A Parametric Freckle Model for Faces

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***Abstract*—We propose a novel stochastic generative parametric freckle model for the analysis and synthesis of human faces. Morphable Models are the state-of-the-art generative parametric face models. However, they are unable to synthesize freckles which are part of natural face variation. The deficiency lies in requiring point-to-point correspondence on the texture pixels. We propose to assume a correspondence between freckle density and not the freckles themselves. We propose a model that is stochastic, generative, and parametric and generates freckles with a point process according to a density and size distribution. The resulting model can synthesize photo-realistic freckles according to observations as well as add freckles to existing faces. We create more realistic faces than with Morphable Models alone and allow for detailed face pigment analysis.**

I. Introduction

Whole industries are concerned with increasing the realism of animated characters in movies, and video games. Artists create face rigs by tediously designing the details necessary to create the impression of realism. We rely on the face to infer different properties about a person for example age, gender, origin, social information, etc. Many of these properties are environmental and reflected in high-frequency details of the texture. Computer graphics models of faces should, therefore, be able to represent and express these details. In this work, we address the parametric and generative modeling of facial freckles. Potential applications of modeling freckles are artificial aging, skin damage quantification [1] and face recognition [2]. The formation of freckles is caused by UV radiation and is influenced by genetic predisposition, and tends to increase with age. Freckle density varies on the face depending on sun exposure, face geometry, and habits. Freckles are not corresponding between individuals. However, there are regions where they are more likely to occur.

Morphable Models[3] are only capable of modeling shape and texture features that correspond between subjects. Such as smooth texture gradients, nasolabial folds, and lips. A freckle on one face is lacking its corresponding counterpart on another face and is therefore not captured in a Morphable Model. The underlying cause of this deficit lies in the assumed point-to-point correspondence.

We propose a generative and parametric freckle model which is independent of the Morphable Model but can be combined with it. To reflect the distribution of freckles on the face, we propose to model freckles with a point process parameterized by a density. Building a PCA freckle density model allows us to model freckle position without leaving the notion of point-to-point correspondence.

We evaluate the density model by comparing the proposed model to the mean density. We use specificity and generalization as model metrics. To compute them, we introduce a new perception-based metric for point process distributions. We show that the model is capable of synthesizing realistic freckle patterns according to data. This is the first facial freckle model.

II. Prior Work

Faces are not made out of low-frequency shape and texture only. High-frequency details can be acquired such as in the approach of Beeler *et al*. [4]. With Visio-lization [5] novel detailed faces can be synthesized in 2d by conditioning a texture synthesis algorithm on a global model trained on pixel values of input images. Xu *et al*. [6] created a parametric model of different facial features in 2d including wrinkles and spots to draw face sketches from photographs with a hierarchical compositional model. Morphable Models [7] are state of the art in parametric 3D face modeling. They can be used to generate new faces according to an underlying independent shape and texture distribution. By using Morphable Models Schumacher *et al*. [8] and Dessein *et al*. [9] restore details from blurred or occluded images. The former adds high-frequency details of Morphable Model texture and the latter fits a patch-based texture model to deficient images. None of the methods mentioned above explicitly model freckles and they do not give control over their synthesis.

III. Model

We propose a parametric and generative model for freckles on the face according to an empirical distribution estimated on face scan textures. The core of the model consists of a density defined on the uv map of a 3D reference mesh. We model density, size, and freckle color independently of each other. First, we will introduce the components of the model and then show how to build it. Figure 1 gives an overview over the process. *Images in the figures are viewed best on a screen.*

A. Components

Position and Density. We model freckle position according to a spatial Poisson point process. We model its density parameter according to a multivariate normal distribution on

978-1-5386-2335-0/18/$31.00

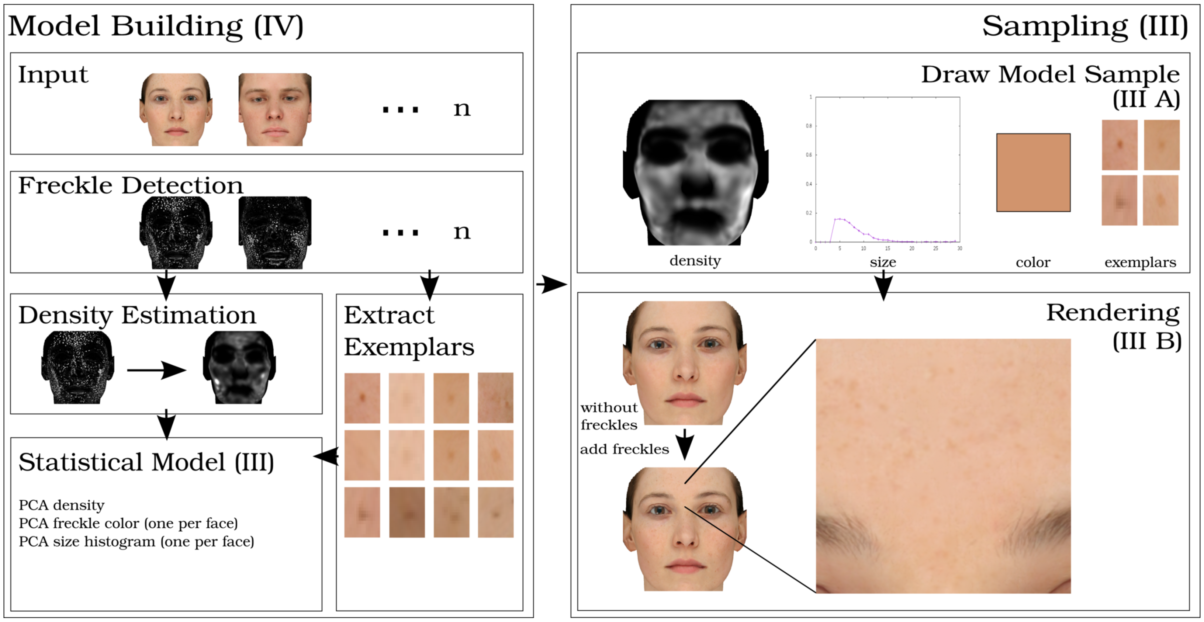

Figure 1. Overview over the proposed freckle synthesis framework. The corresponding chapters are indicate in brackets.

the surface of the shape. The spatially-varying density parameter characterizes the spatial distribution of the freckles. Given a density function we can sample an infinite amount of freckle configurations, all adhering to the given density. Figure 2 shows the first principal component of the density model.

Size. In contrast to the density, the freckle size distribution is not spatially-varying. The size of all freckles of a face are determined independent of position, by the same distribution. We represent the distribution with a histogram and create a multivariate Gaussian model over histograms.

Color. To obtain consistency between freckle color and skin tone we model freckle color depending on skin tone. The skin tone of a given Morphable Model texture is the average texture color of the skin region. Freckle color is the average color of all freckles on a given face. We model the dependency as a multivariate conditional Gaussian distribution of the freckle color given the skin tone.

Appearance. Because freckle appearance is diverse and a large amount of freckles are easily available, we model appearance according to a dictionary of exemplary freckles. We determine concrete freckle appearance by selecting a freckle from a dictionary according to the parameters size, color, and position on the original texture. The freckles are seamlessly cloned into the texture with Poisson image editing [10]. The target texture should be ambient for example a Morphable Model texture.

B. Synthesis

We generate freckles according to a given density, size distribution, and color parameter. These parameters can, for example, be estimated from a given face or by drawing them from the respective models.

First, we draw the positions of the individual freckles from the spatially varying density. It contains at every pixel in the texture the likelihood that there will be a freckle. For each pixel we determine if we should place a freckle there.

Given size and color parameters of a face we select the matching freckles from the dictionary. Per freckle position we draw a size from the size distribution. Additionally, we restrict the selection process to a ball around the current position to remove warping effects due to the texture embedding. Target freckle color is conditioned on the skin tone of the face we want to add the freckle to. We add a selected freckle to the texture with seamless cloning.

IV. Model Building

We estimate freckle position, size, and color as well as skin tone from high-resolution face scans. Then, we build the models for density, size, and color (see Figure 1).

Data. We train the model from 22 high-quality face scans of individuals of Caucasian origin exhibiting varying amounts and configurations of freckles. The scans are acquired in a controlled setting and illuminated with an uniform light source, the same way the Basel Face Model[11] data was acquired. **Density**. We estimate freckle density of a given texture by detecting and segmenting them. We manually annotate freckles in training textures and classify the pixels into freckle and non-freckle. With the interactive pixel classification tool Ilastik [12] we create a probability map. We segment the freckles by thresholding. Each segment is assumed to be a freckle. We determine the position by computing the barycenter per segment. The next step is to turn the positions into a density. Density d on the surface x is a linear combination of Gauss kernels with a specified fall off σ:

$$d(x) = \sum_{c \in \text{centers}} \mathcal{N}(c - x, \sigma) \tag{1}$$

We choose the fall off σ such that there is an overlap between densities of different faces ($\approx 0.7cm$). The result is a spatially-varying density function per scan texture from which we build a PCA model.

Size. The size of a freckle is the radius in pixels of a circle that covers the same area as the freckle ($r = \sqrt{A_{\text{freckle}}/\pi}$). We create a histogram over all the freckle sizes of the whole face.

Color Freckle color is the average color over the area covered by the freckle. The freckle color of a face is the average color over all freckles. The skin tone is the average color of the skin region of the face.

V. Model Selection

We compare different freckle models by computing model specificity and generalization. Both measures build on a distance measure between samples. In our case, a measure between two freckle configurations is required.

A. Model Measure

We evaluate the models by computing generalization to unseen data and specificity of generated samples to a test set [13].

1) Generalization: Generalization measures how the model can represent faithful samples from the original distribution. We build a single model on the training set and validate it on a separated test set. We compute the distance between a sample from the test set and its closest neighbor in model space.

2) Specificity: Specificity measures how close samples from the model are to the real distribution. We compute the distance between model samples and the sample closest from the test set.

B. Point Process Distribution Measure

To judge whether two sets of points are similar, and to be able to compute specificity and generalization, we introduce a new metric on point process distributions. First, we explain shortly the metric introduced by Schuhmacher and Xia [14], which compares two point sets ξ and η by assigning points between them. It consists of two terms, one measures how well assigned points match and the other, U, penalizes unassigned points. Their metric finds the assignment between two sets of points such that the sum of the distances between assigned points is minimal. To measure the matching, we find the assignment from all possible assignments, that minimizes the Euclidean distance between the all pairs of assigned points. Points not assigned impose the maximal distance. This measure, however, does not consider where unassigned points lie. Having points in a very sparse region should be penalized more than in a high-density region.

To ameliorate this, we propose the following modifications to the measure such that we account for the difference in density between the two sets. For an unassigned point x_i in a set ξ we impose the distance to the nearest neighbor (nn) in the set η and weight it by the difference between the number of points in the ϵ-Ball around x_i in ξ and η:

$$U(\xi, \eta) = \sum_{x \in \text{unassigned}} d_0\left(x_i, \text{nn}(x_i, \eta)\right) \left|\rho_\epsilon(x_i, \xi) - \rho_\epsilon(x_i, \eta)\right| \tag{2}$$

This measure is small if unassigned points are close to points in the other set and distributed such that they do not change the density much.

VI. Experiments

A. Quantitative Evaluation

We measure generalization and specificity of different variants of the proposed model. We compare it to a baseline model. It generates points according to the mean density of the training population. We compute Generalization on a test set of 15 examples. We generate 1000 samples from the freckle model to calculate specificity. Table I shows the results for the two models. Also we found that reducing the rank of the model does not lead to an improved model.

Model	Specificity	Generalization	Total
baseline model	110	269	379
proposed	149	143	**292**

Table I

Specificity and generalization for the proposed model and the mean density model. Units are density weighted distances (Equation 2). The full density model leads to a better trade-off (total is sum of both) between specificity and generalization than the mean.

B. Perceptual Evaluation of Point Distribution Measure

There are many different ways of measuring the distance between two point clouds, but not all of them are similar to perception. In the following we aim to find out whether the measure is similar to human perception. We show different point patterns to 5 people and ask them to compare how similar they are to each other. We show them two images, and they have to determine to which of the two a third image is more similar to. We apply the measure to the same task. The images contain randomly generated point patterns with at least 10 and up to 30 spots. Then we count the number cases where the measure agrees with the choice of the participants. We observe an agreement of 74%. The probability to obtain this result or a better one by chance is $p = 0.02$. Therefore, the measure is better than chance to predict how two point patterns will be perceived as similar. Figure 4 shows an example question.

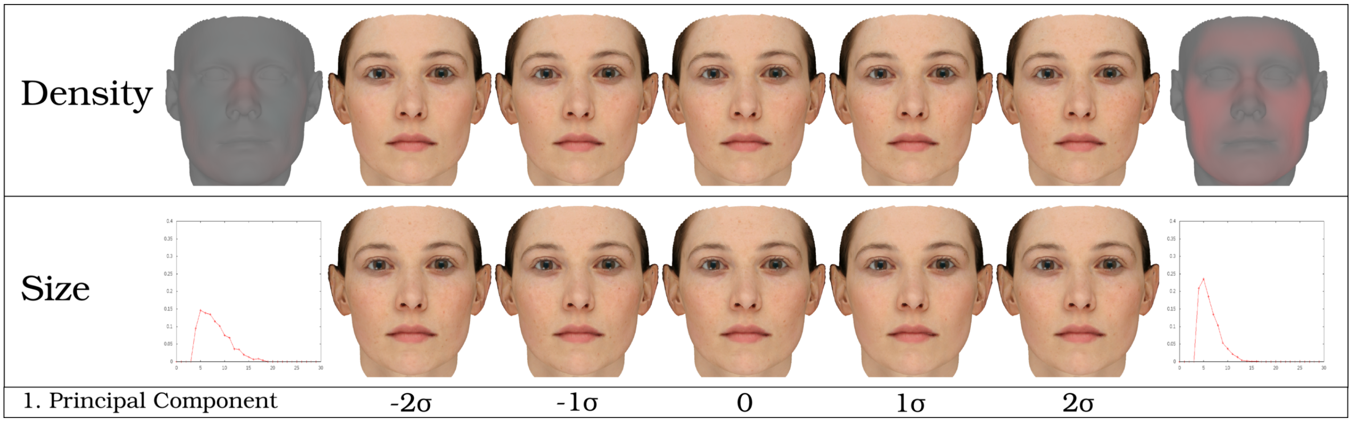

Figure 2. Visualization of the parametric components of our freckle model (along first principal component).

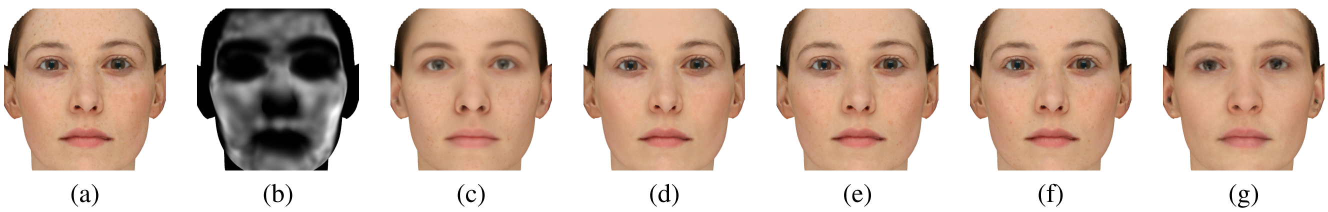

Figure 3. Face analysis: We estimate freckle model parameters from an input face and draw samples from it. From left to right: **a)** Input face **b)** estimated density **c)** freckles drawn from the model at the estimated parameter on an average face **d)** Scan with freckles removed **e)** and **f)** novel freckles synthesized on cleared skin from d) **g)** projection of input texture into Morphable Model space (PCA). (*Details viewed best on screen or in supplementary material*)

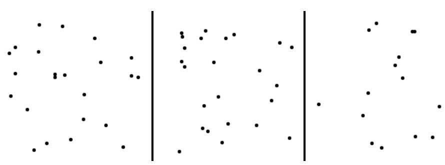

Figure 4. Example question of the perceptual experiment to measure the quality of the point process. Participants had to determine if the pattern in the middle is more similar to the one on the left or the right. Most participants chose left which is consistent to our measure proposed in Section V-B.

C. Model Samples

Figure 3 shows an example face scan projected into the freckle model, the extracted density, freckles removed from the scan, and samples drawn from the model at the projected coefficients.

D. Freckle Removal

We use the freckle detections to determine freckled and non-freckled regions. To remove them, we fill the detected freckles with push-pull interpolation [15] (See Figure 3).

E. Image Manipulation

The freckle model lends itself for image manipulation. We synthesize freckles according to the model and add them to an image. We fit Morphable Model parameters to the input image with the approach of Schönborn *et al.* [17] resulting in an illumination free texture. We synthesize on the Morphable Model texture and add the difference between the freckled and unfreckled texture to the image (Figure 5).

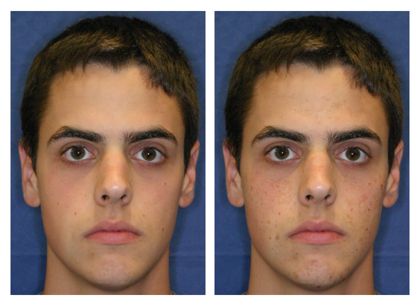

Figure 5. Image manipulation result: Original image and freckles added according to the identity in Figure 3. Image is from Multi-PIE [16].

VII. Conclusion

We presented a stochastic and parametric model for freckles. We model freckle density, size and color parametrically and appearance empirically. The proposed model is capable of generating photo-realistic freckles according to the data. Freckles are synthesized according to a spatially-varying density to respect different facial regions. We proposed a metric to compare point clouds and found the metric to be consistent with perception. We evaluate the model qualitatively and quantitatively and apply it to an image manipulation task.

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