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2D IMAGE TRANSMISSION USING KALMAN-TURBO SYSTEMS

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ABSTRACT

In this paper, in order to compress and enhance 2D images transmitted over wireless channels, a new scheme called Kalman-Turbo (KT) is introduced. In this scheme, the original image is partitioned into 2^N quantization levels and each of the N-bit planes is coded by Turbo encoder. After noise corruption of the channel, each of the noisy bit planes is processed iteratively by a joint equalization block, which is composed of low-complexity 2D binary Kalman filter and the Turbo decoder. In our Kalman filter, state equations are modified in order to take the advantage of two-dimensionality, and, previous soft decisions are taken into account to avoid divergence of Kalman filter. Simulation results show that the performance of the KT system is superior at low SNRs when compared with that of plain Turbo decoding algorithms. We can also achieve compression by any selection of N. Hence, we conclude that KT system will be a compromising approach in 2D image transmission.

Keywords: *Kalman Filtering, Turbo Coding, Image Processing, Iterative Decoding, Wireless Channels.*

1. INTRODUCTION

Image processing and its transmission get importance, since the correlations between pixels are being lost in classical approaches with separate blocks. In literature, there are some studies for combined Turbo coding and image processing [1, 2]. In this paper, we propose a joint structure, denoted as Kalman-Turbo (KT) system employing 2-Dimensional Kalman filtering and Turbo coding. The performance of KT is investigated over Additive White Gaussian Noise (AWGN) channel. It is a combination of Turbo codes and the 2D adaptive noise removal filtering. In KT, each binary correspondence of the amplitude values of each pixel is grouped in bit-planes. Then each bit of bit planes are transmitted and at the receiver side, a combined structure, denoted as Kalman-Turbo decoder is employed. Kalman-Turbo decoder is an iterative structure with a feedback link from the second Turbo decoder and Kalman filtering. The decoding process continues iteratively till the desired output is obtained. The advantage of neighborhood relation of pixels is taken into account in KT scheme, resulting improvement of

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image enhancement. Although each bit slice is transmitted in serial way, the bit string is reassembled at the receiver in such a way that the original neighborhood matrix properties can be used before the decoding process. Thus, instead of classical binary serial communication and decoding, in our scheme, the coordinates of the pixels are kept as in their original input data matrix. And, instead of transmitting the amplitude value of the pixels, each pixel value is mapped to corresponding binary N-level, regarding the quantization.

In KT, data rate can be increased up to N-1 times, by only transmitting most important significant bit. Especially in quick search, such interesting results get importance. Then the other bits can be transmitted to obtain more accurate 2D images. Thus, our bit slicing can be also an efficient way of compressing 2D images.

2. SYSTEM MODEL

The system consists of an image slicer, a Turbo encoder (transmitter), an iterative 2D Kalman filter, a Turbo decoder (receiver), and an image combiner sections as shown in Figure 1. The decoder employs two identical recursive systematic convolutional (RSC) encoders connected in parallel with an interleaver preceding the second recursive convolutional encoder. Both RSC encoders encode the information bits of the bit slices. The first encoder operates on the input bits in their original order, while the second one operates on the input bits as permuted by the interleaver. The decoding algorithm involves the joint estimation of two Markov processes one for each constituent code. Because the two Markov processes are defined by the set of data, sharing information between the two decoders in an iterative fashion can refine the estimated data.

The output of one decoder can be used as a priori information by the other decoder. The iteration process is done until the outputs of the individual decoders are in the form of hard bit decisions. In this case, there is not any advantage to share information anymore.

2.1 Bit plane Slicing/Combining

Highlighting the contribution made to the total image appearance, specific bit plays an important role for KT system. An application of this technique is also for data compression in the image processing area [3]. Imagine that the image is composed of N-1 bit planes, ranging from plane 0 for least significant bit to plane N-1 for the most significant bit. This decomposition reveals that only some highest order bits contain visually significant data. Also, note that plane N-1 corresponds exactly with an image threshold at gray-level 2^{N-1}.

Bit plane combining is the reverse process of the slicing. The planes are recombined in order to reconstruct the image. But it is not needed to take into consideration all the slice contributions. Especially, in the case where the data rate is important, some planes can be ignored until the changes in gray level have an acceptable impact on the image. This approach will increase the data rate. In our study, the image is sliced to 4 planes i.e. each pixel in the image is represented by 4 bits (or 16 gray levels). So, our image is composed of four 1-bit planes, ranging from plane 0 for the least significant bit to plane 3 for the most significant bit.

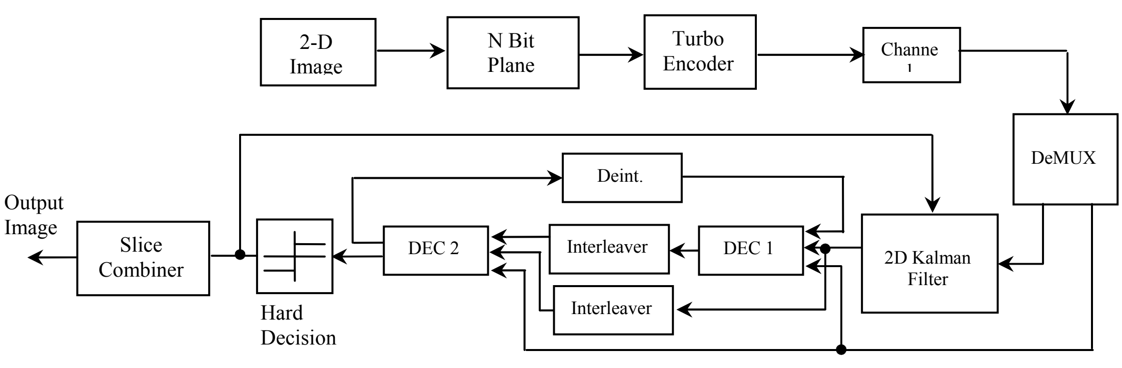


Figure 1. System Model.

Transforming the image in a binary fashion is very suitable before transmission. If the image has been considered without being sliced, then we would have lost the neighborhood relationship and it would be useless to have an adaptive filter at the receiver side and hence the performance of the proposed system would be the same as that of the other conventional techniques. When the image is sliced first and then coded and transmitted, the neighborhood properties would be evaluated. As a result, the noise effect would be reduced before MAP algorithm using an adaptive filter, so the performance is significantly improved.

2.2. The Recursive Systematic Convolutional (RSC) Encoders

In this section, we give general information about Recursive Systematic Convolutional (RSC) codes [4], which will be used in the study. Consider a half-rate RSC encoder with memory size M. If the d_k is an input at time k, the first output pair X_k is equal to

$$X_k = d_k . \tag{1}$$

Remainder $r(D)$ can be found using feedback polynomial $g^{(0)}(D)$ and feedforward polynomial $g^{(1)}(D)$. The feedback variable is

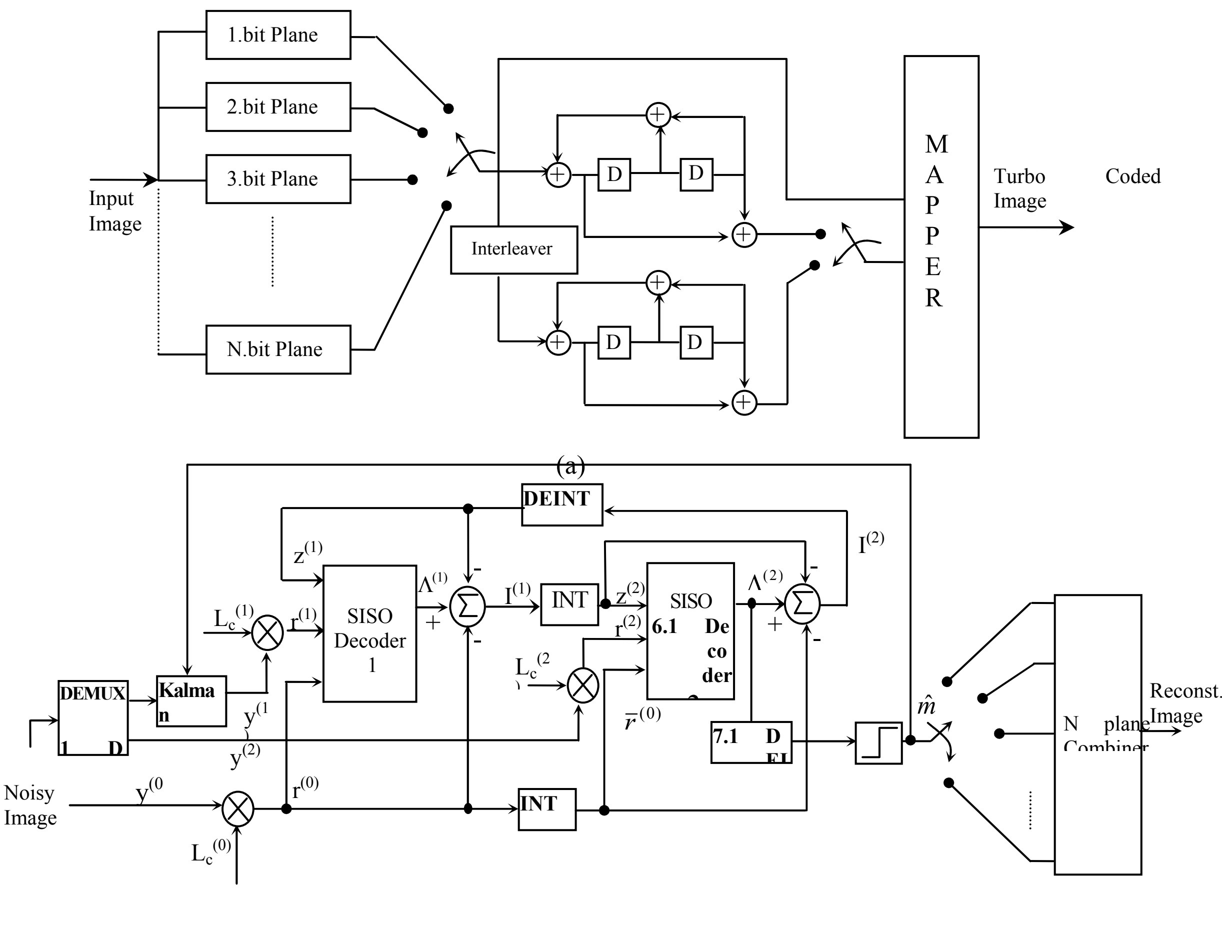
$$r_k = d_k + \sum_{j=1}^{M} r_{k-j} g_j^{(0)} \tag{2}$$

and RSC encoder second output Y_k which called parity data is

$$Y_k = \sum_{j=0}^{M} r_{k-j} g_j^{(1)} . \tag{3}$$

RSC encoder with memory $M = 2$ and rate $R = 1/2$ which feedback polynomial $g^{(0)} = 7$ and feedforward polynomial $g^{(1)} = 5$ is illustrated in Figure 2.a. The generator matrix will be

$$G(D) = \left[1 \quad \frac{1 + D + D^2}{1 + D^2} \right] \tag{4}$$



(a)

(b)

Figure 2. Kalman-Turbo Processing (a) Encoder (b) Decoder.

2.3. Modified 2D Kalman Filter

In this part, a low-complexity but robust two-dimensional Kalman filter for noise reduction will be presented. First we express the received noisy signal $g(n_1, n_2)$ as

$$g(n_1, n_2) = f(n_1, n_2) + v(n_1, n_2) \tag{5}$$

where, $f(n_1, n_2)$ is the under graded signal and $v(n_1, n_2)$ is the white Gaussian noise. Since it is more efficient to track the variations about the mean, we define

$$\begin{aligned} g(n_1, n_2) &= \bar{g}(n_1, n_2) + m \\ f(n_1, n_2) &= \bar{f}(n_1, n_2) + m \end{aligned} \tag{6}$$

where, m is the mean of the image. In order to take the benefit of two-dimensionality, the observation model for the Kalman filter using neighborhoods of size KxL, is modified as

$$\sum_{k=0}^{K-1} \bar{g}(n_1 - k, n_2) = \mathbf{H}^T \bar{\mathbf{f}}(n_1, n_2) + \sum_{k=0}^{K-1} v(n_1 - k, n_2) \tag{7}$$

where

$$\mathbf{H} = \left[\mathbf{1}_{1\text{x}K} \quad \mathbf{0}_{1\text{x}K(L-1)}\right]^T \tag{8}$$

and

$$\begin{aligned} \bar{\mathbf{f}}(n_1,n_2) = \big[&\bar{f}(n_1,n_2) \;\; \bar{f}(n_1-1,n_2) \;\cdots\; \bar{f}(n_1-K+1,n_2) \\ &\bar{f}(n_1,n_2-1) \;\; \bar{f}(n_1-1,n_2-1) \;\cdots\; \bar{f}(n_1-K+1,n_2-1). \\ &\cdots\; \bar{f}(n_1-K+1,n_2-L+1)\big]^T \end{aligned} \tag{9}$$

In (8), $\mathbf{1}$ is the all-ones vector of size 1xK and $\mathbf{0}$ is the all-zeros vector of size 1xK(L - 1). T indicates the transpose. We develop the dynamical signal model as

$$\bar{\mathbf{f}}(n_1, n_2) = \mathbf{A}\bar{\mathbf{f}}(n_1, n_2 - 1) + \mathbf{u}(n_1, n_2) \tag{10}$$

where, $\mathbf{A}$ is the known KLxKL state-transition matrix and $\mathbf{u}(n_1, n_2)$ is the autoregressive model noise vector whose non-zero entries are white and Gaussian. Based on $\bar{\mathbf{f}}(n_1, n_2 - 1)$ the Kalman filter iteratively estimates $\bar{\mathbf{f}}(n_1, n_2)$ using the state models given in (7) and (10) [5]. In the absence of pilot symbols, which are required for the iteration to be start at the beginning of processing each row, we consider the received symbols as pilot symbols and recover the image. Then we reverse the iteration direction and estimate the pixel values that serve as pilot symbols.

In our receiver, since Kalman filter will jointly operate with binary Turbo decoder, binary Kalman filter must be employed for each bit plane separately. For the binary Kalman filter, it is critical to use soft previous decisions instead of hard ones since the binary image fluctuates very suddenly.

2.4. Turbo Decoding Process

We consider the MAP (maximum a posteriori) approach for decoding as illustrated in Figure 2.b. The goal of the MAP algorithm is to find the a posteriori probability of each state transition, message bit, or code symbol produced by the underlying Markov process, given the noisy observation vector **y** [6, 7]. Once the a posteriori probabilities are calculated for all possible values of the desired quantity, a hard decision is made by taking the quantity with the highest probability.

When used for Turbo decoding, the MAP algorithm calculates the a posteriori probabilities of the message bits for the filtered planes, $P\{m_k = 1 \mid \mathbf{y}\}$ and $P\{m_k = 0 \mid \mathbf{y}\}$, which are then put into LLR (log-likelihood ratio) form according to

$$\Lambda_k = \ln \frac{P\{m_k = 1 \mid \mathbf{y}\}}{P\{m_k = 0 \mid \mathbf{y}\}}. \tag{11}$$

Before finding the a posteriori probabilities for the message bits, the MAP algorithm first finds the probability $P\{s_k \to s_{k+1} \mid \mathbf{y}\}$ of each valid state transition given the noisy channel observation **y**. From the definition of conditional probability

$$P\{s_k \to s_{k+1} \mid \mathbf{y}\} = \frac{P\{s_k \to s_{k+1}, \mathbf{y}\}}{P\{\mathbf{y}\}}. \tag{12}$$

The properties of the Markov process can be used to partition the numerator as

$$\begin{aligned} P\{s_k \to s_{k+1}, \mathbf{y}\} &= \alpha(s_k)\gamma(s_k \to s_{k+1})\beta(s_{k+1}) \\ \alpha(s_k) &= P\{s_k, (y_0, ..., y_{k-1})\} \\ \gamma(s_k \to s_{k+1}) &= P\{s_{k+1}, \mathbf{y} \mid s_k\} \\ \beta(s_{k+1}) &= P\{(y_{k+2}, ..., y_{L-1}) \mid s_{k+1}\}. \end{aligned} \tag{13}$$

The probability $\alpha(s_k)$ can be found according to the forward recursion,

$$\alpha(s_k) = \sum_{s_{k-1}} \alpha(s_{k-1})\gamma(s_{k-1} \to s_k) . \quad (14)$$

Likewise, $\beta(s_k)$ can be found according to the backward recursion,

$$\beta(s_k) = \sum_{s_{k+1}} \beta(s_{k+1})\gamma(s_k \to s_{k+1}) \quad (15)$$

Once the a posteriori probability of each state transition $P\{s_k \to s_{k+1} \mid \mathbf{y}\}$ is found, the message bit probabilities can be found according to

$$P\{m_k = 1 \mid \mathbf{y}\} = \sum_{S_1} P\{s_k \to s_{k+1} \mid \mathbf{y}\}$$
$$P\{m_k = 0 \mid \mathbf{y}\} = \sum_{S_0} P\{s_k \to s_{k+1} \mid \mathbf{y}\} \quad (16)$$

where $S_1 = \{s_k \to s_{k+1} : m_k = 1\}$ is the set of all state transitions associated with a message bit of 1, and $S_0 = \{s_k \to s_{k+1} : m_k = 0\}$ is the set of all state transitions associated with a message bit of 0.

This soft bit information is de-interleaved and evaluated at the hard decision section.

3. SIMULATION RESULTS

In this section, we present simulation results that illustrate the performance of the proposed KT system over wireless channel. First, the pixels of the image with 256 gray levels are converted into 16 gray levels and sliced to 4 bit planes. Then, all bit-planes are coded via Turbo encoder. In the Turbo encoder, ½-rate RSC encoders with generator matrices g = [111:101] are employed. A random interleaver is used and the frame size is chosen as 150. The coded bit planes are transmitted over AWGN channel and joint Kalman filtering and Turbo decoding is applied at the receiver. Since 2nd and 3rd bit planes are significant, two separate modified Kalman filters are used. In order to reduce the complexity of the modified Kalman filters, we choose $K = L = 2$. The number of iterations between the Kalman filter and decoder is selected as 3.

Figures 3 and 4 shows the corrupted, plain Turbo processed, and KT processed lena images for SNR values of 0 dB and 2 dB, respectively. From Figures 3 and 4, it can be concluded that, for low SNR values, the proposed KT system offers good performance where plain Turbo decoding results is not satisfying. The SNR improvement obtained by KT processing at a BER of 10^{-3} is 1.4 dB for 3rd bit-plane and 0.9 dB for 2nd bit-plane. We observe that the BER performance of KT processed 3rd bit-plane is the best. This is expected since the local neighborhood relationships of 3rd bit-plane are stronger than that of 2nd bit-plane.

(a)

(b)

(c)

Figure 3. Simulation results for SNR = 0 dB (a) Noisy image (b) Turbo processed image (c) Kalman-Turbo processed image.

(a)

(b)

(c)

Figure 4. Simulation results for SNR = 2 dB (a) Noisy image (b) Turbo processed image (c) Kalman-Turbo processed image.

4. CONCLUSIONS

The images being transmitted over noisy channels are extremely sensitive to the bit errors, which can severely degrade the quality of the image at the receiver. This necessitates the application of error control coding in the image transmission. This work presents an efficient image transmission by means of a new proposed KT (Kalman-Turbo) method, which takes the advantage of the superior performances of Turbo coding and Kalman filtering. We have seen that more than 0.9 dB additional SNR improvement is achieved in the proposed KT algorithm, compared to that of plain Turbo decoding. Hence, we conclude that KT system will be a compromising approach in 2D image transmission, for recovery of noisy signals and image compression.

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