ITERATIVE BLIND IMAGE MOTION DEBLURRING VIA LEARNING A NO-REFERENCE IMAGE QUALITY MEASURE

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ABSTRACT

In this paper, we propose a learning-based image restoration algorithm for restoring images degraded by uniform motion blurs. The motion blur parameters are first approximately estimated from the robust global motion estimation result. Then, we present a novel framework to refine the image restoration iteratively based on recursively adjusting the motion blur parameters for image restoration to achieve the best image quality measure. Note that a no-reference image quality assessment model is learned by training a RBF neural network from a collection of representative training images simulated with different motion blurs. Experimental results blured on real videos are given to demonstrate the performance of the proposed blind motion deblurring algorithm.

***Index Terms*—**Blind image restoration, motion deblurring, machine learning, no-reference image quality measure

1. INTRODUCTION

The problem of image motion deblurring can be described by the following equation:

$$g(n_1,n_2) = d(n_1,n_2) * f(n_1,n_2) + w(n_1,n_2)$$

where f, g, d and w denote the original image, the observed image, the blurring function, and the additive random noise, respectively. The objective of motion deblurring is to estimate the original image f with only the observed image g given.

Many restoration methods have been proposed in the past. A survey on the related techniques can be found in the reviews by Kundur and Hatzinakos [1,2]. In their reviews, a number of important blind deconvolution methods were described, including iterative blind deconvolution (IBD), simulated annealing (SA), and nonnegativity and support constraints recursive inverse filtering (NAS-RIF). In addition, some special hardware designs have been proposed to alleviate the deblurring problem, such as the optically stabilized lenses developed by Cannon, the special CMOS sensor proposed by Liu and Gamal [3], and the hybrid imaging system proposed by Ben-Ezra and Nayar [4].

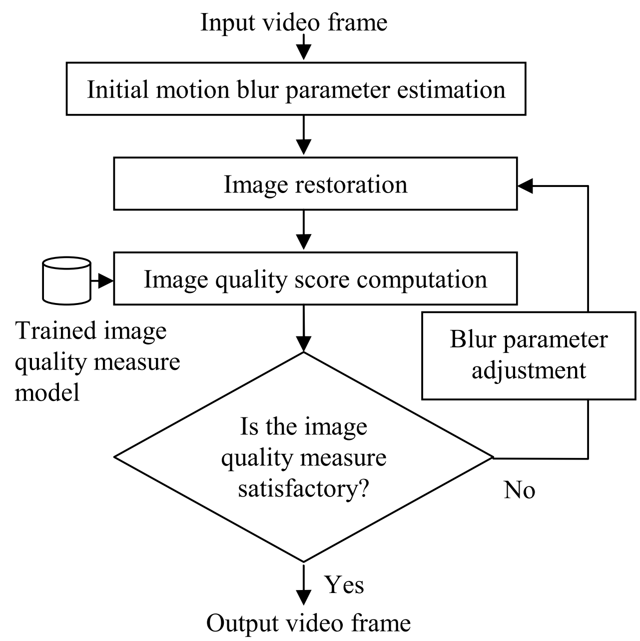

Fig. 1. The flowchart of our system.

In this paper we propose a new blind image restoration framework for the motion deblurring problem. In the proposed system, a no-reference image quality assessment model is learned from representative training examples. Then we use the learned image quality model to measure the image quality of the restored image and adjust the motion blur parameters iteratively until satisfactory restoration result is obtained.

The rest of this paper is organized as follows. In the next section, the flowchart of our system is described. In section 3, we describe how we estimate the initial motion blur parameter based on the robust global motion estimation. The no-reference image quality assessment model is presented in section 4. The blur parameter updating scheme is discussed in section 5. Section 6 gives some experimental results. Finally, we conclude this paper in section 7.

2. THE FLOWCHART OF OUR SYSTEM

The flowchart of the learning-based blind image restoration algorithm is summarized in Fig. 1. At first, we estimate an initial guess for motion blur parameter of the blurred image based on the results of robust global motion estimation. Next, we restore the blurred image by applying a regularization-based image restoration approach [5] with the given motion blur parameter values. Then, a trained image quality assessment model is employed to compute the image quality score for the restored image. Finally, the motion blur parameters are iteratively adjusted to refine the restored image until a satisfactory image score is achieved.

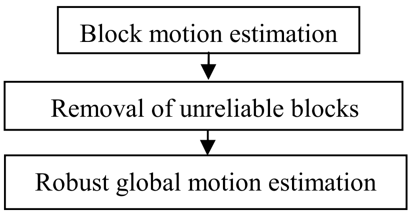

Fig. 2. Initial motion blur parameter estimation

3. INITIAL MOTION BLUR ESTIMATION

This stage includes three steps, as shown in Fig. 2.

1) Block motion estimation

Block motion estimation [6] has been popularly employed to reduce the temporal redundancy in video compression. Here, we apply an optimal motion estimation technique to estimate the block motion vectors for all the macroblocks in the image frame to be restored.

2) Removal of unreliable blocks

Because the estimated motion vectors of homogeneous or linearly structured blocks may not be consistent with the global motion of the motion blurred image, we should not take these blocks into account for the camera motion estimation. Consider the image structure tensor A around a block centered at (x,y), which is given by:

$$A = \begin{bmatrix} <I_x^2> & <I_x I_y> \\ <I_x I_y> & <I_y^2> \end{bmatrix}$$

where angle brackets denote an averaging operation over the local block. The structure of this block can be determined from the eigenvalues of the matrix A. The blocks with two small eigenvalues or large eigenvalue ratios are considered as unreliable blocks, which will be removed from the global motion estimation.

3) Robust global motion estimation

We adopt an affine model to estimate the global motion of the blurred image from the estimated block motion vectors of the 2D structured blocks. The estimation of the global affine motion from these selected motion vectors is accomplished by using the robust RANSAC estimator [7]. Finally, we use the average direction and the length of the estimated global motion model as our initial guess for the motion blur direction and motion blur extent, respectively.

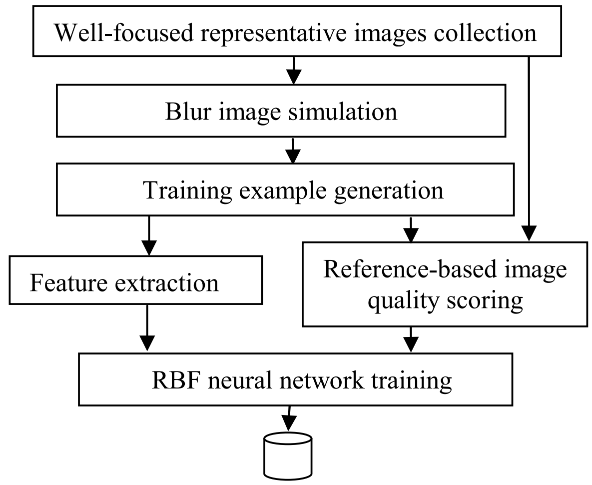

Fig. 3. Flowchart of the no-reference image quality assessment model training procedure.

4. NO-REFERENCE IMAGE QUALITY ASSESSMENT

To measure the quality of the restored image, we utilize a trained image quality assessment model to compute the corresponding image quality score.

In the system setup phase, we apply the Radial Basis Function (RBF) neural network [8] to train a no-reference image quality assessment model from representative training images. The training procedure of the no-reference image quality assessment model includes five steps, as shown in Fig. 3, given as follows:

1) Well-focused representative images collection

For the training of the no-reference image quality measure, we collect a number of well-focused images of different varieties to generate the training data.

2) Blurred image simulation

Several motion blurred images are simulated by convolving the randomly generated blur point spread functions (PSFs) with the well-focused images as the collection of training example images.

3) Training example generation

To generate training examples of restored images with correct and incorrect blur parameters, we use randomly perturbed blur parameter values to restore each simulated blurred image and take all the restored images as the training examples.

4) Image feature extraction

For the deblurring problem, we would like to measure the blur degree, the contrast enhancement and the total variation improvement of the restored image. The extracted image features can be classified into following three groups.

a. Edge width histogram

We first perform canny edge detection on the restored image. For each edge point (x_i,y_i), we search for the starting position (x_{i1},y_{i1}) and the ending position (x_{i2},y_{i2}) along the normal direction of the edge, which are the local extremal locations closest to the edge point. Then the edge width for this edge point (x_i,y_i) is given by $d_i = \sqrt{(x_{i1}-x_{i2})^2+(y_{i1}-y_{i2})^2}$. Then, we make a histogram of all the detected edge widths, and then perform M-bin quantization and normalization to obtain M edge width histogram features, which will be used in conjunction with the other features to access the image quality of the restored image. In our implementation, we set M to 8.

b. Spectral energy distribution

Frequency-domain distribution of an image usually can provide good indication for the degree of blurring in the image. For computing the spectral energy distribution features, we first apply the two-dimensional Fourier transformation to the restored image to get its frequency-domain representation. Then, we divide each dimension in frequency domain into N bins and compute the energy inside each quantized frequency band. Finally, we take the log of these spectral energy and normalize them to form a unit vector. In our implementation, N is set to 3

c. Image contrast improvement ratios

The total variation (TV) [5] improvement ratio and the contrast enhancement ratio between the restored image I_{res} and the original blurred image I_{blur} are given as follows:

$$TV\ improvement\ ratio = \frac{\mathrm{TV}(I_{res})}{\mathrm{TV}(I_{blur})}$$

where $TV(I) = \sum_x \sum_y \sqrt{I_x^2 + I_y^2}$, and

$$Contrast\ enhancement\ ratio = \frac{\sum_x \sum_y \frac{\left|I_{res}(x,y) - \overline{I_{res}(x,y)}\right|}{\left|I_{blur}(x,y) - \overline{I_{blur}(x,y)}\right|}}{\text{total number of image pixels}}$$

where $\overline{I(x,y)}$ denotes the average intensity value of I(x, y) in a local neighborhood

5) Reference-based image quality scoring

After extracting features from the training images, we take all correctly restored images as the reference images and associate them with the highest score. For each of the remaining images, we automatically compute its image quality score by a image-reference-based image quality assessment method based on structural similarity [9].

6) RBF neural network training

The Radial Basis Function neural network [8] is a special type of multilayer feed-forward networks. It consists of three layers. The first layer is the input layer, which receives the input feature vector computed from an input image. The second layer is the hidden radial basis layer. Each neuron in this layer utilizes a radial basis function (the Gaussian function for example) as the activation function. The third layer is the output layer, which linearly combines the outputs from the hidden layer to give the score of the input image.

Because the RBF training is based on least-square minimization, the RBF neural network may be sensitive to large noise or outliers in the training data. More robust regression algorithms, e.g. support vector regression, can be utilized to alleviate this problem.

Given the feature vectors of the training examples and the corresponding scores from the previous step, we can train an RBF neural network to obtain a no-reference image quality assessment model. With the trained image quality assessment model, we perform the same feature extraction process on the restored image and compute its feature vector to feed it into the trained RBF neural network to compute its image quality measure.

5. ITERATIVE PARAMETER ADJUSTMENT

In this proposed framework for blind image restoration, we aim to iteratively adjust the estimated motion blur parameters until a satisfactory restored image quality is achieved. The iterative parameter update process can be formulated as: how to find a point (θ , Δ) in two-dimensional blur parameter space such that the quality score of the restored image, which is obtained by applying Wiener filter on the blurred image with blur direction θ and extent Δ , is greater than some threshold or reaches a local maximum. Many numerical optimization methods can be utilized to search the optimal blur parameter values, such as the Levenberg-Marquardt (LM) algorithm and the downhill simplex search algorithm [10].

6. EXPRIMENTAL RESULTS

In this section, we show some experimental results to show that the proposed no-reference image quality assessment model can be used to iteratively refine the motion blur parameters to achieve satisfactory restoration results.

A number of well-focused natural images are used as the representative original images for generating the training samples. Then, the blurred images are generated by convolving randomly generated blur PSFs with the original images. The blur direction ranges from 0-degree to 90-degree, and the blur extent ranges from 20-pixel to 40-pixel. For each simulated image, we compute 49 restored images with 49 different combinations of the two motion blur parameters, to obtain a training dataset of totally 882 restored images of different blur parameter values. Thus, we used them to train a no-reference image quality RBF network. Fig. 4 and 5 depict two examples of successful blind image restoration for real motion blurred images. Due to the error in initial motion blur parameters, we can not obtain good results using either the regularization-based restoration approach or the deconvolution function in Matlab. After iteratively refining the motion blur parameters, satisfactory results are obtained.

Fig. 4. Top left: blurred image, Top right: restored image by using the regularization-based image restoration method with the initial blur parameter values. The image quality score is 33.2. Bottom left: restored image after the proposed iterative parameter adjustment process. The converged image quality score: 73.5. Bottom right: result from the Matlab blind deconvolution function.

7. CONCLUSION

In this paper, we presented a novel learning-based image restoration framework for restoring images degraded by unknown uniform motion blur. A no-reference quality assessment model trained by restoration examples is also proposed to give an objective measure of the restored image quality. Several different features are computed from the restored images to measure its contrast level and degree of ringing. With this measure, we can iteratively adjust the estimated motion blur parameter to refine the image restoration results.

The limitation of our algorithm is that the blur PSF needs to be approximated by some parametric forms, such as the uniform motion blur and the Gaussian defocus blur. It is not feasible to apply the proposed algorithm to restore images degraded by general or complicated blur functions.

REFERENCES

[1] D. Kundur and D. Hatzinakos, "Blind image deconvolution", *IEEE Sig. Proc. Mag.,* , vol. 13, pp. 43 – 64, 1996.

[2] D. Kundur and D. Hatzinakos, "Blind image deconvolution revisited," *IEEE Sig. Proc. Mag.*, vol. 13, pp. 61 – 63, 1996.

Fig. 5. Top left: blurred image, Top right: restored image by using the regularization-based image restoration method with the initial blur parameter values. The image quality score is 71.3. Bottom left: restored image after the proposed iterative parameter adjustment process. The converged image quality score is 97. Bottom right: result from the Matlab deconvolution function.

[3] X. Liu and A. El Gamal, "Simultaneous image formation and motion blur restoration via multiple capture", *Proc. Intern. Conf. Acoustics, Speech, Signal Processing*, Salt Lake City, UT, 2001.

[4] M. Ben-Ezra and S. Nayar, "Motion-based motion deblurring," *IEEE Trans. Pattern Analysis Machine Intelligence,* vol. 26, no. 6, pp. 689-698, June 2004.

[5] R. H. Chan, T. F. Chan and C. K. Wong, "Cosine transform based preconditioners for total variation deblurring," IEEE Trans. Image Processing, Vol. 8, pp. 1472-1478, 1999.

[6] Y. Wang, J. Ostermann, and Y.-Q. Zhang, *Video Processing and Communications*, Prentice Hall, 2002

[7] M. A. Fischler and R. C. Bolles, "Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography". *Comm. of the ACM* **24**, pp. 381-395, 1981.

[8] S. Chen, C.F.N. Cowan, and P. M. Grant, "Orthogonal least squares learning algorithm for radial basis function networks," *IEEE Trans. Neural Networks*, Vol. 2, no. 2, pp. 302-309, 1991.

[9] Z. Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli, "Image quality assessment: from error visibility to structural similarity", IEEE Trans. Image Processing, vol. 13, no. 4, pp. 600-612, Apr. 2004.

[10] W. H. Press, S. A. Teukolsky, W. T. Vetterling, B. P. Flannery, *Numerical Recipes in C++: The Art of Scientific Computing*, 2nd Ed., Cambridge University Press, 2002.