1.0 Introduction

1.1 Background

By the nature of images, picture elements in local regions are highly correlated with one another. In other words, digitized images contain a large amount of redundant data. As a result, direct representation results in impractical requirements for storage, processing, and communication equipment. In such cases, image compression techniques are introduced to reduce the amount of data needed to represent the same information, either exactly or approximately.

Differential Pulse Code Modulation (DPCM) is a simple coding method. This method codes the difference between the current and the previous value. However, the compression rate is low compared with other more complicated methods. Transform Coding methods transform images into another domain, hopefully resulting in energy-packing characteristics. As a consequence, the relatively small coefficients can be ignored. The advantage of Transform Coding is that many fast transforms are available. A standard image compression method, named JPEG, utilizes the Discrete Cosine Transform.

Another compression approach is to use a codebook which contains representative vectors. A vector to be compressed is mapped with the least distortion to the nearest representative vector in the codebook. This method is called Vector Quantization (VQ) [Baker 1982]. Doing so possibly leads to a high compression ratio. An 8-bit gray scale 4x4 subimage, for example, can be represented by a 16-dimensional vector with 2^{128} possible values. If the vector is mapped to one of 2^8 16-dimensional representative vectors in the codebook, then 8 bits are required for each subimage vector to identify the vector in the codebook. Since 8 bits are required to represent each 16-pixel subimage, 0.5 bit per pixel is needed on average. Originally, each pixel needs 8 bits; the compression ratio, therefore, becomes 1 to 16. Nevertheless, this method requires a full search of the entire vector space. It results in computational complexity. Therefore it is not practical for image compression.

In this thesis, a hybrid compression method that takes advantage of the fast transforms is developed. The method is applied to compress images. The characteristics of the distorted image are then studied. Some a priori information other than the transform coefficients might be additionally included in the transmitted information. The extra information is used to iteratively reconstruct the images at the receiver end. Finally, the performance resulting from each type of a priori information is compared.

1.2 Overview of the Hybrid Compression Method

Transform Coding (TC) is computationally favorable but the choice of basis vectors is limited to one orthogonal set. At the same time, VQ provides a non-orthogonal set of basis vectors that can better accommodate the image data but it needs much more computation. An image data compression technique called Multiple Bases Representation (MBR) takes its advantage from both TC and VQ. MBR acquires basis vectors from more than one orthogonal transform. The benefit, for image processing, of picking basis vectors from properly different orthogonal transforms is that a particular transform, in general, has some weak points that can be compensated for by other transforms.

One way to implement MBR is to first apply several transforms to map the original signal to multiple orthonormal bases. Second, store the largest component and remove that component from the original signal. Repeat the mapping-removing procedures on the residual image until a desired stopping criterion is reached. This algorithm is called Recursive Residual Projection (RRP) [Safar 1988]. It is possible that the current basis vector repeats one of the prior selected basis vectors. That means the RRP distorted signal is not exactly the same as the projection of the original signal onto the set of the vectors selected by the RRP method. Thus, only an approximate version of the multiple bases projection is obtained.

In addition to the coefficients and basic vectors found with the RRP algorithm, a priori information computed from the original image and/or the residual image can be included to improve the reconstructed image at the receiver end. Useful a priori information was determined by Moose [Moose 1994].

1.3 Overview of Iterative Image Reconstruction

Decomposed by RRP, the information transmitted contains the transform basis vector identification and the corresponding gain. The observed signal at the receiver end is decompressed by summing the basis vectors weighted by the associated gain. The restoration process is called an inverse MBR transformation. The MBR coefficients themselves do not describe the original signal. With the assistance of transmitted a priori information about the residual signal, a set of constraints is formed. Then the image is iteratively reproduced to meet the constraints. In general, the iteration stops when it cannot significantly improve the image further.

Basically, the sets formed are convex to guarantee that the iterative algorithm is convergent. This reconstruction algorithm is known as Projection Onto Convex Sets

(POCS). Not only convex sets, but also some additional nonconvex constraints are beneficial. The nonconvex constraints can lower the final mean square error (MSE) [Moose, 1994]. In general, the typical a priori information costs extra bits in storage or transmission. However, if the additional extra information can remove artifacts in the distorted image, it is interesting to investigate this. One aim of this thesis is to determine which a priori information is worth the cost spent on it.

Moose [Moose 1994] points out that the original signal, generally, contains more energy than the MBR observed signal. Thus, the observed signal with energy added is more effective in decreasing MSE and increases the speed of convergence. Furthermore, the observed signal plus a constant does not require extra constraints.

1.4 Thesis Preview

Chapter 2, "Theoretical Review," is a detailed discussion of signal representation. The Multiple Bases Representation is introduced. The RRP algorithm that is used to implement MBR is discussed next. At the end of Chapter 2, the statistics of the MBR solution space are presented.

Chapter 3, "Image Reconstruction," discusses problems related to image reconstruction. The theories related to the reconstruction are briefly illustrated. An algorithm called Projection Onto Convex Sets (POCS) is introduced. Focusing on the MBR distorted signal, the constraints used in Chapter 6 are defined.

Chapter 4, "Blocking Artifact," addresses the problem of dividing the original image into subimages. The boundaries where the blocking effect shows up are investigated. The inter-block constraints are introduced. The extra information for the constraints is determined.

Chapter 5, "Implementation Description," describes the implementation tool, the method of quantization used, and the method of measurement used. In addition, the choices of the initial vector for POCS are listed at the end of this chapter.

Chapter 6, "Performance Improvements due to Constraints," shows performance of the implementation of the image compression and reconstruction. The local composite constraints stated in Chapter 3 are applied to the iterative reconstruction. The inter-block constraints introduced in Chapter 4 are then investigated. The performances associated with the individual constraints are compared in terms of the reconstructed image quality. The amount of extra information to be transmitted for each constraint is also analyzed in this chapter. Chapter 7 summarizes the thesis.