Distributed video coding for wireless sensor networks

S.J. Katti and K.R. Namuduri

Department of Electrical and Computer Engineering, College of Engineering

1. Introduction

In rate distortion theory, the rate R is usually explained as the number of bits per data sample to be stored or transmitted. The distortion D can be defined as the mean squared error (MSE) in case of image and video, but in generic terms, it is defined as the variance of the difference between input and output signal. A rate distortion function R (D) is the infimum of rates R such that (R, D) is in the rate distortion region of the source for a given D.

Wireless sensor networks are one of the fastest emerging technologies. The wireless sensors come in compact size, low-power and are inexpensive, which are programmed to perform a specific operation like the micro-controllers. The sensors are used for applications such as seismic measurement, video surveillance, measurement of temperature, pressure etc. A sensor system is composed of less-complex spatially separated sensor nodes, sending compressed, correlated information to a central processor. Example of such a system is shown in Fig.1. S[n] is a sequence of i.i.d. Gaussian random variables with variance σ_s^2, and $\{W_k[n]\}_{k=1}^{M}$ is a sequence of i.i.d Gaussian random variables N (0, σ_w^2) also called as observation noise. *M* sensors $\{F_k[n]\}_{k=1}^{M}$ with power *P* receive $\{U_k[n]\}_{k=1}^{M}$ as input, which is the corrupted version of the source due to observation noise, and outputs a sequence $\{X_k[n]\}_{k=1}^{M}$. Thus obtained encoded data is summed up at the multi-access channel [1]. Channel noise *Z[n]* is added to the signal to obtain *Y[n]*. Using *Y[n]*, the decoder *G* estimates the original source ($\hat{S}$).

In this paper we investigate progressive and multiple descriptor coding methods for encoding image and video over wireless sensor networks. The performance of the video coding methods is compared with that of theoretical limits for encoding distributed correlated sources. The image and video coding experiments discussed in this paper are aimed at analyzing the achievable rate-distortion regions in encoding correlated sources over wireless sensor networks. We investigate tradeoff between rate and distortion using discrete wavelet transform (DWT) based methods in a wireless sensor network for a distributed video coding, assuming that the channel conditions are ideal.

2. Related Work

Distributed source coding (DSC) refers to compression of multiple correlated sensor outputs that do not communicate with each other and send the compressed output to a central node. Considering the compression is lossless, for $\{X_i, Y_i\}_{i=0}^{\infty}$ i.i.d random variables for the input, the results by Slepian and Wolf in their previous paper, [2] have proved that a combined rate of *H(X,Y)* is sufficient even if the correlated signals are encoded separately. According to the Slepian-Wolf coding theorem, the achievable rate region for distributed sources **X** and **Y** is given by

$$R1 \geq H(X|Y); \quad R2 \geq H(Y|X); \quad \text{and} \quad R1+R2 \geq H(X,Y) \qquad (1)$$

Where R1 and R2 are the rates corresponding to the sources **X** and **Y** respectively. Slepian-Wolf coding is used for lossless compression. Wyner-Ziv [3] proposed a model for lossy compression. Good channel codes like turbo codes and LDPC can be used to achieve the Wyner-Ziv limits and Slepian-Wolf limits.

The rate distortion tradeoff is discussed in [4] along with a coding paradigm proposed by them. They tried to determine minimum distortion for a fixed power *MP* in the sensor network. The distortions according to the separation scheme are compared to their paradigm and have proved that their scheme performs better. The source **S** which undergoes distortion due to observation noise is encoded by *M* sensors and transmitted. This is decoded by a decoder, and from the output of the decoder, the reconstructed value of the source $\hat{S}$ is estimated. The total power utilized is considered to be *MP* for the entire network. Similar problem is discussed in [5], as a CEO problem. The maximum sum rate R_{tot} is upper bounded by the following equation. Where

$R_{tot} = R1+R2+\ldots..+RM.$

$$R_{tot} \leq \log 2(1 + M^2 P / \sigma^2_z) \qquad (2)$$

σ_z^2 refers to the variance of an i.i.d additive Gaussian noise added to the decoded sequence.

3. Experimental model

Assuming the channel to be ideal, and disregarding the observation noise, the experiments were conducted. In this scenario, a cluster of sensor nodes $F_1,..F_M$ are equipped with cameras which take the snapshots at regular intervals for surveillance. For simplicity assume that all the sensors are gathering the information from the same source. Every sensor receives U_k as input, modifies the data and gives X_k as the output. In this setup, the sensors are assumed to be capable of computing DWT to convert the input image in spatial domain to wavelet domain and transmit as desired for source coding. It is computationally efficient and beneficial to have the sensors send only the important data than sending the entire image data.

All the sensors have the entire source data and are capable of applying four levels of wavelet transforms to the original snapshot image. Since the number of sensors $M=4$, the images now at the sensors are decomposed into four levels containing high pass and low pass wavelet coefficients. Sensors F_1 *to* F_4 transmit signals X_1 to X_4 with rates R_1 to R_4, and the variance σ_1^2 to σ_4^2 respectively. Multi access channel is assumed here. The signals X_1 to X_4 are added to yield Y which gives the estimated version of the original source $\hat{S}$ at the decoder G. The source variance is σ_S^2. The variance of the estimated version of source is $\sigma^2_{\hat{S}}$. The distortion measure is defined as the mean squared error between the original source S and the reconstructed source $\hat{S}$.

The total power used on the network is reduced if sensors to decide on which sensor should transmit $\hat{S}$ depending on the channel quality and factors like priority of the data and energy constraints. However $\hat{S}$ will suffer degradation due to the channel noise and will introduce distortion. This can however be overcome by using redundancy or side information at the decoder.

4. Results

Table I shows the results obtained from the experiments conducted on two of the images. Variances var_{ij} are computed on the wavelet coefficients for different images. Where i and j ranges from 1 to 4. For $j=2, 3, 4;$ var_{ij} refers to the variance of the corresponding sub-band. When $j=1$, var_{ij} is called as variance for approximation sub-band. While i refers to the level (scale). These variances may vary from image to image due to the distribution of the intensities in the image. Variances for the entire image in transform domain and spatial domain are also shown in the table.

5. Conclusions

Rate-distortion variation is studied and observed with experiments on different images. It can be noticed that for a video or an image transmission, it is always better to de-correlate the data signal using transforms before transmission. Reconstruction of the image can be done even with fewer wavelet coefficients transmitted by the sensors. In this work, channel has been considered to be ideal. In practical terms, channel properties can be modeled to study the rate-distortion region for video coding in a sensor network.

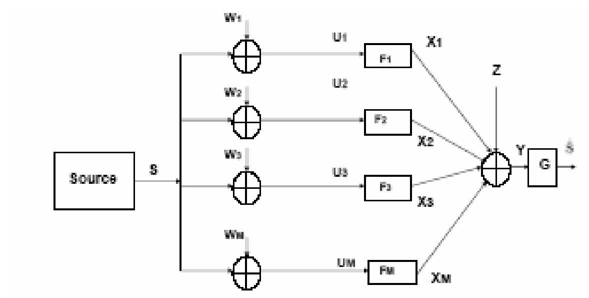

Fig.1Example for a sensor network in a distributed source coding.

Variances for sub bands with different scales					
Variance	var11	var12	var13	var14	var22
Rose Image	3643.01	357.72	162.22	454.83	163.82
Lena Image	1470.31	509.67	122.61	665.82	380.21

Variance for the entire image in Spatial domain and Wavelet domain		
Variance	Spatial domain	Wavelet Domain
Rose Image	4349.40	93.07
Lena Image	2282.50	183.91

Table I: Variances of different images in wavelet domain for different sub bands and varying scales.

6. References

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