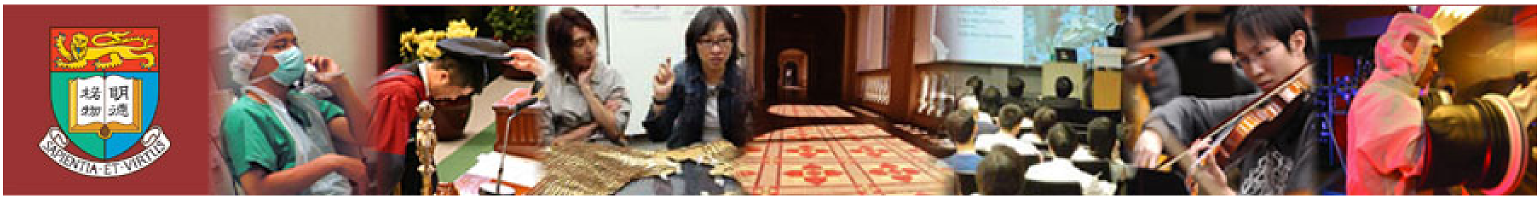

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A Nonlinear Image Restoration Framework using Vector Quantization

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Abstract

Vector quantization (VQ) is a powerful method used primarily in signal and image compression. In recent years, it has also been applied to various other image processing tasks, including image classification, histogram modification, and restoration. In this paper, we focus our attention on image restoration using VQ. We present a general framework that incorporates two other methods in the literature, and discuss our method that follows more naturally from this framework. With appropriate training data for the VQ codebook, this method can restore images beyond its diffraction limit.

1. Introduction

Image restoration is concerned with the task of recovering an original scene given the degraded observations. Despite advancement in optics and sensor technology, such degradations are inevitable due to optical aberrations, motions, and noise. In most cases, the degradations are conveniently modeled as linear space-invariant convolutions with additive noise,

$$g(x,y) = h(x,y) * f(x,y) + n(x,y), \tag{1}$$

where $g(x,y)$ is the observed image, $h(x,y)$ is the point spread function (PSF) modeling the degradation, $f(x,y)$ is the original scene to be estimated, and $n(x,y)$ is the noise. Optimal solution to find $f(x,y)$ using Wiener filter exist and is computationally efficient [3].

This approach, however, requires knowledge of the point spread function and the power spectra of both the original scene and the noise. The power spectra are needed to prevent excessive magnification of the high frequencies. This is essentially regularization of the imaging equation because deconvolution is an ill-posed problem. Another problem with applying Wiener filter in practice is the uncertainty in PSF. Sometimes its measurement may not be accurate, and this would affect the quality of the restored images. In some situations, it may not be available at all, and the image restoration problem is called blind image deconvolution. Much work is still to be done in this area. See [6] for a recent discussion of the many approaches to this problem.

In some situations, we are able to obtain images consisting of pairs of the original and degraded images [8]. We can make use of these image pairs to perform the restoration, without requiring information about the PSF or image spectra. This is achieved through vector quantization (VQ) with different codebooks for encoding and decoding. VQ is originally designed primarily for signal and image compression, as a generalization of scalar quantization to multiple dimensions. However, in recent years, it has also been applied to various other image processing tasks, including image classification, histogram modification, and restoration, with some encouraging results. For image restoration, at least two methods have been proposed [7, 9]. They are, in fact, closely related and can be put under a unifying framework. This will be presented in the next section. We will then explore another alternative that arises from the framework, and present simulation results to compare the different methods. These will be discussed in sections 3 and 4.

2. General Restoration Model

For simplicity in notation, we convert equation 1 above to a matrix multiplication model by raster-scanning the images and converting the PSF to a block-circulant matrix to give [1]

$$\mathbf{g} = H\mathbf{f} + \mathbf{n}. \tag{2}$$

For training of the VQ codebook, assume we have sets of $\{\mathbf{f_i} : i = 1, 2, \ldots, N\}$ and $\{\mathbf{g_i} : i = 1, 2, \ldots, N\}$ available. We can design filter R to operate on $\mathbf{g}$ and S to oper-

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ate on $\mathbf{f}$. Our first goal is to seek a function α that attempts to match $R\mathbf{g_i}$ to $S\mathbf{f_i}$ for all i, *i.e.*,

$$\alpha(R\mathbf{g_i}) \approx S\mathbf{f_i}. \quad (3)$$

This mapping is achieved through the use of different codebooks in encoding and decoding in VQ. Then, in restoring $\mathbf{f}$ from $\mathbf{g}$, we use another function β that involves α, R, and $\mathbf{g}$, *i.e.*,

$$\hat{\mathbf{f}} = \beta(\alpha, R, \mathbf{g}). \quad (4)$$

In this setting, R and S are filters to be designed. Obviously, different filters would imply different α and β. Figure 1 summarizes the method for this VQ image restoration.

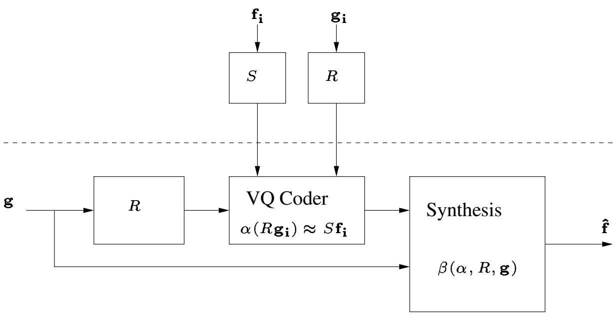

Figure 1. Block diagram of generic VQ image restoration.

In [7], R is taken to be a lowpass filter, and

$$S = I - RH, \quad (5)$$

where I is the identity matrix. Since both R and H are lowpass filters, S is seen to be a highpass filter. The restoration operation according to equation 4 is achieved by

$$\begin{aligned} \hat{\mathbf{f}} &= R\mathbf{g} + \alpha(R\mathbf{g}) & (6)\\ &\approx R\mathbf{g} + S\mathbf{f} & (7)\\ &= RH\mathbf{f} + R\mathbf{n} + (I - RH)\mathbf{f} & (8)\\ &= \mathbf{f} + R\mathbf{n}. & (9) \end{aligned}$$

Because R is a lowpass filter, $R\mathbf{n}$ is dominated by $\mathbf{f}$, so $\hat{\mathbf{f}} \approx \mathbf{f}$.

In [9], a much simpler method is used. Both R and S are considered to be all-pass filters. The VQ operation therefore attempts to match the pair of images with

$$\alpha(\mathbf{g_i}) \approx \mathbf{f_i}. \quad (10)$$

In the restoration step, we have

$$\begin{aligned} \hat{\mathbf{f}} &= \alpha(\mathbf{g}) & (11)\\ &\approx \mathbf{f}. & (12) \end{aligned}$$

Similar methods designed for restoring defocused images to comply with JPEG and JPEG 2000 respectively can be found in [5, 4].

3. A Specific VQ Image Restoration Algorithm

From an information-theoretic point of view, both of these cases may not be optimal. The purpose of the VQ coder is to achieve restoration through the match $R\mathbf{g_i}$ with the target $S\mathbf{f_i}$. The rule in designing R and S should be as follows:

- For S: To capture the most information, it would be advantageous to keep as much detail in the target. As such, we should set $S = I$ so that no information is lost.
- For R: Since $\alpha(R\mathbf{g_i})$ and $\mathbf{f_i}$ usually cannot be matched perfectly, R should be designed so that $R\mathbf{g_i}$ is as close to $\mathbf{f_i}$ as possible before applying α. From linear systems theory, we know that the best R is therefore the Wiener filter [3]. Usually in practice, difficulty arises in estimating the power spectra of the object and the noise when using Wiener filter. In our situation, that is not a major problem because we can estimate these parameters along with the training data set $\mathbf{f_i}$ and $\mathbf{g_i}$.

The algorithm is therefore simplified as in Figure 2.

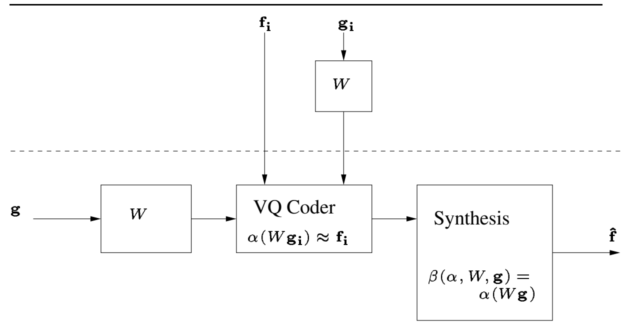

Figure 2. Block diagram of our VQ image restoration.

This method has a further interpretation: essentially, the vector quantization process serves as an additional step to the Wiener filtering of the observed image. Therefore, training data have a dual purpose of helping to estimate the parameters for the optimal Wiener filter, as well as assisting the restoration in calibrating a VQ coder for further restoration.

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4. Simulation

We implement the algorithm according to Figure 2 for testing. To obtain a quantitative comparison among the images, we use the signal-to-noise (SNR) ratio as the metric. Results for using a 256×256 "fountain" image are shown in this paper, while similar tests on other images have also been performed to ensure that the results reported here are representative. Figure 3(a) shows the ideal in-focus image that we would obtain without blur. Figure 3(b) shows the image we get with an out-of-focus aberration. This is simulated with a defocus parameter $W_m/\lambda = 0.5$ [3]. We also add a small amount of Gaussian noise to the defocused image.

(a) Infocus Image.

(b) Defocus Image.

Figure 3. "Fountain" test image.

(a) Restored with R =lowpass and $S = I - RH$.

(b) Restored with $R = S = I$.

(c) Restored with R =wiener and $S = I$.

Figure 4. Graphical comparison of three VQ-based restoration methods.

VQ can be a computationally demanding process depending on the dimension and partition [2]. As with [9] and [5] , we opt to use a DCT-based quantizer design in this simulation. This involves both a MMSE encoder design and a regularization component in the decoder to avoid excessively enhancing the high frequency [5]. This method has the added advantage of being compatible with the JPEG algorithm. The function α is manifested in the use of different encoder and decoder matrices. We compare the three different choices presented in the last section with the images in Figure 3. Figure 4(a) represents the choice of R as a lowpass filter and $S = I - RH$. The lowpass filter chosen in this simulation is a simple 3×3 averaging filter. Figure 4(b) is simulated with $R = S = I$. Figure 4(c) uses a Wiener filter for R and $S = I$. Visually, we can observe that the image in (c) produces the best restoration result. The relative poor performance of (a) is due to the fact that we are relying on the correlation between a lowpass and highpass version of the same image [7]. This assumption is apparently not suitable for the DCT-based implementation. Numerically, the three images give SNRs of 20.66dB, 23.14dB, 26.20dB respectively, as compared to 22.14dB without restoration. Evidently, the numerical results agree with our visual analysis.

5. Conclusions

In this paper we provided a unifying study of image restoration using vector quantization. This model is seen to encompass two different VQ-based image restoration techniques found in the literature, and leads to a new algorithm that leads to better quality in the restored images. This technique can be applied in a diverse array of applications from astronomy to microscopy, provided that we can obtain image pairs consisting of both the degraded and restored images for training in the VQ codebook.

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