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Full Length Research Paper

Improving the quality of pigskin leather texture images using enhanced image processing

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In this paper, we propose a method to improve the quality of pigskin leather texture images using digital image processing approach. The proposed method intends to minimize the imbalance illumination problem that occurs in the images captured from consumer leather products. This method is compared with the other methods in the literature such as contrast adaptive binarization method, and the results showed that the proposed method yielded better results in terms of highlighting the special characteristics of pigskin in consumer leather products.

Key words: Digital image processing, pig skin images, binarization, local global analysis, histogram.

INTRODUCTION

Pigskin leather has been used widely in consumer products such as leather jackets, shoes, handbags, etc. The use of pigskin in leather products has some advantages and disadvantages in terms of the quality, stiffness, toughness, smoothness and cost. For a rapid assessment of the type, digital image processing can be utilized to check the special characteristics of the pigskin, that is, a group of three hair pores. Sometimes, these hair pores can be seen by human eyes, but at other times, they are hidden by the color. However, during the image capturing process, presence of variable illumination distorts the quality of the image. This variable illumination could be extracted as false patterns in the images, thus it could lead to a wrong interpretation. Therefore, in this work, we use the digital image processing to improve the quality of the image by removing the effects of variable illumination. When dealing with a raw image, the imbalance lighting effect is a common challenge that should be corrected before proceeding with further enhancement process (Basri and Jacobs, 2004) especially for the low-contrast image (Chen et al., 2004). With the goal to enhance the texture image, imbalance illumination will affect the performance of any algorithm particularly for automatic image analysis such as segmentation, registration, quantification (Basri and Jacobs, 2004), recognition (Du and Ward, 2005; Gonzalez, 2004) and classification thus could lead to false result. Previously, we have proposed the local-global block analysis to overcome the problem. However, the method leads to a new problem which is the occurrence of boundaries between blocks, also known as blockiness effect (Liu et al., 2001). This new artifact will potentially worsen the quality of the output image after classification procedure. We have discovered the cause of the boundary existence and in this paper we propose a set of modifications to the local-global block analysis to minimize the blockiness effect. Results presented later in

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this paper include the binarization of each output images of contrast adaptive, local-global block analysis and our proposed method to validate the performance of each method.

RELATED/PREVIOUS WORK

Previously, there are numbers of image enhancement algorithms that have been developed to deal with illumination. Generally, we can categorize the enhancement algorithms into two approaches. The former intends to increase the quality of the output image as a whole and may not perform well over some regions while the latter will perform the enhancement process independently on a group of neighbourhood pixels within the image (Jack et al., 1990). The research to date has tended to focus on face recognition and optical character recognition rather than texture recognition and classification. The most popular and well established method used is homomorphic filtering (Juhua et al., 2003). But we showed in (Saripan et al., 2009) that local-global analysis performs better in texture images. The other existing methods include wavelet transform (Lee et al., 2001) logarithm and discrete cosine transform (Meng-Ling and Yap-Peng, 2004) nine points of light (Ruiz-del-Solar and Quinteros, 2011) recursive least squares algorithm (Chen et al., 2004) and many more elaborated in (Du and Ward, 2005).

These methods involve complex calculation and computation-intensive which is not suitable for real-time automatic system. The most popular method used is homomorphic filtering. But we proved in (Lee et al., 2001) that homomorphic filtering technique does not perform better than local-global block analysis. Another interesting method is the local normalization using zero-mean and unit variance (Tomaževič et al., 2002) which considers the quotient value of some parameters obtained within local area in the image. However, this method is mainly developed for face recognition field and its assumptions made are related to face recognition which is not suitable for texture. It assumes that the image of the face is a combination of small and flat facets, the light source is from one direction only and the face is in neutral expression. Another method that attracts our interest is the contrast adaptive binarization (Xudong and Kin-Man 2006). This method works well to improve contrast and remove the random noise of low quality document image but perform poorly in texture image. We will show the output images of this method as a comparison to the proposed method in the result section. In (Saripan et al., 2009) local-global block analysis has been proposed to provide a fast and reliable method for illumination compensation. This technique is developed based on micro and macro levels analysis, a shown in Figure 1. In digital image analysis, images are formed by a series of square pixels.

The image could be divided into non-overlapped blocks in which each block contains group of pixels. Local global block analysis method utilizes the information provided within the block. Local is defined as the area within block while global is the area that covers the whole image. This method assumed that there is very little fluctuation of illumination component exists within local area. Therefore, the size of the block must be small. For each local area, the local mean intensity will be calculated. For example, within 120 × 120 image, there will be 10 × 10 blocks in the image, assuming a block size of 12 × 12. With this configuration, the image is consists of 100 local mean values. If we assume that an image *f(x,y)* has a size of *M* × *N*, and divided into blocks of *f(a,b)*, hence local mean could be expressed as :

$$\mu_{local}(a,b) = \left(\sum_{x=a \times M_a}^{M_a - 1} \sum_{y=b \times N_b}^{N_b - 1} f(x,y) \right) \Big/ (M_a \times N_b) \tag{1.1}$$

Where $\mu_{local}(a,b)$ the local mean of the local blocks is (a,b) is the index number of the blocks and $M_a \times N_b$ is the size of the local blocks. The global mean intensity can be calculated using this equation:

$$\mu_{global} = \sum_{x=0}^{M} \sum_{y=0}^{N} f(x,y) \, / \, M \times N \tag{1.2}$$

Where μ_{global} is the global mean of an image. Then, the difference between local mean and global mean is given by this equation:

$$\Delta(x,y) = f(x,y) - \mu_{local}(x(a), y(b)) \tag{1.3}$$

Finally, to obtain the illumination compensated image, the local residual pixel is normalized to the position of the global mean.

$$\hat{f}(x,y) = \Delta(x,y) + \mu_{global} \tag{1.4}$$

Where $\hat{f}(x,y)$ is the normalized output image. This technique however will produce one new artifact which is the blockiness effect. The blockiness effect is the existence of block pattern within the image, which is in

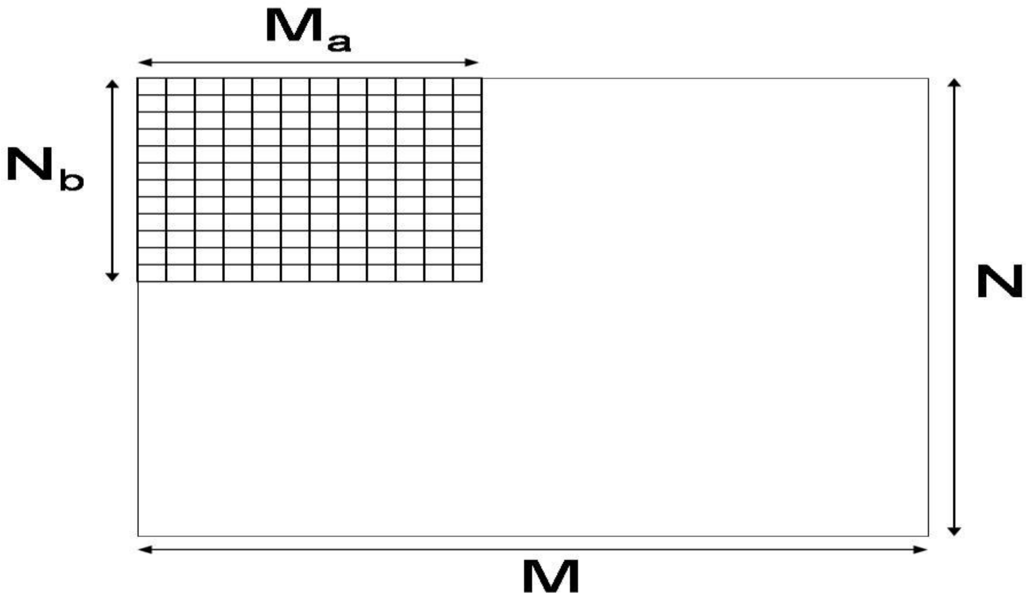


Figure 1. Traditional local-global block analysis.

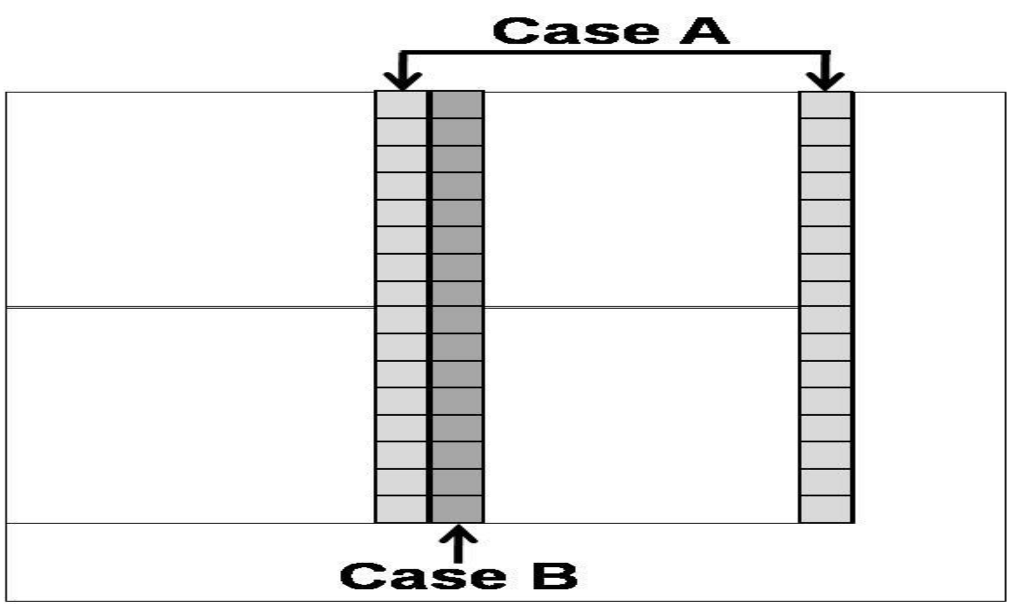


Figure 2. Case A and case B of boundary pixels.

this case, the boundary between certain adjacent local areas become visible (Liu et al., 2001). The boundaries do not occur everywhere else in the image, except in the areas as shown in Figure 2 This effect happens because of the intensity of certain pixels that lies at the boundary of the local block is closer to the adjacent local mean instead of their local mean. For this reason, we can eliminate the blockiness effect by applying a few

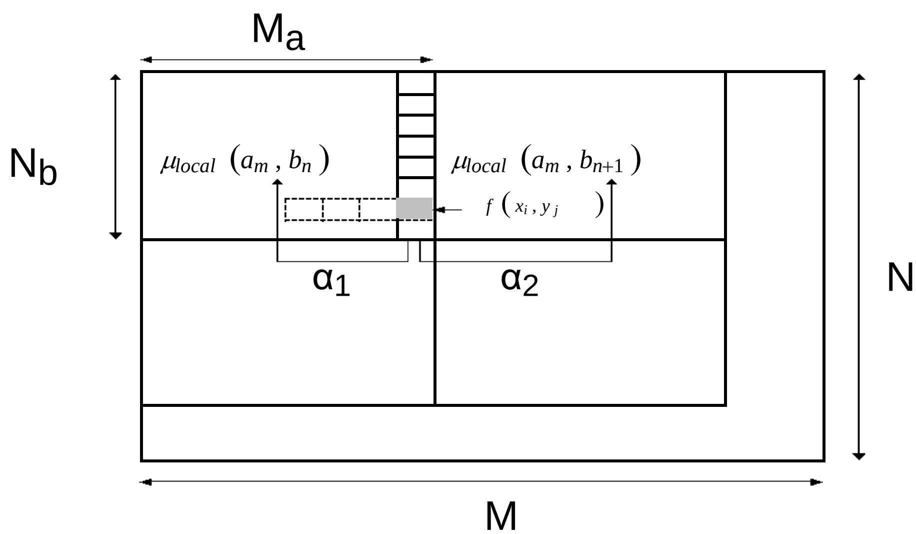


Figure 3. Local-global block analysis with horizontal neighbourhood improvement.

modifications to the residual equation.

PROPOSED METHOD

As explained in previous chapter, blockiness effect occurs because of the intensity value of boundary pixels are closer to the adjacent local mean value instead of their own local mean. When this situation happen, the variations of intensity values across the boundary are obvious, therefore the block pattern is visible. In the traditional local-global block analysis technique, every pixel will be subtracted by their local mean and the residual value will be normalized to the global mean as shown in Equation 1.3 and 1.4. But, in order to minimize the blockiness effect, pixels at the boundary will be subtracted by their local mean and adjacent local mean as shown by α_1 and α_2 in Figure 3. In this paper, only horizontal neighbourhood block will be considered. So, instead of considering only their local mean as in Equation 1.3, we should now also consider the adjacent local mean value by applying Equation 1.5. We know that there are two cases of boundary pixels, either they are located along the column $y = 12n - 1$ or $y = 12n$ where n is integers from 1 to 9. We assume that the pixels located along $y = 12n - 1$ are known as case A while the other are case B. For case A, the residual pixel is calculated by subtracting the pixel intensity value to its right adjacent local mean value as shown in Equation 1.5. For example, for pixel $f(x_i, y_j)$ that is located in block $f(a_m, b_n)$, the residual value can be calculated by subtracting its intensity value to the local mean, $\mu_{local}(a_m, b_n)$. While for case B, as for example pixel $f(x_i, y_{j+1})$, its own local mean is given by $\mu_{local}(a_m, b_{n+1})$ and the neighbour local mean that should be consider is $\mu_{local}(a_m, b_n)$.

$$\hat{\Delta}(x,y) = f(x,y) - \mu_{local}(x(a), y(c)) \begin{cases} c = b + 1 \ for\ y = 12n - 1 \\ c = b - 1 \ for\ y = 12n \end{cases} \quad (1.5)$$

After applying Equation 1.3 and 1.5, we got two residual values which is the difference between boundary pixels and its own local mean and the difference of the boundary pixels and it's adjacent to local mean. Now these values will be compared and the smaller value will be chosen to be normalized to the global mean using Equation 1.4. However, by modifying only the border pixels of each local area, it is not sufficient to totally eliminate the blockiness effect. We need to observe the horizontal neighbourhood pixels of modified image until we found the pixel that has an intensity value closer to its local mean value. The equation to completely calculate all the residual values by considering the boundary pixels and their horizontal neighbor pixels is given as;

Case A:

$$\hat{\Delta}(x,y) = \sum_{j=j-1} f(x_i, y_j) - \mu_{local}(x(a), y(b+1)) \quad (1.6)$$

Case B:

$$\hat{\Delta}(x,y) = \sum_{j=j+1} f(x_i, y_j) - \mu_{local}(x(a), y(b-1)) \quad (1.7)$$

Where case A refers to boundary pixels located at position 12n-1 while case B refers to pixels located at position 12n. This situation is shown in Figure 3, where pixel $f(x_i, y_j)$ is assumed to be pixel that closer to adjacent mean value, $\mu_{local}(a_m, b_{n+1})$ instead of its local mean value, $\mu_{local}(a_m, b_n)$ and the dots boxes show the potential pixel that needed to be modified. The modification will stop at pixel $f(x_i, y_{j-3})$ with assumption that at the

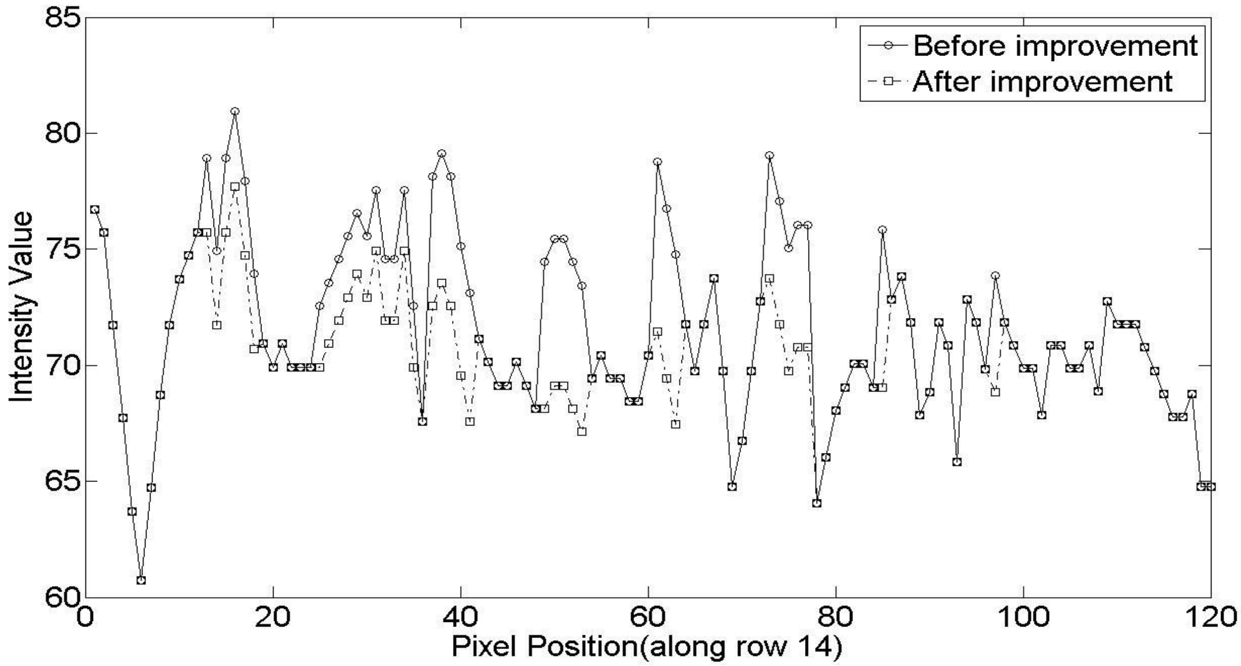


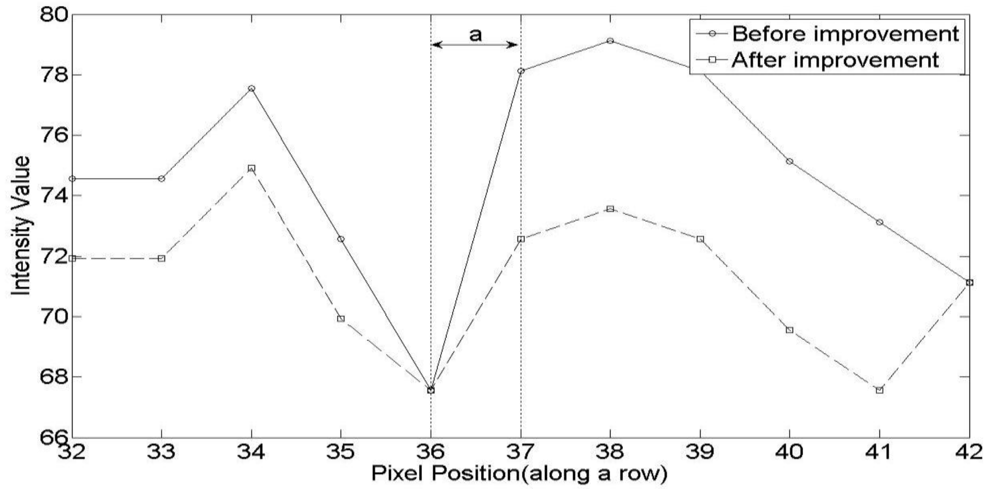
Figure 4. Pixel intensity for the local-global output image and proposed method output image.

position x_i , y_{j-4} , the pixel intensity value is closer to its local area mean.

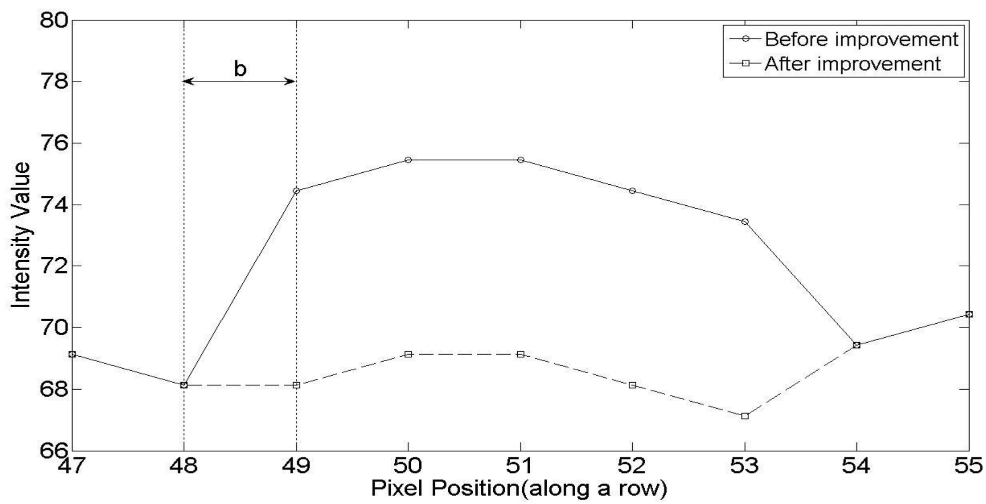
EXPERIMENTAL RESULTS

We have applied our proposed method to several pigskin images taken by digital camera under different illumination conditions with the block size of 12 × 12 pixels. The size of the block can vary based on the illumination condition and characteristic of texture that must be preserved after the process. In our case, 12 × 12 pixels of block size gave the most considerable result in terms of illumination compensation, characteristic kept and minimal blockiness effect. Figure 4 shows the intensity value of pixels along the same selected row in the image after being applied with local-global block analysis with and without improvement. Horizontal axis represents the position of pixels while vertical axis represents the intensity value of each pixel. The solid line shows the intensity value of unimproved image while the dots line shows the intensity value of improved image with proposed method. As we can see, there are improvements occur in several places on the graph. In the range within pixel 36 to 42, the rapid changes of intensity value of pixels that lead to blockiness effect is now reduced. The same trend occurs along the graph where the reductions of variations in pixel's intensity are observed. This characteristic illustrates how the blockiness effect along the horizontal line of the image has been minimized. Figure 5(a and b) highlight the obvious improvement occurrence after we applied the proposed method.

It is noticeable that within region *a* in the graph, the variation of intensities is rapid, which shows the obvious difference level of intensity between pixel 36 and 37, hence leads to blockiness effect. But after we applied the improvement method, the difference value between these two pixels is now reduced. The same goes with region *b* shown in Figure 5(b). The decrement of intensity variation means that the intensity across the boundary is now smoother, which reduced the visibility of block pattern. At the same time, the main characteristic of the graph is still maintained. It shows that the proposed method does not temper the original characteristic of the sample images. Figure 6 shows the comparison of output images after being applied with several methods including our proposed method. Excluding the contrast adaptive, the other output images are then binarized to show whether the methods applied can extract only the information needed of the texture image while sweeping away the unnecessary information. Contrast adaptive comprises



5a



5b

Figure 5. a The variation of pixel intensities located from $f(14, 32)$ to $f(14, 42)$; **b .**The variation of pixel intensities located from $f(14, 47)$ to $f(14, 55)$.

the binarization process in its algorithm, thus we did not need to binarize its output images. The threshold value was manually chosen and set based on the sample image. Each sample has its own unique threshold value and the value is applied to every methods. When a simple thresholding technique is applied directly to the original image, some regions in the image became black because they are affected by illumination and the texture on that region is now concealed. The contrast adaptive binarization method could not manage to preserve the texture of the image; hence it is not suitable to be used in extracting the information of texture images. Local global block analysis succeeds in compensating the illumination, but it leads to blockiness effect. Proposed method finally successfully removes the horizontal blockiness effect by reducing the large fluctuation of intensity amplitudes occur at the boundary of the blocks. Furthermore, it gives the best result among other methods in terms of the occurrence of noise after binarization process. This is significantly helpful for future classification process.

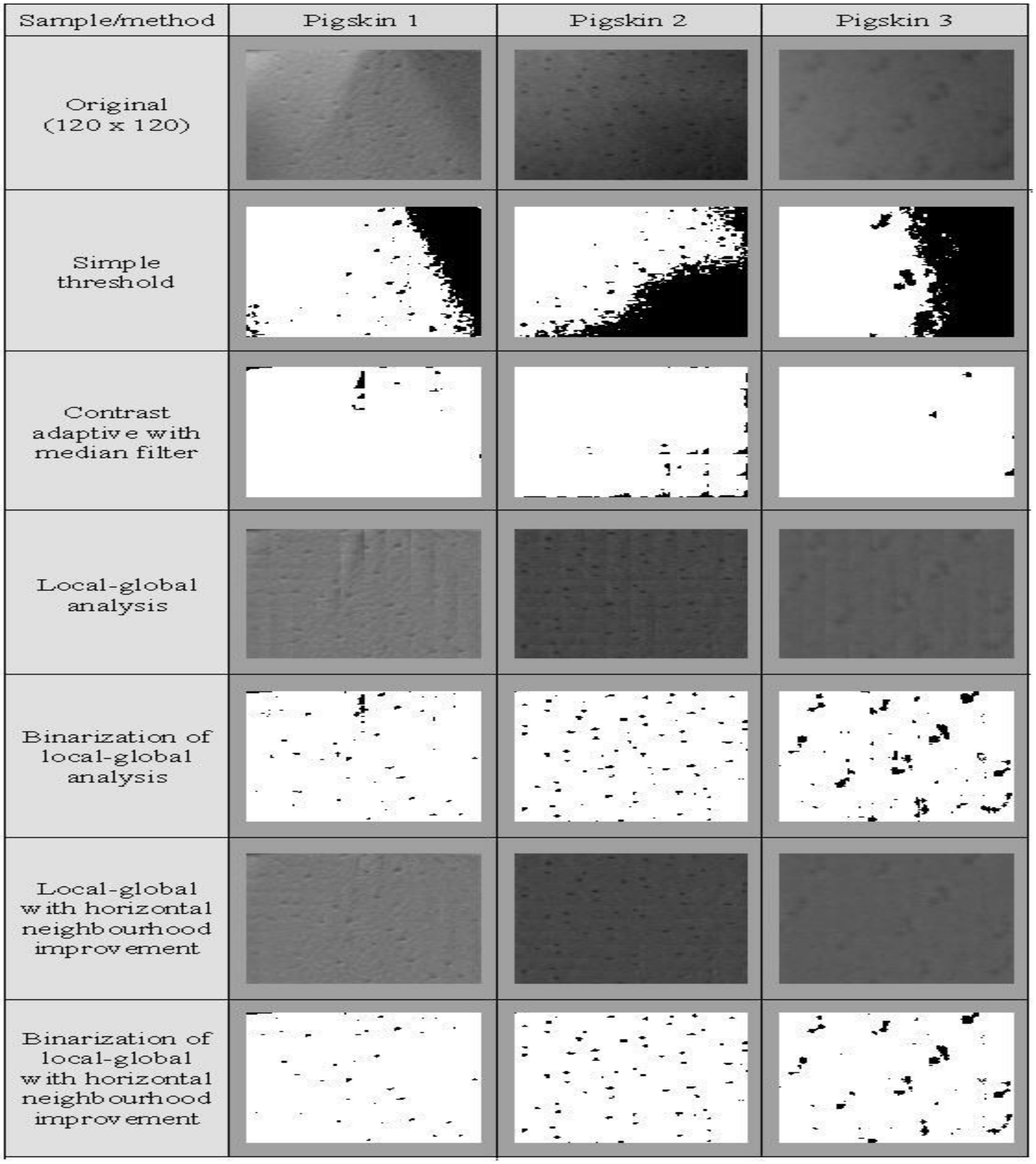


Figure 6. Output images.

Conclusion

We have proposed a method to improve the visibility of the pigskin leather in consumer products using an improved method of local-global block analysis for illumination compensation by considering the horizontal neighbourhood local mean value. Each pixel that lies at the boundary between blocks will be modified based on the information of adjacent block and it follows with the neighbourhood of the modified pixels. In comparison with contrast adaptive and traditional local-global analysis, the proposed method is proven to perform better for correcting the imbalance illumination for texture images. It preserves the characteristic of the texture and reduces noise occurrence after the binarization procedure.

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