An image-processing analysis of skin textures

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Background: This paper discusses an image-processing method applied to skin texture analysis. Considering that the characterisation of human skin texture is a task approached only recently by image processing, our goal is to lay out the benefits of this technique for quantitative evaluations of skin features and localisation of defects.

Methods: We propose a method based on a statistical approach to image pattern recognition. The results of our statistical calculations on the grey-tone distributions of the images are proposed in specific diagrams, the coherence length diagrams.

Results: Using the coherence length diagrams, we were able to determine grain size and anisotropy of skin textures. Maps showing the localisation of defects are also proposed.

Conclusion: According to the chosen statistical parameters of grey-tone distribution, several procedures to defect detection can be proposed. Here, we follow a comparison of the local coherence lengths with their average values. More sophisticated procedures, suggested by clinical experience, can be used to improve the image processing.

Key words: 2D textures – skin texture – texture functions – defect localisation

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Accepted for publication 5 August 2009

A QUANTITATIVE characterisation of human skin textures is a task only recently approached by image processing. This problem is twofold interesting. Besides the computational modelling of skin for realistic rendering in computer graphics (1), we must consider the possibility of applying texture analysis for computer-assisted diagnosis in dermatology (2, 3).

Image processing can analyse the texture of the skin, that is, the appearance of its smooth surface, and extract some data concerning its features. These features are dependent on many factors such as, for instance, diet and hydration, amount of collagen and hormones and, of course, skin cares. A gradual decline in skin is moreover superimposed by age. As skin ages, it becomes thinner and more easily damaged, with the appearance of wrinkles. This deterioration is also accompanied by a darkening of skin colour because of over-absorption of the natural colouring pigment, melanin, by the top-most cell layer in the skin. The skin texture is also dependent on its body location. Moreover, when using image processing, we have to consider the fact that the texture appearance changes with image-recording parameters and with illumination and direction of view.

The task of having a quantitative evaluation of skin features is then quite complex, as in all the cases when image analysis must be applied to surfaces with irregular non-periodic patterns. In digital image processing, several methods have been developed to classify images and define statistical distances among them, with the aim of deciding whether, in a set of many images, there exist some which are close to any arbitrary image previously encountered. Texture discrimination can be obtained by choosing a set of attributes, the texture features, which accounts for the spatial organisation of the image (4–7). For skin textures, approaches based on wavelets (8), adaptive segmentation (9) and genetic image analysis (10) have been proposed. Bevilacqua and Gherardi (11) and Bevilacqua et al. (12) have faced skin topography characterisation by processing the skin profile obtained with a capacitance device, to investigate the effect of ageing.

In this paper, for skin characterisation, we propose to use the image processing procedure previously used to investigate texture transitions
in nematic liquid crystals (13, 14). This processing is suitable for images with smooth, scarcely regular textures, such as those observed in the microscopic investigation of certain nematic liquid crystal cells. The processing is based on a coherence length analysis, described in detail in the following section.

**Method**

As recorded by a CCD camera, an image is a bidimensional array of pixels, contained in a rectangular frame. To each pixel at an arbitrary location \( P(x, y) \) in the image frame, we associate a grey tone \( b \) ranging from 0 to 255. We then obtain a bidimensional function \( b(x, y) \) representative of the image intensity (brightness) distribution. Starting from the map \( b(x, y) \), which gives the pixel grey tone, the following calculations can be performed.

First of all, the average intensity of the pixel tones is determined:

\[
M_0 = \frac{1}{l_x l_y} \int_{0}^{l_x} \int_{0}^{l_y} b(x, y) \, dx \, dy
\]

where \( l_x, l_y \) are the \( x \)- and \( y \)-rectangular range of the frame. More generally, the \( k \)-rank statistical moments of the image are defined in the following way:

\[
M_k = \frac{1}{l_x l_y} \int_{0}^{l_x} \int_{0}^{l_y} [b(x, y) - M_0]^k \, dx \, dy
\]

with this characterisation, we are then able to define the average values of moments for the whole image frame. The distribution of pixel tones is then given according to these moments. The dispersion of pixel tones about their average value turns out to be given by the moment with \( k = 2 \), from Eq. (2).

All integrals can be calculated on the whole image or on a window. When using the image windowing, moments \( M_0 \) and \( M_k \) allow to find the position and shape of objects, because the distribution can change for each specific window. In images where at a first glance no particular objects are present, we can use the same values of moments \( M_0 \) and \( M_k \) given by Eqs. (1) and (2), for the whole image, supposing the image to be characterised by only one statistical distribution. To decide whether an image exhibits irregular domains or localised defects, a useful procedure is to estimate the ratio between the intensity standard deviation and the average intensity and fix an acceptance limit, say, for instance of 50%. Let us stress the fact that a part of the image can be described by an intensity distribution, which can be essentially different from the rest of the image or from the background distribution. In this case, it is misleading to start from the point of view that only one distribution is enough to describe the whole image frame and it is better to share the image in a lattice of windows and discuss the statistic behaviour inside each window.

In any case, among the features of a texture, there are its homogeneity and isotropy characteristics. In particular, to test the hypothesis of isotropy, it is necessary to check the presence of preferred directions in the image frame. For this purpose, we introduced a typical length featuring the texture size, which was very useful for the characterisation of liquid crystal mesophases (13, 14). Instead of measuring the texture homogeneity by evaluating the histogram’s entropy vs. the distance [see for instance (15)], or by calculating the spatial organisation by means of the so-called ‘run-length statistics’ (16, 17), we compute a set of coherence lengths defined in the following way. Starting from an arbitrary point \( P(x, y) \) of the figure \( b(x, y) \), along several radial directions, we calculate the values of \( M_k(x, y) \) moments, that is

\[
M_k^r(x, y) = \frac{1}{l_{o,i}} \int_{0}^{l_{r,i}} b(x + r \sin \theta_i, y + r \cos \theta_i) \, dr
\]

where index \( i \) is ranging over the radial directions, \( r \) is the radial distance from \( P \) and \( \theta_i \) is the angle formed by the \( i \)-direction with \( y \)-axis (see Fig. 1 for the frame of reference). Lengths \( l_{o,i} \) are the radial distances (from \( P \)) at which the values of the moments \( M_k^r(x, y) \) on the chosen direction saturate, within a threshold level \( t \), the choice of which depends on the problem under study, to the image average moments \( M_0 \). This is the way to define the local ‘coherence lengths’ \( L_{o,i}(x, y) \) of the point \( P \) in the image frame. We named these functions as ‘coherence lengths’ because their behaviour is similar to that of some functions used in condensed matter physics. There, coherence length is the distance over which molecular order is maintained. The coherence length then scales the size of ordered domains in condensed matter.

In the calculation of functions \( L_{o,i}(x, y) \), the pixels near the image frame boundaries are not
involved, because in this case it would not be possible to estimate the coherence lengths in all the directions (boundary effect). On the contrary, in standard image-processing techniques (18), the periodicity of the image, originally present or artificially introduced by replication of the frame, is used to overcome the boundary problem. Let us stress the fact that moments $M_i(x, y)$ are not calculated on a window in the image frame, but on specific directions, therefore, the method is different from the standard statistical approach, allowing to take into account in a natural way, the anisotropy in the problem of texture recognition. In our analysis, we will use 32 directions, as shown in Fig. 1.

Actually, we can look for anomalous behaviours of vectors $L_{o,i}(x, y)$ as signals for the presence of a defect in the neighbourhood of point $P(x, y)$ in the image frame. To discuss what can be properly considered as an anomalous behaviour of the coherence lengths, let us introduce the following average values of coherence lengths, averaged over the complete frame, for each specific $i$-direction:

$$L_{o,i} = \frac{1}{l_x l_y} \int_{0}^{l_x} \int_{0}^{l_y} l_{o,i}(x, y) dx dy$$  \hspace{1cm} (4)

If the image frame was strictly homogeneous, such averaged lengths should coincide with the actual local lengths measured for all image points. On the other hand, if the image frame was completely inhomogeneous, the local lengths would be well dispersed around their averages. The same occurs when the image frame is shared in windows, each of them characterised by a different intensity distribution. It is acceptable to average the coherence length over the whole image frame when the image can be considered as characterised by one distribution only, within a reasonable dispersion.

Figure 2 shows the average values $L_{o,i}$ for two images of snake skins from the Brodatz album, which is a collection of images, actually considered as a reference collection for image-processing studies (19). These lengths represent the distances from a generic point of the image along the $i$-direction, at which the average value of the image intensity is practically achieved, according to the chosen threshold. The result of the calculation is proposed as a diagram showing $l_{o,i}$ in the 32 directions of Fig. 1. We can define this diagram has the ‘coherence length diagram’. Figure 2 actually shows two diagrams obtained by fixing two different threshold values. To obtain the inner diagram, we use a threshold corresponding to 50% of the ratio $\sqrt{M_2}/M_o$. The outer diagram is obtained with 20% of the same ratio. The diagrams reveal preferential directions in the image texture, that is the anisotropy of the texture.

Lengths $L_{o,i}$ are giving a visually appreciable result with the following meaning. The diagram of $L_{o,i}$ lengths represents the boundary of the smallest area about a generic point in the image frame, on which using area averaging, we obtain the average value $M_o$ of the grey-tone intensity. The diagram then represents the boundary of a unit cell of the image, which contains the typical features of the whole image (this is easy to see by comparing the diagram with the images of the snake scales). As a consequence, this unit cell has a behaviour similar to that of the primitive unit cell in crystal lattices (see Ashcroft and Mermin (20), for the properties of crystal lattices). We can also consider the cell boundary, that is the coherence length diagram, as a measure of the grain size and use it for evaluating the coarseness of the image texture. Any object in the image frame with a shape different from the shape of the unit cell or any object with a different cell average colour tone, can be considered as a defect in the image texture.

We used snake skins to illustrate the behaviour of coherence length diagram, because the comparison of this diagram with the image texture provides immediately the meaning of it. In case of repetitive geometric textures, as snake skin textures usually are, the coherence length diagram calculation can be implemented together with the Fourier analysis of frequencies. As we observed using our approach in the microscopic investigation of liquid crystals (13, 14), it is in the
investigation of almost smooth and homogenous images, where the Fourier analysis is scarcely active, that the coherence lengths are truly useful. In the next section, we will apply our image-processing method to one of these cases, that is, to human skin analysis. We will discuss in particular the detection of defects displayed by the skin texture.

**Results**

Let us analyse with the coherence length diagrams some human skin textures (21, 22). A result is shown in Fig. 3. The original map is on the left of the figure; in the middle, we see the coherence length curves evaluated for two different values of the threshold, those already used to obtain the diagrams of Fig. 2. The shape of the two diagrams does not substantially change. The area is changed; this is due to the fact that to be fulfilled, a lower threshold requires a wider area.

On the right part of Fig. 3, we propose a detection of defects; the points marked in dark grey are considered as ‘defects’, whereas the pixels in light grey are the normal ones. It is not a segmentation procedure at the origin of these maps, but a criterion involving the local behaviour of coherence lengths $L_{0,i}(x,y)$.

To detect a defective region, we reasonably assumed that a point $P(x,y)$ in the image frame does not belong to a defect, when the local values of coherence lengths $L_{0,i}(x,y)$ are coincident, within a proper threshold, with the global values $l_{0,i}$. The procedure is discussed with all details in Sparavigna and Marazzato (23). We can then prepare a map with, for instance, a red–green layer superimposed to the original grey map. The defects are marked in red, whereas the points with a local behaviour coincident with the global one are marked in green.

With a commercial software, the most common procedure used to identify a defect is based on
the thresholding of grey tone (15). This means that the procedure is simply a check of the pixel intensity, to see whether it is, within a fixed tolerance, coincident or not with a specific chosen grey tone. The processing is known as ‘image segmentation by thresholding’ and produces images segmented in two or more regions according to the thresholds used. This technique is not investigating the neighbourhood of the pixel and then it is impossible to ascertain if it is truly belonging to a defect or not. With the analysis previously discussed, the detection of defects is glocal, that is global and local, obtained by comparing the local coherence lengths $L_{o,i}(x,y)$, that is a local neighbourhood about the pixel $(x,y)$, with the global coherence length $L_{o,i}$ diagram.

In the case of human skin, a defect could be a region with a paler or darker colour or a region with wrinkles, for instance. Fig. 3 shows an
almost regular texture, with a darker region. The coherence length diagrams are indicating that the texture is almost isotropic, and actually we have no wrinkles. The defect map, obtained using the previously explained procedure, places in evidence the darker regions, marking them in dark grey. In Fig. 4, other examples of defect detection are shown. We apply the procedure to an image of the forehead skin with wrinkles (upper part) and to an image of the palm skin (lower figure). Note that the method is able to map the location of wrinkles.

Another interesting test is mapping using coherence length diagrams of the textures obtained from the capacitance system, discussed in Bevilacqua and Gherardi (11). In the upper part of Fig. 5, we can see the image as it is obtained from the capacitance system. In the lower part, we see the same image after normalisation of the image contrast; the capacitance image is sensitive to different hydration and to the presence of sweat, which give darker regions, and then a renormalisation is required. The coherence length diagrams of the two images (without and with renormalisation) changes because the pixel tone distributions are different. The differences between images (a) and (b) are enhanced by the procedure of defect detection. In the upper part, we see the dark grey pixels concentrated where the renormalisation procedure must act in changing the pixel tone distribution. In the lower image, the number of defects is strongly reduced.

The aim of Bevilacqua and Gherardi (11) was the development of a device to characterise the skin topography to measure the skin profile and the presence of wrinkles. Renormalisation of images is then necessary for the segmentation of skin topography, to correlate it with skin ageing. In the case of images recorded by cameras, where illumination and direction of view are important, a similar normalisation procedure can be quite useful too.
Conclusion

Our image analysis of the human skin texture is based on the evaluation of the global grey-tone distribution of the whole image frame and then on the coherence length diagrams. These diagrams are also able to estimate the texture features, such as anisotropy and coarseness. Moreover, the coherence length diagrams can be used to adequately describe the presence of wrinkles, by means of a defect map. According to the chosen statistic parameters of the grey-tone distribution, several procedures to defect detection can be proposed. We followed a comparison of local coherence lengths with their average values. More sophisticated procedures, suggested by clinical experience, can be easily approached.

Acknowledgement

Many thanks are due to A. Bevilacqua and A. Gherardi for the images obtained with the capacitive system (11), used in Fig. 5.

References

1. Cula OG, Dana KJ, Murphy FP, Rao BK. Skin texture modeling. Int J Comp Vision 2005; 62: 97–119.
2. Liu J, Bowyer K, Goldgof D, Sarkar S. A comparative study of texture measures for human skin treatment. Information, Communications and Signal Processing ICICS ’97. Proc Int Conf 1997; 1: 170–174.
3. Pope TW, Williams WL, Wilkinson SB, Gordon MA. Textural parameters based on the spatial gray level dependence method applied to melanocytic nevi. Comput Biomed Res 1996; 29: 429–437.
4. Haralick RM. Statistical and structural approaches to texture. Proc IEEE 1979; 67: 786–804.
5. Weszka JS, Der CR, Rosenfeld A. A comparative study of texture measures for terrain classification. IEEE Trans Syst Man Cybern 1976; 6: 269–285.
6. Azencott R, Wang J, Younes L. Texture classification using windowed Fourier filters. IEEE Trans Pattern Anal Mach Intell 1997; 19: 148–153.
7. Haralick RM, Shanmugan K, Dinstein I. Textural features for image classification. IEEE Trans Syst Man Cybern 1973; 3: 610–621.
8. Doi M, Tominaga S. Image analysis and synthesis of skin color textures by wavelet transform. IEEE Southwest Symp Image Anal Interprett 2006; 1: 193–197.
9. Phung SL, Chai D, Bouzerdoum A. Adaptive skin segmentation in color images. Proc IEEE Int Conf Acoust Speech Signal Proc 2003; 3: 173–176.
10. Nishioka M, Fukumi M, Akamatsu N, Mitsukura Y. 2004, measurement of skin texture using genetic image analysis. Proc Int Symp Intell Signal Process Commun Syst 2004; 1: 787–791.
11. Bevilacqua A, Gherardi A. Age-related skin analysis by capacitance images. Proc Int Conf Pattern Recogn 2004; 2: 703–706.
12. Bevilacqua A, Gherardi A, Guerrieri R. In vivo quantitative evaluation of skin aging by capacitance image analysis. Proc IEEE Workshop Appl Comput Vision WACV/MOTION 2005; 1: 342–347.
13. Montrucchio B, Sparavigna A, Strigazzi A. A new image processing method for enhancing the detection sensitivity of smooth transitions in liquid crystals. Liquid Crys 1998; 24: 841–852.
14. Sparavigna A, Mello A, Montrucchio B. Pattern recognition in the microscopy of liquid crystals: description, comparison and choice. Recent Res Devel Patterns Rec 2000; 1: 29–40.
15. Pitas I. Digital image processing algorithms. Prentice-Hall, Englewood Cliffs, 1993.
16. Levine MD. Vision in man and machine. Mc-Graw Hill, New York, 1985.
17. Galloway MM. Texture analysis using grey level run lengths. Comp Graph Image Process 1975; 4: 172–179.
18. Jahne B. Digital image processing. Springer Verlag, Berlin, 1993.
19. Randen T. The Brodatz Online Texture Archive. Available at http://www.ux.uis.no/~tranden/brodatz.html, Accessed at 31 August, 2009
20. Ashcroft NW, Mermin ND. Solid state physics. Saunders College Publishing, New York, 1976.
21. Free texture maps. Available at http://freetexturemaps.com/gallery/gallery2/v/rawtextures/people, Accessed at 10 March, 2009
22. Free human skin texture. Available at http://www.3dmd.net/gallery/index.php, Accessed at 10 March, 2009
23. Sparavigna A, Marazzato R. Mapping images with the coherence length diagrams. Computer Vision and Pattern Recognition (arXiv:0807.4701v1) 2008.

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