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Detection and Inpainting of Facial Wrinkles

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Abstract - *Professional software usually require a minimum level of user expertise to achieve the desirable results. Facial retouching is widely used in media and entertainment industry. In this paper, we present an algorithm to detect facial wrinkles/imperfections. The detection of wrinkles/imperfections can allow these skin textures to be processed differently than the surrounding skin without much user interaction. For detection, Gabor filter responses along with texture orientation field are used as image features. A bimodal Gaussian Mixture Model (GMM) represents distributions of Gabor features of normal skin versus skin imperfections. Then, a Markov Random Field model (MRF) is used to incorporate the spatial relationships among neighboring pixels for their GMM distributions and texture orientation. Once detected automatically, wrinkles/imperfections are removed completely instead of being blended or blurred. We propose an exemplar-based constrained texture synthesis algorithm to inpaint irregularly shaped gaps left by the removal of detected wrinkles/imperfections.*

***Key Words*: Facial wrinkles, skin imperfections, Markov random field, Gaussian mixture model, Gabor features, texture orientation fields.**

1.INTRODUCTION

Traditionally beautification of skin and facial retouching in images has been done by professionals using high-end software e.g. Adobe Photoshop. Several user friendly applications which provide minimum user interaction for facial touch ups have also been introduced. However, both professional and user-friendly software have limitations. Professional software require significant user interactions where results are subjective, depending on user's expertise. Whereas user-friendly applications developed for smart phones, while performing an overall beautification or making up of skin with minimum user interaction, do not target specific skin imperfections e.g. deep wrinkles, acne, scars etc. Regarding image inpainting techniques, both structure and texture inpainting techniques are not applicable directly to the skin. Wrinkles and skin imperfections do not appear as edge/ boundaries and, hence structural inpainting is not appropriate. Also, as wrinkles are not homogeneous texture patterns, texture inpainting is not effective.Digital inpainting is the process of reconstructing lost or deteriorated parts of images and videos filling gaps of arbitarly shapes in an image so that they seem to be parts of the orginal image. Several applications of digital inpainting have been include filling occlusions/gaps, removal of objects, image reconstruction by removing scratches or other degradation. In the existing system poisson image editing[5], as a "seamless blending" of two images together. Source image can be cloned to the destination image. The processing of skin in an image smoothes wrinkles and skin imperfections but does not remove them completely. Due to this limitations, we propose new techniques for detection and inpainting. An image inpainting technique for texture has three main steps, (a) finding a suitable texture template in the image to fill in the gap with, (b) calculating the seamless warping between the template and the gap and (c) filling the gap via texture synthesis. The detection techniques includes Gaussain Mixture Model (GMM) based Markov Random Field (MRF) impose spatial smoothness among neighboring pixels. The process of wrinkling creates deep creases and causes curvature in the surrounding skin. The resulting skin curvature causes specific intensity gradients in skin images which look like discontinuities in surrounding skin textures.

2.AUTOMATIC DETECTION OF FACIAL WRINKLES

For the detection of images features we use orientation field and gabor filter responses. The orientation field highlights the discontinuities in the normal flow of skin texture whereas the Gabor filter responses highlight the intensity gradients in any directions. The two types of features are fused using Gaussian Mixture Model (GMM) and Markov Random Field (MRF) representation[1]. The GMM classifies filter responses as a bimodal distribution for skin vs. skin imperfections. The MRF representation allows us to incorporate spatial relationship among GMM distributions of neighboring pixels and to fuse the orientation fields to reshape the class probabilities.

2. 1 Computation Of Orientation Fields Using Gabor Filters

Gabor filter is used for edge detection. At high resolution, the skin texture appears to be granular resulting in random orientation angles. However, the skin creases of wrinkles and the skin pigments related to other imperfections (e.g. brown spot, moles) smooth out the granular skin texture. As a result, the orientation field depicts two significant properties in wrinkled regions, (a) a dominant angle of zero degrees and (b) pixels with zero orientation angle appear in clusters.

2.2 Gaussian Mixture Model Based on Markov Random Field (GMM-MRF)

The motivation behind using the GMM-MRF model is the fact that the Gabor filter responses or the texture orientation field, when used exclusively, are important but insufficient features to detect the wrinkled regions. Thresholding is maximum when Gabor amplitude at value 35. Texture orientation field has to be incorporated to aid thresholding by reshaping the probability of each class. An MRF framework enables not only the incorporation of spatial dependencies among neighboring pixels but also the fusion of texture orientation fields and Gabor amplitude responses. Gaussian mixture models based on Markov Random Field Modelling(GMM-MRF) are proposed to impose spatial smoothness constraints between neighboring pixels.

3. AUTOMATIC REMOVAL OF FACIAL WRINKLES

The detected wrinkled regions are inpainted by surrounding skin texture using texture synthesis. Texture synthesis techniques can be categorized as parametric or exemplar based. In parametric methods, the parameters of a generative texture model are learned from a sample texture. A texture image can then be synthesized by sampling the learned model. The exemplar-based methods focus on sampling patches from a sample texture and then stitching them seamlessly, incorporating neighborhood details, to synthesize larger texture images. The exemplar-based methods have become popular in recent years to synthesize 2D texture image. Parametric methods are appropriate for homogeneous (spatially non-varying) textures where a single set of parameters can represent the whole texture sample completely. Since, skin textures are slowly varying, inhomogeneous natural textures within face, we adopt examplar-based approach for efficiency and accuracy.

3.1 Constrained Texture Synthesis to Fill Image Gaps

The algorithm performs two steps for every gap detected by the GMM-MRF algorithm. The first step consists of finding the bounding box for the current gap and fitting it with a rectangular grid of square patches. Then, each patch in the grid is visited to determine if it overlaps with any pixel(s) in the gap. In the second step, the patches containing image gap pixels are replaced with the patches of the source skin texture.

3.2 Selection of Texture Source Template

In our case, to minimize the user interaction, a skin texture source template has to be determined automatically. Since facial skin texture varies greatly, for every patch to be inpainted, we use the skin texture nearest to that patch as a source template.

3.3 Compensation for Skin Tone Variations

This is a post processing step and is applied specifically to the areas under eyes. This is due to the fact that the skin under eyes is not only wrinkled, but, frequently, has discolorations due to sagging, under-eye bags or dark circles as well. Although image quilting provides seamless stitching of two patches, its main focus is the overlapping areas of the two patches. In under-eye regions, the interior of such patches may still present a significant skin tone difference. Therefore, a simple stitching step cannot provide the needed adjustment to the overall tone of the inpainted patch. We use the Poisson image editing to compensate for this tone variation. In our constrained texture synthesis algorithm, once the patch has been stitched, in case of eyes, the Poisson image editing is used as a post-processing step to compensate for the tone variation.

4. RESULTS AND DISCUSSION

Figure shows the results of removal of wrinkles. In the figure, the orginal image are shown parts (a), the gaps resulted by GMM-MRF algorithm are shown in parts (b) and inpainted images are shown in parts (c). All the images were of high resolution, larger than 1024 pixels × 768 pixels, showing detailed texture of skin. Here we make an interesting observation that facial wrinkles were more prominent in images of female celebrities. Regarding areas under eyes, the algorithm removes most of the wrinkles while maintaining the skin tone variation due to dark circles. This effect was desirable as the goal was to remove wrinkles without other beautification of the skin. Overall, our experiments demonstrate that most of the wrinkles and skin imperfections are detected and inpainted[1]. However, a few with less contrast with the surrounding skin are not detected. Our quantitative evaluation is based on the calculation of gradient orientation histograms since the presence of skin imperfections' causes dominant orientations in otherwise random skin texture orientation field.

(a) (b) (c) (d)

Fig -1: (a) Original image. (b) Gabor filtered image. (c) Orientation image (d) Threshold orientation field at an angle values of less than 5 degrees

(a) (b) (c)

Fig -2: Results of wrinkles and removal of acne (a) original image. (b) Detected wrinkled and acne areas. (c) Image after inpainting.

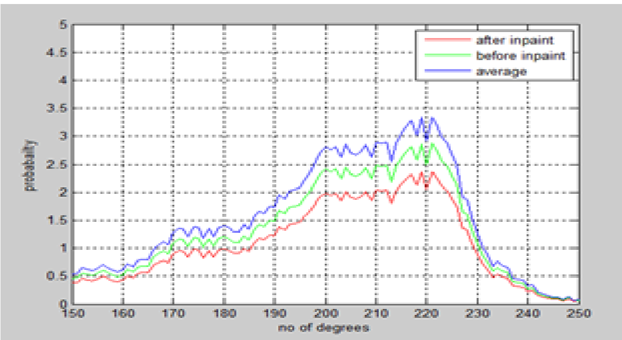

Fig -3: Histograms of gradient orientations

5. CHALLENGES

5.1 Effect of Age/Sagging Skin

In advanced ages, wrinkles are present very closely, and the area of the non-wrinkled skin is limited. Facial images where subjects had sagging of skin along with the wrinkles posed specific challenges to inpainting. This results in the selection of the same patch as a source skin texture for several patches to be inpainted and results in detectable repetitive patterns in the inpainted skin. Then, the overall sagging of skin results in changes of facial muscles and shape which are visible to the eye but are not to the GMM-MRF algorithm and hence cannot be detected and removed.

5.2 Effect of Illumination

Overall, small illumination variations did not affect the detection results. However, in cases of significant illumination variations e.g. due to pose or bright spots on skin, the intensity changes due to wrinkles were masked by those due to illumination. The wrinkles not masked by illumination were correctly detected by the GMM-MRF algorithm.

6. CONCLUSIONS

We present an algorithm for both detection and inpainting of facial wrinkles. Wrinkles plays an important role in age estimation. Exemplar based synthesis technique is used in inpainting .With minimum user interaction, the algorithms are able to detect and remove most of the wrinkles/imperfections. An algorithm based on the fusion of Gabor features and texture orientation fields in the framework of Markov Random Field (MRF) is proposed to detect wrinkles and other imperfections in the surrounding skin.

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BIOGRAPHIES

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