Effective Resource Management in Visual Sensor Networks With MPSK

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***Abstract*—The problem of resource management in a Direct Sequence Code Division Multiple Access (DS-CDMA) wireless Visual Sensor Network (VSN) with M-array Phase Shift Keying (MPSK) modulation in an Additive White Gaussian Network (AWGN) channel was considered in this paper. Achieving maximum video quality, in spite of the prevailing network resource constraints, is of utmost importance in VSN applications. Our optimization scheme is based on the Nash Bargaining Solution (NBS). The nodes in the network negotiate in order to determine their transmission parameters (transmission powers; source and channel coding rates for each node). The task is to optimize the transmission powers (which are continuous) and the source and channel coding rates (which are discrete) for all the network nodes, while taking advantage of the improved bandwidth spectral efficiency provided by the higher order constellation.**

***Index Terms*—Cross layer optimization, game theory, MPSK, Nash bargaining solution, visual sensor network.**

I. Introduction

THE reliability of streaming applications over wireless links suffers, as a result of the challenges associated with wireless networks. The output at the application layer can be improved by jointly optimizing parameters at the various layers of the network stack, while considering quality of service (QoS) requirements. This can be achieved by allocating resources (compression ratio at the application layer, channel coding rate at the data link layer, and transmit power at the physical layer) to video camera nodes that negotiate according to the Nash Bargaining Solution (NBS) approach, in order to improve the overall objective video quality of the VSN.

Previous research in this field focuses on the important issue of controlling power consumption in VSN [1], [2]. However, solutions presented in [1] did not optimize the overall end-to-end video quality. In other recent work, several approaches have been presented towards achieving an end-to-end video quality by reducing the intra-cell interference with the aid of cross-layer optimization schemes [3]–[5]. However, in previous work only BPSK modulation was considered. Using BPSK limits the bandwidth spectral efficiency (information rate that can be transmitted over a given bandwidth), so a higher spectral efficiency can be obtained by using higher order constellations such as QPSK and 8-PSK. Also in [6], though the authors look at optimizing the cross layer design techniques for video streaming over cooperative wireless networks with distributed control, they did not consider the effect of higher order constellation schemes.

Our framework considered spatially distributed nodes, each equipped with a camera capable of recording scenes with high motion and low motion. In order to reduce the effect of interference and operate optimally within the limits of the network resource constraints, we need to establish a joint network resource allocation scheme that can enhance the global video quality.

In this paper, the cross-layer resource allocation scheme is based on the Nash Bargaining Solution (NBS) from game theory. Resources are allocated by the NBS based on negotiations between the nodes, coordinated by the centralized control unit. A Centralized Coordination Unit (CCU) coordinates the resource allocation among the nodes. A multi-user/multi-access channel access method (DS-CDMA) was employed, as well as H.264 AVC video codec. In order to achieve a flexible coding scheme, Rate Compatible Punctured Convolutional Codes (RCPC) were used. Our method ensures fair allocation of resources to obtain satisfactory utilities for all nodes and takes into consideration the various channel conditions, the video content characteristics, and the resource needs of the other nodes so as to achieve the required level of *Quality of Service* (QoS). The source coding rate and the channel coding rate take on discrete values, whereas the transmission power is allowed to take on values from a continuous set. Hence, the resulting optimization problem is a mixed-integer problem, and it is solved using Particle Swarm Optimization (PSO) [7].

The remainder of the article is organized as follows; in Section II, we discuss the system model and the MPSK modulation scheme using trellis coding. The node clustering and optimization framework is presented briefly in Section III. Selected computational results are provided in Section IV which is followed by some concluding remarks in Section V.

II. System Model

The focus of this work is the analysis of a multi-node cross-layer optimization technique for resource management in VSNs. This is a cross-layer network performance optimization scheme involving three different layers (physical, data link, and application): optimization of the transmission powers at the physical layer, optimal channel coding rates at the data link layer, and compression rates at the application layer. Using BPSK modulation and RCPC codes, allowed the channel coding rate to be optimized because variable rates are allowed, however the

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channel coding rate has to be fixed for Trellis Coded Modulation when using higher order constellations.

Our framework assumes that the network nodes access the wireless VSN using the DS-CDMA channel access method. The VSN is comprised of low-weight spatially distributed video cameras (referred to as nodes) and a CCU which coordinates the resource allocation activities of the nodes, so as to maintain good end-to-end video quality. All nodes in a DS-CDMA system transmit over the same bandwidth, while a unique spreading code is used to identify the transmission of each node. The power S_k of node k (measured in Watts) is given by $S_k = E_k R_k$, where E_k is the received energy-per-bit and R_k is the total transmission bit rate which is defined as $R_k = R_{s,k}/R_{c,k}$, for a node $k = 1, 2, \ldots, K$. $R_{s,k}$ is the source coding rate, and $R_{c,k}$ is the channel coding rate. Therefore, the energy-per-bit to multiple-access-interference (MAI) ratio can be defined as:

$$\frac{E_k}{l_0} = \frac{\frac{S_k}{R_k}}{\sum_{j \neq k}^{K} \frac{S_j}{W_t}}, \quad k = 1, 2, \ldots, K \tag{1}$$

where $l_0/2$ is the two-sided power spectral density due to MAI, and it is measured in Watts/Hertz. W_t is the total bandwidth measured in Hertz. The subscript k denotes the current node while j denotes the interfering nodes.

The video coding was based on the H.264/MPEG-4 AVC video coding standard. Channel coding is required in order to prevent channel errors and as such improve the overall video quality. In this paper, for BPSK modulation scheme, channel coding is achieved by using the Rate Compatible Punctured Convolutional (RCPC) codes [8]. The Viterbi upper bound for bit error probability, P_b is given by:

$$P_b \leq \frac{1}{P} \sum_{d=d_{free}}^{\infty} c_d P_d \tag{2}$$

where P is the code period, d_{free} is the free distance of the code, c_d is the information error weight and P_d is the probability that the wrong path at distance d is selected. In an AWGN channel using the Binary Phase Shift Keying (BPSK) modulation scheme, P_d is given by:

$$P_d = Q\left(\sqrt{\frac{2dR_cE_k}{N_0}}\right) \tag{3}$$

R_c is the channel coding rate, and E_k/N_0 is the energy-per-bit normalized to the MAI ratio for the corresponding node k.

MPSK Trellis Coding Modulation: Our goal is to investigate the performance of the VSNs when different modulation schemes such as QPSK and 8-PSK were used for modulation as opposed to BPSK. With QPSK, a rate 1/2 convolutional codes can be used. Using QPSK gives the same performance, in terms of bit error probability evaluation, because although the free squared Euclidean distance is halved in comparison to BPSK, the amount of information transmitted has doubled [9]. However, using higher-order constellations with RCPC codes constitutes some problems for our coding scheme to effectively recover the signals at the receiver side; hence the need to use Trellis Coded Modulation (TCM).

Trellis Coded Modulation is a bandwidth-efficient modulation that is based on convolution coding. This consists of a combined convolutional codes and MPSK, e.g. rate 2/3 convolutional codes and 8-level Phase Shift Keying (8-PSK). With TCM, higher-order constellation modulation is combined with convolutional codes to improve the error rate performance while keeping the bandwidth unaltered. At the receiver, the received signal is demodulated and then decoded. The performance is dependent on the Euclidean distance between the transmitted signal sequences instead of the free Hamming distance of the convolutional code. The Viterbi ML-decoding algorithm is used to decode the trellis code.

The basic idea involves transmitting h bits/waveform in each signalling interval using a modulator with a set of $2^{\mathrm{h}+1}$ constellation points such that the signal gets further apart, increasing the Euclidean distance between the signals in the set.

The redundancy in the number of available waveforms is exploited through a proper choice, in each signalling interval, of the 2^{h} waveforms necessary to transmit h bits. The choice in each interval is made on the basis of the past transmitted signals through the memory of the encoder. A detailed description and tutorial of TCM schemes and their applications can be found in [9], [10].

The union upper bound for the bit error probability, P_b, for TCM is given by [9]:

$$P_b \leq \frac{1}{n} \sum_{\substack{i \\ \{d_i^2 \in D\}}} B_i Q\left[\sqrt{\frac{d_i^2 R_c E_k}{2N_0}}\right] \tag{4}$$

where n is the number of bits per symbol, B_i is the average number of bit errors on error paths with distance d_i^2, and R_c is the channel coding rate.

As mentioned earlier, the work of the CCU is to allocate network resources to the nodes. Degradation due to lossy compression and channel error affects the video received by the CCU. The CCU need to be able to estimate the expected video quality at the receiver prior to resource allocation. In this work, in order to estimate the expected video distortion $E[D_{s+c,k}]$ for each node k at the receiver, we assumed the Universal Rate Distortion Characteristics (URDC) for each node k:

$$E[D_{s+c,k}] = \alpha\left[\log_{10}\left(\frac{1}{P_b}\right)\right]^{-\beta} \tag{5}$$

where α and β are positive parameters which depend on both the motion level sequence and the source coding rate of each node k [6]. Their values are determined by using the mean square optimization from some $(E[D_{s+c,k}], P_b)$ pairs that are obtained experimentally. Once the values of α and β are determined from some experimental values, the expression in (5) can be used to estimate the expected video distortion given $\mathrm{P_b}$.

There exist limitations concerning the total available bit rate that can be used by each node for both source and channel coding. The maximum bit rate at which each node should transmit data is the same. Hence the source coding rate and channel coding rate are interdependent, increasing one leads to a reduction of the other.

Taking into considerations the required constraints, the goal is to enable the CCU to optimize the allocation of network resources (source coding rate, channel coding rate, and the power level) to each node k in order to minimize the end-to-end expected distortion. Combining all previous equations, the expected distortion $E[D_{s+c,k}]$ for node k can be written as a function of the source coding rate $R_{s,k}$, the channel coding rate $R_{c,k}$, as well as of the transmission powers, $S = (S_1, S_2, \ldots, S_K)^{\mathrm{T}}$ of all nodes participating in the network. $E[D_{s+c,k}]$ expression for BPSK is given in (6) while similar expression can be obtained for MPSK by substituting (4) into (5).

$$E[D_{s+c,k}](R_{s,k}, R_{c,k}, S) = \alpha \left[\log_{10} \left(\frac{1}{\frac{1}{P} \sum_{d=d_{free}}^{\infty} c_d Q\left(\sqrt{\frac{2dR_c E_k}{N_0}}\right)} \right) \right]^{-\beta} \quad (6)$$

where $k = 1, 2, \ldots, K$ denotes the corresponding node.

III. Node Clustering and Optimization Framework

Our framework divides the available nodes into two major categories in order to characterize heterogeneous data. The first group of node cluster captures videos with high levels of motions whereas the other group cluster captures video with low levels of motion or relatively stationary fields. It was assumed that the nodes can only detect high-motions and low-motions scenes. The classification was done in order to avoid the confusion caused by the high computational complexity in cases where the different video sequences contain a range of different motion levels. Therefore, the vectors can be identified as $R_{s+c,high} = (R_{s,high}, R_{c,high})^T$, $R_{s+c,low} = (R_{s,low}, R_{c,low})^T$, and $S = (S_{high}, S_{low})^T$, where $R_{s+c,high}$ is a vector that represents the high-motion class nodes combining both the source coding rate $R_{s,high,}$, as well as the channel coding rate $R_{c,high}$; in a similar manner $R_{s+c,low}$ represents the combination for the low-motion class nodes and S is a vector that includes the powers for the high and low motion class respectively.

For the network resource allocation, we employed quality-driven optimization criteria using the Nash Bargaining Solution (NBS), which is based on game theory. In NBS, the nodes try to find the Nash equilibrium (maximize the Nash product) based on the bargaining power of each node and the disagreement point. For a detailed discussion of the Nash Bargaining Solution see [11], [12].

The utility function, $\mathrm{U_k}$, constitutes a measure of relative satisfaction for each user. In our problem, the PSNR is used as the utility function and it is defined as:

$$\mathrm{U_k} = 10 \log 10 \left(\frac{2552}{\mathrm{E[D_{s+c,k}]}} \right) \quad \text{for a node } \mathrm{k} = 1, 2, \ldots, \mathrm{K}.$$

In order to achieve global optimization among the nodes, we employed the particle swarm optimization (PSO) algorithm. PSO was used due to its ease of implementation, and its quick convergence. These are essential characteristics for optimality in several wireless VSN applications.

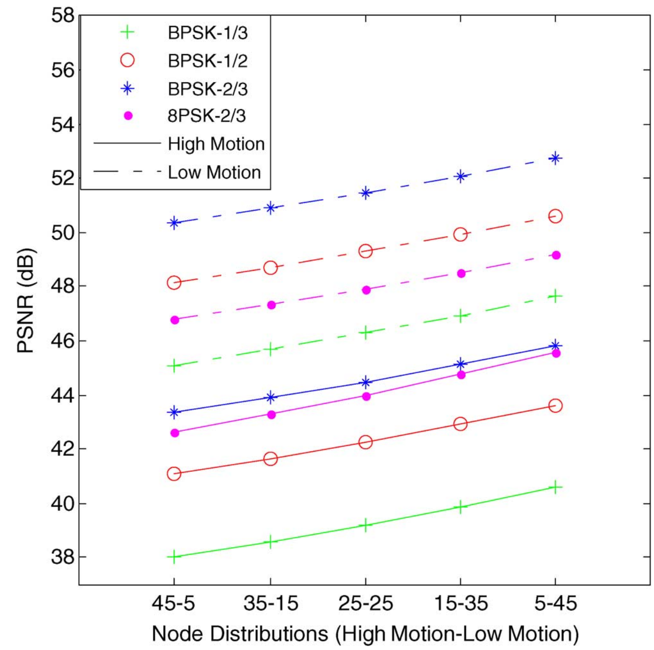

Fig. 1. PSNR under different modulation using n.NBS.

IV. Computational Results

We considered a VSN comprising of 50 nodes, clustered in two motion classes. The bit error probabilities that were used for the calculation of α and β for the expected video distortions equation were $P_b = 10^{-7}$, 10^{-6}, and 10^{-5}, while the distortions for each video sequence was assessed on an average over 300 repetitions. We use RCPC code with $\mathrm{R_{c,z}}$ rates 1/3, 1/2 and 2/3 for BPSK, and Ungerboeck 16-state 8-PSK trellis code with rate 2/3. Subscript z represents the class of nodes (high, low). The transmission power, S. can take on continuous values from 5.0 to 15.0 measured in Watts.

For the implementation of the NBS, two assumptions were made concerning the bargaining powers. The first approach considers that each node has the same weight, and it is referred to as n.NBS criterion, on the other hand the second approach consider that each class of nodes has an equivalent role in the resource allocation game, and it is referred to as c.NBS criterion. This implies that for the n.NBS criteria, the number of nodes in the cluster determines the weight ratio (no. of nodes in low-motion cluster: no. of nodes in high-motion cluster) whereas for the c.NBS the weight ratio is always 50-50 regardless of the number of nodes in each cluster.

The bandwidth, Wt is chosen to be 60 MHz and the disagreement point dp is taken to be (28, 28)T dB. The result listed in Table I is for the n.NBS criterion, while Table II result is for c.NBS criterion. The results in the tables were used to generate the plots in Fig. 1 and Fig. 2. The result implies that it is better to take advantage of better spectral efficiency provided by the higher order constellations since the PSNR values are still within acceptable limit.

Fig. 1 and 2 illustrated the performance of the NBS for different constellation sizes. The system performed better with BPSK modulation schemes in comparison to higher order constellation schemes as expected. However the performance with

TABLE I
N.NBS FOR VARIOUS NODE DISTRIBUTIONS, $\mathrm{R_k} = 96\ \mathrm{KBPS}, \mathrm{dp} = (28, 28)^{\mathrm{T}}\ \mathrm{dB}$

N.NBS for various node distributions, R_k = 96 KBPS, dp = $(28,28)^T$ dB								
Node Distribution	BPSK 1/3		BPSK/QPSK 1/2		BPSK 2/3		8PSK 2/3	
	$PSNR_h$	$PSNR_l$	$PSNR_h$	$PSNR_l$	$PSNR_h$	$PSNR_l$	$PSNR_h$	$PSNR_l$
45 - 5	38.0094	45.1009	41.0828	48.1693	43.3247	50.3686	42.6278	46.7804
35 - 15	38.577	45.6738	41.6522	48.7234	43.8869	50.911	43.2933	47.3295
25 - 25	39.1896	46.2819	42.261	49.3142	44.4839	51.4851	43.9996	47.9129
15 - 35	39.8549	46.9349	42.913	49.9448	45.1194	52.0938	44.7492	48.5322
5 - 45	40.5792	47.6408	43.6126	50.6189	45.7974	52.7404	45.5451	49.1894

TABLE II
C.NBS FOR VARIOUS NODE DISTRIBUTIONS, $\mathrm{R_k} = 96\ \mathrm{KBPS}, \mathrm{dp} = (28, 28)^{\mathrm{T}}\ \mathrm{dB}$

C.NBS for various node distributions, R_k = 96 KBPS, dp = $(28,28)^T$ dB								
Node Distribution	BPSK 1/3		BPSK/QPSK 1/2		BPSK 2/3		8PSK 2/3	
	$PSNR_h$	$PSNR_l$	$PSNR_h$	$PSNR_l$	$PSNR_h$	$PSNR_l$	$PSNR_h$	$PSNR_l$
45 - 5	36.3761	54.9473	39.3922	57.9396	41.6013	60.0708	40.7501	55.7083
35 - 15	37.2669	48.9952	40.1683	52.2372	42.3124	54.4906	41.7761	50.4044
25 - 25	39.1896	46.2819	42.261	49.3142	44.4839	51.4851	43.9996	47.9129
15 - 35	42.4758	44.75	45.7592	47.6686	48.0902	49.772	47.6354	46.5276
5 - 45	45.0784	46.6586	48.3663	49.618	50.736	51.7188	50.2825	48.331

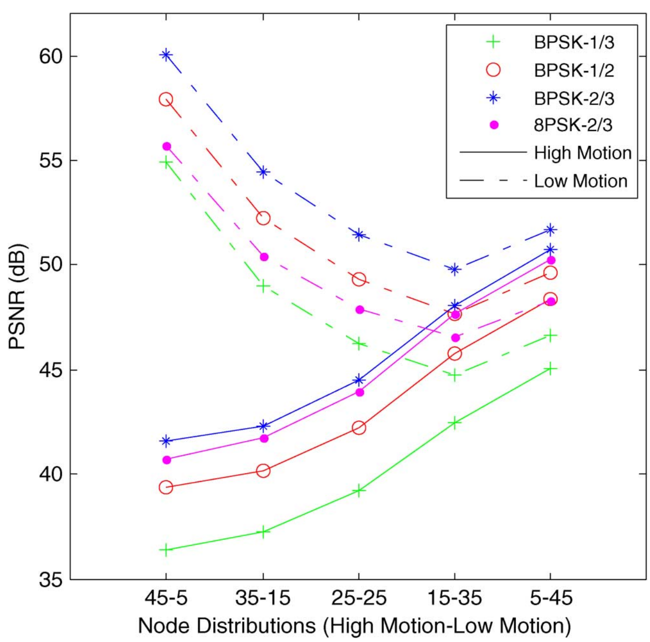

Fig. 2. PSNR under different modulation using c.NBS.

higher order constellation schemes falls within the acceptable QoS required for video applications. The system model will allow us to determine when to use higher order constellation without violating the QoS requirements. The added advantage of using higher order constellation is that we can achieve a better bandwidth spectral efficiency.

V. Conclusion

We considered the problem of optimizing network resources (source coding rate, channel coding rate, and transmission powers) between a high-motion and a low-motion class of nodes in wireless DS-CDMA VSNs using different constellation sizes (MPSK). We have been able to show that we can achieve an acceptable PSNR with better bandwidth spectral efficiency, while using MPSK with the TCM scheme. In the future we intend to look at MPSK modulation scheme under multipath fading environment.

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