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HANDWRITING IMAGE ENHANCEMENT USING LOCAL LEARNING WINDOWING, GAUSSIAN MIXTURE MODEL AND K-MEANS CLUSTERING

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ABSTRACT

In this paper, a new approach is proposed to enhance the handwriting image by using learning-based windowing contrast enhancement and Gaussian Mixture Model (GMM). A fixed size window moves over the handwriting image and two quantitative methods which are discrete entropy (DE) and edge-based contrast measure (EBCM) are used to estimate the quality of each patch. The obtained results are used in the unsupervised learning method by using k -means clustering to assign the quality of handwriting as bad (if it is low contrast) or good (if it is high contrast). After that, if the corresponding patch is estimated as low contrast, a contrast enhancement method is applied to the window to enhance the handwriting. GMM is used as a final step to smoothly exchange information between original and enhanced images to discard the artifacts to represent the final image. The proposed method has been compared with the other contrast enhancement methods for different datasets which are Swedish historical documents, DIBCO2010, DIBCO2012 and DIBCO2013. Results illustrate that proposed method performs well to enhance the handwriting comparing to the existing contrast enhancement methods.

Index Terms— Handwriting image enhancement, contrast enhancement, learning-based windowing, gaussian mixture modeling, k -means clustering.

1. INTRODUCTION

Perceiving, reading and searching handwritten from an archived and old documents through human efforts can be cumbersome. Recently, it has become an important task to collect and store the archived and old documents as a digital data in clouds and there are various techniques to digitize those documents such as scanning by laser scanner or taking snapshot by a camera. Latter approach is easier and faster than the former one to digitize the documents but it may bring undesired artifacts on the document images. On the other hand, digitized documents are widely used in the areas of image processing and pattern recognition to resolve the

text image problems such as character detection and recognition [1, 2], text binarization and reduction of the noise [3, 4]. Another important problem is to enhance the quality of handwriting on the images which will affect the accuracy of the other text image problems.

Digitized documents may be affected with various factors which may reduce the handwriting legibility and cause the degradation of handwriting and image. Some of these factors are camera characteristics, noise, different lighting conditions, deterioration and loss of visibility of handwriting on documents etc. These factors are often observed on images and current handwriting enhancement methods have mostly ignored such important factors in their methods when they are applied to the degraded images. This may cause reducing the visibility of handwritten and quality of image. Therefore, it is necessary to consider these factors to enhance the handwriting on the degraded images for perceiving and reading it better.

Handwriting enhancement is a critical and difficult task and it is essential prerequisite to perceive and read the handwritten on the images. There are local-based and global-based methods currently employed to enhance the visibility of text on the old document images [3, 4, 5, 6, 7]. Global enhancement methods are based on the general enhancement of all pixels on the images and enhancement of all image pixels improves text quality. However, it also increases aliasing, noise and other artifacts. Applying enhancement methods to the whole document image will cause reducing both perceiving the handwritten on the image and the overall reproduction quality.

In [4], threshold approach combined with artificial neural network (ANN) is proposed for removing the noise and enhancing the handwriting on the scanned image for text recognition. The method uses several preprocessing methods such as noise reduction by using median filter, threshold technique and normalization. However, the details of the handwriting will be lost by using those techniques on the image and the method may not provide good results in terms of quality enhancement of text and the quality of image. In [5], windowing method is proposed as a local-based method to enhance

Fig. 1. Different handwritten window examples extracted from the original image, (a) Original good quality, (b) Original bad quality, (c) Enhanced handwritten window by using General Histogram Equalization [3], (d) Enhanced handwritten window by using proposed method.

the contrast of the image. Bilateral filter is used within a window to smooth pixels in the center of the window relative to the rest of pixels. Another local-based contrast enhancement technique was proposed in [6] and it uses a small window that slides through every image pixel sequentially. However, the method enhances all pixel intensities in the image and enhances any noise in the input image. Besides this, there are other methods for enhancing the images such as general and adaptive histogram equalization [3, 7], wavelet-based contrast enhancement [8] and others [5, 9].

In this paper, we propose a new method which is a learning-based windowing combined with contrast enhancement and Gaussian Mixture Model (GMM). A fixed size window moves over the document image to obtain the quality of handwriting based on two different quality measurement techniques which are discrete entropy (DE) and edge-based contrast measure (EBCM). Estimated results are used in the unsupervised learning method by using k -means clustering to assign the quality of patch of the handwritten document as a bad or as a good. Thus, we will have two different cases. In the case of low quality of handwriting in the window, contrast enhancement method is first applied to the window to increase the quality of handwriting. After that, GMM is used to the both original and enhanced part of the image to smoothly combine information between each other to create the final patch. The second case if the quality of handwriting is high in the window or there is not text in the window. In this case, window moves to the next part of the document image and continues until it finds a low quality of handwriting on the image. Proposed method is combined with the modified histogram for contrast enhancement (MHCE) method [10] to understand and analyze the performance of the proposed

Fig. 2. Example for overenhanced handwriting images.

approach. Simulation results demonstrate an improvement in the objective measure of DE, EBCM and peak signal to noise ratio (PSNR) comparing to the other contrast enhancement methods. Numerical experiments, on different test images, illustrate the effectiveness and efficiency of our approach.

The rest of the paper is organized as follows. In Section 2, we describe the steps of our proposed method. Section 3 demonstrates the performance of the proposed system and Section 4 concludes the paper.

2. PROPOSED HANDWRITING ENHANCEMENT METHOD

The purpose of the proposed method is to enhance the handwriting on the degraded images. Proposed method has three different steps which are 1) Learning-based windowing, 2) Quantitative measurement and assigning the quality of patch, and 3) GMM for image representation. These steps are applied to the windowing image if the handwritten within the window is low quality. Otherwise, the learning-based windowing moves to the next patch of the image until it estimates the low quality of handwriting. Fig. 2 shows the block diagram of the proposed method.

2.1. Learning-Based Windowing

Current global and local contrast enhancement methods are not suitable to resolve the handwriting image enhancement problem. Global enhancement methods are designed to apply to the image to enhance the contrast of all image pixel intensities as well as undesired artifacts on the image such as noise. This will cause more degradation on the image as shown in Fig. 1(c) and it will cause reducing both perceiving the handwriting on the image and the overall quality of document image. Existing local-based methods are non-learning-based methods and they are applied to the image without decision making [4, 5, 6, 9]. By enhancing contrast of an image without learning-based method, the contrast of handwriting can be overenhanced which will decrease the quality of handwriting or empty area of the document will be enhanced which is not

Fig. 3. Example for overenhanced handwriting images, (a), (c) Original images of DIBCO [17], (b), (d) Enhanced by GHE.

necessary. Fig. 3 depicts example of overenhanced handwriting images by using contrast enhancement method [3]. For instance, Global histogram equalization method (GHE) [3] applied to the two original images as shown in Fig. 3 (a) and the Fig. 3 (c) (DIBCO dataset [17]), respectively. Result images, as illustrated in Fig. 3 (b) and Fig. 3 (d), show that using contrast enhancement directly to the whole image causes bad illustration of the handwritten document images. Besides this, figures also depict that enhancing the empty areas of original images cause improvement of noise on the images only. Because of above reasons, it is necessary to apply a new method to analyze the input image before using contrast enhancement method and we propose a learning-based approach to increase the quality of handwritten document images.

Window method is widely used as a local-based method to enhance the contrast of the images. However, these methods mostly use filter techniques in window to reduce the noise by considering local parameters. For instance, Varghahan et al. [4] proposed a window approach which uses median filter within the window to smooth pixels in the center of the window relative to the rest of pixels. Another window-based contrast enhancement technique was proposed in [6] and it uses a small window that slides through every image pixel sequentially. However, the method enhances all pixel intensities and noise in the input images. In this work, we use learning-based window which makes decision about the contrast quality of handwriting within the window. Thus, contrast

enhancement method will be applied only to the low contrast of the document image.

2.2. Quality Measurement Within the Window and using k -means clustering

In order to understand the quality of handwriting in the window, it is necessary to estimate the quantitative results of each window because they are used in the unsupervised learning technique. However, it is difficult to estimate the quantitative results of a single window image X_P and assign the quality of each patch as bad or good. The following quantitative measurement methods are used to estimate the quantitative results of X_P and we use two quantitative methods which are discrete entropy (DE) [11], and edge-based contrast measure (EBCM) [12]. Note that, measurements have been completed before applying k -means clustering.

1) DE [11]: The DE measures the content of X_P and a greater value indicates more details on the windowing image. DE is defined as

$$DE(X_P) = - \sum_{\forall j} p(a_j) \log(p(a_j)) \quad (1)$$

$p(a_j)$ is the probability of the pixel intensity a_j , which is estimated from the normalized histogram.

2) EBCM [12]: It is based on the observation of edges on the windowing image. EBCM value of output image should be smaller than the EBCM value of the input image for better result and it is defined as

$$EBCM(X_P) = \sum_{\forall(i,j)} c(i,j) / H \times W \quad (2)$$

where

$$c(i,j) = \frac{|x(i,j) - \mu(i,j)|}{|x(i,j) + \mu(i,j)|}, \quad (3)$$

$$\mu(i,j) = \frac{\sum_{(k,l) \in N(i,j)} g(k,l)x(k,l)}{\sum_{(k,l) \in N(i,j)} g(k,l)}$$

where x, y denote the pixel coordinates of the X_P and $N(i,j)$ is the set of all neighboring pixels of pixel (i,j) . We use 15×15 map for the image to estimate the EBCM. After obtaining quantitative results of the X_P , they are used in the unsupervised algorithm to assign the patches into two different clusters which are as a bad or as a good. To partition them, we used k -means clustering method which is an efficient and fast unsupervised learning approach [13]. The k -means clustering method is one of the most used clustering approach and it has been used in many different problems in image processing such as quantization, satellite images, segmentation etc.

Let A and B be the two different clusters which were obtained by using the k -means clustering for a set of data (quantitative results) and μ_A and μ_B be the centroid of the two clusters, respectively. Centroid of the two clusters in the clustering method are initialized with the first two different values of DE and EBCM results which are computed from the handwritten document image and they are updated in the method.

Fig. 4. Illustration of enhanced three windows, (a) Original window. Enhanced windows generated by (b) BPHE, (c) FHCE, (d) GHE, (e) Proposed method.

Note that, A indicates low contrast and B indicates high contrast of the window. Thus, obtained all DE and EBCM results are used for the distance based estimation approach in k -means clustering as follows:

$$d_A = \sqrt{(k_{DE} - \mu_{ADE})^2 + (k_{EBCM} - \mu_{AEBCM})^2},$$

$$d_B = \sqrt{(k_{DE} - \mu_{BDE})^2 + (k_{EBCM} - \mu_{BEBCM})^2} \quad (4)$$

where k_{DE} and k_{EBCM} denote the quantitative results of the windowing image by using Eqns. 1 and 2, d_A and d_B show the distance between the estimated value and centroid of the clusters. Besides this, they are used to update the centroid of each cluster μ_A and μ_B . Based on the decision making strategy, the contrast of the window image is low if d_A is greater than d_B and contrast enhancement method is applied to the window. After that, the final window image is obtained by using the GMM. On the other hand, window moves to the next part of the document image.

2.3. Gaussian Mixture Model (GMM) For Image Representation

GMM is a technique to shape a single image histogram into the several Gaussian-shaped histograms where the mean of them shows the corresponding average pixel intensity levels and the variance corresponding to their texture details [14]. They are divided by their mean values and spread out based on their variances which will indicate the global histogram of GMM of the input image [14]. In this work, GMM is used to find two different Gaussian-shaped histograms on the original windowing image and enhanced windowing image. After that, it is used to exchange the information between the original and enhanced images smoothly in order to discard the undesired artifacts and create final document image. Thus, the proposed method provides information preservation of input document image by using GMM. Let X_1 and X_2 be the original windowing image and enhanced windowing image respectively. The gray-level Gaussian distribution $p(x_1)$ of the X_1 and $p(x_2)$ of the X_2 can be modeled with two mixture

functions by using the GMM as follows:

$$P(x_1) = P(w_1)p(x_1|w_1) + P(w_2)p(x_1|w_2),$$

$$P(x_2) = P(w_1)p(x_2|w_1) + P(w_2)p(x_2|w_2)$$

where

$$p(x) = \sum_{i=1}^M P(w_i) \frac{1}{\sqrt{2\pi}\sigma_{w_i}} \exp\left(-\frac{(x-\mu_{w_i})^2}{2\sigma_{w_i}^2}\right) \quad (5)$$

where $p(x|w_i)$ is the i th component density and $P(w_i)$ is the prior probability of the data points generated from component w_i of the mixture, and μ_{w_i} and $\sigma_{w_i}^2$ are the mean and the variance of the i th component, respectively. By combining Gaussian distributions of X_1 and X_2 , we obtain the distribution of final enhanced handwriting image as follows:

$$P(x_3) = P(w_1)p(x_1|w_1) + P(w_2)p(x_2|w_2) \quad (6)$$

As a result, important parts of two windowing images can be combined to represent the final windowing image which is better than the both X_1 and X_2 in terms of quality of handwriting and quality of image.

3. EXPERIMENTAL RESULTS

To assess the qualitative performance, proposed method was compared with the various contrast enhancement methods which are General Histogram Equalization (GHE) [3], Brightness preserving histogram equalization (BPHE) [15], Flattest histogram contrast enhancement (FHCE) [16]. Note that, proposed method was combined with the modified histogram for contrast enhancement (MHCE) [10]. In the first experiment, four different methods have been applied to the three different windowing images as shown with labels in Fig. 4. Existing contrast enhancement methods enhance the contrast of the input image but they also enhance the noise on the windowing image. Therefore, the quality of three different windowing images are very low and it is hard to perceive the handwriting within each window. On the other hand, proposed method enhances the contrast of the handwriting as well as provides information preservation of the input document image.

Dataset Type	Proposed Method			BPHE			FHCE			GHE		
	DE	EBCM	PSNR	DE	EBCM	PSNR	DE	EBCM	PSNR	DE	EBCM	PSNR
Swedish	3.03	0.092	21.36	3.01	0.12	18.80	2.91	0.14	15.05	2.98	0.32	16.42
DIBCO2010 [17]	3.22	0.103	20.12	3.08	0.16	19.21	2.87	0.21	16.25	3.02	0.25	13.87
DIBCO2012 [17]	3.14	0.091	21.18	2.98	0.11	19.40	2.82	0.14	16.05	3.13	0.21	14.61
DIBCO2013 [17]	3.31	0.094	23.19	3.13	0.15	18.65	2.76	0.16	17.23	2.86	0.26	18.23
avg.	3.17	0.095	21.46	3.05	0.14	19.02	2.84	0.16	16.15	2.99	0.26	15.78

Table 1. Quantitative performance results on 4 different set of images (bit per pixel (bpp) for DE, decibel (dB) for PSNR).

Fig. 5. Illustration of enhanced handwritten images of DIBCO2010, DIBCO2012 and DIBCO2013 [17], (a) Original. Enhanced by (b) BPHE, (c) FHCE, (d) GHE, (e) Proposed method.

In the second experiment, implemented methods were applied to four different datasets which are low contrast Swedish handwritten images, selected images of DIBCO 2010, DIBCO 2012 and DIBCO 2013 in a single run. Table 1 depicts the computational results of handwritten images which are computed using DE, EBCM and PSNR methods. Based on the results, proposed method is the best performing approach of the comparison, with the average quality estimation of 3.17 bpp, 0.095, and 21.46 dB for the DE, EBCM and PSNR, respectively. According to the DE and EBCM results, it is clearly seen that the highest contrast quality of handwriting windows are obtained by using the proposed method and the lowest qualities are estimated by using the GHE method [3]. Besides this, the proposed method provides the highest quality of PSNR value of the output image. Consequently, the proposed method enhances the contrast and overcomes the problems of artifacts on the document image since other methods suffer from these artifacts, overenhance the handwriting and they are unable to preserve brightness on

the image.

In the third experiment, we used document images of DIBCO2010, DIBCO2012 and DIBCO2013 [17]. As an example, four different methods have been applied to the three different document images as shown in Fig. 5. Using existing contrast enhancement methods provide bad results as they enhance the noise on the image and overenhance the handwritten text. The main reason that they provide bad results is they applied to the whole input image directly. Therefore, the quality of images are very low and it is hard to perceive the text. However, the contrasts of texts are enhanced by using the proposed method and the quality of the handwritten images are preserved as original input image.

4. CONCLUSION

In this paper, we have presented a new approach to enhance the handwriting image by using learning-based windowing combined with contrast enhancement and Gaussian Mixture

Model (GMM). To perform it, a fixed size window moves over the document image and qualitative measurement methods are applied to each window to estimate the quality results of the window. Estimated results are used in the unsupervised learning algorithm which is k -means clustering to assign the quality of windowing and make a decision whether the handwriting is low contrast or not. After that, contrast enhancement method is applied to the windowing image if it is low contrast and GMM is used to exchange information between the original and enhanced images to discard the undesired artifacts to create final document image. The proposed work provides a better contrast enhancement of handwriting and information preservation of input document image. The experimental results show the improvement of the contrast enhancement approach to perceive the handwriting better than the other contrast enhancement methods.

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6. REFERENCES

- [1] M.T.M. Gary, J.C.H. Poon, "A fuzzy-attributed graph approach to handwritten character recognition", in Proc. IEEE Int. Conf. on Fuzzy System, pp. 570-575, 1993.
- [2] H. Chen, S. S. Tsai, G. Schroth, D. M. Chen, R. Grzeszczuk and B. Girod, "Robust Text Detection in Natural Images With Edge-Enhanced Maximally Stable Extremal Regions", in Proc. IEEE Int. Conf. on Image Processing (ICIP), pp. 2609-2612, 2011.
- [3] R. C. Gonzalez and R. E. Woods, "Digital Image Processing". Upper Saddle River, NJ: Prentice-Hall, 2006.
- [4] B. Z. Varghahan, M. C. Amirani and S. Miandoost, "Enhancement and Cleaning of Handwritten Data by using Neural Networks and Threshold Technical", in Proc. IEEE Int. Conf. on App. of Inf. and Comm. Tech., pp. 1-4, 2011.
- [5] O. A. Nina, "Interactive Enhancement of Handwritten Text through Multi-resolution Gaussian", in Proc. IEEE Int. Conf. on Frontiers in Handwriting Recog., pp. 769-773, 2012.
- [6] T. K. Kim, J. K. Paik, B. S. Kang, "Contrast enhancement system using spatially adaptive histogram equalization with temporal filtering", IEEE Trans. Consum. Electron., vol. 44, no. 1, pp. 8287, 1998.
- [7] J. A. Stark, "Adaptive Image Contrast Enhancement Using Generalizations of Histogram Equalization", IEEE Trans. on Image Proc., vol. 9, no. 5, pp. 889-896, 2000.
- [8] J. C. Fu, H.C. Lien, S.T.C. Wong, "Wavelet-based histogram equalization enhancement of gastric sonogram images", Computerized Medical Imaging and Graphics, vol. 24, pp. 5968, 2000.
- [9] H. Yoon, Y. Han, H. Hahn, "Image Contrast Enhancement based Sub-histogram Equalization Technique without Over-equalization Noise", Int. J. of Electrical and Electronics Eng., vol. 3, no. 6, pp. 323-329, 2009.
- [10] T. Arici, S. Dikbas, Y. Altunbasak, "A histogram modification framework and its application for image contrast enhancement", IEEE Trans. Image Process., vol. 18, no. 9, pp. 1921-1935, 2009.
- [11] C. E. Shannon, "A mathematical theory of communication", Bell Syst. Tech. J., vol. 27, pp. 379-423, 1948.
- [12] A. Beghdadi, A. L. Negrata, "Contrast enhancement technique based on local detection of edges", Comput. Vis. Graph. Image Process., vol. 46, no. 2, pp. 162-174, 1989.
- [13] T. Kanungo, D. M. Mount, N. S. Netanyahu, C. D. Piatko, R. Silverman, A. Y. Wu, "An Efficient k -Means Clustering Algorithm: Analysis and Implementation", IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 881-892, 2002.
- [14] M. Abdoli, H. Sarikhani, M. Ghanbari, P. Brault, "Gaussian mixture model-based contrast enhancement", IET Image Processing, vol. 9, no. 7, pp. 569-577, 2015.
- [15] C. Wang, Z. Ye, "Brightness preserving histogram equalization with maximum entropy: A variational perspective", IEEE Trans. Consum. Electron., vol. 51, no. 4, pp. 1326-1334, 2005.
- [16] C. Wang, J. Peng, Z. Ye, "Flattest histogram specification with accurate brightness preservation", IET Image Process., vol. 2, no. 5, pp. 249-262, 2008.
- [17] DIBCO Dataset, (Accessed: August 2016). Available: <http://users.iit.demokritos.gr/~kntir/HDIBCO2014>,