Image warping in dermatological image hair removal

Alexandra Nasonova[1], Andrey Nasonov[1], Andrey Krylov[1], Ivan Pechenko[1], Alexey Umnov[1], Natalia Makhneva[2]

[1] Laboratory of Mathematical Methods of Image Processing, Faculty of Computational Mathematics and Cybernetics, Lomonosov Moscow State University
[2] Moscow Scientific and Practical Center of Dermatology and Venereology and Cosmetology of Moscow Healthcare Department
kryl@cs.msu.ru

Abstract. The paper focuses on solving the problem of hair removal in dermatology applications. The proposed hair removal algorithm is based on Gabor filtering and PDE-based image reconstruction. It also includes the edge sharpening stage using a new warping algorithm. The idea of warping is to move pixels from the neighborhood of the blurred edge closer to the edge. The proposed technique preserves the overall luminosity and textures of the image, while making the edges sharper and less noisy.

Keywords: Image warping, edge sharpening, hair detection, inpainting, dermatology

1 Introduction

One of the main problems of image processing in dermatology applications is the presence of hair which should be removed before image analysis. The survey of state of the art hair removal methods for dermoscopy images is presented in [2]. All existing hair removal algorithms consist of two main stages: detection of pixels covered by hair and restoration of pixels in hair regions with minimal distortion. Hair-removal methods can be broadly classified as linear interpolation techniques, inpainting by non-linear-PDE based diffusion algorithms and example based methods. An example of linear interpolation hair removal algorithm can be found in [18, 21, 23, 24]. There are works which utilized the concept of non-linear PDE based diffusion [5, 9, 13, 26]. Also, an attention has been paid to remove hair by example based inpainting technique [1, 3, 14, 25].

The paper introduces a new method for the problem of hair removal which adds the edge sharpening as the third main stage additional to hair pixel detection and restoration stages. The hair pixel detection stage of the proposed method is based on the algorithm [4] and improves it using Gabor filters for line detection instead of difference of Gaussians. For the pixel restoration stage we use PDE-based algorithm [10].

In the case of large size of regions covered by hair, the reconstructed image is usually blurred so image sharpening algorithms are used to improve its quality. Image sharpening is generally viewed as the problem of image deconvolution [6]. In this case the blurred image is usually modeled as a convolution of the original image with some blur kernel [8, 22]. This problem is ill-posed, and even the slightest error in the estimation of the blur kernel may introduce strong artifacts in the resulting image.

A new two-dimensional warping algorithms for solving the problem of image sharpening is used in this work. The idea of warping is to move pixels from the neighborhood of the blurred edge closer to the center of the edge. There is no need for an accurate estimation of the blur kernel. The input parameters of the proposed method are the edge map and the approximate blur level.

The warping approach for image enhancement was introduced in [7]. The warping of the grid is performed according to the solution of a differential equation that is derived from the warping process constraints. The solution of the equation is used to move the edge neighborhood closer to the edge, and the areas between edges are stretched. The method has several parameters, and the choice of optimal values for the best result is not easy. Due to the global nature of the method the resulting shapes of the edges are sometimes distorted.

In [16] the warping map is computed using simple local measures of the image. This approach does not introduce edge overshoot and does not amplify the noise. The measures are computed separately for rows and for columns of the image with restrictions that prevent two consecutive samples from interchanging their order in the 1D sequence, but it can introduce small local changes in the direction of edges.

In [15] an edge width estimation algorithm has been introduced. The method is based on the assumption that the blur of the image is close to Gaussian. The image is divided into blocks, and the blur kernel is supposed to be uniform inside the block. The estimation of the blurriness of the block is based on the maximum of difference ratio between an original image and its two re-blurred versions. In this work we use edge width estimation method [20] that works under the same assumption that the blur of the image is close to the Gaussian blur. We estimate the dispersion of the Gaussian kernel such that its convolution with the ideal step edge function gives the edge of interest.

2 Hair detection

Hair pixel detection consists of initial detection of suspicious image fragments containing hair followed by connecting broken lines and removing possible mole contour which is often detected as hair region.

2.1 Initial hair pixel detection

Initial hair pixel detection is usually performed by common line detectors [11]. In this work we use convolution with Gabor filters with different angles and scales to detect hair regions.

We use the Gabor filter kernel in the following form

$$g(x, y; \lambda; \theta; \psi; \sigma; \gamma) = \exp(-\frac{X^2 + \gamma^2 Y^2}{2\sigma^2}) \cos(\frac{2\pi X}{\lambda} + \psi),$$

where $X = x\cos\theta + y\sin\theta,\ Y = -x\sin\theta + y\cos\theta$.

To combine the results of the convolution with Gabor filters with different parameters, the maximum value is taken in every pixel. For the posed problem we use $\gamma = 1$, $\lambda = \frac{4}{\pi^2}$, $\psi = \frac{\pi}{2}$, $\theta = \frac{n\pi}{N}$, $n = 0, 1, \ldots, N-1$, $N = 8$, $\sigma = 2, 3, 4$. The initial hair region image is constructed by applying threshold to the combined Gabor filter response.

2.2 Accurate hair pixel detection

We apply morphological closing to the initial hair pixel detection result to connect broken lines. Then we remove mole contour from the obtained mask using the algorithm that assumes that the mole is darker than outer skin. It consists of the following steps:

1. Calculate entire image histogram.
2. Take the part of the most dark pixels using the histogram — the set U.
3. Apply erosion to the set U with circular structure element with the radius n.
4. Apply dilation to the obtained set with the radius m and take only added pixels as pixels of the mole contour.

We use $n = m = 5$.

3 Hair removal

The PDE-based method [10] was used to reconstruct the missing pixels after removing hair regions. It iteratively interpolates the pixels on the border of the reconstructed area until the area is completely filled. Local structures are smoothly inpainted from the outer part of the reconstructed area to the inner part. The pixels are interpolated using the method

$$u(x) = \frac{\sum_{y\in\varepsilon(x)} w(x, y)u(y)}{\sum_{y\in\varepsilon(x)} w(x, y)},$$

where

$$w(x, y) = \frac{1}{|x - y|} \exp\left(-\frac{1}{2\sigma^2}(c^{\perp}(x)(x - y))^2\right).$$

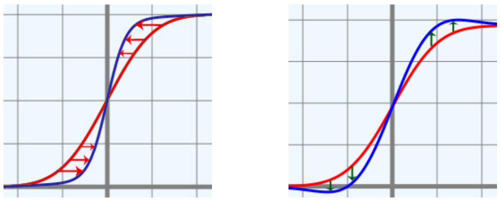
Here $\varepsilon(x)$ is the neighborhood of the reconstructed pixel with known pixel values, $c^{\perp}(x)$ is the direction tangential to the edge [10], σ is the parameter of the method. We use $\sigma = 1$.

4 Edge sharpening by image warping

Finally the reconstructed image is sharpened using image warping.

4.1 One-dimensional edge sharpening

Grid warping Compared to a sharp edge profile, the profile of a blurred edge is more gradual. So in order to make the edge sharper its transient width should be decreased (see Fig. 1).



a. Proposed approach b. Unsharp masking approach

Fig. 1. One-dimensional edge sharpening

For any edge $g(x)$ centered at $x = 0$ its sharper version $h(x)$ can be obtained shifting the pixels from the neighborhood of the edge towards its center. The *displacement function* $d(x)$ describes the shift of a pixel with coordinate x to a new coordinate $x + d(x)$: $h(x + d(x)) = g(x)$.

The warped grid should remain monotonic (i.e. for any $x_1 < x_2$ new coordinates should be $x_1 + d(x_1) < x_2 + d(x_2)$), so the displacement function should match the following constraint:

$$d'(x) \geq -1. \tag{1}$$

Another constraint localizes the area of warping effect near the edge center:

$$d(x) \to 0, \qquad |x| \to \infty.$$

The displacement function $d(x)$ greatly influences the result of the edge warping. The displacement function should be chosen in a way that the slope of the edge becomes steeper yet the warping does not stretch the edge over some predefined limit. In the case of a discrete edge the rarefication is supposed to avoid wide gaps between adjacent pixels, and the values on the new warped grid are then interpolated to the old uniform grid.

Edge model The choice of the displacement function is based on the assumption that the blurred edge $E_\sigma(x)$ can be approximated by an ideal step edge $H(x)$ convolved with Gaussian filter with known parameter σ [12]:

$$H(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x < 0, \end{cases} \qquad E_\sigma(x) = [H * G_\sigma](x),$$

where $G_\sigma(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$.

Proximity function The displacement function $d(x)$ is connected with the *proximity* of image pixels $p(x)$:

$$p(x) = 1 + d'(x).$$

The proximity is the distance between adjacent pixels after image warping. This value is inverse to the density value. If the proximity function $p(x)$ is less than 1, then the area is densified at the point x. If the proximity is greater than 1, then the grid is rarefied. For an unwarped image $p(x) \equiv 1$.

The constraint (1) leads to non-negativity of the proximity function. Also high values of the proximity function should be avoided, because it will be hard to perform interpolation in rarefication areas if the rarefication is too strong.

We use the proximity function $p(x)$ to calculate the displacement function:

$$d(x) = \int_{-\infty}^{x} (p(y) - 1)dy.$$

For the problem of edge sharpening, we use the difference of two Gaussian functions as the proximity function in order to control the areas of rarefication and densification independently:

$$p(x) = 1 + \kappa(G_{\sigma_1}(x) - G_{\sigma_2}(x)), \quad \sigma_2 > \sigma_1. \tag{2}$$

For the edge blurred with σ, we use $\sigma_1 = \sigma$. Parameter σ_2 is taken as $k\sigma_1 = k\sigma$. Good results are obtained with $1.5 \leq k \leq 2$. To achieve the strongest sharpening effect, we use the maximal values of κ that matches the constraint (1):

$$\kappa = 1/\left(G_{\sigma_1}(0) - G_{\sigma_2}(0)\right).$$

We use $\sigma_1 = \sigma, \sigma_2 = 2\sigma$.

4.2 Two-dimensional edge sharpening

The 2D case is similar to 1D case with the following changes:

1. The displacement is a vector field $\boldsymbol{d}(x, y)$.

2. There cannot be any turbulence: rot $\boldsymbol{d} = 0$. Therefore, the displacement field is assumed to be gradient of some scalar function $u(x, y)$: $\boldsymbol{d}(x, y) = \nabla u(x, y)$.

3. The derivative of d is replaced by divergence so the condition (1) looks as div $\boldsymbol{d} \geq -1$ and the proximity function takes the form $p(x, y) = 1 + \text{div}\, \boldsymbol{d}(x, y)$.

Since div$\nabla \equiv \Delta$, where Δ is a Laplacian, the warping problem can be posed as follows

$$\begin{cases} \Delta u &= p(x, y) - 1, \\ \frac{\partial u}{\partial n} &= 0. \end{cases} \tag{3}$$

We solve the equation (3) by Gauss-Zeidel method.

Constructing the warping equation In order to get the same results as in the 1D case and to keep the edge pixels unwarped, the proximity value should be equal to the 1D proximity function depending on the distance to the edge. To take into consideration multiple edge information, we suggest the following method for calculating the proximity function:

$$p(x_0, y_0) = \frac{\sum\limits_{(x,y)\in E(x_0,y_0)} p(x_n) G_\sigma(x_t) |\boldsymbol{g}(x,y)|}{\sum\limits_{(x,y)\in E(x_0,y_0)} |\boldsymbol{g}(x,y)|}$$

where $E(x_0, y_0)$ is the set of edge points in the neighborhood of (x_0, y_0).

The values x_n and x_t are projections of the vector $(x_0 - x, y_0 - y)$ on the edge gradient vector $\boldsymbol{g}(x, y)$ and on the tangent to the edge respectively.

The function $p(x_n)$ is the 1D proximity function, $G_\sigma(x_t)$ is the weighting function with standard deviation equal to the edge's blur σ.

Interpolation The idea of interpolation from the warped grid to the uniform grid is as follows: the intensity of the image at pixel (i, j) is computed as a weighted sum of intensities of all points on the warped grid in the neighborhood of that pixel: for a given radius r and all neighboring points $\{(x_k, y_k) : d_k = \sqrt{(i - x_k)^2 + (j - y_k)^2} \leq r\}_{k=1}^{K}$ the intensity of a sharpened image I_s at (i, j) is computed as

$$I_s(i, j) = \sum_{k=1}^{K} \frac{1}{D}_k I(x_k, y_k), \text{ where } D_k = d_k / \sum_{l=1}^{K} d_l.$$

We use the interpolation radius $r = 1.5$.

5 Results and Discussion

The proposed hair removal algorithm was tested for a set of melanoma images and showed its effectiveness. Some results of hair removal and edge sharpening with comparison to other methods are illustrated in Fig. 2. It can be seen that the proposed method sharpens the mole border while keeping the other image part almost intact.

It is necessary to mention that the proposed warping algorithm corrupts the fractal structure of the mole border and should be taken into consideration in medical practice. The analysis of the fractal structure is to be performed before the hair removal method.

In this work we used $\sigma = 2$ for the warping algorithm. The future work will include an method to estimate the edge blur value σ basing on the number of inpainted mole boundary pixels.

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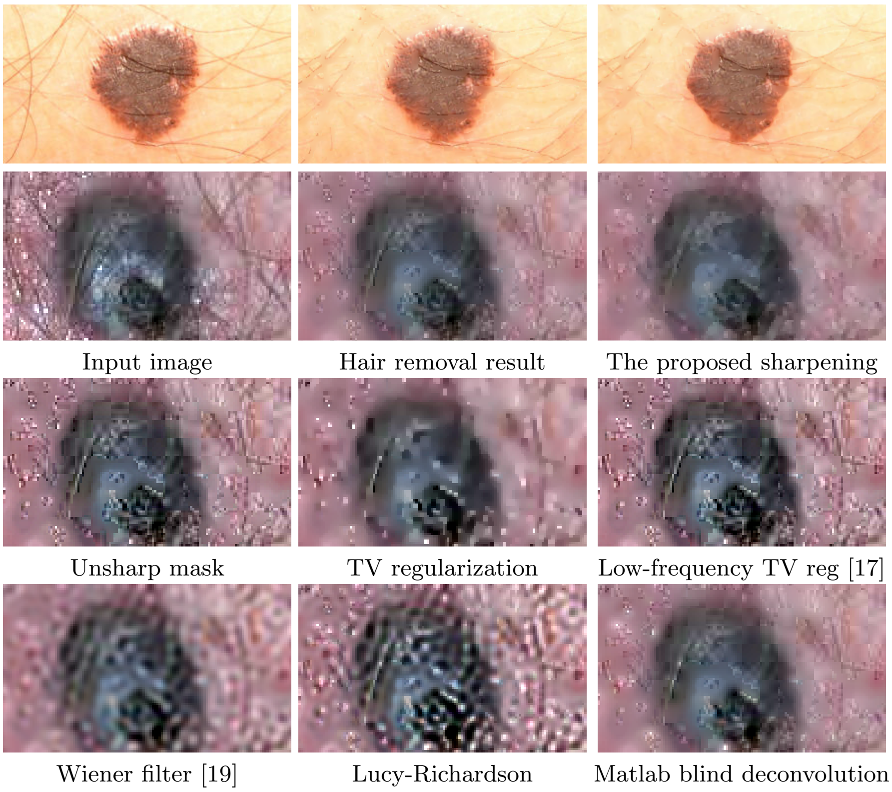

Fig. 2. The results of hair removal and sharpening using image warping

References

1. Feature-preserving artifact removal from dermoscopy images. Proc. SPIE Med. Imaging pp. 1–9 (2008)
2. Abbas, Q., Celebi, M.E., Garcia, I.F.: Hair removal methods: a comparative study for dermoscopy images. Biomed Signal Process Control 6, 395–404 (2011)
3. Abbas, Q., Fondon, I., Rashid, M.: Unsupervised skin lesions border detection via two-dimensional image analysis. Computer Methods and Programs in Biomedicine 27(1), 65–78 (2010)
4. Abbas, Q., Garcia, I.F., Celebi, M.E., Ahmad, W.: A feature-preserving hair removal algorithm for dermoscopy images. Skin Research and Technology 19(1), 27–36 (2013)
5. Abbas, Q., Garcia, I.F., Rashid, M.: Automatic skin tumor border detection for digital dermoscopy using a novel digital image analysis scheme. British Journal of Biomedical Science 67, 177–183 (2010)
6. Almeida, M., Figueiredo, M.: Parameter estimation for blind and non-blind deblurring using residual whiteness measures. IEEE Trans. Image Processing 22, 2751–2763 (2013)

7. Arad, N., Gotsman, C.: Enhancement by image-dependent warping. IEEE Trans. Image Proc. 8, 1063–1074 (1999)
8. Babacan, S.D., Molina, R., Katsaggelos, A.K.: Variational bayesian blind deconvolution using a total variation prior. IEEE Trans. Image Process. 18, 12–26 (2009)
9. Barcelos, C., Pires, V.: An automatic based nonlinear diffusion equations scheme for skin lesion segmentation. Appl. Math. Comput. 215, 251–261 (2009)
10. Bornemann, F., Marz, T.: Fast image inpainting based on coherence transport. Journal of Mathematical Imaging and Vision 28, 259–278 (2007)
11. Canny, J.: A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence 8, 679–714 (1986)
12. Chernomorets, A.A., Nasonov, A.V.: Deblurring in fundus images. In: 22-th Int. Conf. GraphiCon'2012. pp. 76–79. Moscow, Russia (2012)
13. Chung, D., Sapiro, G.: Segmentation skin lesions with partial-differentialequation-based image processing algorithms. IEEE Trans. Med. Imaging 19, 763–767 (2000)
14. Criminisi, A., Perez, P., Toyama, K.: Region filling and object removal by exemplarbased image inpainting. IEEE Trans. Image Process. 13, 1–13 (2004)
15. Hu, H., de Haan, G.: Low cost robust blur estimator. In: IEEE International Conference on Image Processing. pp. 617–620 (2006)
16. J. Prades-Nebot et al.: Image enhancement using warping technique. IEEE Electronics Letters 39, 32–33 (2003)
17. Krylov, A.S., Nasonov, A.V.: Adaptive image deblurring with ringing control. Fifth International Conference on Image and Graphics (ICIG '09) pp. 72–75 (2009)
18. Lee, T., Ng, V., Gallagher, R., Coldman, A., McLean, D., Dullrazor, A.: Software approach to hair removal from images. J. Comput. Biol. Med 27, 533–543 (1997)
19. Nagy, J.G., Palmer, K., Perrone, L.: Iterative methods for image deblurring: A matlab object-oriented approach. Numerical Algorithms 36(1), 73–93 (2004)
20. Nasonova, A.A., Krylov, A.S.: Determination of image edge width by unsharp masking. Computational Mathematics and Modelling 25, 72–78 (2014)
21. Nguyen, N., Lee, T., Atkinsa, M.: Segmentation of light and dark hair in dermoscopic images: a hybrid approach using a universal kernel. Proc. SPIE Med. Imaging pp. 1–8 (2010)
22. Oliveira, J., Bioucas-Dia, J.M., Figueiredo, M.: Adaptive total variation image deblurring: A majorization-minimization approach. Signal Process. 89, 1683–1693 (2009)
23. Saugeona, P.S., Guillodb, J., Thiran, J.P.: Towards a computer-aided diagnosis system for pigmented skin lesions. Comput. Med. Imag. Grap. 27, 65–78 (2003)
24. Schmid, P.: Segmentation of digitized dermatoscopic images by twodimensional color clustering. IEEE Trans. Med. Imaging 18, 164–171 (1999)
25. Wighton, P., Lee, T., Atkinsa, M.: Dermoscopic hair disocclusion using inpainting. Proc. SPIE Med. Imaging pp. 1–8 (2008)
26. Xie, F.Y., Qin, S.Y., Jiang, Z.G., Meng, R.S.: Pde-based unsupervised repair of hair-occluded information in dermoscopy images of melanoma. Comput. Med. Imag. Grap. 33, 275–282 (2009)