A DESIGN OF SOURCE MATCHED MAP RECEIVER FOR IMAGE TRANSMISSION

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ABSTRACT

In this paper we will discuss the MAP receiver design for the reception of the image signal. It is impractical to use the MAP algorithm for the source detection because of its huge calculation costs. To solve this problem we propose a novel MAP receiver structure, where the receiver contains a predictor within it. With an aid of the predictor we can reduce the calculation. Furthermore we can approximate the a priori probability by the prediction error distribution.

1. INTRODUCTION

In this paper we consider the reception of the image signal using the stochastic characteristics of the image.

For an efficient reception of image signal, transmitted through noisy wireless channel, it is desirable to use its characteristics fully at the receiver side if it is available. Let us call the criterion based on such concept "source matched" criterion, and the receiver as "source matched receiver." From this point of view some considerd channel coding [1, 2]. They use the source characteristics for the design of the channel codes, and are known as "joint source channel coding." Others consider the transmission [3, 4], and these are known as "hierarchical transmission."

As for the receiver, the MAP(maximum a posteriori probability) decision criterion is well-known as the optimum. The MAP criterion is based on selecting the signal corresponding to the maximum of the set of a posteriori probability, where an a posteriori probability is the product of a conditional probability density function of the received (observed) signal and an a priori probability of the transmitted signal. We interpret the MAP criterion as a kind of source matched receiver in the sense that uses source stochastic characteristic, i.e. the a priori probability, at the receiver side. However we note that the MAP receiver may be impractical for the reception of the image signals because 1) its calculation cost is huge, and 2) it is difficult to obtain the a priori probability at the reception side.

Fortunately, such difficulties can be solved by introducing the source predictor in the receiver. Since a natural image can be modeled as a Markovian source, it is possible to predict the present signal by a prediction filter. Such a predictor provides a reduction of the calculation of the MAP algorithm and also an approximated value of the a priori probability.

In this paper we introduce a novel MAP algorithm with a predictor for the reception of wireless transmitted image signal. By the introduction of the predictor, we can reduce the calculation of the MAP algorithm and obtain the approximated value of the a priori probability. Numerical results show that the proposed receiver structer is effective and feasible for the reception of the image signals.

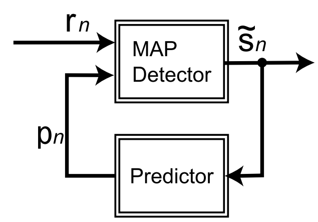

Figure 1: Concept of the new MAP receiver

2. MAP RECEIVERS FOR SOURCE DETECTION

In this section we introduce our proposed MAP receiver. Before introducing the proposed receiver we consider two conventional receivers and discuss the problem when they are applied to the source decoding.

2.1. Sequential MAP receiver (conventional)

Let the transmitted image be expressed as a sequence of the vector,

$$\mathbf{S} = [\mathbf{s}_0^{(m)}, \mathbf{s}_1^{(m)}, \cdots, \mathbf{s}_n^{(m)}, \cdots, \mathbf{s}_{N-1}^{(m)}] \quad (1)$$

and the received sequence of the vector as

$$\mathbf{R} = [\mathbf{r}_0, \mathbf{r}_1, \cdots, \mathbf{r}_n, \cdots, \mathbf{r}_{N-1}] \quad (2)$$

where $\mathbf{s}_n^{(m)}$ and $\mathbf{r}_n$ are the transmitted vector of source image and the received vector respectively, where n denotes the time index and m is the index of the source alphabet. Let $\mathbf{r}_n$ denotes the corresponding receiving vector of $\mathbf{s}_n^{(m)}$.

The sequential MAP algorithm calculates the a posteriori probability $p(\mathbf{S} \mid \mathbf{r})$ for all possible sequence of the vector, and search the maximum. Using Bayesian theorem, we get

$$p(\mathbf{S} \mid \mathbf{R}) = \frac{p(\mathbf{R} \mid \mathbf{S}) P(\mathbf{S})}{p(\mathbf{R})} \quad (3)$$

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where $P(\mathbf{S})$ is the a priori probability of the transmitted sequence of the vector.

The difficulty in the realization of the sequential MAP algorithm is twofold:

1. The calculation of equation (3) is exponentially proportional to the length of N, i.e. the order of the calculation is M^N, where M is the size of the source alphabet. This makes the sequencal MAP receiver impractical.
2. The a priori probability $P(\mathbf{S})$ is not available at the receiver side. So transmitter needs to send the a priori probability $P(\mathbf{S})$ together with the source data.

To implement the MAP receiver for the source decoding we have to reduce the calculation eventually. One of the easiest reduction methods is to relinquish the sequential detection. If the receiver detects symbol-by-symbol, the order of the calculation is reduced from $\mathcal{O}(M^N)$ to $\mathcal{O}(M)$. We call this MAP receiver symbol MAP receiver, and discuss in the following subsection.

2.2. Symbol MAP receiver (conventional)

The symbol MAP algorithm maximizes the a posteriori probability for each symbol expressed as,

$$p(\mathbf{s}_n^{(m)} \mid \mathbf{r}_n) \quad , m = 0, 1, \cdots, M-1 \tag{4}$$

Using Bayesian theorem, we get

$$p(\mathbf{s}_n^{(m)} \mid \mathbf{r}_n) \quad = \quad \frac{p(\mathbf{r}_n \mid \mathbf{s}_n^{(m)}) P(\mathbf{s}_n^{(m)})}{p(\mathbf{r}_n)} \tag{5}$$

where $P(\mathbf{s}_n^{(m)})$ is the a priori probability of the m-th alphabet being transmitted. In this case the number of the possibilities of the source vector is M, so order of the calculation is $\mathcal{O}(M)$.

It is true that the reduction of the calculation is eventually large compared to the sequential MAP receiver. However it is regretful to relinquish the sequential detection because the correlation of the neighboring symbol is quite large in the case of the image source. Are there any methods to use the correlation between neighboring symbols without an introduction of calculation explosion? To solve this problem we propose a new MAP receiver that contains the predictor with in it.

2.3. MAP receiver with predictor (proposed)

Figure 1 shows the concept of our MAP receiver. Our proposed receiver contains a predictor within it. The introduction of the predictor brings out two merits. One is the reduction of the calculation, the other is the replacement of the a priori probability to the prediction error probability.

2.3.1. Reduction of the calculation costs

Suppose $\mathbf{s}_n^{(m)}$ is transmitted at the time n. Because of Markovian characteristic, one can predict $\mathbf{s}_n^{(m)}$ from the previous sequence. Such a prediction can be expressed as

$$\mathbf{p}_n \quad = \quad h(\tilde{\mathbf{s}}_{n-1}, \tilde{\mathbf{s}}_{n-2}, \cdots, \tilde{\mathbf{s}}_0) \tag{6}$$

Table 1: Order of the calculation

algorithm	order of the calculation
sequential MAP	$\mathcal{O}(M^N)$
symbol MAP	$\mathcal{O}(M)$
MAP with prediction	$\mathcal{O}(M) + \mathcal{O}(N)$
	M:size of the source alphabet N:length of the sequence

where $\mathbf{p}_n$ is the predicted vector, and $\tilde{\mathbf{s}}_i$ is the previously detected vector. For the case of the natural images, it is sufficient to use the simple prediction function $h(\cdot)$. To do this, the receiver only searches the possibility of the transmitted vector at the time n and does not need to observe the whole sequence. Then the calculation cost depends on the size of the alphabet M and the prediction. If we use linear prediction method, this brings the reduction of the calculation form the order of $\mathcal{O}(M^N)$ to $\mathcal{O}(M) + \mathcal{O}(N)$. The calculation costs are summarized in the table 1.

2.3.2. Approximation of a priori probability

The MAP algorithm calculates metrics with the aid of predicted vector $\mathbf{p}_n$. The algorithm decides $\tilde{\mathbf{s}}_n$ as a transmitted value that maximizes the a posteriori probability $p(\mathbf{s}_n^{(m)} \mid \mathbf{r}_n, \mathbf{p}_n)$. From Bayesian theorem,

$$p(\mathbf{s}_n^{(m)} \mid \mathbf{r}_n, \mathbf{p}_n) \quad = \quad \frac{p(\mathbf{r}_n, \mathbf{p}_n \mid \mathbf{s}_n^{(m)}) P(\mathbf{s}_n^{(m)})}{p(\mathbf{r}_n, \mathbf{p}_n)} \tag{7}$$

where the numerator $p(\mathbf{r}_n, \mathbf{p}_n)$ has no effect on the decision. So we get the decision algorithm as

$$\tilde{\mathbf{s}}_n \;=\; \arg\max_{\mathbf{s}_n^{(m)}} \{p(\mathbf{r}_n, \mathbf{p}_n \mid \mathbf{s}_n^{(m)}) P(\mathbf{s}_n^{(m)})\} \tag{8}$$

With the assumption that $\mathbf{r}_n$ and $\mathbf{p}_n$ are mutually independent, we approximate $p(\mathbf{r}_n, \mathbf{p}_n \mid \mathbf{s}_n^{(m)})$ as,

$$p(\mathbf{r}_n, \mathbf{p}_n \mid \mathbf{s}_n^{(m)}) \quad \approx \quad p(\mathbf{r}_n \mid \mathbf{s}_n^{(m)}) p(\mathbf{p}_n \mid \mathbf{s}_n^{(m)}) \tag{9}$$

This assumption is valid if the predictor can predict without an effect of the channel noise, and two vector $\mathbf{r}_n$, $\mathbf{p}_n$ are mutually independent. Using this equation,

$$\tilde{\mathbf{s}}_n \;=\; \arg\max_{\mathbf{s}_i} \{p(\mathbf{r}_n \mid \mathbf{s}_n^{(m)}) p(\mathbf{p}_n, \mathbf{s}_n^{(m)})\} \tag{10}$$

In equation(10) the MAP detector only view the magnitude of the probability. Then we can get the metric by taking the logarithm of equation(10).

$$M(\mathbf{s}_n^{(m)}, \mathbf{p}_n, \mathbf{r}_n) \quad = \quad M_c(\mathbf{s}_n^{(m)}, \mathbf{r}_n) + M_p(\mathbf{s}_n^{(m)}, \mathbf{p}_n) \tag{11}$$

where $M_c(\mathbf{s}_n^{(m)}, \mathbf{r}_n)$,$M_p(\mathbf{s}_n^{(m)}, \mathbf{p}_n)$ are as follows, respectively.

$$M_c(\mathbf{s}_n^{(m)}, \mathbf{r}_n) \quad = \quad \ln p(\mathbf{r}_n \mid \mathbf{s}_n^{(m)}) \tag{12}$$

$$M_p(\mathbf{s}_n^{(m)}, \mathbf{p}_n) \quad = \quad \ln p(\mathbf{p}_n, \mathbf{s}_n^{(m)}) \tag{13}$$

Note that the metric $M(\mathbf{s}_n^{(m)}, \mathbf{p}_n, \mathbf{r}_n)$ is divided into two terms. The first term is dependent on the channel condition,

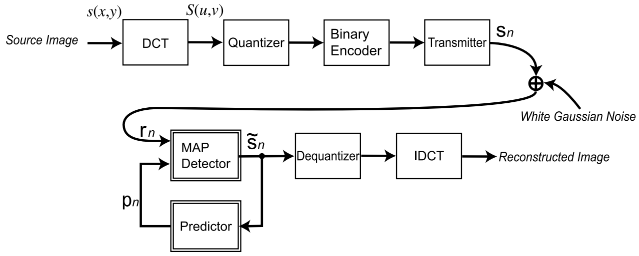

Figure 2: System model

such as noise, fading, interference and so on. The second term is dependent on the prediction.

In the equation the probability $p(\mathbf{s}_n^{(m)}, \mathbf{p}_n)$ can be seen as the prediction error probability. This fact is quite important for the case of Markovian sources. Because the symbol MAP receiver needs the a priori probability $p(\mathbf{s}_n^{(m)})$ at the receiver side, the transmitter should send additional information before communication. In the case of the MAP receiver with the predictor the a priori probability $p(\mathbf{s}_n^{(m)})$ is replaced to the prediction error distribution $p(\mathbf{s}_n^{(m)}, \mathbf{p}_n)$. Fortunately for the case of Markovian sources the prediction error probability $p(\mathbf{s}_n^{(m)}, \mathbf{p}_n)$ can be approximated relatively simple distribution such as Laplace distribution, Gaussian distribution, and so forth [7, 8].

3. SIMULATION MODEL

Figure 2 shows the transition system model.

Source image is first divided into 8×8 blocks, and discrete cosine transformed.(DCT) 8×8 block pixels $s(x, y)$ is transformed to DCT coefficient $S(u, v)$ and then quantized according to the quantization matrix (Quantization) In this paper we use the quantization defined in JPEG standard. After Quantization the quantized value is encoded to binary digits, BPSK modulated, and then transmitted thorough AWGN channel.

At the receiver, the received sequence is detected by our proposed MAP detector. In the proposed MAP predictor the predictor predicts the transmitted vector from the a priori received vector. In this paper, the predictor simply uses neighboring (left) block value as a predicted value, i.e. $\mathbf{p}_n = \tilde{\mathbf{s}}_{n-1}$.Dequantization is the inverse process of Quantization. It just multiply the quantization matrix value to the received DCT coefficients. (Dequantization) After this operation DCT coefficients are inverse discrete cosine transformed and the image is reconstructed. Finally we can get the reconstructed image.

4. NUMERICAL RESULTS

4.1. PSNR performance

The PSNR performance for the AWGN channel and the Rayleigh fading channel are shown in Figure 3. We assume the receiver knows the probability $p(\mathbf{s}_n^{(m)})$ and $p(\mathbf{s}_n^{(m)} \mid \mathbf{p}_n)$ a priori. Here we note that the aproximation of the $p(\mathbf{s}_n^{(m)})$ is far more difficult than that of $p(\mathbf{s}_n^{(m)} \mid \mathbf{p}_n)$ in the actual system. This is the great advantage of the proposed system.

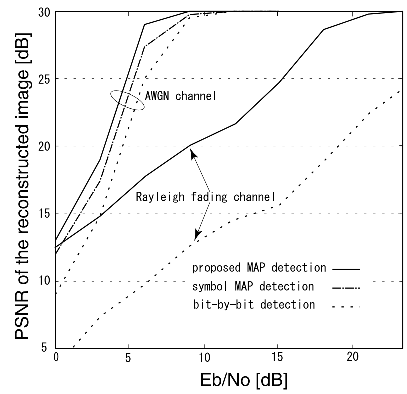

Figure 3: PSNR performance

Figure 4: Reconstructed image of the bit-by-bit receiver (Eb/No=3dB)

Examples of the reconstructed images are shown in Figure 4 and 5. The proposed receiver apparently outperforms the bit-by-bit detector. In the case of AWGN channel the proposed receiver can achieve over 3dB gain in PSNR when the channel is very noisy ($E_b/N_0 \leq 6$[dB]). In the case of the Rayleigh fading channel the gain of the proposed receiver is much greater than that of AWGN channel. This means that the metric compensation by the equation (13) has a great impact on the performance. By using the predicted vector, the receiver compensates the metric adaptively according to the signal strength. If the received signal is weak then the first term of the equation(11) is smaller compared to the second term. On the other hand, if the received signal is strong then the first term is larger than the second term.

However, in Figure 5, because of its feedback structure, the proposed receiver causes error propagation. Once a severe decision error occurs, it causes some prediction errors. The effect of error propagation is investigated in section 4.2.

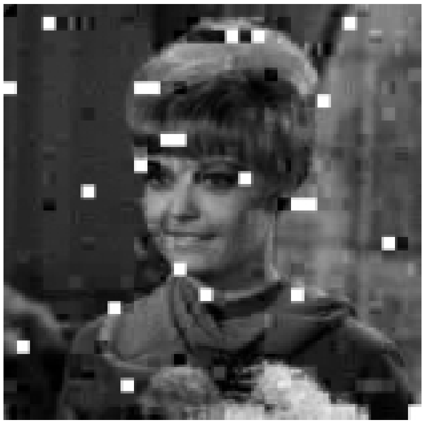

Figure 5: Reconstructed image of the proposed MAP receiver (Eb/No=3dB)

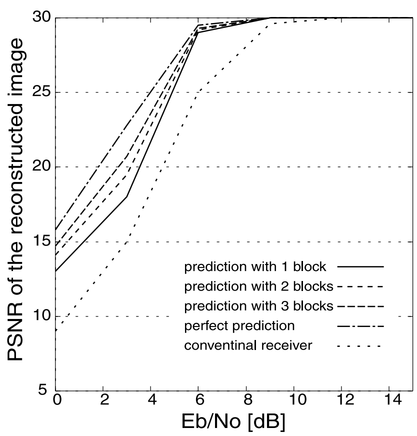

Figure 6: PSNR for different prediction

4.2. Prediction error sensitivity

We have described that the proposed receiver causes error propagation. This is inevitable for this kind of feed back systems. To reduce this error, the predictor should predict the vector more accurately. In the previous subsection predictor simply uses the neighboring block coefficient as a predicted value. For accurate prediction we take the average of the neighboring blocks. Figure 6 shows the PSNR performance. We will take the number of averaging blocks as a parameter. The perfect prediction refers to the case that the predictor predicts the transmitted vector with no error. So this case gives the upper bound of the achievable performance for the proposed MAP receiver. It can be seen that the accuracy of the prediction directly affects the performance. Furthermore, under noisy environment the degradation caused by prediction error is relatively larger.

5. CONCLUSION

In this paper we have discussed the receiver design that matched to the image signal. We have proposed the MAP receiver that contains a predictor within it. In the conventional system, it is impractical to use the MAP receiver for image signals, because of its huge calculation costs. However, with an aid of the predictor we can reduce the calculation and make it possible to use the MAP at the front of the receiver. Furthermore we can approximate the a priori probability by the prediction error distribution.

The numerical results show the validity of our proposed receiver. Especially under very noisy environments, such as wireless channels, it can achieve larger gain compared to the conventional receiver.

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6. REFERENCES

[1] J. W. Modestino et al.:"Combined Source-Channel Coding of Images",IEEE Trans. Commun., COM-27, No.11, pp.1644-1659 (Nov. 1979)

[2] J. W. Modestino et al.:"Combined Source-Channel Coding of Images Using the Block Cosine Transform",IEEE Trans. Commun., COM-29, No.9, pp.1261-1274 (Sept. 1981)

[3] Makido et al. : "Hierarchical Transmission of Huffman Code Using Multi-Code/Multi-Rate DS/SS Modulation with Appropriate Power Control",IEICE Trans. Commun., Vol.E81-B, No.12, pp.2283-2289 (Dec. 1998)

[4] Kannan Ramchandran et al.:"Multiresolution Broadcast for Digital HDTV Using Joint Source/Channel Coding",IEEE JSAC., Vol.11, No.1, pp6-23 (1993)

[5] Nam Phamdo et al.: "Optimal Detection of Descrete Markov Sources Over Discrete Memoryless Channels — Applications to Combined Source-Channel Coding",IEEE Trans. Inform. Theory, Vol.40, No.1, pp186-193 (Jan. 1994)

[6] David J. Miller et al.: "A Sequence-Based Approximate MMSE Decoder for Source Coding Over Noisy Channels Using Discrete Hidden Markov Models.",IEEE Trans. Inform. Theory, Vol.46, No.2, pp222-231 (Feb. 1998)

[7] S. Takamura et al.: "A Framework for the Coding of Prediction Error",International Picture Coding Symposium, pp.515-518, Melbourne, Australia, (March, 1996)

[8] J. J. Hwang et al.: "Transmission noise eliminations in BDPCM image",IEEE Trans. Consumer Electronics, vol. 39, pp.151-158, (Aug. 1982)