Medical Image Compression by Sampling DCT Coefficients

Yung-Gi Wu

Abstract—**Advanced medical imaging requires storage of large quantities of digitized clinical data. Due to the constrained bandwidth and storage capacity, however, a medical image must be compressed before transmission and storage. Among the existing compression schemes, transform coding is one of the most effective strategies. Image data in spatial domain will be transformed into spectral domain after the transformation to attain more compression gains. Based on the quantization strategy, coefficients of low amplitude in the transformed domain are discarded and significant coefficients are preserved to increase the compression ratio without inducing salient distortion. In this paper, we use an adaptive sampling algorithm by calculating the difference area between correct points and predicted points to decide the significant coefficients. Recording or transmitting the significant coefficients instead of the whole coefficients achieves the goal of compression. On the decoder side, a linear equation is employed to reconstruct the coefficients between two sequent significant coefficients. Simulations are carried out to different medical images, which include sonogram, angiogram, computed tomography, and X-ray images. Consequent images demonstrate the performance at compression ratios of 20–45 without perceptible alterations. In addition, two doctors are invited to verify that the decoded quality is acceptable for practical diagnosis. Therefore, our proposed method is found to preserve information fidelity while reducing the amount of data.**

Index Terms—**Adaptive sampling, discrete cosine transform (DCT), medical image compression.**

I. Introduction

DATA COMPRESSION techniques play a key role as a leveraging technology in all data-management systems. The increasing demands for rapid communication and storage go beyond the current limited capacity. Data compression balances the situation between the limited capacities and the limited user demand. It reduces the storage requirements and transmission time, which makes the data management more effective and efficient [1]–[3].

In medical application, where inherently large volumes of digitized images are presented, image compression is indispensable. There are two categories of compression: lossy and lossless methods. The choice between the two depends on the system requirements. Lossless compression ensures complete data fidelity after the reconstruction, and yet the compression ratio is limited in general to 2 : 1 to 3 : 1. The application of lossy techniques results in information loss to some degree, but it can provide more than 10 : 1 compression ratio with little perceptible difference between reconstructed and original images. Lossy compression techniques have been widely utilized for image compression applications. Unlike other compression applications such as TV and multimedia systems, the loss of fidelity must be reduced as much as possible in medical application so as not to contribute to diagnostic errors [4].

In this paper, an adaptive sampling algorithm imposed on the spectral domain, achieved by discrete cosine transform (DCT), is proposed. This algorithm records significant coefficients as compressed data for transmission or storage. For the working of the decoder, significant coefficients can be retrieved from compressed data directly. As to other coefficients that exist between two significant coefficients, a linear function is derived to reconstruct them. There are many sampling algorithms from the literature. In [5], an irregular sampling algorithm was proposed for wavelet compression. In that paper, an adaptive sampling algorithm in the discrete time domain is constructed by finding a univocal relation between the signal's samples and the nonzero wavelet transform coefficients. Reconstruction is performed through repeated projections of an approximation of the initial signal based on the arriving samples. The computational burden is heavy.

The method proposed here is straightforward and simple. It does not need complicated calculation; therefore the hardware implementation is easy to attach. The rest of this paper is organized as follows. An adaptive sampling algorithm generated by our proposed method is addressed in Section II. Descriptions of DCT will be given in Section III. Section IV depicts how to apply our adaptive sampling algorithm to medical image compression system. There are simulation results and conclusions, respectively, in Sections V and VI.

II. Adaptive Sampling Algorithm

This algorithm essentially provides the adaptive sampling scheme for one-dimensional signals. The original form of this adaptive sampling algorithm was published in [6], which applies the algorithm to ECG processing successfully. This paper, however, applies the adaptive sampling algorithm to image compression. The main feature of this algorithm includes two schemes: the method of computing approximate distorted area and the method of adaptive sampling. The first method is based on the following criterion: when linking a line between two significant samples of the original waveform, we can get the approximate distortion of the area formed by the line of the two significant samples and the original waveform. The distorted area is the absolute sum of the difference between the predicted samples and the original ones. The proposed sampling algorithm selects the significant samples by calculating the distorted area that is formed by the starting point and candidate point sequentially. If the approximate distortion area exceeds

Manuscript received September 7, 2000; revised July 9, 2001.
The author is with the Department of Computer Science and Information Engineering, Leader University, Tainan City, 709 Taiwan, R.O.C.
Publisher Item Identifier S 1089-7771(02)02007-1.

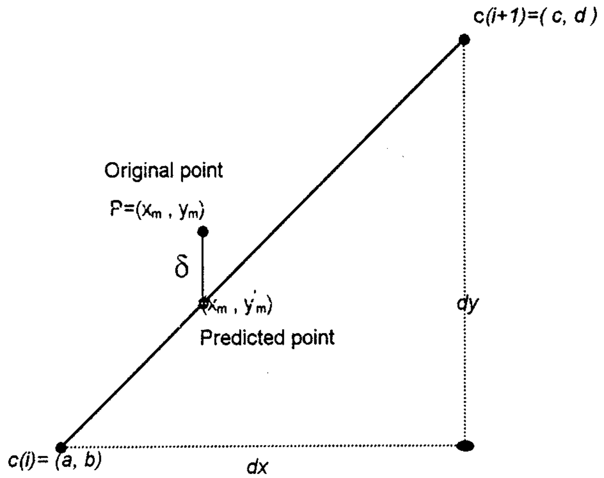

Fig. 1. Displacement of a sample $(x_m,\ y_m)$ to the linear segment formed by $c(i)$ and $c(i+1)$.

the defined threshold, then we store the samples forming the area as nonredundant samples. As to the other samples, those that can be approximately predicted are taken as redundant samples, which are not necessary to be stored or transmuted.

A. Linear Interpolation, Linear Segments, and Displacement

We use linear segments for representing an encoded signal. Consider Fig. 1. Let $c(i) = (a,\ b)$ and $c(i+1) = (c,\ d)$ be two consecutive significant samples selected. Connecting these two significant samples by linear interpolation constitutes an approximation to the original fragment. The value of y_m of any sample $(x_m,\ y_m)$ on this linear segment can be estimated as follows:

$$y'_m = \frac{d-b}{c-a} \times (x_m - a) + b \tag{1}$$

where $a < x_m < c$ and all computations use integer operations. Let $p = (x_m,\ y_m)$ be the original sample and x_m be the x-coordinate of the sample between $c(i)$ and $c(i+1)$. Accordingly, the displacement value of δ between the original sample $(x_m,\ y_m)$ and the decoded (predicted) sample $(x_m,\ y'_m)$ is $\delta = |y_m - y'_m|$.

The distortion area is a criterion for us to decide significant points. The regions of A and B between the original and predicted lines in Fig. 2 form the distorted area. This area can be calculated by mathematical integration. Consider Fig. 2. The distortion area ψ bounded by $g(x)$ and $f(x)$ is

$$\psi = \int_a^b (f(x) - g(x))\,dx + \int_b^c (g(x) - f(x))\,dx. \tag{2}$$

Before integration, we first have to know the mathematic equations of $f(x)$ and $g(x)$. $g(x)$ is a linear function that is easy to obtain from starting and ending points, i.e., $(a,\ g(a))$ and $(c,\ g(c))$. However, $f(x)$ could have different patterns. If the unprocessed data are simple, it is easy to get the equation. Nevertheless, if it is as complicated as chaotic distribution, it will become very hard to get the function.

In the discrete case, as illustrated in Fig. 3, however, the distortion area between a and c is defined as

$$\psi = \sum_{i=0}^{(c-a)/\Delta t} |f(a + i\Delta t) - g(a + i\Delta t)|. \tag{3}$$

Δt is the sampling interval to convert continuous signals into discrete forms. As we know, smaller Δt achieves precise approximated area to the continuous form. However, it has more computational burden. In our case, since the data that we process have been converted into digital forms, (3) is adopted here.

Consider Fig. 1 again. Let ψ be the distorted area generated by p and $c(i)$, $c(i+1)$. If $\psi > \varepsilon$, which is a constant specified by the user, then p is selected as a significant sample, and the linear segment that connects $c(i)$ and $c(i+1)$ is broken into two linear segments that connect $c(i)$ and p, p and $c(i+1)$, respectively. Recursively, the same tests are carried out on each of these two linear segments. It is clear that the number of recursive iterations depends on the value of ε. A smaller value of ε causes the number of recursive iterations needed for the distorted area computations to increase.

The significant samples selected here are used to represent the original signal, and the other samples are discarded. On the decoder side, a linear segment to connect two consecutive significant samples is used to reconstruct the decoded signal sequences. All points between $c(i)$ and $c(i+1)$ can be yielded from (1).

III. Discrete Cosine Transform to Medical Image

DCT has been successfully used in many coding systems due to its energy compactness in the frequency domain. That is, the original signals can be represented within a relatively narrow range of frequencies. The description and application of DCT can be found in [7] and [8]. Fig. 4 illustrates the coefficient distribution after 8 × 8 DCT transformation to a subpart of a medical angiogram image. All the coefficients have been rounded to the nearest integers. It is quite obvious that most of the energies are concentrated into the regions of low frequency, discarding the higher frequency components that do not give rise to salient perceptual distortion after inverse DCT operation. Such an employment of DCT in medical image compression schemes can be found in [9]–[13]. However, due to its heavy computational burden in the implementation of full-frame DCT, the detailed characteristics of image content will be sacrificed after quantization. As a result, in many of the DCT compression schemes, the original image is divided into nonoverlapped subimages, e.g., 8 × 8 or 16 × 16 submatrices. Small coding size has the advantages of simple computational complexity and very moderate memory requirements, but the compression ratio is normally low. In general applications, consider the compromise between computational burden and the characteristics preserving ability; 8 × 8 and 16 × 16 are the widest used processing sizes on current DCT-based image-compression products or research. As we know, pure regions occupy most of the image content in nearly all the medical images. Large coding size can attain higher compression ratio for the consequent coefficients of small magnitude. Because we do not want to increase computational burdens on the calculation of distortion area and DCT implementation, we adopt a large processing size. Finally,

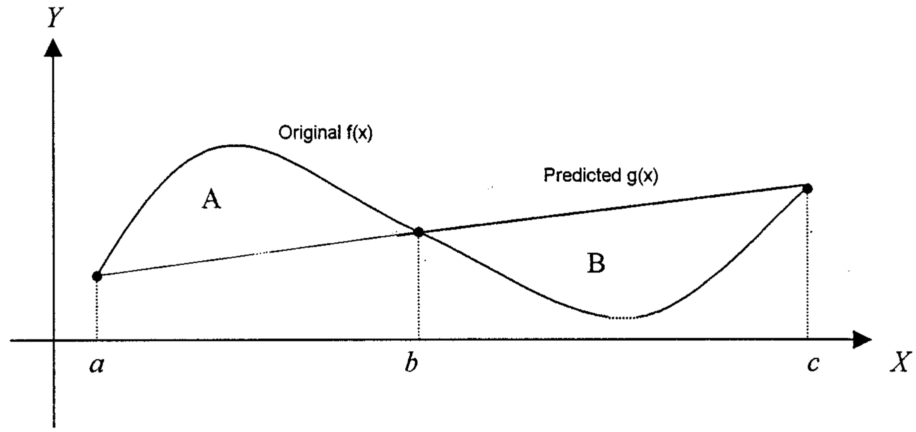

Fig. 2. Area calculation for continuous form.

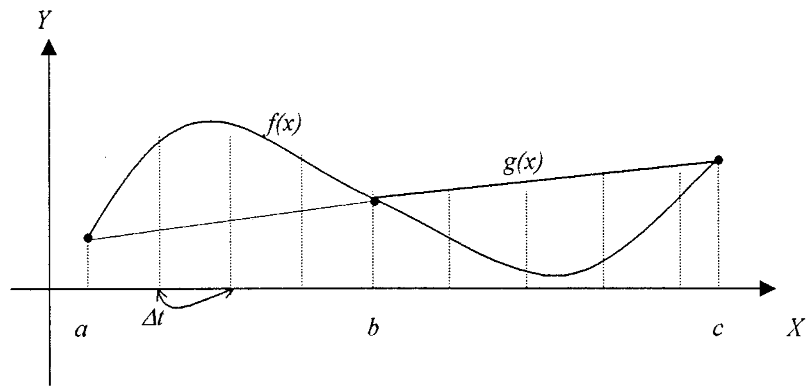

Fig. 3. Distortion area for discrete form.

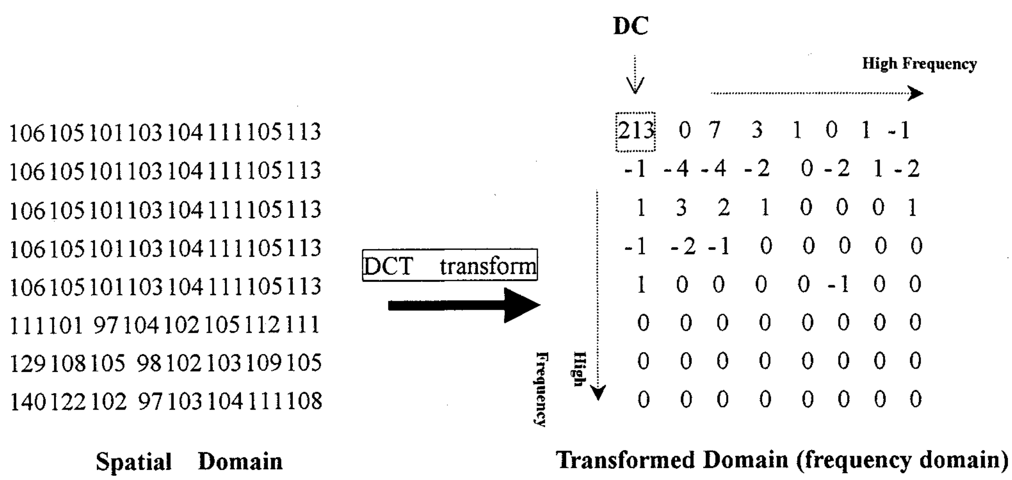

Fig. 4. An example of DCT transformation.

we get the tradeoff by adopting a 16 × 16 processing size between computational complexity and compression ratio from empirical methods.

IV. Incorporating Adaptive Sampling Algorithm Into Frequency Domain

Incorporating the proposed sampling algorithm to the spatial domain does not work as well as the frequency domain after DCT transformation. That is because the complexity of the signal has been decreased after DCT. Such a phenomenon is particularly evident for most medical images because most of the content is pure background. In addition, the contrast of the major part is not serious. After the operation of DCT, the benefit of fulfilling com-

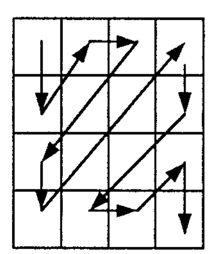

Fig. 5. Zigzag scanning patterns.

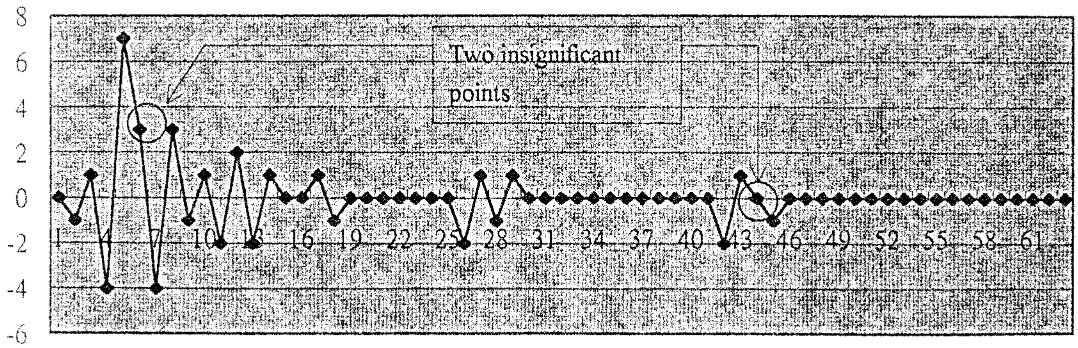

Fig. 6. An example of zigzag scan converting the data in Fig. 4 (DC is excluded).

pression is obvious. Therefore, the incorporation of the sampling algorithm into medical image compression works well.

Our algorithm achieves the goal of compression by sampling one-dimensional (1-D) signals. The spectrum for still images, however, is two-dimensional signals (2-D). Consequently, a tool to transform two-dimensional signals into one dimension is needed. There are many schemes to convert 2-D into 1-D, including row-major scan, column-major scan, peano-scan, and zigzag scan. Almost all the DCT coding schemes adopt zigzag scan to accomplish the goal of conversion, and we use it here. The benefit of zigzag is its property of compacting energy to low frequency regions after discrete cosine transformation. The arrangement sorts the coefficients from low to high frequency. Therefore, the employment of our proposed method will evidently work well. Fig. 5 shows the zigzag scanning order for 4×4 block. Fig. 6 shows the relation between the original 2-D coefficient distribution (Fig. 4) to its correspondent 1-D distribution after zigzag scanning. Then our adaptive sampling algorithm will be employed for the 1-D coefficients that are generated by zigzag scanning in the previous procedure. Notice that the DC term is not included in our sampling algorithm. The DC term is always considered an important sample, and it is transmitted in its original form. What follows are the Huffman codes for the linear segments that connect the selected significant samples. Referring to Fig. 1 again, the linear segment with start sample $c(i)$ and end sample $c(i+1)$ can be described by $\{dx, dy\}$, which is encoded by Huffman coding, and is transmitted by the encoder. The training sets for generating Huffman codes for each symbol $\{dx, dy\}$ are from 20 different medical images. The detailed description of Huffman coding procedure can be found in [1] and [2].

A detailed description of the incorporation of the adaptive sampling algorithm into the 1-D sequence is given as follows:

Input: 1-D sequence $z(k)$; k: $0 \sim n-1$
Output: Significant points
Step 1: Initial point $= (0, z(0))$; $i = 0$; $j = 2$
  Record point $(0, z(0))$ as a significant point
Step 2: Calculate distorted area

$$\{\Psi = \Omega(i, z(i), j, z(j))\}$$

/* Ω is a function to calculate the distorted area between two points: start $(i, z(i))$ and end $(j, z(j))$;
*/
Step 3: If $[(\Psi < \Upsilon)$ and $j < (n-1)]$ /* point $(j - 1, z(j-1))$ is not significant; Υ is a threshold */
{ $j = j+1$; Go to Step 2; }

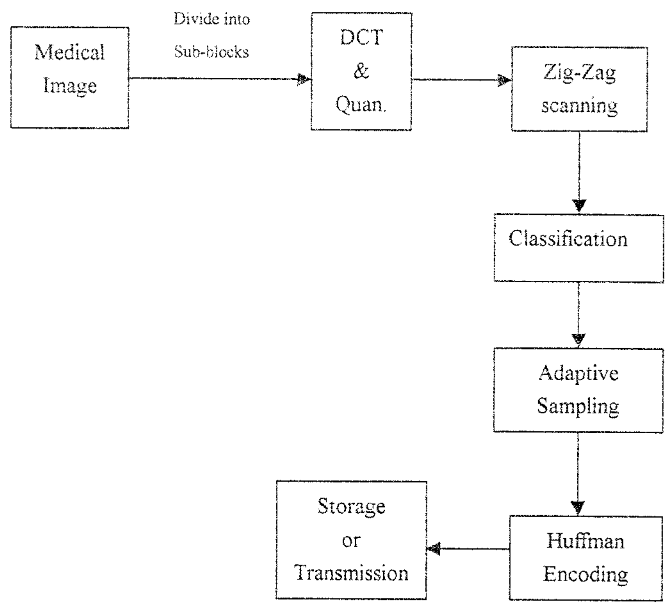

Fig. 7. Encoder system configuration.

Else If $(j == (n-1))$ /* End of sequence */
{ Save EOS;
Exit ( ); }
Else /* point $(j-1, z(j-1))$ is significant */
{ Record point $(j-1, z(j-1))$ as a significant point;
Initial point $= (j-1, z(j-1))$;
$i = j-1$; $j = j+1$;
Go to Step2; }

The algorithm of function $\Omega(\,)$ is depicted as follows:
Input: data sequence $z(i)$; start point $(a, z(a))$; end point $(b, z(b))$;
Output: distorted area Ψ
Step 1: Create a linear equation between start point $(a, z(a))$ and end point $(b, z(b))$;
The equation is denoted as $\xi(k)$, where k ranges from a to b; Goto Step 2;
Step 2: Calculate distorted area as follows

$$\psi = \sum_{i=a+1}^{b-1} |z(i) - \xi(i)| \tag{4}$$

Return Ψ; Exit ( );

Refer to Fig. 6 again. The two points drawn circularly are insignificant points. There are many insignificant points in Fig. 6. Two points are simply picked out randomly.

Before the adaptive sampling operation is used to transform coefficients, a classification procedure is needed to increase the benefits of compression. The importance of every subblock inside the medical image is not equivalent. Therefore, the allowable sampling distortion area for different regions can be adopted adaptively as well to achieve a higher compression ratio. For example, the sampling distortion for those regions located on the background can be set higher but is not harmful to the primary image content. Most of the primary objects are located on the central regions of the medical images, and dark gray occupies all the background. Here, the criterion to determine the complexity of unprocessed block data is based on the variety of the one-dimensional data sequences $z(i)$, which can be obtained as follows:

$$\mu = \frac{1}{n}\sum_{i=0}^{n-1} z(i) \tag{5}$$

$$\nu = \frac{1}{n}\sqrt{\sum_{i=0}^{n-1}(z(i)-u)^2} \tag{6}$$

where μ denotes the mean value of $z(i)$ and ν can be expressed as the complexity of $z(i)$. If ν is greater than the threshold φ, then sequence $z(i)$ is regarded as complicated class. Otherwise, it will be assigned to pure class. By adjusting the threshold, we can get the suitable classification for every data sequence. A smaller ν value allows bigger distorted area ψ while complicated sequences adopt restrained ψ. Since the pure region occupies most of the image content, such a classification raises the compression ratio greatly. However, it preserves significant visual content without doing harm to diagnosis. As to the consequent classification information, it needs to be transmitted or stored completely to the decoder side. Then, original signal sequences $z(i)$ can be reconstructed precisely. The overhead of classification is given as follows:

$$o = \frac{\log_2(\text{numbers of classification})}{\text{size of } z(i)} \text{ bits/pixel.} \tag{7}$$

The overhead of classification in our case is little because we only have two kinds of classification and the size of $z(i)$ is 16 $\times$ 16 (256). It only costs 1/256 bits/pixel here. The configuration of our proposed method for the encoder is illustrated in Fig. 7.

V. Simulation Results

The performance is evaluated by the following two criteria: 1) subjective quality of decoded image, which is verified by two doctors from the Radiation Department to judge if the result is acceptable for practical application, and 2) peak signal-to-noise ratio (PSNR), expressed in decibels (dB). PSNR is a mathematical evaluation expression that can be calculated as

$$\text{PSNR} = 10\log_{10}\frac{255^2}{\frac{1}{n^2}\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}(x_{i,j}-x'_{i,j})^2}. \tag{8}$$

In the above formula, x and x' denote original and decoded pixels, respectively. $n \times n$ is the image size. PSNR has been accepted as a widely used quality measurement in the field of image compression. In addition, subjective judgment from the doctors is also employed to evaluate decoded image quality to avoid poor decoded quality that may cause misdiagnosis. Two doctors are invited to help in the judgment.

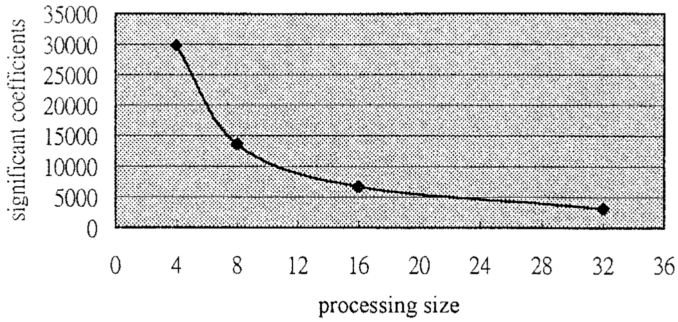

Fig. 8. Curve of processing size and time.

Refer to Figs. 8–10, which illustrate the relationship among processing block sizes, implementation time, preserved significant coefficients, and reconstruction quality. The processing sizes are 4×4, 8×8, 16×16, and 32×32, respectively, and the simulation process is manipulated on an Ultra-SPARC 2 workstation whose CPU is 168 MHz. The threshold Υ of distorted areas in all the various processing sizes is 4.0. The test image is a CT image. In this experiment, there is no classification process. All the numerical data are listed in Table I. Fig. 7 shows the time to run the adaptive sampling algorithm, which does not include the operation of DCT manipulation. If the size is larger than 16 $\times$ 16, the implementation time becomes very long. Considering the case of 4 $\times$ 4, the time to implement adaptive sampling is short and the reconstructed quality is the best. However, it preserves too many coefficients to achieve a low compression ratio. A size of 32 $\times$ 32 is capable of preserving minimum significant coefficients, but its implementation time is intolerable. After considering the factors of time and quality, the DCT processing size is selected to be 16 $\times$ 16 in the following experiments.

We first demonstrate the effectiveness of the employment of the adaptive sampling algorithm to the DCT spectral domain. Test data are shown in Fig. 11. Employing adaptive sampling to the spatial domain can achieve a bit rate of 0.33 bpp with a PSNR value of 37.85 dB. The bit rate achieved from spectral domain is 0.18 bpp with a PSNR value of 42.82 dB. The processing size is 16 $\times$ 16.

To demonstrate the effectiveness of our proposed technique, it is carried out for several medical images, including sonogram, X-ray, CT, and angiogram. The size for all of these is 512 $\times$ 512 with 8-bit monochromes gray images. The threshold value of φ to classify if the sequence is a complicated class is 2.5. We obtained this value empirically. The two allowed distorted area threshold values of Υ for pure and complicated sequences are 10.0 and 4.0, respectively. The threshold values are roughly selected after considering the bit rate and reconstructed quality from empirical experiments. Modifying these thresholds affects the decoded quality and bit rate. The optimal threshold sets can be attained for every kind of medical image if repetitive experiments are conducted. However, the threshold values are the same as we set above for all kinds of medical images in our experiments.

All of the test medical images and decoded images are shown in Figs. 11–18. All of the test results are presented in Table II.

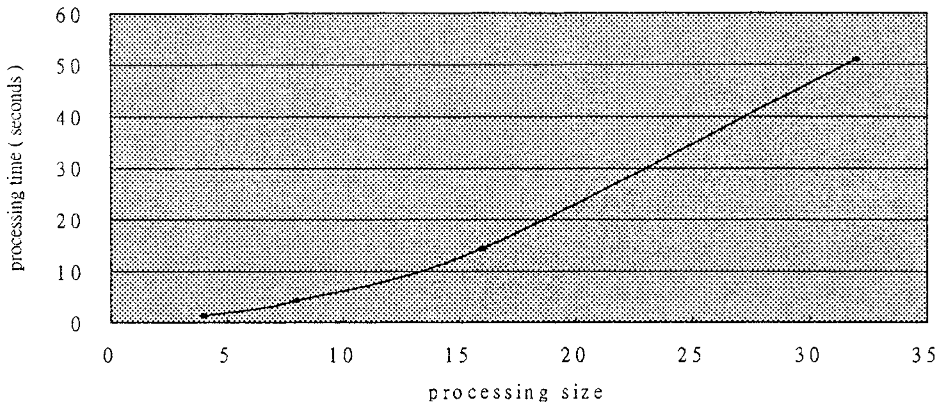

Fig. 9. Curve of significant coefficients and processing time.

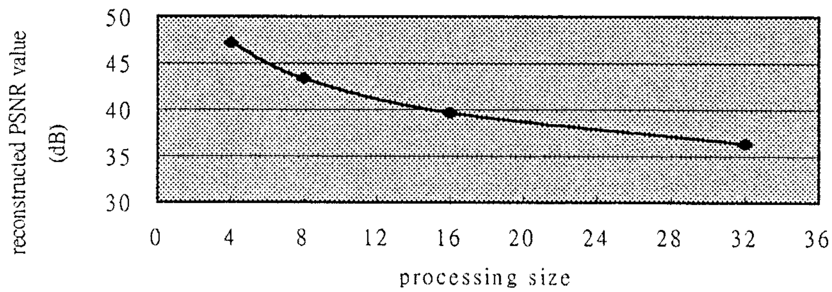

Fig. 10. Curve of processing size and reconstructed quality.

TABLE I
PROCESSING SIZE VERSUS TIME, NUMBER OF SIGNIFICANT COEFFICIENTS, AND RECONSTRUCTED QUALITY

Processing size	Time (second)	Number of significant coefficient	Reconstructed quality expressed by PSNR (dB)
4	1.33	29820	47.18
8	4.28	13626	43.35
16	14.43	6698	39.68
32	51.08	3198	36.36

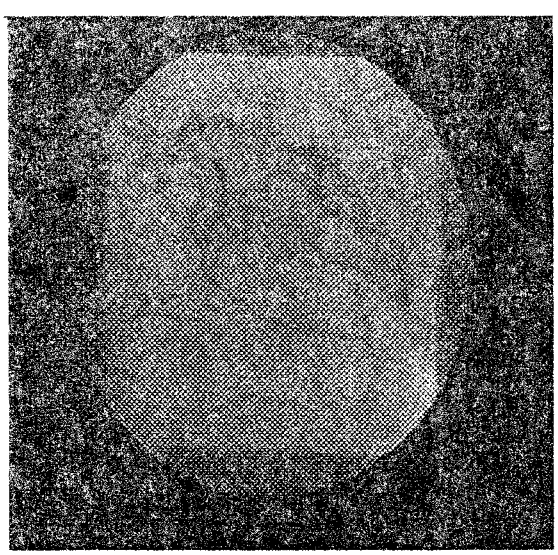

Fig. 11. Original angiogram image.

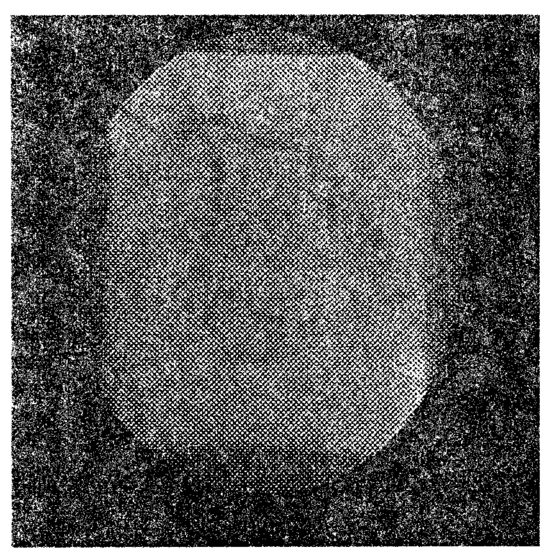

Fig. 12. Decoded angiogram image.

Fig. 13. Original X-ray image.

Fig. 14. Decoded X-ray image.

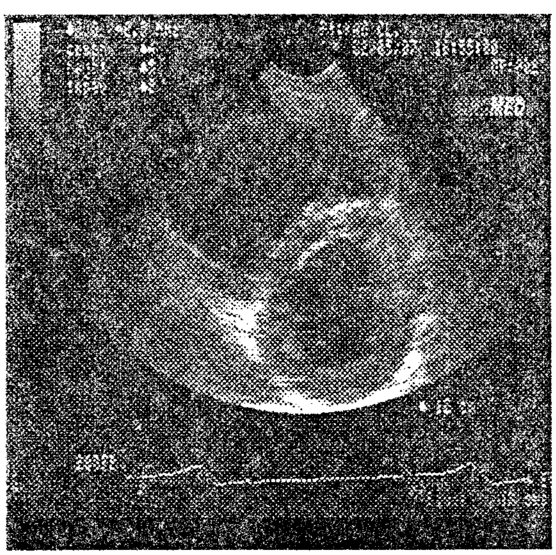

Fig. 15. Original sonogram image.

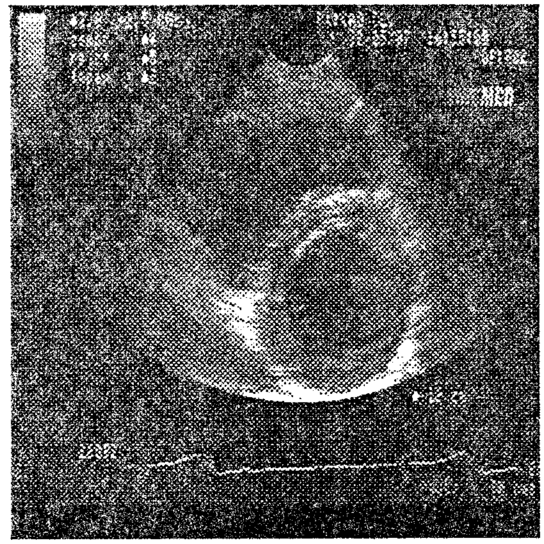

Fig. 16. Decoded sonogram image.

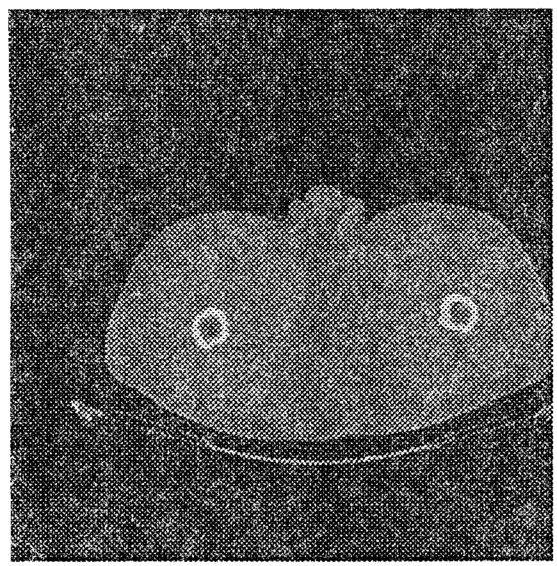

Fig. 17. Original CT bone image.

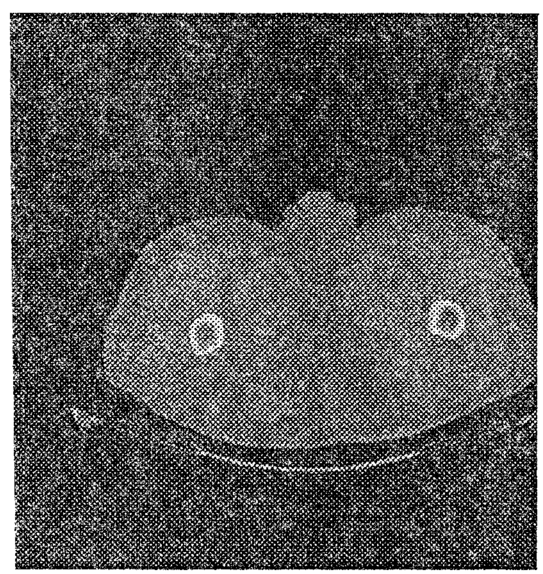

Fig. 18. Decoded CT bone image.

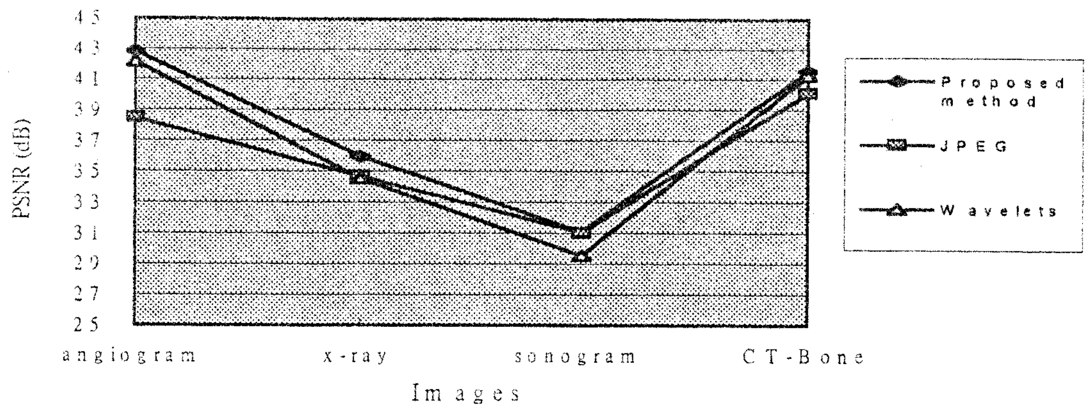

Fig. 19. Comparison curves of proposed method, JPEG, and wavelet compressions.

TABLE II
PERFORMANCE RESULTS OF PROPOSED ALGORITHM AND OTHER STRATEGIES

Medical Images	Bit Rate (bpp) : (Compression Ratio)	PSNR (dB)		
		Proposed method	JPEG	wavelets
Angiogram	0.18 : (44)	42.82	38.49	42.12
X-ray	0.28 : (28)	35.95	34.67	34.51
Sonogram	0.42 : (19)	31.06	31.02	29.55
CT-Bone	0.25 : (32)	41.54	40.11	41.27

To demonstrate the performance of our strategy, the same test images are also coded by a JPEG compressor, the widest used compression tool today for comparison. Owing to the graceful characteristics of intensity variety and dull background content that exist in most of the medical images, the adaptive sampling algorithm achieves good results, especially in X-ray, CT, and angiogram images. The performance of the proposed method is much better than JPEG under the same bit rate (compression ratio) in the above kinds of images. In the case of the sonogram image, there are texts and waveform within the image. In addition, the main object has complicated content. It is difficult to get high fidelity at high compression ratio, no matter what methods are used. Our method achieves a slightly higher PSNR value than JPEG does. Considering Fig. 16, the texts and waveform are still recognizable after decoding. Therefore, the important information for patients will not disappear after processing. In addition, we use a wavelet provided by Matlab software to compress the same images for comparison. Their experimental results are listed in Table II. The results yielded by wavelet are better than JPEG in angiogram and CT bone images only. Compared to our proposed method, the performance in terms of reconstructed quality is worse at the same bit rate. Fig. 19 is an illustration of these comparisons. We find that our proposed strategy achieves lower bit rates with higher PSNR values for all test images, which demonstrates its performance. The mathematical evaluation of the proposed method outperforms JPEG and wavelets. However, if we set the threshold of the distorted area too large to achieve high compression, the blocky effect will rise. Refer to Fig. 14, which is a decoded X-ray image. Visible vertical stripes are shown at the upper left. The quality is not acceptable for practical application after the verification of the two doctors, even after some deblocking techniques are employed. Deblocking will also sacrifice the detailed characteristic of the major component in the medical image. A topic of further investigation is to find a deblocking technique that does not smooth out the important information in the medical image. Two radiologists judge the acceptance of a decoded medical image from a professional viewpoint and adapt the sophisticated statistical methods in [14] for consideration. Notice that if we modify the threshold value set to get the compression ratio below 20, the decoded X-ray image is acceptable for practical applications. The decoded quality for an angiogram image below the compression ratio of 45 is acceptable. For the CT bone image, it is acceptable for the compression ratio to be 35. As to the sonogram image, its content is very complicated; the compression ratio below 15 is acceptable.

VI. CONCLUSION

In this paper, we employ the adaptive sampling algorithm to medical image data compression. The proposed algorithm has been adapted to the compression of ECG signals successfully [15]. By employing the adaptive sampling algorithm to medical image compression, its performance is still as good as the employment of ECG compression. Due to the merit of simple computational burden in terms of the calculation of distorted area, which needs addition operation only, the proposed method does not increase heavy computational complexity in achieving a higher compression ratio compared to other published strategies in [10]–[13]. For the case of a 2-D signal as image data, we use zigzag scanning to convert spectral coefficients into 1-D sequences. Adaptive sampling is used to record those significant coefficients. Simulation results demonstrate that our proposed algorithm preserves the essential information while achieving the data minimum for the purpose of transmission or storage. Therefore, it is an efficient information processing technique in the field of medical signal processing. In fact, every kind of medical image has its own characteristics. If we modify the threshold sets for one kind of medical image specifically, the result will be better than listed in the previous section.

REFERENCES

[1] M. Nelson and J. L. Gailly, *The Data Compression Book*, 2nd ed. New York: M & T Books, 1996.

[2] A. K. Jain, "Image data compression: A review," *Proc. IEEE*, vol. 69, pp. 349–389, 1981.

[3] R. C. Gonzales and P. Wintz, *Digital Image Processing*, 3rd ed. Reading, MA: Addison-Wesley, 1992.

[4] S. Wong, L. Zaremba, D. Gooden, and H. K. Huang, "Radiologic image compression—A review," *Proc. IEEE*, vol. 83, pp. 194–219, Feb. 1995.

[5] V. Fillimon, "An irregular sampling algorithm adapted to the local frequency content of signals and the corresponding on-line reconstruction algorithm," in *Proc. IEEE ICASSP*, vol. 3, 1998, pp. 1837–1840.

[6] S. C. Tai, "Adaptive sampling algorithm for one-dimensional digital signals," R.O.C. Patent 835 011, Jan. 1997.

[7] W. H. Chen and C. H. Smith, "Adaptive coding of monochrome and color images," *IEEE Trans. Commun.*, vol. COM-25, pp. 1285–1292, 1977.

[8] K. R. Rao, "Theory and the applications of the discrete cosine transform," in *Jordan Int. Electrical Electronic Eng. Conf.*, Amman, Jordan, Apr.–May 1985, pp. 259–264.

[9] Y. G. Wu and S. C. Tai, "Medical image compression by 2×2 discrete cosine transform," *Opt. Eng.*, vol. 37, no. 5, pp. 1539–1546, May 1998.

[10] D. Ho, D. Feng, and K. Chen, "Dynamic image data compression in spatial and temporal domains: Theory and algorithm," *IEEE Trans. Inform. Tech. Biomed.*, vol. 1, pp. 219–228, Dec. 1997.

[11] H. Lee, Y. Kim, A. H. Rowberg, and E. A. Riskin, "Statistical distributions of DCT coefficients and their applications to an interframe compression algorithm for 3-D medical images," *IEEE Trans. Med. Imag.*, vol. 12, pp. 478–485, Sept. 1993.

[12] A. Ramaswamy and W. B. Mikhael, "A mixed transform approach for efficient compression of medical images," *IEEE Trans. Med. Imag.*, vol. 12, pp. 803–811, 1996.

[13] S. C. Tai, Y. G. Wu, and C. W. Lin, "An adaptive 3-D discrete cosine transform coder for medical image compression," *IEEE Trans. Inform. Tech. Biomed.*, vol. 4, pp. 259–263, 2000.

[14] O. Baudin, A. Baskurt, T. Moll, R. Prost, D. Revel, F. Ottes, M. Khamadja, and M. Amiel, "ROC assessment of compressed wrist radiographs," *Eurpo. J. Radiology*, vol. 22, pp. 228–231, 1996.

[15] W. L. Lin, "Design and implementation of a VLSI real time ECG adaptive sampling chip," master's thesis, Inst. Elect. Eng., Nat. Cheng Kung Univ., Tainan, Taiwan, R.O.C., 1998.

Yung-Gi Wu received the B.S. degree in information and computer engineering from Chung Yuan Christian University, Chung-Li, Taiwan, R.O.C., in 1992 and the M.S. and Ph.D. degrees in electrical engineering from National Cheng Kung University, Tainan, Taiwan, in 1994 and 2000, respectively.

From 1994 to 1996, he was an Officer in the army. He is currently an Assistant Professor in the Department of Computer Science and Information Engineering and Institute of Applied Information, Leader University, Tainan. His research interests include biomedical signal processing, image processing, and multimedia database systems.