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Efficient Automatic Detection and Removal of Facial Wrinkles

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ABSTRACT

Nowadays many facial retouching applications are applicable. The best photo editing software will have an almost bottomless toolbox full of editing tools and options. Features like red-eye correction, lighting and contrast adjustment, color management,layers,cloning,touch-up tools, get rid of skin blemishes and whiten teeth. Fortunately, editing software has come a long way, becoming even more user friendly over the past few years. Now it is easy to edit the pictures even without any previous experience.The widely used photo editors in smart phones are Shift, Rage Comics Photo Editor, PicsArt, Photo Studio, Photoshop Touch for phone, Photo Mate R2etc…These photo editing softwares can take some time to learn and get used to. But those applications doesnot produce efficient results. Here we are detecting and removing the facial wrinkles by using the MRF,GMM and Gabor filter algorithms.We present results conducted on images downloaded from the Internet to show the efficiency and easy use of our algorithms.

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INTRODUCTION

Facial retouching encompasses the processes of altering images, whether they are digital photographs, traditional photochemical photographs, or illustrations. Image inpainting techniques are in use over a long time for various applications like removal of scratches, restoring damaged/missing portions or removal of objects from the images, etc. Inpainting, a set of techniques for making undetectable modifications to images, is as ancient as art itself. Here we propose a specific application of digital inpainting to remove facial wrinkles and imperfections. raditionally, beautification of skin or facial re-touching in images has been done by professionals using high-end software e.g. Adobe Photoshop. Several user friendly smart phone applications (e.g. Visage Lab, Beautify, Perfect365) which provide minimum user interaction for facial touch ups have also been introduced.In these applications user have to do the editing. The latter deals with the automatic filling of a gap/occlusion,mostly provided by the user, in an image based on local and/orglobal image characteristics and does not require a source image. Our work is closer to image inpainting than image painting because both source and destination image areas are selected automatically. An algorithm based on the fusion of Gabor features and texture orientation fields in the framework of Markov field modeling (MRF) is proposed to detect wrinkles and other imperfections in the surrounding skin.A variation of exemplar-based texture synthesis is pro-posed to fill the gaps of irregular shapes.Both detection and inpainting of wrinkles are unsuper-vised with minimum user interaction thus minimizing the subjectivity introduced by the user's expertise.No'retouching' or 'beautification' of the rest of the facial skin is done while inpainting skin wrin-kles/imperfections. Image inpainting methods target one or both of the *structure* and *texture* of an image. The specific application of wrinkle removal is different as wrinkles are not artifacts or separate objects to be removed. Wrinkles are inherent to skin and are visible only due to their discontinuous nature in surrounding skin texture. Our wrinkle inpainting approach is based on Poisson editing and a variation of exemplar-basedtexture synthesis. However, we use a novel approach to detect wrinkles and skin imperfections.

Related Works:

An image inpainting technique for textures has three main steps, (a) finding a suitable texture

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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. Since we are proposing unsupervised image inpainting, an additional step is required to detect wrinkles automatically.

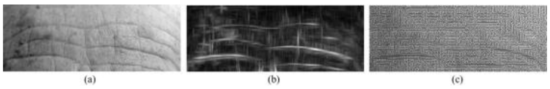

Fig. 1: Image features used for segmentation. (a) Forehead image in gray scale. (b) Maximum Gabor amplitude response (values [4.8, 132] scaled to thegray scale values [0,255]. (c) Texture orientation field.

Existing System:

In the Existing system,Significant user interaction is required with the Adobe Healing Tool for the selection of source and destination skin patches resulting in subjective results depending on user expertise.In the case of more user-friendly applications, facial retouching results in the so-called flawless skin. The processing of skin in an image smoothes wrinkles and skin imperfections but does not remove them completely.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 edges/boundaries and, hence, structural inpainting is not appropriate. Also, as wrinkles are not homogeneous texture patterns, texture inpainting is not effective.

Proposed System:

An algorithm based on the fusion of Gabor features and texture orientation fields in the framework of Markov field modeling (MRF) is proposed to detect wrinkles and other imperfections in the surrounding skin. A variation of exemplar-based texture synthesis is proposed to fill the gaps of irregular shapes. Both detection and inpainting of wrinkles are unsupervised with minimum user interaction thus minimizing the subjectivity introduced by the user's expertise.No 'retouching' or 'beautification' of the rest of the facial skin is done while inpainting skin wrinkles/imperfections. An image inpainting technique for textures 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. Since we are proposing unsupervised image inpainting, an additional step is required to detect wrinkles automatically. 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. An accurate inpainting of wrinkles will require both the wrinkle crease and the surrounding curved skin to be removed. In we present our approach for detection. Regarding step (a) of image inpainting mentioned above, we select skin patches surrounding the detected wrinkles. This is due to the fact that the skin texture can vary significantly within a small region of face. The skin patches closest to the wrinkles have the most similar looking skin texture.The architecture diagram for the proposed system is given below:

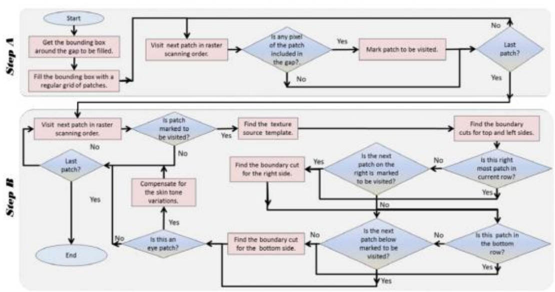

Fig. 2: Flow chart for our Constrained Texture Synthesis algorithm to fill image gaps.

Terminologies:

A. Detection of Regions with Wrinkles:

We use the texture orientation field proposed by Rao and Schunk and Gabor filter responses as image features. 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 Models (GMM) and Markov random field representation. 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.

1) Computation of Orientation Fields Using Gabor Filters:

Several oriented feature detectors have been developed including steerable Gaussian second-derivative filters, line operators and Gabor filters. A comparative study can be found in previous papers, where the real Gabor filters were assessed to be the best detector of oriented features. The real Gabor filter kernel is given by

$$g(x_1, x_2) = \frac{1}{2\pi \sigma_{x_1}\sigma_{x_2}} \exp\left[\frac{-1}{2}\left(\frac{x_1'^2}{\sigma_{x_1}^2} + \frac{x_2'^2}{\sigma_{x_2}^2}\right)\right] \cos(2\pi f x_1')$$

where,

$$\begin{bmatrix} x_1' \\ x_2' \end{bmatrix} = \begin{bmatrix} \cos\alpha & \sin\alpha \\ -\sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

The parameters α and f denote the orientation angle and frequency of the sinusoidal factor respectively and $\{\sigma x1,\ \sigma x2\}$ denote the standard deviations of the Gaussian envelope in 2D plane.

The orientation angle is calculated at every pixel. Every needle is of length of 3 pixels and is placed in the direction of the orientation angle.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.

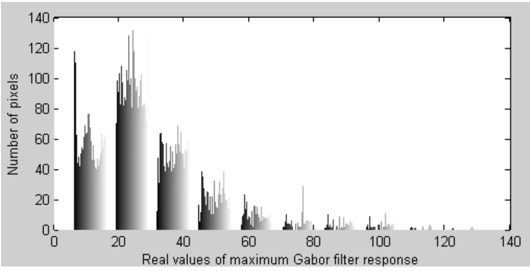

Fig. 3: Histogram of the Gabor features.

B. 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 images. 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. In addition, examplar based methods are more suited to the ‘constrained texture synthesis’. Our method is based on the exemplar-based texture synthesis method proposed by Efros and Freeman. In their work, Efros and Freeman introduced a novel method called image quilting for seamless stitching of small patches of the exemplar texture. We use their method to stitch skin patches together to fill the gaps left by removal of wrinkled regions.Filling of gaps in images using texture synthesis is also called as ‘constrained texture synthesis’ for the reason that the boundaries between the original texture and the synthesized texture have to be invisible.

1. Patch Based Image Quilting:

Let ST denote a small source texture sample from which the bigger texture image has to be synthesized. Let T1 andT2 denote two square patches to be stitched together and lT denote the length of a side of a patch. Let T1 and T2 denote portions of the patchesT1and T2 from any side as is shown in Fig. 8. The portions are set to be of width l< lT. The problem of seamless stitching of the two patches then boils down to finding a ragged boundary in the overlap portionsT1 and T2 such that a minimal discontinuity in texture flow is caused across the boundary. Let E be a matrix of size $lT \times l\Delta$representing the square difference between $\Delta T1$ and $\Delta T2$ as follows:

$$E^{i,j} = (\Delta_{T_1}^{i,j} - \Delta_{T_2}^{i,j})^2$$

where the superscripts i, j designate row and column of the matrix.

2. Constrained Texture Synthesis to Fill Image GAPS:

Removal of wrinkled skin results in several gaps of irregular shapes as can be seen in example images. Filling such gaps requires modifications to the texture synthesis method presented in the last Section which was originally used to synthesis rectangular texture samples. presents our algorithm to fill irregular gaps using constrained texture synthesis. 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. This image illustrates this step. The patches which do not overlap with the gap are marked as 'X' and are not considered in the second step. In the second step, the patches containing image gap pixels are replaced with the patches of the source skin texture. Each patch is stitched from two (top and left) or more sides depending on its location in the grid. Fig. 10 illustrates this step. Patches are visited in a raster scanning manner. Patch 'A' is stitched from top and left side with the rest of the skin image. Patch 'B' is stitched from all four sides because there is no patch to be visited on its right or bottom side. Patch 'C' is stitched from bottom side as there is no patch below it to be visited. depicts an example of detected wrinkles and a regular grid of patches to remove one of the detected wrinkles shows a further close up of the process of the removal of a wrinkle.

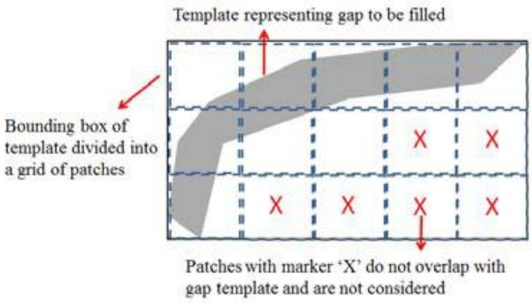

Fig. 4: The constrained texture synthesis algorithm divides an irregular shaped gap into a regular grid of patches. Each patch is then marked to be painted if it overlaps any pixels of the gap.

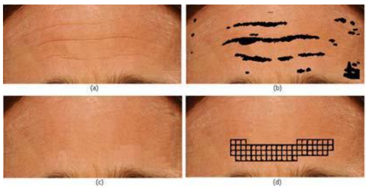

Fig. 5: (a)Original Image (b) Several wrinkled areas detected by GMM-MRF(c) Inpainted image after removal of wrinkles. (d) Patches from regular grid fitted on one gap which were actually inpainted.

3. *Selection of Texture Source Template:*

Usually a texture sample image, ST, is provided to a texture synthesis algorithm. However, in our case, to minimize the user interaction, a skin texture source template has to be determined. Since facial skin texture varies greatly, for every patch to be inpanited, we use the skin texture nearest to that patch as a source template. A texture source template is selected so that (a) it is of size 1.3×T, where we choose 1.3 because it is small enough for faster computation time and big enough to provide a compatible texture source, (b) it does not overlap with any of the wrinkle gaps and (c) it is nearest to the current patch to be inpainted. Once an ST is selected this way, a suitable patch, T, can then be found within this texture source template.

4. *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 δT 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. This is illustrated in result where boundaries of several patches stitched together are obvious due to the skin tone variation. We use the Poisson image editing to compensate for this tone variation. Bugeau etal used a similar approach as a post-processing step to compensate for the illumination discontinuities. 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. The difference in the inpainting results with and without Poisson image editing is clearly visible in result images.

Fig. 6: Poisson compensation for color variation under eyes. (a) Inpainted skin without Poisson compensation. (b) Inpainted skin with Poisson compensation.

Experimental Results:

Experiments were conducted on two sets of images downloaded from the Internet. The first set consists of images of public figures, e.g. celebrities and politicians, and was used to remove facial wrinkles. The second set consists of portions of facial images of other people and was used to remove other skin imperfections.All the images were of high resolution, larger than 1024 pixels × 768 pixels, showing detailed texture of skin.

The only constraint for these patches was to contain skin and no other facial parts. Since GMM-MRF detection is based on Gabor features which depend on image gradients, the inclusion of facial features other than skin, e.g. hair, eyes, would result in erroneous detection results.

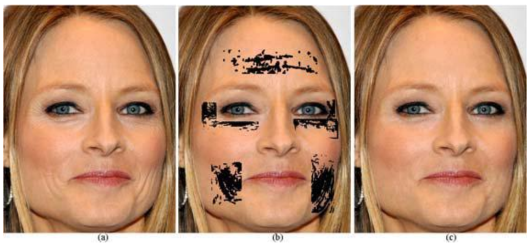

Fig. 7: Results of wrinkle detection and removal for a subject. (a) Original image. (b)Detected wrinkled areas. (c) Image after wrinkle removal.

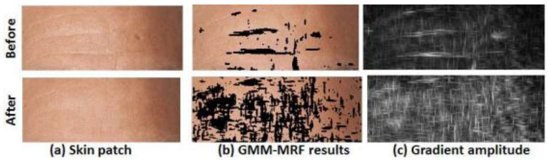

Fig. 8: Changes in skin texture and corresponding GMM-MRF detection results and Gabor amplitude response after inpainting.

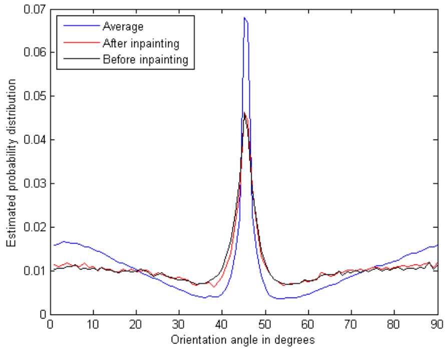

Fig. 9: Histograms of gradient orientations.

C. Removal of Wrinkles:

These experiments demonstrate that most of the wrinkles and skin imperfections are detected and inpainted. 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.

Removal of Moles/Dark Spots/Scars:

We also applied our algorithm on other types of skin imperfections, e.g. moles, dark/brown spots, acne, wound scars and freckles. These imperfections also appear as a disruption in the surrounding texture. Since these images did not contain full facial images to hide the identities of the subjects, these was resized to have the maximum dimension equal to 500 pixels instead of 1100 pixels in case of full facial images. The imperfections are removed irrespective of the cause, color, size and shape. We observe that acne or wound scars, moles and darker brown spots are detected and removed. Lighter and smaller brown spots were the most difficult kind of imperfection to be detected. Several moles/dark spots on cheeks which are removed along with wrinkles by the inpainting algorithm.

Quantitative Evaluation of Inpainting Results:

In this Section, we present quantitative analysis of detection and inpainting results by evaluating smoothness of the inpainted skin texture. In texture synthesis community, visual evaluation of results is usually deemed sufficient. Overall, we conclude that our algorithm performs much better when the wrinkles, scars and moles are prominent in the surrounding texture.

ComparisonWith Existing Techniques:

Although our method performs both detection and inpainting, in this Section,we persent comparison of our inpainting results only with existing inpainting techniques , and with two pieces of software, Adobe Photoshop and Perfect365. Our algorithm removes most of the wrinkles (except expression wrinkles around mouth) without any beautification of skin whereas in Photoshop results, facial skin has been changed drastically in addition to removal of wrinkles.

Conclusion:

In this paper, we addressed some of the limitations of current facial retouching applications. We presented an algorithm incorporating Gabor features and texture orientation field of facial skin in the framework of GMM and MRF representations to detect wrinkles and other skin imperfections. Then, we presented an algorithm based on examplar-based texture synthesis to inpaint the irregular gaps left by the removal of skin wrinkles/imperfections. Experiments on images downloaded from the Internet show the effectiveness of our algorithms. With minimum user interaction, the algorithms are able to detect and remove most of the wrinkles/imperfections. We discussed some of the challenges in detection and inpainting. Overall, our algorithm presents significant improved inpainting in cases where skin imperfections are more visible in the surrounding skin. This work can be extended to address the sagging of skin in more advanced stages of aging as well as to improve inpainting to address the artifacts caused by repetition.

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