A VQ-BASED BLUR IDENTIFICATION ALGORITHM

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ABSTRACT

The estimation of the point spread function (PSF) of the degradation system is often a necessary first step in the restoration of blurred images. In this work, a novel Vector Quantization (VQ)-based blur identification algorithm is presented. A number of codebooks are designed corresponding to various versions of the blurring function. Prototype images blurred by each candidate blur are used. Only the non-flat regions for specific frequency bands are represented by the entries of the codebooks. Given a noisy and blurred image, one of the codebooks is chosen based on a similarity measure, therefore providing the identification of the blur. Simulations are performed for various blurring functions and noise levels. The results demonstrate the effectiveness of the proposed algorithms.

1. INTRODUCTION

Image restoration deals with the estimation of the original image from a recorded image which is corrupted by blurring and noise. The standard linear degradation model is given by [1]

$$g = Df + n \ , \tag{1}$$

where the vectors g, f and n represent, respectively, the lexicographically ordered noisy blurred image, the original image, and the noise, and matrix D represents the linear degradation process. If the degradation process is linear and space-invariant, matrix D is block circulant (assuming the images are padded by zero appropriately so that the results of linear and circular convolution are identical) and is formed by the point-spread function (PSF) of the degradation system. Despite the large number of image restoration techniques (for recent reviews see [2], [3]), most methods assume *a priori* knowledge of the PSF. In many practical situations, however, the PSF is not known *a priori* and must be estimated from the degraded image itself.

Most existing blur identification methods are based on one of the following approaches (for recent reviews see [4], [5]):

(a) Use of local image characteristics;
(b) Spectral analysis of the PSF;
(c) Simultaneous estimation of image and blur parameters;
(d) Selection of blur parameter from the finite set of candidates.

In the first category, a single feature of the recorded image is used to estimate the PSF. For example, an isolated bright point in the original image is transformed into the PSF in the blurred image. In the second category, the methods are founded on an examination of the Fourier spectrum of the recorded image. These methods utilize the fact that the width and the shape of the PSF are related to the location of the spectral nulls. The approaches in the third category employ constrained optimization techniques, in which the constraints are usually derived from prior knowledge about the original image and the PSF [6]. The techniques in the forth category is based on the selection of the PSF from a set of candidates based on a similarity measure [7], [8]. Many of the early techniques fall into the first or the second categories and work well when the signal-to-noise ratio (SNR) in the observed image is high. Most of the recent approaches fall into the third and forth categories.

The work presented in this paper falls into the fourth category and is related to an approach by Panchapakesan et. al. [8]. The proposed method is based on the selection of the appropriate codebook from a set of VQ-codebooks that correspond to various versions of the blurring function. Blurred prototype images are used for the codebook design, in which only the information of the non-flat regions in specific frequency bands is encoded. Given a noisy and blurred image, a codebook providing the smallest distance or error is chosen and the blurring

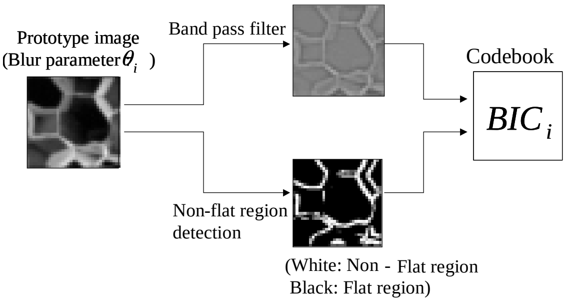


Figure 1. Block diagram of the design of the blur identification codebook (BIC_i)

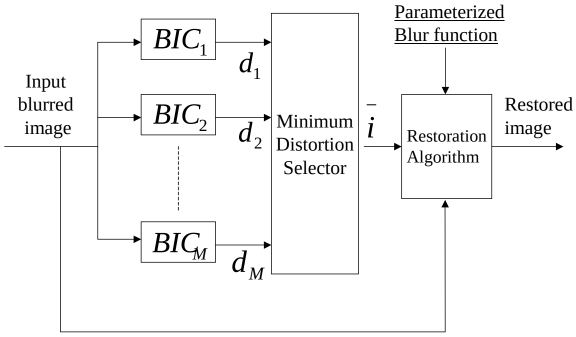


Figure 2. Block diagram of the proposed blur identification and restoration approach

function corresponding to the codebook is identified as that of the given image.

The rest of the paper is organized as follows. In section 2, we provide the framework of our blur identification algorithm. Simulation results are presented in section 3 demonstrating the effectiveness of the proposed algorithm. A summary is given in section 4.

2. Blur Identification Algorithm

Given that the blur type is known and a parametric PSF is available, blur identification reduces to the estimation of the PSF parameters from an observed image. For example, if we know that the PSF of the degradation system is a two-dimensional zero-mean Gaussian function, all we have to do is to estimate the variances of the Gaussian.

The basic element of the approach is that the codebooks are generated using the prototype images that are blurred by the same type of blur, but with different degrees of severity. Given a degraded image, the distance between the image and each codebook is calculated and a codebook with the minimum distance value is selected. The blurring function corresponding to the codebook is identified as that of the given image. The details of the codebook design and blur identification process are described in the following subsections.

2.1 Codebook Design

We assume that we have a set of blur functions each of them parameterized by the parameter vector θ_i (i=1,.., M). M blur identification codebooks (BIC s) are designed using each blur function.

In designing the BIC s, mid-range frequency information is only used. This is based on the following two facts: (i) flat (low-frequency) regions in the blurred image convey little or no information about the blur function, since they remain unchanged by the blurring operation; (ii) high frequencies in the blurred image also contain little differentiating information among the different blur functions because they are considerably attenuated by the low-pass blurring operation and in addition they are dominated by noise. The following steps are taken in the design of each codebook BIC_i as depicted in Fig. 1.

1. The original images are blurred by the blur functions parameterized by θ_i .
2. The blurred prototype images are band-pass filtered. The band-pass filter is designed according to the characteristics of the blurring function, so that the pass band includes the frequency range over which the blur functions exhibit the largest differences.
3. The non-flat regions of each blurred image are detected. Various techniques can be used to accomplish this task. In our implementation we used the local variance as a measure of the local activity. A predefined threshold was used for the classification of flat and non-flat regions.
4. Only the vectors extracted from the band-pass filtered image that belong to non-flat regions are used for the creation of the codebook. The LGB algorithm with the Euclidean distance metric was used [9].

2.2 Blur Identification Process

After the BIC s are designed, they are used for the identification of the blur and the restoration of the image as shown in Fig. 2. Given a degraded image, the distortion for each codebook (BIC_i) is calculated as follows:

1. The available blurred image is band-pass filtered by the same band-pass filter used in the codebook design.
2. Non-flat regions in the given image are detected by the same method outlined in step 3 of the codebook design procedure.

3. For each non-flat region, the closest codevector in the codebook to the one extracted from the band-pass filtered available blurred image is selected and the distortion (Euclidean distance) is stored.
4. The mean value of the distortion over all non-flat regions (d_i) is calculated.

The codebook i with the minimum mean distortion is selected to best represent the available blurred data. The blur function used to generate the codebook (BIC_i) is identified as the blur that gave rise to the available blurred data. If the actual blur is not represented exactly by any of the codebooks the blur that generates blurred data closest to the available ones is identified. Once we identify the blur, common restoration techniques can be used to estimate the original image.

In some blurring systems, the blurring function can be characterized by the measurable parameter (such as a focal point distance in optical cameras) without the specific knowledge of the blur function. In that case, the blur identification codebooks can be designed by using the blurred images with different severity taken by the real system. A combination of the proposed blur identification algorithm and a VQ-based image restoration algorithm [10], [11] can provide a restoration system that does not require specific knowledge about the blurring function.

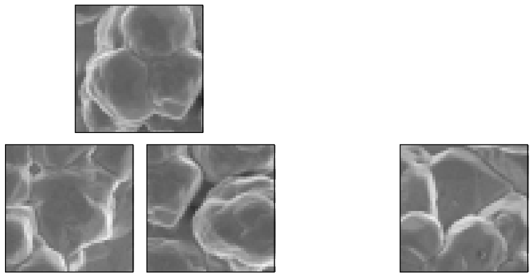
3. EXPERIMENTAL RESULTS

In this section, we show experimental results obtained by the proposed blur identification algorithm. In the first experiments, we assume that the blur function is Gaussian and is parameterized by σ^2, that is

$$h(i,j) = K\exp\left(-\frac{i^2+j^2}{2\sigma^2}\right) , \tag{2}$$

where K is a normalizing constant ensuring that the blur is of unit volume and σ^2 is the variance. Our objective is to identify the variance σ^2 of the Gaussian function for a given degraded image.

The images used for designing the blur identification codebooks (BICs) are shown in Fig. 3(a). We used 5 codebooks, each of them designed using the images degraded by the Gaussian function with σ^2 equal to {1.5,2.5,3.5,4.5,5.5}. The image in Fig. 3 (b) is also degraded by the 5 Gaussian functions and used as a given degraded image. To see the effect of noise on the algorithm, we performed three groups of experiments, in which the blurred image is contaminated by noise with BSNR=∞[dB] (noise-free), 30 [dB] and 20 [dB]. As a band pass filter for the BIC codebook design, we used the Laplacian of Gaussian (LOG) filter given by



(a) (b)

Figure3. Sample images used in the simulation experiments: (a) images used for codebook design; (b) an available image used for blur identification.

$$l(i,j) = \frac{i^2+j^2-2\sigma_l^2}{2\pi\sigma_l^6}\exp\left(-\frac{i^2+j^2}{2\sigma_l^2}\right) . \tag{3}$$

By changing the variance σ_l^2 of the LOG filter, the frequency response of the bandpass filter changes. For our experiments, we set σ_l^2 = 2.5.

Figure 4 shows the relationship between the calculated mean distortion value d_i in Fig. 2, for a given degraded image and the blur identification codebook for 3 noise levels. The graphs (a)-(e) correspond to the cases when the blur parameter of a given blurred image is equal to =1.5, 2.5, 3.5, 4.5, and 5.5, respectively. In each graph, the Y-axis shows the distortion between the given image and the BIC, and the X-axis shows the σ^2 of the blurred image used for the BIC design. We can see that in all cases the larger the noise power, the larger the distortion. The plots in Fig. 4 demonstrate the existence of a minimum point. This means that we can identify the correct parameter by selecting the codebook with the minimum distortion.

Another experiment was carried out by assuming the blur function is a pillbox function that is parameterized by the radius r according to

$$h(i,j) = \begin{cases} \frac{1}{\pi r^2}, & \text{if } \sqrt{i^2+j^2} \le r \\ 0, \text{otherwise} \end{cases} . \tag{4}$$

The obtained results demonstrate the same trend as shown in Fig. 4 and the correct blurring parameter was identified by selecting a codebook with the minimum distortion. For both cases, the accuracy of the identification result does not seem to depend on the noise power.

4. CONCLUSIONS

In this paper we presented the development of a novel VQ-based blur identification algorithm. A number of VQ codebooks, each corresponding to a candidate blurring function are designed using bandpass filtered prototype images. A codebook with the minimum average distortion for a given degraded image is selected and the blur function used to create the codebook is identified as the unknown blurring function.

Experimental results demonstrate that the proposed blur identification algorithm correctly identifies the blurring function, in a number of experiments, including the cases of a Gaussian and pillbox blurring functions. The proposed blur identification algorithm has been combined with a VQ-based image restoration algorithm [10], resulting in an efficient blind VQ-based image restoration algorithm [11].

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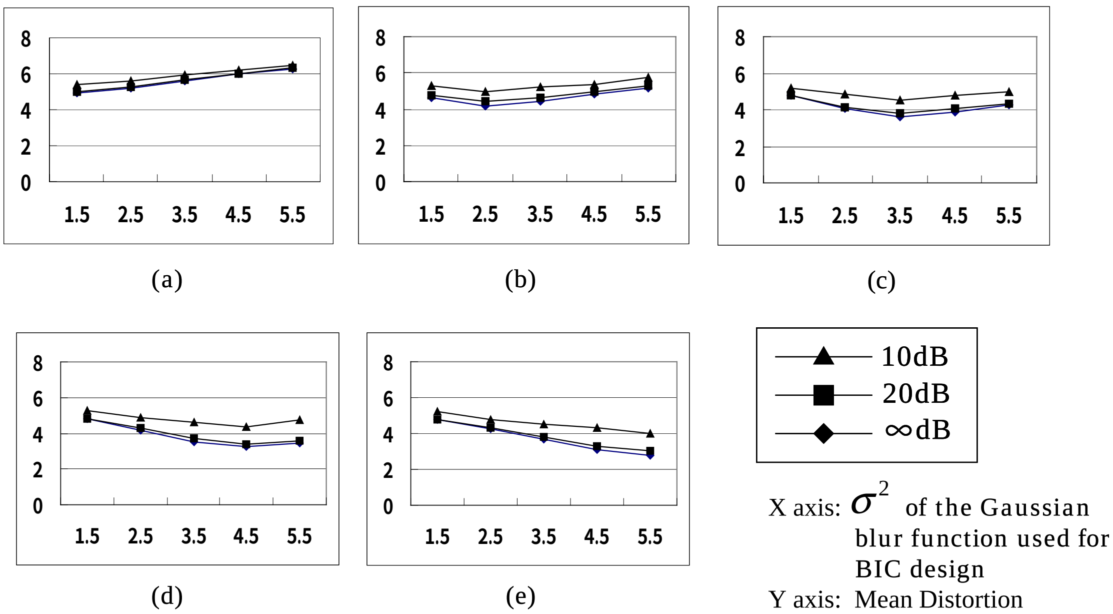

Figure 4. Mean distortion d_i between a given degraded image and the blur identification codebook (BIC). The variance σ^2 of the Gaussian blur function resulting in the degraded data is equal to: (a) 1.5, (b) 2.5, (c) 3.5, (d) 4.5, (e) 5.5 .