In this work, a novel adaptive source-channel coding with feedback is proposed for the progressive transmission of medical images. The transmission starts from the region of interest (RoI), and the parity length in the channel code varies with respect to both the proximity of the image subblock to the RoI and the channel noise, which is iteratively estimated in the receiver. The overall transmitted data can be controlled by the user (clinician). In the case of medical data transmission, it is vital to keep the distortion level under control as in most of the cases certain clinically important regions have to be transmitted without any visible error. The proposed system significantly reduces the transmission time and error. Moreover, the system is very user friendly since the selection of the RoI, its size, overall code rate, and a number of test features such as noise level can be set by the users in both ends. A MATLAB-based TCP/IP connection has been established to demonstrate the proposed interactive and adaptive progressive transmission system. The proposed system is simulated for both binary symmetric channel (BSC) and Rayleigh channel. The experimental results verify the effectiveness of the design.
that incorporates the features of zerotree and zero-block based algorithms. The main contribution in this recent algorithm is partitioning the wavelet-transformed image into coefficient blocks and to generate roots in top-most subband by using a block tree. In [7], another progressive image transmission method has been proposed based on a quadtree segmentation procedure in order to provide fairly good quality transmitted images while keeping the computational cost low. The authors in [8] have developed strategies to exploit the wavelet coefficients in different subbands for designing different vector quantization (VQ) coding to achieve a fast and efficient progressive transmission.

Shannon’s information theory states that the performance of transmission schemes can be optimized in source and channel coding separately. However, the result holds with infinite block size, infinite coding complexity, and stationary channels. Such conditions are difficult to meet in practice. Hence, joint source-channel coding (JSCC) scheme attracts the interest of many. The JSCC scheme consists of a quantizer, an entropy, and channel coders to meet the target source rate, to achieve the required robustness in channel coding, and to find an optimal bit allocation between source and channel coding systems. Several methods have focused on designing adaptive joint source-channel coding (JSCC) schemes and introducing the properties of unequal error protection (UEP) and rate allocation between source and channel coding systems. The UEP strategies for efficient progressive transmission are proposed in [18]. Under the condition of a target transmission rate, the JSCC algorithm computes a UEP scheme that maximizes the number of corrected bits over a noisy channel. In [19], authors have used a concatenation of rate-compatible punctured convolution code and cyclic redundancy check (CRC) code to form a UEP scheme and find the optimal rate allocation solutions for progressive image transmission.

Many communication systems allow two-way communication implying that the signals are back from receiver to transmitter to adjust the system parameters and obtain better system performance. The authors in [20–23] have utilized the concept called hybrid automatic repeat request (HARQ) to ask for retransmission of erroneously received data and tradeoff allocation between the source and channel codes according to a rate-distortion optimization policy. Many researches on tradeoff allocation bits between source codes and channel codes assume that the noise-level in the channel is known in advance. Therefore, the feedback signal is figured out based on the known noise levels and the constraints set by the user. In the proposed algorithm, this has been modified since the parity lengths change according to the noise level in the received data whereby the amount of detected incorrect data is used to predict the conditions of the practical transmission channel. For medical image transmission, the quality of the reconstructed images (especially in the RoI) should be acceptable. This can be set as the constraint for the quantizer and the compression algorithm in advance. Therefore, the quality of the reconstructed image is only affected by the channel state and the proximity to the image RoI. The feedback signal in the proposed scheme updates the parity length without the need for retransmission of the data or adding any extra overhead.

The principal idea behind all these methods is that in a progressive transmission framework, the receiver reconstructs the transmitted image at various bit rates, which makes the fast and reliable retrieval of large images possible. In other words, the quality of the reconstructed image totally
depends upon the volume of the received data, and the images can be reconstructed in any bitrate. Furthermore, the image subblocks are coded separately. Due to the high sensitivity to transmission noise, progressive transmission of images over noisy channels has to be accompanied by an appropriate channel coding, or a joint source-channel coding scheme [12]. The noise in the current communication systems can be due to the electronic components, fading, Doppler shift for mobile systems, bad weather, interferences, attenuations, and so forth.

The Reed-Solomon (RS) codes utilized here are block-based error correcting codes and are widely used for channel coding. The RS\((p, q)\) codes correct the symbol error and not the bit error; lengths in terms of symbols. Thus, RS is suitable for burst error detection and correction [23].

### 2. Joint Source-Channel Coding

In this paper, we propose a novel interactive and adaptive joint source-channel coding with feedback algorithm for progressive transmission of medical images. This approach benefits from the idea of the JSCHC, RoI, UEP, and feedback technique together as follows.

(1) The conventional RS channel coding has been used.

(2) The variability of the parity code corresponds to both the proximity to the center of RoI and the state of the practical transmission channel at the same time; this makes an efficient source-channel coding possible.

(3) The selectivity of the RoI is totally interactive and can be defined by the user in the receiver. This makes the method favorable to be used by clinicians who require fast access to the RoI in the image.

(4) An algorithm for detection of the blocks in error is developed to detect and recover the corrupted data, estimate the noise level in the practical transmission channel, and feedback the information of the noisy channel to the transmitter to control the error rate in the reconstructed images in the subsequent transmission.

By utilizing our flexible system, a minimum distortion of the transmitted images in a fairly shorter transmission time is achieved. As the main contribution of this research, we adaptively control the lengths of parity code streams simultaneously with respect to the selected region (i.e., longer lengths correspond to the areas closer to the center of RoI) and the amount of corrupted received data in the receiver. The system block diagram is shown in Figure 1.

This paper is organized as follows. Section 3 briefly describes the concepts of DWT and EZW. Following that, we provide the details of RoI selection. In Section 2, application of RS channel coding in a variable-parity length scheme will be explained. In Section 4, an algorithm for detection of the blocks in error is developed to evaluate the amount of incorrect received data in the receiver. Simulation results are subsequently reported in Section 5 followed by concluding remarks in Section 6.

### 3. Discrete Wavelet Transform and Embedded Zerotree Wavelet

Wireless transmission of medical images involves construction of an effective joint source-channel coding to not
only preserve the diagnostic information but also to enable progressive streaming of the data from the host to the receiver. EZW is a simple, efficient, and flexible compression algorithm for low bitrate image coding. The properties of DWT and EZW allow us to code and compress the data blocks individually and also compress it at any bitrate. Therefore, based on progressive encoding, we can compress a block into a bitstream with increasing accuracy. Traditionally, the input images are decomposed into many subblocks each to be coded, compressed, and transmitted individually. Therefore, the input image is segmented into a number of subblocks firstly. And then wavelet transform (WT) decomposes each subblock into different time-frequency components.
As it is detailed in [24], EZW codes the image into streams of six symbols, namely, \( p, n, z, t, 0 \), and 1. In mathematical terms, considering the image amplitude at location \((x, y)\), is denoted by \( y(x, y) \), and \( t_0 \) is the threshold in \( n \)th iteration, the definitions of the symbols are given in Table 1. EZW suits progressive data transmission since it enables hierarchical encoding and decoding.

In the proposed system, we chose a 3-level Haar wavelet transform (HWT) to perform the DWT for each subblock due to its simplicity and being faster and easier to implement in comparison with other DWT methods [21]. The coefficients in the lowest frequency subbands show the background information of the subblocks. The coefficients in the higher frequency subbands represent the details and edges. After computing the HWT, we compress the coded data according to a variable thresholding mechanism governed by the EZW. Hence, a suitable approach is to use a variable threshold and transmit only those coefficients to the decoder that are larger than the threshold. The first step in the EZW algorithm is to determine the initial threshold level \( t_0 \) and then repeatedly lowering the threshold by half at a time until the threshold has become smaller than the smallest coefficient to be transmitted; or the iteration is stopped by request. The initial threshold \( t_0 \) is set as follows:

\[
t_0 = 2^N, \quad N = \log_2 \max(|y(x, y)|),
\]

where \( \max(\cdot) \) refers to the maximum value. The final threshold level determines the length of the bitstream output through the EZW process, the compression ratio of the input images, and the resolution of the reconstructed image. The length of the output bitstream \( M_i \) is related to the number of times the threshold is halved as

\[
M_i = \sum_{k=0}^{n_{T_i}} B \left( \frac{t_0}{2^k} \right),
\]

where \( B(t) \) is the output bitstream of EZW based on the threshold \( t \). \( n_{T_i} \) is the initial threshold in the \( i \)th subblock, and \( n_{T_i} \) is the number of times the threshold is halved in the \( i \)th subblock. Therefore, potentially, we can achieve any resolution in the reconstructed images through setting the initial threshold, and the number of times the threshold is halved. As an example, Figure 2 shows the three regions of RoI, \( R_1, R_2 \) centered at point \((x, y)\). In Figure 2, the resolution in area \( R_2 \) is the lowest and that of RoI is the highest. Therefore, the quality of the reconstructed subblocks and consequently the compression rate depends on the size of the embedded zerotree. This is set based on the distance from the center of RoI. Based on the assigned parameters for EZW, the data in each subblock would be compressed with different rates depending on the location of the subblock. Often, the physician is only interested in a particular part of the image. Therefore, the system is designed in such a way to enable changing the location and size of the RoI without any emphasis on the other regions. In this example, the RoI, \( R_i \), and \( R_2 \) may be defined as

\[
\sqrt{(i-x)^2 + (j-y)^2} \leq r_x,
\]
Figure 9: The transmitted image over the low noise: (a) the background image at stage $P_1$ and the location of RoI in the center of the image, (b) the transmitted image after stage $P_2$, (c) the transmitted image after stage $P_3$, and (d) shows the completely decoded image after stage $P_4$.

Figure 10: Similar results as in Figure 9 when the RoI is selected in the corner of the image.
is a subset of BCH codes; they are linear block codes and are efficient for bursty-type transmission channels. The RS codes are constructed by considering a polynomial for the input information and then use the polynomial coefficients instead of the original data for transmission. In an RS\( (p, q) \) code, \( p = 2^m - 1 \) is the number of symbols in a codeword, and \( m \) is the number of bits in each symbol. In the proposed algorithm, the data in different image regions, as denoted in Figure 2 for three regions, are protected by variable length parity codes as for the UEP. The data in the RoI is treated as the most important information and protected by longer length parity codes. The rest of the data is protected by shorter parity codes.

Figure 3 illustrates the channel coding strategy and Figure 4 shows the receiver. The overall channel code length remains fixed and the length of message \( k, q_k; k = 1, 2, \ldots, n \), and the parity length \( C \) are variable. For RS codes, \( (255 - qn)/2 \) indicates the error-correction capability of RS coder. Here, the RS codes, RS(255, \( q \)), have 255 symbols in length. According to the UEP, the ratio of parity to overall code length for the \( n \) regions should follow

\[
C_{\text{RoI}} > C_{R_1} > C_{R_2} \cdots > C_{R_{n-1}},
\]

where \( C_{\text{RoI}}, \) the length of parity code, is for the RoI and so on. Furthermore, the length of parity code is also affected by the noise in the channel, that is, \( C_{\text{region}} \sim (r, N) \), where \( r \) is the
Figure 12: The decoded image with variable length of parity codes over the noisy channel. (a) A background image and the location of RoI selected in the center of image reconstructed after stage \( P_1 \), (b) the reconstructed image after stage \( P_2 \), no error subblocks are found in the reconstructed image because the lengths of parity codes are adjusted automatically based on the previous volume of incorrect data in the receiver, (c) the reconstructed image after stage \( P_3 \); the lengths of parity bits in stage 3 are as same as in stage 2 because no incorrect data was found in the reconstructed image after stage 2, (d) the complete transmitted image with no error subblocks.

An adaptive variable parity allocation requires the error between the transmitted image \( I(x, y) \) and the received image \( \hat{I}(x, y) \) to be minimized under the desired conditions. Suppose that the error is defined as

\[
\varepsilon = \| I(x, y) - \hat{I}(x, y) \|_2,
\]

where \( \| \cdot \|_2 \) denotes the \( L_2 \)-norm. Generally, we wish to have the optimum parity length such that

\[
C_{opt} = \min_C \varepsilon \text{ subject to } \varepsilon \leq \varepsilon_T,
\]

where \( \varepsilon_T \) is an acceptable error level in the receiver. According to the above discussion, the parity length can be defined as

\[
C = g \left( r, \frac{S}{N} \right) = f(r, \text{BER}),
\]

where \( S/N \) and BER stand, respectively, for signal-to-noise ratio and bit-error rate (the BER here represents the noise situation in the channel and does not refer to the output bit-error rate). The functions \( g \) and \( f \) are generally nonlinear functions, which can be defined empirically based on a number of trials. From Figure 5, \( f \sim (\alpha_0 - \alpha r) \) for a fixed BER, where \( r \) is measured with respect to the number of pixels, and from Figure 6, it can be concluded that \( f \sim (\beta \text{BER} + \beta_0) \) for fixed proximity distance \( r \). In more general applications, a more accurate and possibly complicated function may be adopted. Therefore, a reasonably accurate function can be modeled as

\[
f(r, \text{BER}) = (\alpha_0 - \alpha r) (\beta \text{BER} + \beta_0),
\]

or

\[
f(r, \text{BER}) = \mu_3 \text{BER} - \mu_2 r \cdot \text{BER} - \mu_1 r + \mu_0,
\]

where \( \mu_i \)s are constant coefficients and can be easily found based on Figures 5 and 6.

4. Detection of the Blocks in Error

Embedded coding has many advantages, especially for progressive image/video transmission, because the reconstructed images can be decoded at any bitrate. However, it is highly sensitive to transmission noise and frequently collapses if even a single transmitted information bit is incorrectly decoded. In most cases, the receiver sends back a signal called HARQ to the transmitter requesting for retransmission under the new constraints. Here, the channel noise level has to be somehow estimated in the receiver. This
Figure 13: A decoded image with variable length of parity codes over noisy channel: (a) several error subblocks are detected in stage 1, (b) several error subblocks still are found in stage 2 indicating that the feedback message is incorrect or the channel condition becomes noisier. However, RoI is still error-free based on the UEP. (c) No error subblock is detected in stage 3 because the length of parity is adjusted again according to previous channel state, although there can still be some error. (d) The complete transmitted image with no error subblocks.

will enable the change in the parity length in the following transmissions. The estimation process is blind since there is no a priori information about the channel. In some practical cases however, a test image can be transmitted occasionally and evaluated in the receiver.

In the proposed scheme, we have developed an algorithm to detect the corrupted data in the receiver. This algorithm detects the address in which the number of symbols for each subblock is indicated. The algorithm reassigns the number of symbols to each subblock according to a built-in decision making criterion (policy) when the number of symbols within the received data is determined incorrectly by the receiver. Since the header information provides the number of symbols per each data package, an extra check can be carried out to ensure that the header is divisible by 4 and is not greater than 64 (to address each pixel) for the $8 \times 8$ subblocks. For more accuracy, the algorithm checks the next address of the number of symbols to ensure that the current data is correct. If successive error data is detected, the algorithm is able to determine the number of subblocks and reassign the number of symbols for each subblock in the set of detected incorrect data. Although, the proposed algorithm does not have capability of recovery of the current corrupted package, but it can conjecture an appropriate number to replace the corrupted data based on the built-in decision making criterion (policy) to avoid the reconstructed image to collapse. This adjusts the system for the transmission of the subsequent package and prevents propagation of the error. This not only enhances the quality of the reconstructed image but also provides a feedback for the adjustment of parity length.

The performance of the system in different noise-levels is evaluated using the peak signal-to-noise ratio (PSNR) defined as

$$\text{PSNR(dB)} = 10 \log_{10} \frac{A^2}{\text{MSE}},$$  \hspace{1cm} (12)

where $A$ is the maximum image amplitude, and MSE is defined as

$$\text{MSE} = \frac{||\hat{I} - I||_2^2}{||I||_2^2},$$ \hspace{1cm} (13)

where $\hat{I}$ represents the reconstructed subblock of the image, and $I$ is the subblock of the original input image.

Finally, the parallel structure of the channel coding and decoding scheme is very suitable in hardware implementation of the system. A number of parallel boards can be easily used in order to speed up the overall process.
5. Simulation Results

In this work, the proposed system is simulated in both binary symmetric channel (BSC) and flat-fading Rayleigh channel. The BSC is the simplest channel model, only zeros and ones are conveyed in the channel. Therefore, we can simplify the analysis and enable a fast software implementation. But the wireless mobile communication channels are often considered to be with flat-fading Rayleigh noise. In this paper, we simulated both BSC and flat-fading channel models and tested the performance of the proposed techniques against both models. RS(255, q) is used in the proposed scheme. The RS codes correct the symbol error and not the bit error. The noise in the simulated channel has been considered in such a way to set a BER of 0.01 in the received end. For when the errors are uniformly distributed, the average parity length is 42 for a 255 length code length. This recovers the RoI perfectly when either BSC or Rayleigh channel is considered and the channel noise is equivalent to BER = 0.01.

The developed algorithm has been tested for a number of images, two of which are analyzed here. The first image is a 150 × 123 pixels color dental implant image, and the second image is a 508 × 512 pixels monochrome X-ray bone image. Both are to be transmitted via TCP/IP. The proposed system follows the diagram in Figure 1. Each noisy channel involves a binary symmetric channel (BSC) and flat-fading Rayleigh channel with a certain BER. In this simulation, the error bits are generated by randomly inverting a certain percentage of bits in the EZW bitstream. To verify the effectiveness of the system, the image regions are progressively transmitted through four stages of $P_1$, $P_2$, $P_3$, and $P_4$. During $P_1$, the background image is transmitted. $P_2$ and $P_3$ are the second and third stages, both for transmission of RoI, $R_1$, and $R_2$. $P_4$ is the fourth stage mainly to transmit the details of the RoI (and the rest of the image if necessary). In the approach presented here, firstly, the user (physician) specifies the address of the transmitted medical image in the transmitter within the dialogue-based software. After receiving the low-resolution background image, the user identifies the center of RoI by a mouse and the radius of RoI by entering a value within the dialogue-based software. Then, the algorithm adjusts the length of the parity codes initially proportional to the proximity of the image regions to the center of RoI as $C_0$, $C_0 - 2$, $C_0 - 4$ for RoI, $R_1$, and $R_2$, respectively.
Table 2: The information percentage transmitted for each area during the stages $P_1$ to $P_4$ images.

| Percentage of area | $P_1$ | $P_2$ | $P_3$ | $P_4$ |
|--------------------|-------|-------|-------|-------|
| RoI                | 0%    | 18.15%| 41.86%| 100%  |
| $R_1$              | 0%    | 37.04%| 44.07%| 0%    |
| $R_2$              | 100%  | 44.81%| 14.07%| 0%    |

Table 3: The average compression ratio for various regions for the four stages of the progressive image transmission.

| Compression ratios | $P_1$ | $P_2$ | $P_3$ | $P_4$ |
|--------------------|-------|-------|-------|-------|
| Overall image      | 3.063 | 1.069 | 0.716 | 0.405 |
| RoI                | 0.003 | 0.353 | 0.401 | 0.405 |
| $R_1$              | 0.003 | 1.232 | 1.814 | 0     |
| $R_2$              | 3.063 | 3.746 | 3.387 | 0     |

Accordingly, the receiver detects and counts the packages in error by estimating the status of the channel. The parity lengths remain the same if the distortion in the reconstructed image is acceptable. Otherwise, the codes will be adjusted automatically. Typically, the ratio of parity code to the overall code length is larger for the clinically higher priority areas, that is, the areas closer to the center of RoI as stated in (6). Figure 5 indicates the ratios of parity length and the overall codeword according to the experimental results.

Table 2 gives an example of the percentage of information for the regions $R_1$, $R_2$, and $R_3$ for fixed proximity levels of $r_a$ and $r_b$, as in Figure 9. Table 3 indicates the average compression ratios for various regions before the channel coding during the four successive transmission stages. The compression ratio is defined as the ratio between the data volume of the coded data and the original data. However, by changing one of RoI coordinates, or $r_a$ and $r_b$, data in Tables 2 and 3 are also changed.

In Figure 6, the parity lengths are found by averaging the results of 10 trials under various noise levels. These are estimated by the algorithm developed for detection of the blocks in error in the receiver. Data in RoI is the most important data in the overall image; therefore, the length of parity codes is longer than that in $R_1$ and $R_2$. In the proposed system, the codeword length of RS codes is 255, and the number of error bit is generated.

Figure 7 shows the frequency of the set of parity lengths in 10 trials for when the channel noise is set by BER = 0.003 equivalent to the occurrence of 7 errors. As long as the error in the receiver remains higher than a threshold $t_h$, the length of parity increases. Consequently, if the error falls below a level $t_l < t_h$ the parity length increases. These threshold levels are empirically selected by following the constraint in (8). In these cases, the parameters in (10) and (11) are approximately $a_0 = 0.08$, $a = 2 \times 10^{-4}$, $b_0 = 5$, $\beta = 5 \times 10^5$ and accordingly $\mu_0 = a_0 b_0 = 0.4$, $\mu_1 = a b_0 = 10^{-3}$, $\mu_2 = a b = 1$, and $\mu_3 = a_0 b = 4 \times 10^{-2}$.

Figure 8 shows the PSNRs for successive transmission of four stages under various noise-level conditions.

Figure 9(a) shows the background image sent during $P_1$ stage. Figure 9(b) is progressively reconstructed image after stage $P_2$ in which the RoI, $R_1$, and $R_2$ are reconstructed. At this stage, the center of RoI is denoted by the user via mouse click. Figure 9(c) represents the reconstructed image at stage $P_3$ during which the regions RoI, $R_1$, and $R_2$ are reconstructed. The regions of RoI and $R_1$ are gradually increased in resolution. Figure 9(d) is the final and complete image after stage $P_4$. The same procedure can be followed for encoding and transmission of any other medical image. However, the coordinates of the center of RoI as well as the size of RoI maybe adjusted according to the requirement by the user. For example, in Figure 10, the RoI is selected in the corner. Figure 11 demonstrates that a fixed-size parity code is not suitable for an efficient transmission system. However, the system has been modified based on the proposed method in Sections 2 and 4 to allow variable lengths of parity. Figures 12 and 13 show no error in the RoI stating that the overall system has been remarkably improved. In Figure 14, another example of a decoded image (a 508 $\times$ 512 monochrome X-ray bone image) is given, and the variable length parity has been examined. The background image suffers from heavy noise. However, the transmission can continue until the last stage during which a complete error-free image is reconstructed.

6. Conclusion

In this paper, we presented a new adaptive source-channel coding with feedback for the progressive transmission of medical images. The system is adaptive to both image content and channel specifications. However, this application is merely for wireless channels (generally narrowband). The capability of data error detection and correction with automatic adjustment, low image transmission time, and efficient communication are the key features in this proposed system. Therefore, the length of parity codes can be adjusted automatically based on the location of the image subblocks and the practical characteristics of the communication channel to provide an adequate data protection. The overall code length for the channel encoder/decoder is fixed. This makes it easy for hardware implementation. A wide range of fluctuations in the channel characteristics (mainly noise level) can be tolerated in the system. The algorithm of detection of subblock in errors can detect the packages in error in the receiver and feed it back to the transmitter for adjustment of the parity length. The proposed system has also been tested for the communication channels with different capacities and noise levels. The presented results verify the effectiveness of the system in terms of both adaptivity and flexibility of interaction. A MATLAB-based TCP/IP connection has been established to demonstrate the proposed interactive and adaptive progressive transmission system. Although some theoretical results are comparable to those of other new techniques such as the UEP or rate allocation approaches, this contribution provides a practical, flexible, and interactive method which suits medical applications.
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