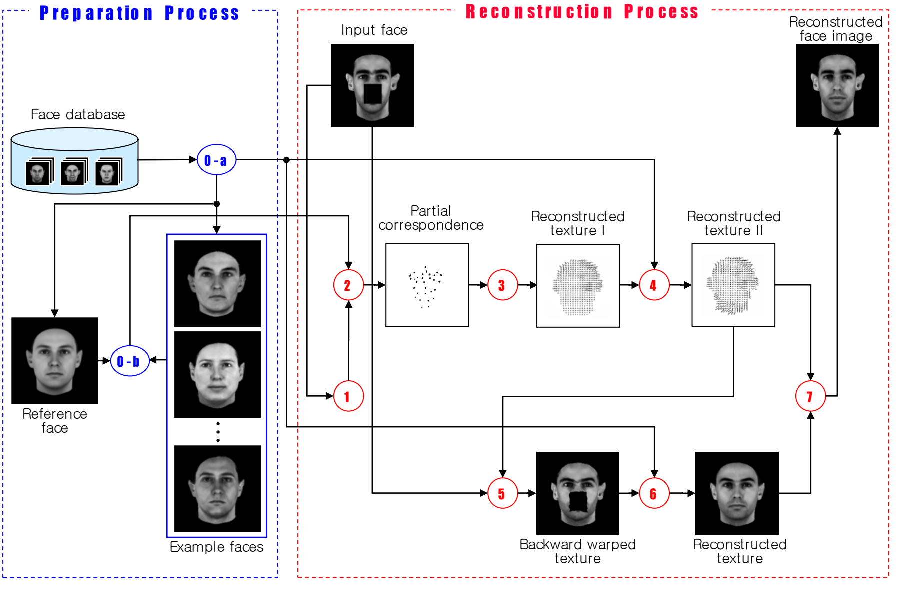

Figure 1. Face reconstruction procedure: off-line(steps 0-a and 0-b) and on-line (steps 1 to 7) processes

SVDD-based complete shape generation, corrupted texture generation based on backward warping, SVDD-based complete texture generation and complete facial image synthesis based on forward warping. In step 4, Backward warping warps an input facial image onto the reference face by using its shape information and yields a texture expressed in reference shape. In step 7, Forward warping warps a texture expressed in the reference face onto each input face by using its shape and results in a facial image. For more information on the mathematical expressions of forward and backward warping, refer to [20]. The steps of the reconstruction process are explained in detail as follows:

Step 1: Matching feature descriptors

- Obtain SIFT descriptors at key points of the input face by using the SIFT algorithm
- Match the SIFT descriptors of the input face with those of multiple example faces.

Step 2: Partial shape generation

- Obtain the indirect correspondences between the input face and the reference face by integrating correspondences between the input face and example faces and those between example faces and the reference face obtained in Step 0-b (Figure 2).

Step 3: Complete shape generation based on linear interpolation

- Generate complete shape from the partial shape from step 2 by linear interpolation.

Step 4: SVDDbased complete shape generation

- Reconstruct refined complete shape using SVDD with the interpolated shape.

Step 5: Corrupted texture generation

- Generate texture of the input image by back-warping the input image using the reconstructed shape.

Step 6: SVDD-based complete texture generation

- Reconstruct complete texture of the corrupted region by applying SVDD-based data reconstruction method on the corrupted texture.

Step 7: Synthesis of complete facial image

- Forward warp the complete texture with the complete shape only for the inside region defined by the internal face mask. This step results in a reconstructed facial region containing eyebrows, eyes, a nose and a mouth.
- Overlay the reconstructed facial region on the input face to evaluate the reconstruction results.

2.2 Morphable Face Model

The facial data in this paper are defined in the morphable facial model. A facial image is divided into shape and texture based on the pixel correspondences between the input facial image and the reference face [20]. The multivariate normal distributions of shape S and texture T from a data set of faces are obtained.

The multivariate normal distributions are expressed by the average shape $\bar{S}$ and average texture $\bar{T}$ and the covariant matrix Σ_S of the differences between the shape and the average shape in Equation (1), X^s, and covariant matrix Σ_T of the differences between the texture and the average texture, X^T.

$$X^S = S - \bar{S}, X^T = T - \bar{T} \tag{1}$$

By Principal Component Analysis (PCA), a basis transformation is performed to an orthogonal coordinate system formed by eigenvectors S_i and T_i of the covariance matrices Σ_S and Σ_T on our data set of N faces (Equation (2)).

$$S = \bar{S} + \sum_{i=1}^{N-1} \sigma_i^S S_i, T = \bar{T} + \sum_{i=1}^{N-1} \sigma_i^T T_i \tag{2}$$

where $c = \{c_1, c_2, \cdots, c_{m-1}\} \in R^{N-1}$ and σ_i^S and σ_i^T are the standard deviations of the shape and texture. The dimension of the space spanned by S_i and T_i is at most $N1$.

3 FACE RECONSTRUCTION

3.1 Generating Example Images and Descriptors

In the multiple example images generation steps of the preparation process, example images of various textures and shapes are generated in order to extract sufficient feature points needed for input image matching in reconstruction. Firstly, we generate morphable face models which be composed of shape and texture basis based on morphable model from face database with shape and texture information, and then we can generate sufficient number of shapes and textures applying multivariate normal coefficients to shape and texture basis. In this paper, forward warping is performed to different combinations of 1 000 shapes and 1 000 textures information to generate 1 000 example facial images.

In the step of feature point descriptor generation in the reconstruction process, the feature points that are robust to noise and illumination variations are extracted and feature descriptors that express the inherent texture around the feature points are obtained. The correspondence between point on the reference and a feature point on the example face is computed by using the known shape for the example face and triangle mesh interpolation algorithm. In this case, the feature descriptor information of the feature points of each example facial image and the position information of the features points on the reference face can be saved in the feature information reference table. Using this table, the correspondences of the input image can be rapidly obtained in the reconstruction process. In this paper, feature points were extracted and their feature descriptors were generated by using the SIFT method and SIFT descriptor of Lowe [15].

3.2 Extracting Correspondences from Corrupted Images

If an input face is given for the reconstruction, the SIFT descriptors at feature points are obtained and matched with those of multiple example faces by one by one. Then, the ratio of the similarity level of the most similar feature descriptor information M_{first} and the similarity of the second most similar feature descriptor information M_{second}, R_M ($= M_{second}/M_{first}$) is obtained in each example image. If the similarity ratio R_M is greater than the threshold value, then the feature points of the input image are assumed not to match those of the example facial images [18].

Once the feature descriptors for the specific example image that correspond to those of the input facial image are determined, correspondence of feature points between input face and reference face can be easily obtained by referring to the feature information. Although the number of corresponding feature points between

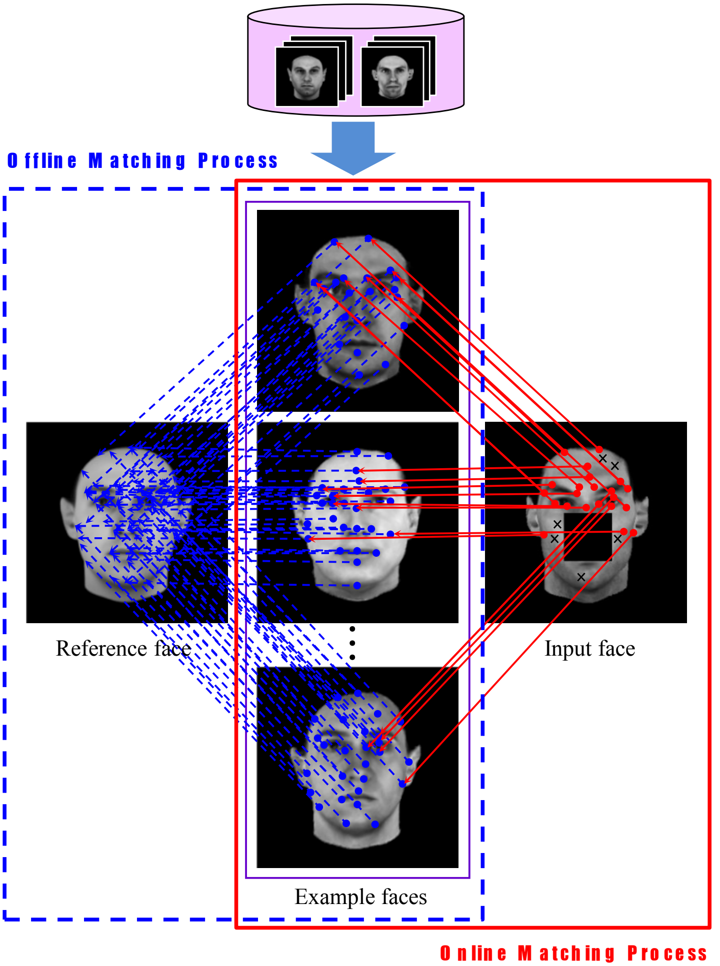

Figure 2. Indirect matching between the reference face and an input via example faces

the input image and each example facial image is small, through multiple example facial image matching sufficient number of corresponding feature points can be obtained indirectly for shape reconstruction (Step 2). In this paper, since the input image and reference face are assumed to have normalized size and position, if any corresponding feature points are at a distance greater than the defined threshold value, these points will be eliminated from the set of corresponding feature points.

Figure 2 shows the correspondences between the input image and the reference face obtained indirectly via example facial images. The dots on the example facial images and the dots and x marks on the input facial image are the feature points

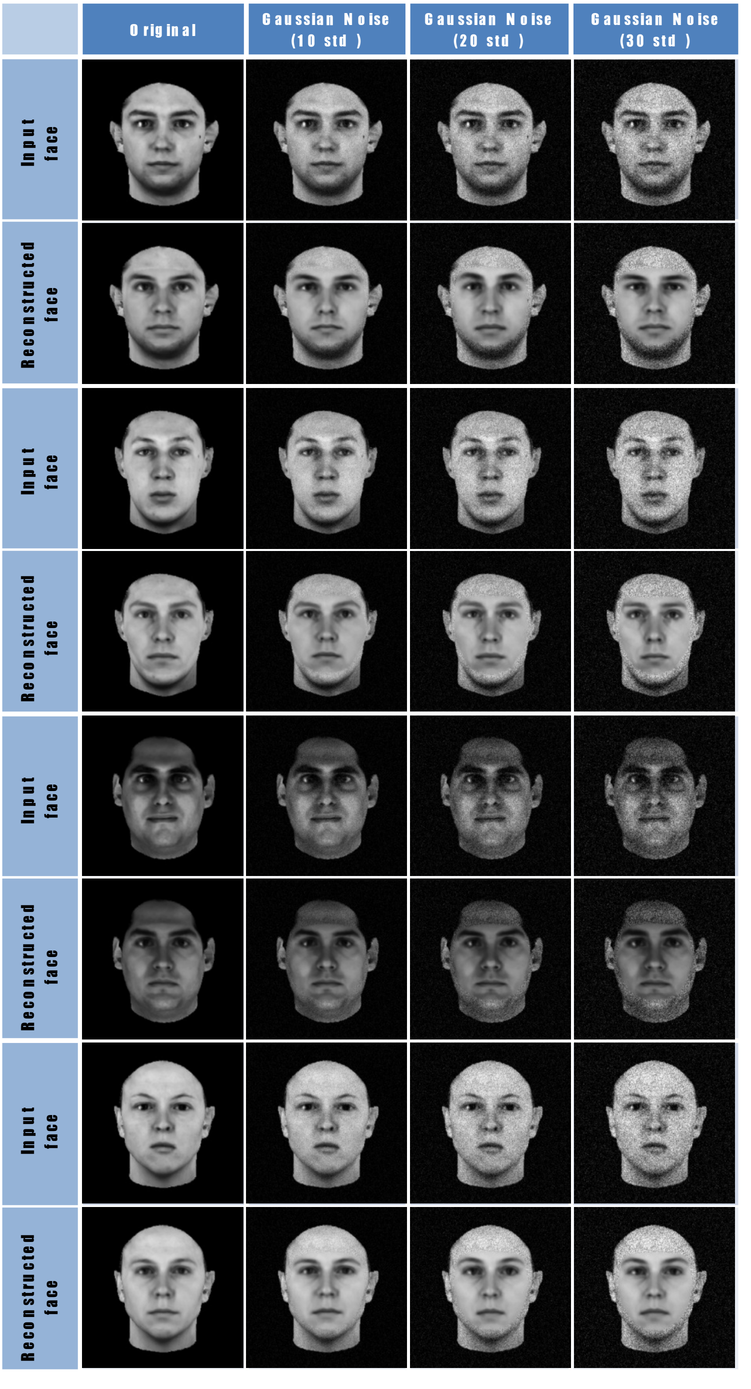

Figure 3. Examples of input faces

extracted by the SIFT method. The correspondences between the example facial images and the reference face which are given by shape of example faces are indicated by the dotted lines. Those between the input facial image and the example facial images by the SIFT matching are represented by the solid lines. The dot feature points on the input facial image have the correspondences to those on the example facial images. On the other hand, the x mark feature points on the input facial image represent that those do not have any correspondences to points on the example facial images. Generally, the feature points extracted from the input facial image do not all correspond to the reference face, but the results of our experiment showed that at least 30 feature points from the input facial image corrupted by either Gaussian noise (with standard deviation of 30 in 256 gray level image) or object occlusion (20 % of facial area) ultimately correspond to the reference face. These corresponding feature points are sufficient for image reconstruction, as shown in Figures 3 and 4.

3.3 Reconstructing Shape and Texture Based on SVDD

In this paper, a method for reconstructing the shape and texture by Support Vector Data Description (SVDD) is presented. Unlike the linear projection method, in which the area of study was projected onto a linear space, SVDD directly estimates the existing space of the training data by a hyperball. SVDD aims to find the smallest hyperball that will include the maximum number of the training data from a specified domain. Generally, SVDD would be more effective if the input space can be converted to feature space, where the input image can be better expressed. Therefore, the Gaussian kernel is applied in this paper.

We consider each corrupted test pattern x. When the decision function yields a nonnegative value for x, the test input is accepted normal as it is, and the reconstruction process is bypassed. Otherwise, the test input is considered to be abnormal and corrupted or corrupted. To reconstruct the corrupted area, an SVDD based projection approach that we recently proposed [12] is used, in which we move the feature vector toward the center up to the point where it touches the hyperball. Obviously, this movement is a kind of the projection, and can be interpreted as performing reconstruction of the corrupted area in the feature space. Note that as a result of the projection we have the obvious result. Here, we try to find the pre-image of the refined feature. If the inverse map is well-defined and available, this final step attempting to get the reconstructed image. However, exact pre-image typically does not exist. Thus, we need to seek an approximate solution instead. For this, we follow the strategy of [19], which uses a simple relationship between feature-space distance and input space distance together with the multi-dimensional scaling. The overall proposed step is introduced in [1]. After obtaining the reconstructed vectors from the above SVDD method, we synthesize a facial image by forward warping the texture onto the input face by using the shape. This synthesis step 7 is well explained in [20].

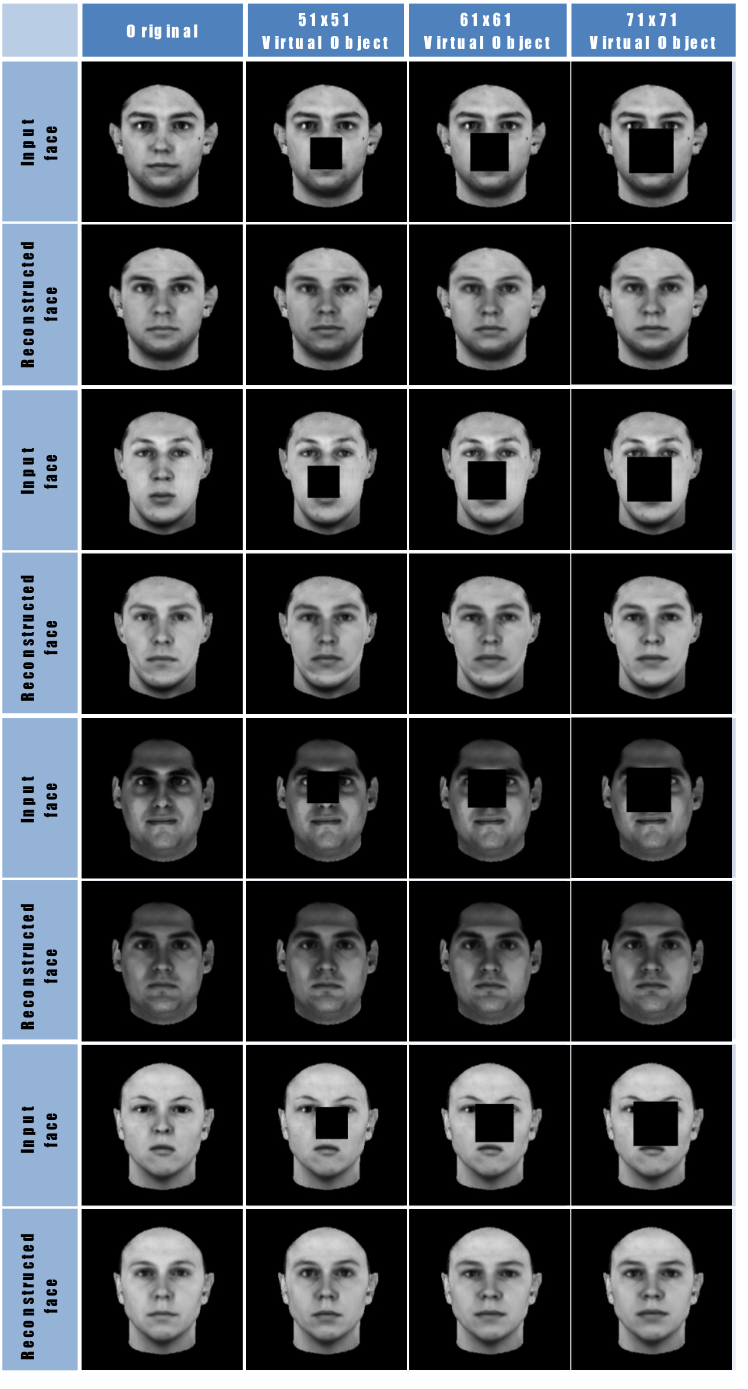

Figure 4. Examples of reconstructed faces

4 EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Face Database

Face data from 200 subjects were used to verify the proposed method. The 3-D laser scanned face data (CyberwareTM) were rendered into an input image by using ambient light [2, 20]. The input image, 256x256 pixel in size, was converted to a black and white image expressible in 256 gray levels. The 200-person facial data included not only the rendered facial images but also shape obtained from correspondences with the reference face as well as texture resulting from backward warping of the facial images. Of the data, facial data from 100 persons were chosen randomly for the generation of morphable facial model based on Principal Component Analysis, and the facial data of the remaining 100 persons were used for the reconstruction experiment carried out to verify the algorithm of this study. The 100 persons facial data used in the experiment were strictly separated from the 100 persons facial study data used in the generation of facial models and multiple facial example images to prevent any overlap.

4.2 Face Reconstruction Experiments

A corrupted facial image is reconstructed as described in Section 2.1. Figures 3 and 4 show the facial reconstruction of 4 persons: the even rows show the input faces and the odd rows show the reconstructed faces by the proposed method. In Figure 3, the first column shows the original images and the reconstructed images from the original ones, and columns 2–4 show the Gaussian noise-added images for standard deviations 10, 20, and 30, respectively and their reconstructed images.

As in Figure 3, the first column in Figure 4 shows the original images and the reconstructed images, and columns 2–4 show the facial images corrupted by virtual objects for pixel sizes 51×51, 61×61 and 71×71, respectively and their reconstructed image by the proposed method. The virtual object is located in each face randomly. The reconstructed faces of original faces in the first column and even rows of Figures 3 and 4 represent the highest of quality because they do not include the reconstruction error due to corruption, but include the error of step 2 in which the partial shape is obtained from corresponding points, the error of step 3 in which the whole shape is obtained by linear interpolation, and the error of steps 4–6 in which the whole shape and texture are obtained from the SVDD-based projection method. Therefore, the reconstruction result of a corrupted input is less accurate than that of an original image. Nevertheless, the reconstructed facial images of input images corrupted by Gaussian noise or object occlusion were very similar to the original facial images, as shown in Figures 3 and 4.

Figure 5 shows the reconstruction errors of shape, texture, and synthesis of the linear projection method (SVDwR) [10] and the proposed method. The x-axis represents the different types of input facial images: uncorrupted original image, Gaussian noise-added image of 30 % standard deviation, and 71×71 dark virtual

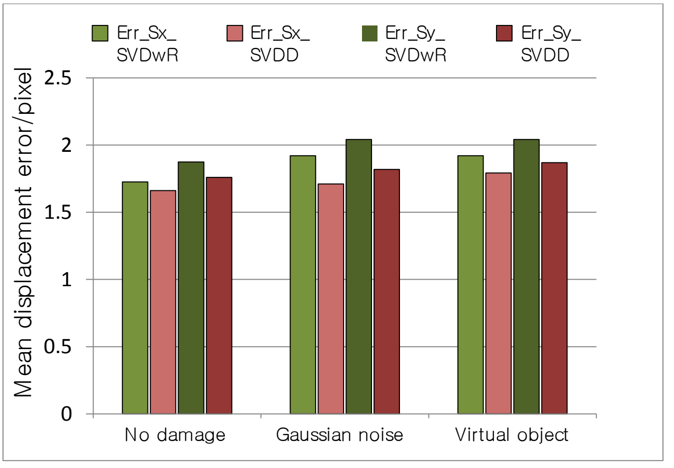

Figure 5. Mean displacement errors for shape, texture and synthesized images

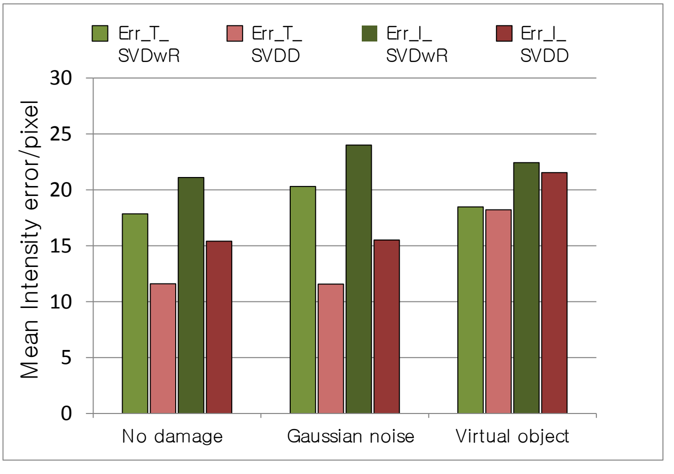

Figure 6. Mean intensity errors for shape, texture and synthesized images

object corrupted facial image. The y-axis represents mean displacement error per pixel and mean intensity error per pixel of 256×256 size and 256 gray level image. In Figure 5, Err_Sx and Err_Sy are the mean displacement errors of the reconstructed shape in the x and y directions and in Figure 6, Err_T and Err_I are the mean intensity errors per pixel of the reconstructed texture and image, respectively. As expected, both methods of reconstruction gave the lowest errors when the original image was used instead of the Gaussian-noise image and virtual object-occluded image. The mean x-direction displacement errors of the SVDD reconstructed images of the original, Gaussian and virtual images were less by 0.06, 0.21 and 0.13 than those of the linear projection method (SVDwR) reconstructed images, and the mean y-direction displacement errors were less by 0.11, 0.22 and 0.17. Furthermore, for the three input images, the mean intensity errors per pixel of texture of the SVDD reconstructed images were less by 6.27, 8.2 and 0.25 than those of the SVDwR reconstructed images, and the mean intensity errors per pixel of the SVDD reconstructed images were less by 5.70, 8.48 and 0.90, showing the superior performance of the SVDD method over the SVDwR method. Overall, compared to SVDwR method, the SVDD method showed its superior performance in being able to reduce the mean intensity error per pixel of the reconstructed Gaussian-noise corrupted images by 35 % (24.0 to 15.5), although it reduced the mean intensity error per pixel of the virtual object occluded images by only 3 %. This result shows that the proposed method shows better reconstruction performance for uniformly distributed corrupted images than for locally corrupted images. This is because the proposed method performs texture reconstruction by using as input the whole image including the corrupted region, whereas the existing method uses the texture of the feature points in the uncorrupted region. As in the experiment, a large corrupted region will have some effect on SVDD-based reconstruction. In reality, a dark virtual object will slightly darken the overall skin color. Although our paper presents only the results for Gaussian-noise corrupted images and 71x71 dark virtual object occluded image, as in Figures 5 and 6, a similar trend could be found in the experimental results for wider corrupted images (with standard deviation of 10, 20, 30 Gaussian noise, 51×51, 61×61, 71×71 size virtual object).

5 CONCLUSIONS

We proposed a method for aligning the input facial image whether it was corrupted or not by Gaussian noise or an object to the reference face in order to reconstruct an uncorrupted facial image. Finding the correspondence between a corrupted input facial image and the reference face is considered as a difficult task.

We were able to obtain sufficient numbers of corresponding feature points for reconstructions by applying feature points matching method between input image and multiple example images having known correspondence to the reference face, which has been limitedly used in finding correspondence between very similar images such as sequential frames and stereo pairs. Furthermore, the whole shape and texture of the input image were reconstructed from the matching feature points by using the SVDD method, a type of non-iterative data reconstruction method. The SVDD method can perform effective reconstructions even when some of the input information has errors or when there are few matching feature points. The proposed method was applied to original facial images, Gaussian noise-added facial images, and object occluded facial images in the experiments. The reconstructed facial images were very natural-looking and similar to the original facial image. Especially, for images with global corruption, like Gaussian noise-added images, the proposed method showed higher reconstruction performance than the linear projection method with the regularization factor.

In the future, the proposed method will be applied to actual facial images covered by objects such as sunglasses, cloth masks, hands etc. or affected by camera noise, as well as possibly to facial images recorded from various angles and in various illumination environments.

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