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Computerized Medical Imaging and Graphics 31 (2007) 1–8
Computerized Medical Imaging and Graphics
www.elsevier.com/locate/compmedimag

Wavelet-based medical image compression with adaptive prediction

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Received 4 November 2005; received in revised form 17 August 2006; accepted 31 August 2006

Abstract

A lossless wavelet-based image compression method with adaptive prediction is proposed. Firstly, we analyze the correlations between wavelet coefficients to identify a proper wavelet basis function, then predictor variables are statistically test to determine which relative wavelet coefficients should be included in the prediction model. At last, prediction differences are encoded by an adaptive arithmetic encoder. Instead of relying on a fixed number of predictors on fixed locations, we proposed the adaptive prediction approach to overcome the *multicollinearity* problem. The proposed innovative approach integrating correlation analysis for selecting wavelet basis function with predictor variable selection is fully achieving high accuracy of prediction. Experimental results show that the proposed approach indeed achieves a higher compression rate on CT, MRI and ultrasound images comparing with several state-of-the-art methods.

Keywords: Image compression; Medical image; Selection of predictor variables; Adaptive arithmetic coding; Multicollinearity problem

1. Introduction

Medical images are a special category of images in their characteristics and purposes. Medical images are generally acquired from special equipments, such as computed tomography (CT), magnetic resonance (MRI), ultrasound (US), X-ray diffraction, electrocardiogram (ECG), and positron emission tomography (PET). In practice, the compression of medical images must be lossless because a minor loss may result in a serious consequence. We here accordingly focus on the development of an adaptive prediction scheme for lossless medical image compression.

One of the key techniques for efficient compression is prediction. The function of a prediction is to infer the current data by means of the previously known data. The predicted value should approximate the original value; in other words, the differences between the original data and the predicted values are expectedly minimal. In general, the compression efficiency is highly related to the accuracy of the prediction scheme [1]; thus a high accuracy prediction scheme is pursued. Many advanced image compression techniques have been developed in response to the increasing demands for medical images. JPEG2000 [2–4] combines embedded block coding with optimized truncation (EBCOT) technique with lifting integer wavelet transform to offer plenty of advanced features. It is able to provide a high performance lossless compression that is superior to JPEG standard at low bit rate. Wu and Memon [5,6] proposed the context-based adaptive lossless image codec (CALIC) approach utilizing *enclosing* (360°) *modeling contexts* to obtain the distribution of the encoded symbols and the prediction scheme. Moreover, an interband version of CALIC [7] which incorporates interband prediction technique into the original CALIC was proposed for multispectral and remotely sensed images. Przelaskowski [8] proposed the scanning statistical modeling (SSM) method providing a lot of experimental evidences in a series of processes: raster scan, 5/11 filter, and quincunx decomposition, for medical image compression. For lower-quality *ultrasound* images, SSM can achieve a high compression rate. Buccigrossi and Simoncelli [9] proposed the lossy embedded predictive wavelet image coder (EPWIC) adopting conditional probabilities calculated from their proposed statistical model for prediction. Although the experimental results show that the conditional probability model appears to be incompatible with CT images, its statistical analysis is still helpful understanding image properties to enhance the compression capability.

To achieve a higher compression rate for lossless-compressed medical images, we propose a wavelet-based compression scheme incorporated with an adaptive prediction (WCAP). At first, we initiate a correlation analysis of wavelet coefficients to identify a proper basis function for wavelet decomposition,

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doi:10.1016/j.compmedimag.2006.08.003

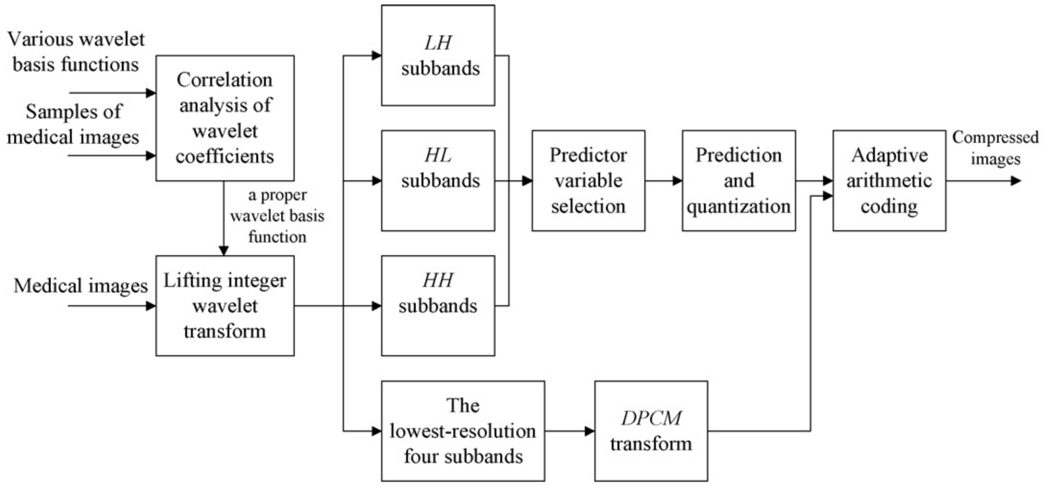

Fig. 1. The block diagram of the proposed WCAP scheme.

where wavelet coefficients are regarded as the predictor (independent) and response (dependent) variables of a prediction equation. Then we launch the selection of predictor variables based on a statistic test to determine which predictor variables should be included in the prediction equation. The generated prediction equations are then applied to predict most wavelet coefficients except the lowest-resolution coefficients. Finally, an *adaptive arithmetic encoder* is adopted to encode the differences between the original and corresponding predicted coefficients.

The proposed WCAP method consists of five stages: correlation analysis of wavelet coefficients, lifting integer wavelet transform, predictor variable selection, prediction and quantization, and adaptive arithmetic coding, as shown in Fig. 1 and briefly described as follows:

i. Analyze the correlations between wavelet coefficients to identify a proper wavelet basis function and the higher-correlation coefficients.
ii. Decompose a medical image using a lifting integer wavelet transform with the identified basis function.
iii. Construct adequate prediction equations to describe the relationship of wavelet coefficients in LH, HL, and HH subbands, respectively.
iv. Apply the prediction equations to compute the differences between the original and corresponding predicted values.
v. Use adaptive arithmetic coding [10,11] to code the differences.

The remaining sections of this paper are organized as follows. Section 2 describes the correlation analysis of wavelet coefficients for identifying a proper wavelet basis function and higher-correlation coefficients. The selection of predictor variables and prediction are presented in Section 3. Experiments are reported in Section 4. Conclusions are given in Section 5.

2. The correlation analysis of wavelet coefficients

The wavelet transform records the differences between neighboring signals in several different scales [12]. The wavelet coefficients have the locality, multiresolution, compression, clustering, and persistence properties [13] and therefore are suitable for signal/image analysis. Lifting integer wavelet decomposition has further properties for signal/image analysis: (i) it transforms integers to integers and allows perfect reconstruction of the original data; (ii) it is capable of accomplishing fast in-place computation. The persistence and clustering properties mean that a large/small wavelet coefficient tends to have large/small values in its neighbors and across scales. Hence, wavelet transform simultaneously take advantages of the interscale and intrascale dependencies among wavelet coefficients.

To select a proper wavelet basis function, the high intrascale and interscale dependencies are pursued. We take wavelet coefficients as random variables and use correlation of coefficients to evaluate the dependencies. The correlation of wavelet coefficients x and y is given as

$$r_{xy} = \frac{\mathrm{SS}_{xy}}{\sqrt{\mathrm{SS}_{xx}}\sqrt{\mathrm{SS}_{yy}}}, \quad (1)$$

where SS_{ij} is the covariance of coefficients i and j, and SS_{ii} is the variance of coefficient i,

$$\mathrm{SS}_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{n},$$

$$\mathrm{SS}_{xx} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n},$$

and

$$\mathrm{SS}_{yy} = \frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n}.$$

We consider several wavelet basis functions. For each basis function, we examine all coefficients in the *parent*, *aunt*, and *current* subbands of every processing coefficient to find the higher-correlation coefficients as illustrated in Fig. 2. The higher-correlation coefficients are firstly used to determine which wavelet basis function is the best for the prediction and secondly used in the following stage to select the final predictor variables.

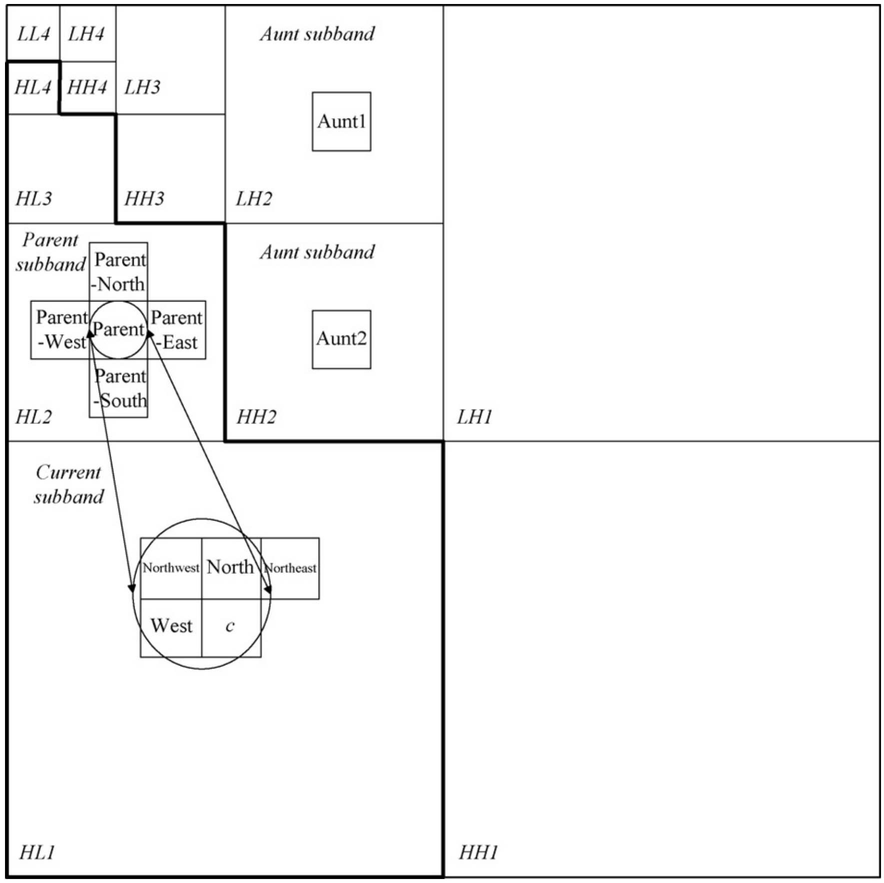

Fig. 2. The relation map for computing correlation between coefficient c and the coefficients in the parent, aunt, and current subbands.

3. The selection of predictor variables

Prediction [9,14] estimates response (dependent) variable y from the values of predictor (independent) variables x_i, $i \geq 1$. The linear prediction model containing k independent variables can be expressed as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon, \tag{2}$$

where y is the response variable, x_1, x_2, ..., x_k the predictor variables, β_0, β_1, ..., β_k the model parameters, and ε is the random error.

Inadequate model may result in seriously biased estimates. To avoid gaining uncertain results, many prediction methods use predictor variables as many as possible even if the effect of the predictor variables is insignificant. Such an over-specified model with extraneous predictor variables may suffer from the *multi-collinearity* problem [15,16]. On the other hand, to minimize the size of storage, the number of predictor variables should be duly reduced within an acceptable error.

In most previous studies [5,6,17,18], the prediction was generally conducted with a fixed number of predictor variables at fixed locations. Actually, every kind of medical images not only has its own statistical distribution but also demonstrates different properties in different wavelet subbands. To achieve more accurate prediction, the number of predictor variables must be adaptively adjusted based on the image's properties.

In the proposed WCAP method, an image is first decomposed into wavelet coefficients using the selected basis function. The coefficients in LH, HL, and HH subbands describe strengths of the horizontal, vertical, and oblique edges of the image, respectively. Furthermore, wavelet transform have strong interscale persistence property between parent–child wavelet coefficients in a wavelet tree and weaker intrascale clustering property. Thus, traditional approaches [9,17,18] applying a single prediction equation are not adequate for accurate prediction in wavelet domain. We here use different prediction equations for different subbands to achieve a more accurate prediction.

Let $S_{\text{ind}} = \{x_1, x_2, \ldots, x_k\}$ be the set of the higher-correlation coefficients found in the previous stage. We want to find a subset $S_{\text{o}} = \{x'_1, x'_2, \ldots, x'_j\}$, where $j \leq k$, such that the subset is better to predict the response coefficients. Here *backward elimination procedure* [15] for data-driven variable selection was used to obtain the S_{o} subset. In the procedure, the partial F test statistic [15,16] is used to help selecting predictor variables. Initially, all higher-correlation coefficients are taken as predictor variables and considered in the prediction model. Each predictor x_i has a specific partial F test value, F_i^*, defined as

$$F_i^* = \frac{\text{MSR}(x_i \,|x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_k)}{\text{MSE}(x_1, x_2, \ldots, x_k)}, \tag{3}$$

where

$$\begin{aligned}\mathrm{MSR}(x_i\,|x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_k) \\ = \frac{\mathrm{SSR}(x_i\,|x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_k)}{1} \\ = \mathrm{SSR}(x_1, x_2, \ldots, x_{i-1}, x_i, x_{i+1}, \ldots, x_k) \\ -\mathrm{SSR}(x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_k),\end{aligned}$$

$$\begin{aligned}\mathrm{SSR}(x_1, x_2, \ldots, x_k) &= \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2 \\ &= \sum_{i=1}^{n}(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik} - \bar{y})^2,\end{aligned}$$

$$\begin{aligned}\mathrm{MSE}(x_1, x_2, \ldots, x_k) \\ = \frac{1}{n-(k+1)}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \\ = \frac{1}{n-(k+1)}\sum_{i=1}^{n}(y_i - \beta_0 - \beta_1 x_{i1} - \cdots - \beta_k x_{ik})^2,\end{aligned}$$

and n is the sample size of predicted coefficients.

The partial F test value, F_i^*, given the importance ratio of predictor variable x_i with respect to all other predictor variables in the prediction model. If the partial F test value of a predictor variable is less than the pre-defined threshold value, the predictor variable is redundant to the prediction model and should be removed. To avoid *multicollinearity* problem and minimize the number of parameters, the less important predictor variables are removed one after one. That is, we do not remove more than one predictor variable at one time. The steps for predictor variable selection are summarized as follows.

Step 1. Based on all predictor variables in the prediction model, we calculate a F^* value for every predictor variable.
Step 2. Find a predictor variable that has the minimum F^* value.
Step 3. If the minimum F^* value is less than the pre-defined threshold value, the predictor variable is removed from the prediction model and goes to Step 1; otherwise, the process is stopped.

After the model is defined, the prediction for each subband is estimated by minimizing the prediction error defined as

$$\begin{aligned}\sum_{i=1}^{n} e_i^2 &= \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \\ &= \sum_{i=1}^{n}(y_i - (\beta_0 + \beta_1 x'_{i1} + \beta_2 x'_{i2} + \cdots + \beta_j x'_{ij}))^2, \quad (4)\end{aligned}$$

where $\beta_0, \beta_1, \ldots, \beta_j$ are the parameters of the prediction equation, n is the sample size of predicted coefficients, e_i is the prediction error of coefficient i, and $\hat{y}_i$ is the predicted value of y_i.

The prediction is performed in an order from the coarse subband to the fine subband and from the left-up coefficient to the right-down coefficient in a subband. (The coefficients in the coarsest subbands are not predicted.) For example, coefficient c is predicted, then its right-hand coefficient is being predicted. After all coefficients in the ith level are predicted, the prediction for the $(i-1)th$ (finer) level is then launched.

After the prediction, all parameters β_i for all subbands are recorded and the prediction errors e_is will be encoded. To increase compression rate, the prediction errors e_is are transformed from real numbers into integers by the following truncation processes,

$$e'_i = \begin{cases} 0, & \text{if } y_i \geq \hat{y}_i \text{ and } y_i - \hat{y}_i < 1; \\ \lfloor y_i - \hat{y}_i \rfloor + 1, & \text{if } y_i - \hat{y}_i \geq 1; \\ \lceil y_i - \hat{y}_i \rceil - 1, & \text{if } y_i < \hat{y}_i, \end{cases} \quad (5)$$

where $\lfloor x \rfloor$ takes the maximum integer which is less than x and $\lceil x \rceil$ is the minimum integer which is greater than x. In the decoding, we can completely restore the wavelet coefficients y_is to match the lossless property. The same ceiling operators achieve the lossless restoration from the encoded integer errors e'_is and predicted values $\hat{y}_i$s which are calculated from the recorded parameters β_i,

$$y_i = \begin{cases} \lceil \hat{y}_i \rceil, & \text{if } e'_i = 0; \\ \lceil e'_i + \hat{y}_i - 1 \rceil, & \text{if } e'_i \geq 1; \\ \lfloor e'_i + \hat{y}_i + 1 \rfloor, & \text{if } e'_i \leq -1. \end{cases} \quad (6)$$

At last, all coefficients in the coarsest subbands LL_4, LH_4, HL_4, and HH_4 are directly processed by *DPCM transform* and *adaptive arithmetic coding*.

4. Experiments

The experiments on the correlation analysis of wavelet coefficients for choosing wavelet basis function, predictor variable selection, and lossless compression are reported. Fifteen medical images containing CT, MRI, and US images partially provided by *National Library of Medicine* were served as the test images as shown in Fig. 3. The image sizes of CT, MRI, and US images are 512×512, 256×256, and 640×480, respectively. All images have been re-quantized into 8 bits/pixel.

Every image was decomposed into four scales with 13 wavelet subbands. Seven wavelet basis functions were taken for correlation analysis of wavelet coefficients, which are (2,2), (2,4), (4,2), (4,4), (6,2), (2 + 2,2), and $S+P$ transforms [19–21]. With the 7 basis functions, 11 higher-correlation coefficients to the dependent coefficient c are selected and listed in Table 1, which are *Parent*, *Parent-East*, *Parent-West*, *Parent-South*, *Parent-North*, *North*, *Northeast*, *Northwest*, *West*, *Aunt1*, and *Aunt2* as shown in Fig. 2. The higher correlation means the correlation being greater than 0.001 or less than −0.001. In Table 1, different rows indicate the different coefficients described in Fig. 2; different columns represent the lifting integer wavelet transform with different basis functions. In the table, each wavelet basis function reveals a strong interscale persistence property in the parent–child coefficients and weaker intrascale clustering properties to other coefficients. Table 1 also

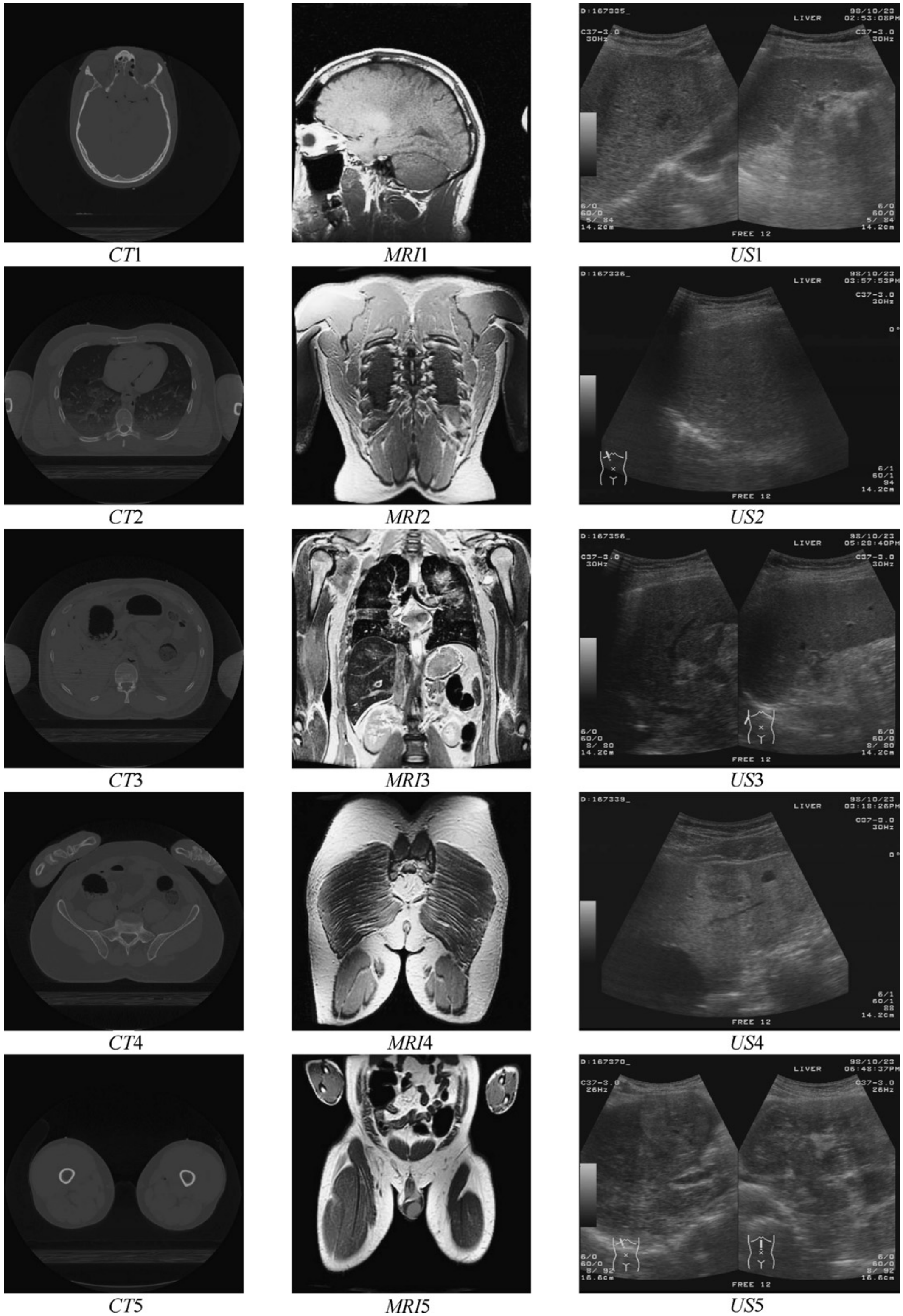

Fig. 3. Fifteen medical images used for evaluation. CT1–5 are CT images, MRI1–5 are MRI images, and US1–5 are US images.

shows that $S+P$ wavelet basis function has the largest sum of absolute correlation values of coefficients in all considered basis functions. In addition to the correlation analysis, the experiments on bit rate of medical image compression with different wavelet basis functions had also identified that $S+P$ wavelet basis function is significantly better for CT, MRI, and US image compression [21]. Thus, we adopt $S+P$ transform for the following processing.

Based on the backward elimination procedure, the prediction equations for coefficients in HL_i, LH_i, and HH_i subbands,

Table 1
The correlations of wavelet coefficients with different wavelet basis functions using the 15 medical images

Location	Basis function						
	(2,2)	(2,4)	(4,2)	(4,4)	(6,2)	(2 + 2,2)	$S+P$
Parent	−0.243	−0.246	−0.254	−0.258	−0.265	−0.270	0.291
Parent-East	0.004	0.003	0.005	0.008	0.005	0.007	0.006
Parent-West	0.006	0.004	0.011	0.003	0.012	0.012	0.027
Parent-South	0.010	0.004	0.011	−0.020	0.009	0.011	−0.035
Parent-North	0.011	0.011	0.016	0.009	0.016	0.017	−0.006
North	−0.020	−0.025	−0.038	−0.067	−0.044	−0.033	0.201
Northeast	−0.006	−0.001	−0.014	0.025	−0.015	−0.015	0.098
Northwest	0.004	0.006	−0.006	−0.004	−0.011	−0.004	0.025
West	0.110	0.118	0.157	0.186	0.168	0.141	0.213
Aunt1	0.001	0.002	−0.001	0.050	−0.001	−0.001	0.029
Aunt2	−0.003	−0.003	−0.003	−0.050	−0.002	−0.003	0.033

$i = 1, 2, 3$, were individually derived. For example, the prediction equations for HL, LH, and HH subband coefficients of CT1 image were individually derived as,

$$y_{\mathrm{HL}} = \beta_0 + \beta_1 x_{\mathrm{P}} + \beta_2 x_{\mathrm{PE}} + \beta_3 x_{\mathrm{PW}} + \beta_4 x_{\mathrm{PN}} + \beta_5 x_{\mathrm{N}} + \beta_6 x_{\mathrm{NE}} + \beta_7 x_{\mathrm{W}},$$

$$y_{\mathrm{LH}} = \beta_0 + \beta_1 x_{\mathrm{P}} + \beta_2 x_{\mathrm{PE}} + \beta_3 x_{\mathrm{PW}} + \beta_4 x_{\mathrm{PN}} + \beta_5 x_{\mathrm{N}} + \beta_6 x_{\mathrm{NE}} + \beta_7 x_{\mathrm{W}},$$

and

$$y_{\mathrm{HH}} = \beta_0 + \beta_1 x_{\mathrm{P}} + \beta_2 x_{\mathrm{PE}} + \beta_3 x_{\mathrm{PW}} + \beta_4 x_{\mathrm{PS}} + \beta_5 x_{\mathrm{PN}} + \beta_6 x_{\mathrm{N}} + \beta_7 x_{\mathrm{NE}} + \beta_8 x_{\mathrm{NW}} + \beta_9 x_{\mathrm{W}},$$

where subscripts P, PE, PW, PS, PN, N, NE, NW, and W mean the *Parent*, *Parent-East*, *Parent-West*, *Parent-South*, *Parent-North*, *North*, *Northeast*, *Northwest*, and *West* locations relative to the predicted coefficient as shown in Fig. 2.

The compression rates for the 15 medical images using the proposed WCAP method are listed in Table 2. The comparison of the proposed method with four famous lossless compression methods: SPIHT, JPEG2000, CALIC, and SSM, are also given in Table 2. Through the specific wavelet basis function and the adequate predictor variables, the proposed WCAP method almost achieves the highest compression rates for CT, MRI, and US images.

The five methods can be categorized into two classes: SPIHT and JPEG2000 are based on the wavelet zerotree concept while CALIC, SSM, and WCAP methods are based on the prediction principle. The prediction-based methods have better compression rate than the zerotree-based methods. The proposed WCAP method has individually improved 20.7, 12.6, 8.02, and 3.47% compression rates with respect to SPIHT, JPEG2000, CALIC, and SSM methods.

All five algorithms were executed on a general personal computer with an AMD 1.1 GHz processor. The average encoding/decoding time of five algorithms are given in Table 3. The zerotree-based methods (SPIHT and JPEG2000) have better performance than the prediction-based methods (CALIC, SSM, and WCAP). In the three prediction-based methods, the proposed WCAP method has the best execution performance.

The proposed WCAP method makes effective use of statistical measurement; thus, it can successfully serve as an advanced method for lossless compression on medical images; moreover,

Table 2
Compression rates of SPIHT, JPEG2000, CALIC, SSM, and the proposed WCAP approach in bits/pixel

Type	Method				
	SPIHT	JPEG2000	CALIC	SSM	WCAP
CT1	1.45	1.32	1.21	1.20	1.18
CT2	2.07	1.95	1.74	1.71	1.71
CT3	1.88	1.73	1.57	1.48	1.39
CT4	1.89	1.77	1.60	1.63	1.61
CT5	1.46	1.37	1.34	1.24	1.23
CT average	1.75	1.63	1.50	1.45	1.42
MRI1	2.51	2.44	2.42	2.37	2.38
MRI2	3.33	3.27	3.25	3.17	3.00
MRI3	3.61	3.53	3.50	3.45	3.31
MRI4	3.06	3.00	2.99	2.93	2.72
MRI5	2.40	2.33	2.31	2.27	2.08
MRI average	2.98	2.91	2.89	2.84	2.70
US1	2.93	2.38	2.22	2.04	1.95
US2	2.32	1.81	1.66	1.45	1.45
US3	2.79	2.29	2.11	1.92	1.87
US4	2.49	1.99	1.83	1.61	1.59
US5	2.78	2.22	2.03	1.79	1.78
US average	2.66	2.14	1.97	1.76	1.73
Average	2.46	2.23	2.12	2.02	1.95

Table 3
The average encoding/decoding time of SPIHT, JPEG2000, CALIC, SSM, and the proposed WCAP approach in second

Type	Method				
	SPIHT	JPEG2000	CALIC	SSM	WCAP
CT average	2.3/2.7	1.1/1.0	5.5/3.5	6.8/5.2	5.4/2.9
MRI average	1.8/1.8	0.8/0.8	3.2/2.4	4.8/3.3	3.4/2.1
US average	2.7/2.9	1.4/1.3	6.6/4.1	7.9/6.1	6.3/3.4
Average	2.3/2.4	1.1/1.1	5.1/3.4	6.5/4.9	5.0/2.8

There are two numbers in each field, the former number is the encoding time and the latter number is the decoding time.

progressive transmission technique can be integrated into the proposed WCAP method to further enhance the clinical diagnosis for telemedicine.

5. Conclusions

Lossless compression for medical images has been investigated by examining dependencies among wavelet coefficients to improve the compression rate. Instead of traditional approaches relying on a fixed number of predictors on fixed locations, we performed correlation analyses to select a wavelet basis function for lifting integer wavelet decomposition and launched predictor variable selection to obtain more accurate prediction models. Since each step can definitely obtain an appropriate treatment by statistical test or experimental proof, the compression results are expected to be satisfied. Using the correlation analysis to obtain a proper wavelet basis function and applying the adaptive predictor variable selection to overcome the *multicollinearity* problem with emphasizing the wavelet inter persistence and intra clustering properties are the main contributions of the proposed WCAP method.

CALIC [5,6] is a spatial-domain coder defining three kinds of contexts for prediction and uses three prediction equations for three successive steps of interleaved data prediction. Two major assumptions are that: (i) the shorter the distance between a predicted pixel and a predictor pixel in a context, the higher their correlation; (ii) using pixels with higher correlation as predictors can achieve more accurate results for the prediction. The wavelet coefficients have stronger interscale dependencies than the correlation between pixels. The proposed WCAP method used the higher-correlation coefficients for better prediction in the wavelet domain. We firstly identify the wavelet coefficients with higher correlation; these coefficients are then used to predict the specific coefficients. On the other hand, all pixels participating in CALIC prediction are treated as predictors with the same influence degree to the predicted variable no matter how far they are to (i.e., how much correlation it is with) the predicted variable. Here, we only took higher-correlation coefficients for the prediction to avoid the *multicollinearity* problem. Comparing with SSM method [8] using bit rate experiments to obtain wavelet basis function, the proposed WCAP method not only analyzed the correlation between wavelet coefficients with various wavelet basis functions but also referred to the bit rate experiments [21] to identify which basis function is most compatible with medical images. EPWIC [9] is a lossy coder in wavelet domain. EPWIC uses conditional relationship of a specific statistic model to achieve the coefficient prediction, but EPWIC only use one prediction equation and seems to be incompatible with CT images. The proposed WCAP method adaptively filters out higher-correlation predictors for prediction; moreover, we employ three prediction equations for different subbands. Thus, the proposed WCAP method can more accurately predict the coefficients.

Comparing to the CALIC, SSM, and EPWIC methods, the proposed WCAP method endeavors to promote the ability of prediction by exploring the advantages of accurate statistical analyses and data dependencies. We believe that a more effective compression scheme for medical images can be obtained if the related statistical analyses can be practiced prior to all processes of compression.

6. Summary

We propose a wavelet-based compression scheme with an adaptive prediction for medical images. At first, we analyze the correlations between wavelet coefficients to identify a proper wavelet basis function and the higher-correlation coefficients, where wavelet coefficients are regarded as the predictor (independent) and response (dependent) variables of a prediction equation. Then based on the higher-correlation coefficients, we launch the selection of predictor variables using a conditional statistical test to determine which relative predictor variables should be included in the prediction equation. The generated prediction equations are then applied to predict most wavelet coefficients except the lowest-resolution coefficients. Finally, an *adaptive arithmetic encoder* is adopted to encode the differences between the original and corresponding predicted coefficients.

In most previous studies, the prediction was generally conducted with a fixed number of predictor variables at fixed locations. Actually, every kind of medical images not only has its own statistical distribution but also demonstrates different properties in different wavelet subbands. To achieve a more accurate prediction, the number of predictor variables must be adaptively adjusted based on the image's properties. Thus, instead of relying on a fixed number of predictors on fixed locations and only using one prediction equation, we proposed the adaptive prediction approach to overcome the *multicollinearity* problem and employ three prediction equations for different wavelet subbands to achieve a more accurate prediction.

The proposed WCAP method and four famous lossless compression methods: SPIHT, JPEG2000, CALIC, and SSM, are experimentally compared. The experimental results showed that the proposed WCAP method almost achieves the highest compression rates for CT, MRI, and ultrasound images; moreover, WCAP has individually improved 20.7, 12.6, 8.02, and 3.47% compression rates with respect to SPIHT, JPEG2000, CALIC, and SSM methods in average. In all three prediction-based methods, the proposed WCAP method has the best execution performance.

The proposed WCAP method endeavors to promote the ability of prediction by exploring the advantages of accurate statistical analyses and data dependencies. Using the correlation analysis to obtain a proper wavelet basis function and applying the adaptive predictor variable selection to overcome the *multicollinearity* problem with emphasizing the wavelet interscale persistence and intrascale clustering properties are the main contributions of the proposed WCAP method.

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