

A NEW POSTPROCESSING METHOD FOR THE BLOCK-BASED DCT CODING BASED ON THE CONVEX-PROJECTION THEORY

Chi-Min Liu, Member, IEEE, Chung-Neng Wang and Jine-Yi Lin
 Department and Institute of Computer Science and Information Engineering
 National Chiao Tung University, Hsinchu, 30050, Taiwan
 E-mail: cmliu@csie.nctu.edu.tw

Abstract— The block-based DCT coding has been adopted in image compression standards such as JPEG and MPEGs. This type of coding causes some noticeable artifacts known as the blocking effect. Various post processing methods have been devoted to removing the blocking effect; however, these methods also unavoidably blur the decoded image. Removing the blocking effect while avoiding blurring is the main issue of the postprocessing. This paper presents a new postprocessing method based on convex-projection theory. This method is shown to have keep good tradeoff for the blocking effects and the blurring effects.

I. INTRODUCTION

THE block-based discrete cosine transform (DCT) coding is one of the most popular transform techniques for image and video compression, and has been adopted in compression standards such as JPEG and MPEGs. Fig. 1 illustrates the block diagram of the block-based DCT coding algorithm. An image is partitioned into non-overlapping 8x8 blocks and each block is individually processed through the DCT and the quantization. Since that the DCT and the quantization are individually applied to each block, quantization errors between adjacent blocks are discontinuous. Such an encoding process will magnify the difference between neighboring blocks. This

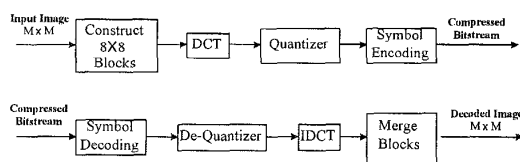


Fig. 1. The block diagram illustrating the processing of the block-based DCT encoders and decoders.

artifact which is obvious at very low bit rate coding has been referred to as the *blocking effect*. Fig. 2 demonstrates the blocking effect of the Lena picture that is coded at JPEG standard with quantization table scaled by 3.

Recently, there have been many postprocessing methods [1]-[17] proposed to reduce the blocking effect. We can group the existing methods on postprocessing into three categories: space-variant lowpass filtering (SVLP) [1]-[7], block-difference



Fig. 2. The decoded image of the JPEG with quantization table scaled by 3.

minimizing (BDM) [10], [11], and convex-projection (CP) [4], [8], [9], [13], [15]-[17]. All these methods try to reduce the blocking effect through a smoothing manner; however, the smoothing also unavoidably blurs the image. Hence, removing blocking effect while preserving the edges is the main issue of the postprocessing. This paper presents a new postprocessing method. The method has been shown to keep balance on the blocking effect and the blurring effect as compared with the SVLP, BDM, and the existing CP methods through the subjective measure and the objective measure which we have developed [12].

The information available for removing blocking effect can be considered from the spatial domain and the frequency domain. The spatial-domain information is from the discontinuity among blocks. The space-variant lowpass filtering (SVLP) [1]-[7] and the block-difference minimizing (BDM) [10], [11] are to remove the discontinuity through smoothing or minimizing manners. The frequency domain information is from the quantization process where the coefficients are quantized through a scaled quantization table. The scaled quantization table provides the range of the unquantized coefficients and can be used as an effective information to reconstruct the original coefficients and hence the original image. However, it is not an easy way to collaborate the frequency information and the spatial information for postprocessing. The convex projection (CP) theory provides an iterative approach to integrate various processing schemes for a processing objective. The postprocessing

methods in [4], [8], [9], [13], [15]-[17] have been developed based on the CP theory. The key issue of the CP theory [18], [19] is the way to develop the schemes in each iteration to achieve the processing objective and simultaneously meet the constraints from CP theory for convergence. Sometimes, to meet the constraints of the convergence, the scheme in each iterative process has to be developed less effective for easing the blocking effect. However, the theoretical framework of the convex projection is good in bridging the various information. This paper presents a new postprocessing method based on the CP theory and shows that the method is better than other methods in the tradeoff between the blocking effect and the blurring effect.

The rest of the paper is organized as follows: Section II presents the new postprocessing method based on the convex projection theory. Section III demonstrates the experiment results. Section IV gives a concluding remark.

II. NEW POSTPROCESSING METHOD

The CP theory has been adopted in [4], [8], [9], [13], [15]-[17] to process the decoded images. The key issue of the CP theory [18], [19] is the way to develop the schemes in each iteration to achieve a processing objective and simultaneously meet the constraints from CP theory for convergence.

By the CP theory, the known features of the processing objective are expressed as the closed convex sets. On each convex set, the associated projection operator is defined. The projection operators alternatively map the input vector onto the convex sets. The restriction of non-expansive of the projection operators can guarantee the convergence of the iterative projections.

When applying the CP theory for postprocessing, we consider two critical issues. The first is on the selection of the convex sets and associated projector satisfying the desired features of images. In the postprocessing method based on the convex-projection theory, we first define some closed convex sets. Each set is designated to bind the images matching one property of the original image. On the various convex sets, we define the associated projection operators. If all sets can satisfy the requirements of the theory, the image will converge to the intersection set in iteration. That is, the resultant image will satisfy all properties. However, it is not easy to find the ideal closed convex sets. If the set is large, you may find the solution in the intersection set; but the intersection solution can not guarantee the good image quality. Inversely, the set of smaller size may lead to an empty intersection set.

The second issue is on the initial images of the CP. Since that there are difficulty in defining the convex sets, the image in the intersections of sets does not guarantee the better image quality. Hence, the initial image will play an essential role in CP iteration.

This paper presents postprocessing method based on the CP theory with five features. First, we develop a window-adaptive lowpass filter to smooth the blocking image according to image contents. The smoothed image can provide an initial image for

the CP iteration a better initial condition for the final image. Second, the edge preservation set and the associated projector are defined to preserve or reconstruct edges of an image in iteration. Third, the texture areas have been kept in each CP iteration because that preserving edge may also magnify the blocking effect in the processed image, especially in the texture areas where the intensities of neighboring pixels vary slightly (for example, the hair areas in Lena image). Fourth, to reconstruct the original coefficients and hence the original image, the de-quantized DCT coefficients of the processed image shall be retained in the range of the scaled quantization table. Finally, the intensity the pixels of gray-level image is restricted to be between 0 and 255.

A. Processing for the Initial Image

The initial image is obtained by processing the decoded image. The processing has two considerations. First, the pixels near the block boundaries are processed to keep good tradeoff between blocking effects and the blurring effects. Second, the pixels off the block boundaries are processed to preserve edge information. On the two considerations, this paper derives the window-adaptive method to process the image. The method consists of two steps.

The first processing step is to classify the pixels into four types: uniform, sparse, texture, and edge. The classification is based on the Sobel operator defined as

$$x_{edge}(i, j) = \nabla^{\max} = \max\{\nabla_h(i, j), \nabla_v(i, j)\} \quad (1)$$

for $0 \leq i, j \leq M-1$

where M is the image size, $\nabla_h(i, j)$ is the output value of the Sobel operators for detecting horizontal edges and $\nabla_v(i, j)$ for detecting vertical edges. The classification types are decided according to

$$\text{pixel type}(i, j) = \begin{cases} \text{uniform,} & \nabla_{i,j}^{\max} \leq T_u \\ \text{sparse,} & T_u < \nabla_{i,j}^{\max} \leq T_t \\ \text{texture,} & T_t < \nabla_{i,j}^{\max} \leq T_e \\ \text{edge,} & \nabla_{i,j}^{\max} > T_e \end{cases} \quad (2)$$

where the threshold T_u is a very smaller value to ensure no pixel with blocking effects included, and the others are dependent on the histogram of the edge image in Eq. (9). T_t is the mean of the edge image and T_e the mean plus the variance. It is feasible that the pixels among the different classes have mutual exclusive properties in the space domain while those in separate class have similar properties. The pixels in each the four mutual exclusive classes is processed individually.

The second step has two processing methods separately for pixels on the block boundaries and off the block boundaries. For those on the block boundaries, two low pass filtering is adopted. For a pixel having the same pixel type as the majority of the nearest 24 pixels, the pixel are processed through a lowpass/bandlimit filter:

$$F = \begin{bmatrix} w_{-1,-1} & w_{-1,0} & w_{-1,1} \\ w_{-1,0} & w_{0,0} & w_{0,1} \\ w_{-1,1} & w_{0,1} & w_{1,1} \end{bmatrix} \quad (3)$$

where

$$w_{i,j} = \begin{cases} \left(\frac{T_u}{T_l}\right)^{\frac{1}{2}} & i = 0 \text{ and } j = 0 \\ \frac{(1-w_{0,0})}{8} & \text{otherwise} \end{cases} \quad (4)$$

This filter is designed to reserve the edges through the two factors T_u over T_l . Therefore, to gradually decrease the discontinuities between adjacent blocks, the ratio of T_u over T_l is used. Since the T_u and T_l are the thresholds extracting from a two dimensional (2-D) image, the squared-root operation is required for 1-D threshold.

For a pixel not having the same pixel type as the majority of the nearest 24 pixels, the pixel are processed through a 3×3 equal-weight average filter:

In extreme cases of this specific filter in Eq. (3), as $w_{0,0}$ approaches to one, F becomes all-pass filter; inversely, the pixel approaches to a equal-weight average filter. Namely, the separate filters of size 3×3 are separately employed for gradually controlling the blurring effect by considering the correlation of gradients in the local area.

For pixels off the boundaries, the window adaptive lowpass filters are adopted to smooth the areas. The applying lowpass filters having three different sizes: 7×7 , 5×5 , and 3×3 . The maximum window size is determined according to whether or not the pixels in the window have been classified as edge type. The pixels of edge type remain unfiltered. These filters are defined in the following form

$$w_{i,j}^N = \begin{cases} \frac{2}{N^2 + 1} & i = 0 \text{ and } j = 0 \\ \frac{1}{N^2 + 1} & \text{otherwise} \end{cases} \quad (5)$$

where $N=3, 5$, and 7 .

B. Five Convex Sets

For the postprocessing based on the CP theory, the known properties have been expressed as the closed convex set. Given the decoded image, therefore, this paper selects four closed convex sets C_E , C_T , C_Q , and C_I for iteration. Besides, the decoded image can be found in each of the four sets, the method ensures $(C_E \cap C_T \cap C_Q \cap C_I) = C_0 \neq \emptyset$. In this paper, C_E preserves the edges with the introducing of the psychovisual effects and is the edge preservation set. C_T keeps the textures and is the texture preservation set. C_Q retains the dequantized DCT coefficients of the processed image in the range of the scaled quantization table. C_I is the intensity normalizing set.

The associated projector for the C_E in the space-domain is

defined as

$$P_{space}[x(i,j)] = \begin{cases} a, & x(i,j) < a \\ x(i,j), & a \leq x(i,j) \leq b \\ b, & x(i,j) > b \end{cases} \quad (6)$$

The bounds a and b are determined by pixel classes:

$$a = x_D(i,j) - \Delta_B, \quad b = x_D(i,j) + \Delta_B \quad (7)$$

where $x_D(i,j)$ denotes the decoded image and $x_S(i,j)$ the initial image.

$$\Delta_B = \begin{cases} \frac{1}{2} JND_k & x(i,j) \text{ is off block border} \\ \Delta_h & x(i,j) \text{ is on block border} \end{cases} \quad (8)$$

where JND_k is the threshold of the k -th block based on the model for contrast sensitivity [20]. Δ_h is decided by the pixel type as listed in the following table.

Pixel class	uniform	sparse	texture	edge
Δ_h	32	32	24	8

Similarly, P_I is the associated projector for C_I and has the bounds to be 0 and 255.

The associated operator P_Q is for C_Q : $0 \leq u, v \leq M-1$.

$$P_T[X(u,v)] = \begin{cases} A, & X(u,v) < A \\ X(u,v), & A \leq X(u,v) \leq B \\ B, & X(u,v) > B \end{cases} \quad (9)$$

where $X(u,v)$ is the DCT coefficient of the currently processed image. The bounds of P_Q are dependent on the scaled step size:

$$\begin{aligned} A &= X_D(u,v) - q \cdot \Delta_Q(u,v), \\ B &= X_D(u,v) + q \cdot \Delta_Q(u,v) \end{aligned} \quad (10)$$

where $X_D(u,v)$ denotes the DCT components of the decoded image and $X_S(u,v)$ the DCT components of the initial image. q is the quantization scale factor and $\Delta_Q(u,v)$ is the step size on the (u,v) -position of the quantization table of JPEG.

The associated operator P_T is for C_T and is applied just to the texture blocks. The P_T is formulated as P_Q in Eq. (9). The upper and lower bounds of P_T are determined from the DCT coefficients of the initial image and the decoded image as follows:

$$\begin{aligned} A &= \min\{X_S(i,j), X_D(i,j)\}, \\ B &= \max\{X_S(i,j), X_D(i,j)\} \end{aligned} \quad (11)$$

It is feasible to prove that the operators are nonexpansive. Therefore, CP theory guarantees the convergence of the iteration.

C. Iteration

In brief, the new postprocessing method is formulated as

$$\hat{x} = \lim_{m \rightarrow \infty} (P_V P_Q P_T P_E)^m F x_0 \quad (12)$$

where \hat{x} is the processed image.

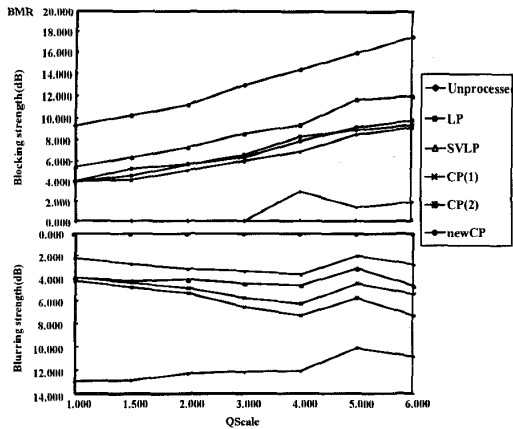


Fig. 4. The performances of various postprocessing methods on the Lena image.

To seek for the maximum iterations required for convergence, the metrics such as BMR[12] and PSNR are used. As the difference between the outputs of the selected metric is smaller than a threshold, the iteration stops. That is, the iterations will be terminated as the convergence conditions are satisfied. If the BMR is used, the blocking strength and the blurring strength must be converged into a fixed range. By BMR, the resultant image is a satisfactory solution with better perceptibility.

III. EXPERIMENT RESULTS

This section demonstrates the experiment results through two sample images, which are called as Lena and Ken image. Figs. 4 and 5 illustrate the performance by the new method and other existed methods. The resultant images are demonstrated in Figs. 7 and 8. In both illustrations, the values of the measures are arranged in an ordered form as $\nu_{dB} = (SNR, PSNR, [Blk, Blur])$, where $[Blk, Blur]$ is the measure we present as BMR in [12]. The *Unprocessed* indicates the BMR value of the unprocessed image. One method which employs only a 3×3 average filter is labeled as *LP*. The space-variant lowpass filtering [3], which applies four equal-weight average filters into the low frequency areas, are labeled as *SVLP* [3]. The filters used have the size 3×3 , 5×5 , 7×7 , and 9×9 . The iterative method based on CP theory, which includes the smoothing operator in iterations [8], is then denoted as *CP(k)*, where *k* means the *k*-th iteration as illustrated in [8]. The perceptual based postprocessing is denoted as *newCP*. For each method, the contrast between the blocking strength and the blurring strength provides the subjective quality of the reconstruction [12]. In Figs. 4 and 5, the *Unprocessed* case has the strongest blocking strength and is assumed to have no blurring. Due to the nature of the lowpass filter, *LP* case has little or even no blocking effect but the strongest blurring strength. Since, in the *SVLP* case, the edge information was extracted from the decoded image and only the low frequency areas were smoothed, the blurring strength is conducted. However, as the compression rate is increasing, the

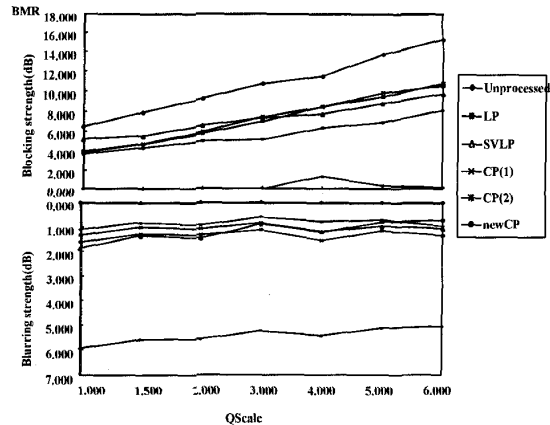


Fig. 5. The performances of various postprocessing methods on the Ken image.

edge information is more and more difficult to extract. Thus, the blocking strength of the *SVLP* case increases. The iterative method *CP(1)* performs similar as *CP(2)* in total; but the *CP(2)* is slightly blurred due to applying the lowpass filter to the resultant image of *CP(1)* once again. Both *CP(k)* cases smooth all areas except for the edges to get a slightly blocky reconstruction. However, serious distortion of edges as the compression being increased leads *CP(k)* cases to be oversmoothed. In the case of new postprocessing method, the perceptually optimized image is obtained that the blocking strength and the blurring strength are shown to be balanced.

The convergence rates of iterative methods, *CP(k)* in [8] and the proposed method, for Lena image are illustrated in Fig. 6. It demonstrates that the proposed method converges to a satisfactory solution after about 2-4 iterations in terms of SNR and PSNR and after about 4-5 iterations based on BMR [12]. In Fig. 6, there is an abrupt change at the third iteration for the *CP(k)*. This abrupt change is due to smoothing the image again such that the blurring strength of BMR is increased and the PSNR is decreased. To avoid oversmoothing is, thus, to exclude the smoothing operators out of the CP iterations.

In addition, the details like at the left hat and the hair areas are more similar to the original image in Fig. 7. The recovery of the Ken image demonstrates the balance of the blocking strength and the blurring effects by the new CP method. This can be shown by the clearness of the objective edges and the smoothness of the flat areas. All these environments indicate the feasibility of the new method.

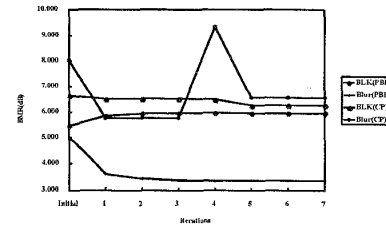
IV. CONCLUSIONS

This paper has presented a new postprocessing based on the CP theory. The new method is distinct in the initial processing and the convex iteration. For the initial processing, the decoded image was smoothed according to the space-domain psychovisual effects of the image. The perceptual-based initialization has been shown to provide an initial image for a

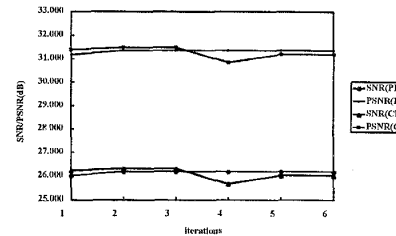
better condition to converge to the final image. For the convex iteration, this paper has presented four convex sets and the associated operators. Because the visibility thresholds were introduced into the edge preserving set, the final image which fits with all constraints simultaneously can be claimed to be the perceptually optimized or acceptable reconstruction. The simulations have shown that the iterations converge to the desired image in a very efficient way. By comparing with the existing methods, all the environments indicate the feasibility of this new method.

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(a) BMR=[Blk, Blur]



(b) SNR/PSNR

Fig. 6. The illustration of the performance on convergence rates for two images with quantization table scaled by 3.

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(a) The original image



(b) $Unprocessed v_{dB} = (25.67, 30.84, [12.94, 0.00])$



(c) $LP v_{dB} = (25.68, 30.85, [0.00, 12.12])$



(d) $SVLP v_{dB} = (26.01, 31.18, [8.51, 4.48])$

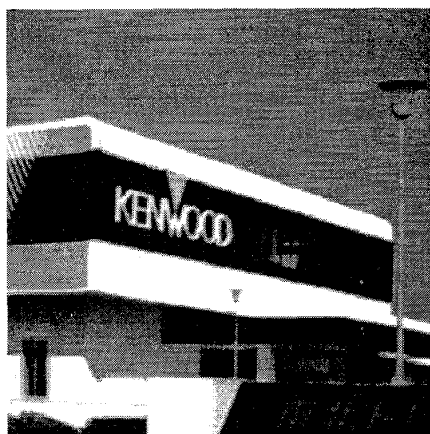


(e) $CP v_{dB} = (26.31, 31.48, [6.52, 5.75])$



(f) $NEWCP v_{dB} = (26.18, 31.35, [5.95, 3.37])$

Fig. 7. The recovered images of the decoded image named as Lena by JPEG with quantization table scaled by 3. The comparisons of the postprocessing methods is based on the measures SNR, PSNR, and BMR[12].



(a) The original image

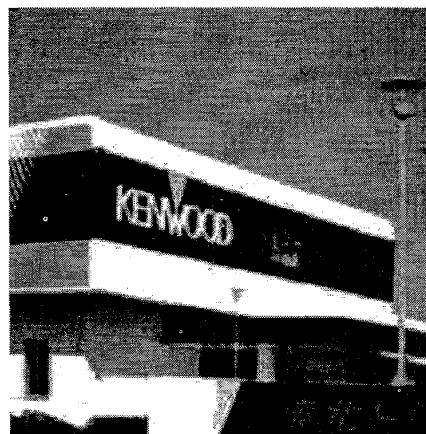
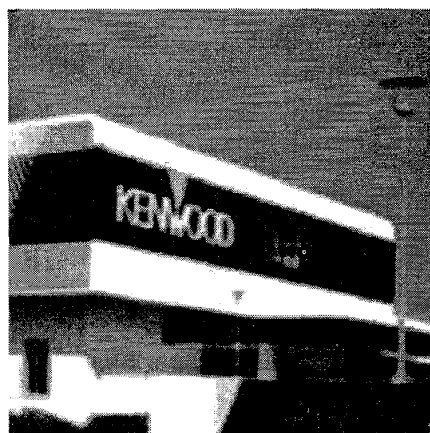
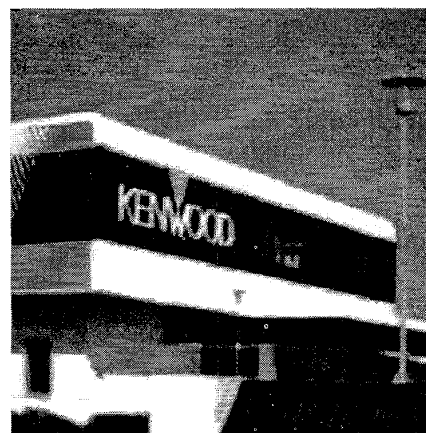
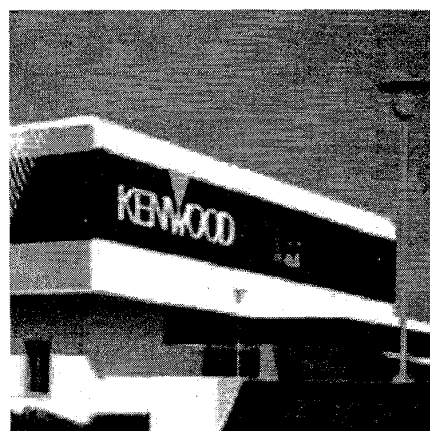
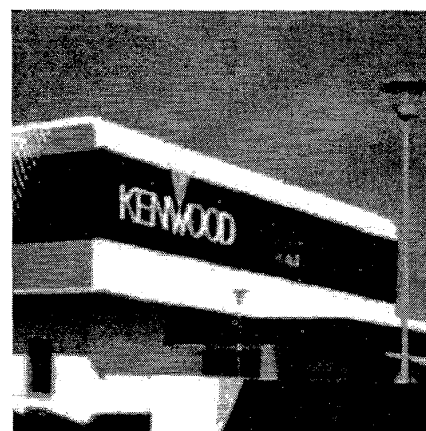
(b) $Unprocessed v_{dB} = (28.03, 32.37, [10.75, 0.00])$ (c) $LP v_{dB} = (26.52, 30.86, [0.00, 5.25])$ (d) $SVLP v_{dB} = (27.67, 32.02, [7.29, 0.89])$ (e) $CP v_{dB} = (28.63, 32.97, [7.40, 0.84])$ (f) $NEWCP v_{dB} = (28.48, 32.82, [5.12, 0.61])$

Fig. 8. The recovered images of the decoded image named as Ken by JPEG with quantization table scaled by 3. The comparisons of the postprocessing methods is based on the measures SNR, PSNR, and BMR[12].



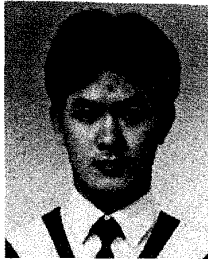
Chi-Min Liu received the B.S. degree in electrical engineering from Tatung Institute of Technology, Taiwan, R.O.C. in 1985, and the M.S. degree and Ph. D. degree in electronics from National Chiao Tung University, Hsinchu, Taiwan, in 1987 and 1991, respectively.

He is currently an Associate Professor of the Department of Computer Science and Information Engineering, National Chiao Tung University, Hsinchu, Taiwan. His research interests include video/audio compression, speech recognition, radar processing, and application-specific VLSI architecture design.



Jine-Yi Lin graduated from the Department of Computer Science and Information Engineering, National Chiao Tung University (NCTU), Taiwan, R.O.C., in 1995. He received his M.S. degree in the Institute of Computer Science and Information Engineering, NCTU. He is currently in military service. His current research interests are image

and video compression.



Chung-Neng Wang was born in Pingtung, Taiwan, in 1972. He graduated from the Department of Computer Science and Information Engineering, National Chiao Tung University (NCTU), Taiwan, R.O.C., in 1994. He is now pursuing his ph.D. degree in the Institute of Computer Science and Information Engineering, NCTU. His current research interests are video/image

compression and artificial intelligence.