PRIORITY–BASED CROSS-LAYER OPTIMIZATION FOR MULTIHOP DS–CDMA VISUAL SENSOR NETWORKS

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ABSTRACT

We propose a novel priority–based approach that enables the optimal control of the transmission power and the use of the available network resources of a multihop *Direct Sequence Code Division Multiple Access* (DS–CDMA) *Wireless Visual Sensor Network* (WVSN). The WVSN nodes can either monitor different scenes (source nodes) or retransmit videos of other nodes (relay nodes). Moreover, in real environments the source nodes monitor different scenes that may be of dissimilar importance. Hence a higher end–to–end quality is demanded for those nodes that are assigned a higher priority. Overall, each node has different power and resource requirements, and therefore a global optimization approach is required. For the purpose of enhancing the delivered video quality of the source nodes with respect to their priorities, we define and suggest the use of priority–based optimization criteria. Experimental results that assess the proposed approach are provided and conclusions are drawn.

***Index Terms*—** Multihop Wireless Visual Sensor Network, Prioritization, Cross–Layer Resource Allocation, DS–CDMA.

1. INTRODUCTION

Traditional *Wireless Visual Sensor Networks* (WVSNs) consist of low–weight, energy–constrained sensors with wireless communication capability that are equipped with video cameras, and a *Centralized Control Unit* (CCU) that collects the information from the visual sensors, applies channel and source decoding to the received video of each sensor and manages the resource allocation among all the network nodes. Since the transmission range of a sensor is limited, the recorded video sequences may need to be transmitted using relay nodes until they reach the CCU via a multihop path. An example of a two–hop WVSN is depicted in Fig. 1. In addition, a node's transmissions cause interference to other transmitting nodes within its transmission range, leading to degradation of the quality of the received videos. Moreover, the nodes may record scenes with different amounts of motion, so their resource requirements are different. Due to all these factors, resources (transmission power, source coding rate, channel coding rate) have to be optimally allocated using a quality–aware joint strategy, in order to maintain the end–to–end distortion at a low level for all nodes.

Over the last few years, several techniques have considered the problem of power and rate allocation in a multihop wireless network. A game–theoretic analysis is proposed in [1], based on the Nash Equilibrium, where the selection of the transmission powers of the nodes aims at maximizing the total number of bits they transmit per unit of energy. The problem of transmission power control (TPC) so as to prolong the lifespan of the WVSNs is also considered in [2]. Specifically, a study is conducted on TPC at the physical layer, which incorporates all the components of energy consumption. Furthermore, various algorithms, such as the LEACH protocol and the Directed Diffusion algorithm tackle the routing problem of WVSNs in an energy–aware manner [3]. The present work proposes a cross–layer optimization scheme across the physical, network and application layer to achieve optimal video transmission over multihop DS–CDMA WVSNs. Our work moves beyond the state–of–the–art, since along with the problem of efficiently allocating the transmission power, we appropriately assign the source coding rate and the channel coding rate to each visual sensor while at the same time we determine the transmission power and the channel coding rate for each relay node. Furthermore, the optimization is quality–driven, i.e. the objective is to optimize a function of the received video qualities for each visual sensor, as opposed to optimizing network parameters such as bit error rate, throughput, etc.

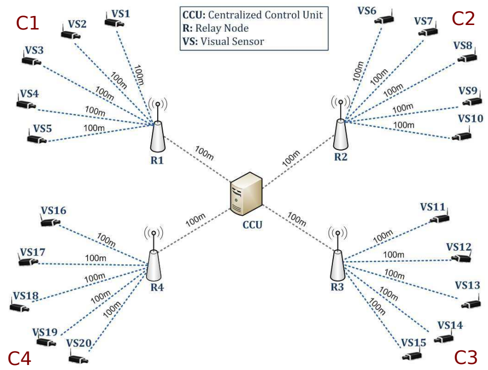

Fig. 1. Example of a WVSN topology with two hops.

A priority–based approach for resource allocation in a multihop wireless network is presented in [4], according to which the transmission rates of prioritized flows are adjusted in a way that the global network utility is maximized under the delay constraints of the transmitted flows. Each flow may have different delay constraints, thus different time priority. Another approach, applied however on a simpler, single–hop WVSN topology, uses a criterion based on the Nash Bargaining Solution from Game Theory [5]; the nodes join the bargaining game with bargaining powers that conform to the motion level of their recorded video. For the priority–based optimization of our considered resource allocation problem we introduce a novel priority–based criterion, which aims at minimizing the weighted aggregation of the expected end–to–end distortion of all videos. The weights are defined with the purpose of assigning different priority to the transmitted video of each source node. The priorities reflect the requirements for the delivered video quality, namely the higher the priority of a source node, the higher its requirement for video quality.

The rest of the paper is organized as follows. The architecture of the considered multihop WVSN is described in Section 2. The resource allocation problem and the employed optimization criteria are presented in Section 3. Experimental results are presented in Section 4, while conclusions are drawn in Section 5.

2. SYSTEM MODEL

We consider a multihop WVSN with K source nodes and M relay nodes. All nodes communicate with each other using DS–CDMA at the physical layer. Each node uses L chips for a single bit transmission, thus a node n is associated with a spreading sequence of length L. As in [6], the interference from other nodes to the node of interest is modeled as additive white Gaussian noise. For a WVSN with $N = K + M$ nodes, a node's received power at a specific distance from node n is $S_n^{\text{rec}} = E_n R_n$ in Watts. E_n is the energy–per–bit and $R_n = R_{\text{s},n}/R_{\text{c},n}$, $n = 1, 2, \dots, N$, is the total transmission bit rate for source and channel coding, where $R_{\text{s},n}$ is the source coding rate and $R_{\text{c},n}$ the channel coding rate. We assume that interference exists on each link across the path to the CCU from nodes that are in the effective transmission range. Letting $\mathbf{J}$ be the set of interfering nodes for each hop h, it is assumed that $|\mathbf{J}| \leq N$, where $|.|$ denotes the cardinality of a set. The energy–per–bit to *Multiple Access Interference* (MAI) and noise ratio is different in each link, depending on the nodes causing interference to the considered node n and can be expressed for the h–th hop of a path as follows:

$$\frac{E_n}{I_0 + N_0} = \frac{\frac{S_n^{\text{rec}}}{R_n}}{\sum_{j=1, j\neq n}^{|\mathbf{J}|} \frac{S_j^{\text{rec}}}{W_{\text{t}}} + N_0} \tag{1}$$

where $I_0/2$ is the two sided noise power spectral density due to MAI, $N_0/2$ is the two sided noise power spectral density of background noise in W/Hz, W_{t} is the total bandwidth in Hz and $S_{\text{j}}^{\text{rec}}$ is the received power of node $j \in \mathbf{J}$ that causes interference to node n. Given that the transmission bit rate is equal to R_{chip}/L, where the chip rate R_{chip} is the same for all nodes of the network, we can obtain different values for the transmission bit rates of each hop using a different spreading code length L. A smaller L increases the transmission bit rate but it also decreases the energy per bit. Thus, the bit error rate is also increased.

As signal energy decreases across the link from a source node to a receiver node, the effective transmission range of a node n and the received signal power S_n^{rec} at a distance d from node n have to be estimated. For this purpose, we take into account two well–known radio propagation models; the Free Space model and the Two Ray Ground model [7]. Regarding these models, let h_r and h_t be the heights of receiver and transmitter antennas respectively, $l \geq 1$ the system loss factor, λ the wavelength of the carrier signal, G_t and G_r the transmit and receive antenna gains, respectively, and S_n^{trans} the transmission power of node n. For a node n at distance d from the receiver, the *cross–over distance* $d_0 = (4\pi h_r h_t \sqrt{l})/\lambda$ determines which model is used as follows:

(i) If $d < d_0$, the received power is given by the Friis formula of Free Space model: $S_n^{\text{rec}}(d) = S_n^{\text{trans}} \dfrac{G_t G_r \lambda^2}{((4\pi)^2 d^2 l)}$.

(ii) If $d > d_0$, the received power is given by: $S_n^{\text{rec}}(d) = S_n^{\text{trans}} \dfrac{G_t G_r h_t^2 h_r^2}{(d^4 l)}$.

For a certain transmission power of a node, the received power at a distance d can be derived from the aforementioned models.

The video sequences are compressed using the H.264/AVC standard. Also, regarding channel coding, we used *Rate Compatible Punctured Convolutional* codes (RCPC) [8], so as to estimate the bit error probability using Viterbi's upper bounds. The nodes of the considered WVSN may transmit video sequences with different motion levels. The CCU manages the received power, source coding and channel coding rate aiming at the optimal performance for all nodes.

3. PROPOSED METHOD

We propose an efficient method for solving the resource allocation problem for a multihop DS–CDMA WVSN, formulated as follows: Under the constraint that imposes the same transmission bit rate R_j, $j \in \mathbf{J}$, for the interfering nodes of hop h, determine for each source node k the source coding rate $R_{\text{s},k}$, the channel coding rate $R_{\text{c},k}$ and the received power $S_{\text{S},k}^{\text{rec}} \in \left[S_{\text{S}}^{min}, S_{\text{S}}^{max}\right]$, and for each relay node m the channel coding rate $R_{\text{c},m}$ and the received power $S_{\text{R},m}^{\text{rec}} \in \left[S_{\text{R}}^{min}, S_{\text{R}}^{max}\right]$, so that a function of the overall end–to–end expected video distortion $E\{D_{\text{s+c},k}\}$ for each source node k is minimized, i.e.

$$(R_{\text{s}}^*, R_{\text{c}}^*, S^{\text{rec}*}) = \arg \min_{R_{\text{s}}, R_{\text{c}}, S^{\text{rec}}} f(E\{D_{\text{s+c},1}\}, \dots, E\{D_{\text{s+c},K}\}),$$

where $S^{\text{rec}} = (S_{\text{S},1}^{\text{rec}}, \dots, S_{\text{S},K}^{\text{rec}}, S_{\text{R},1}^{\text{rec}}, \dots, S_{\text{R},M}^{\text{rec}})^\top$;
$R_{\text{s}} = (R_{\text{s},1}, \dots, R_{\text{s},K})^\top$;
$R_{\text{c}} = (R_{\text{c,S},1}, \dots, R_{\text{c,S},K}, R_{\text{c,R},1}, \dots, R_{\text{c,R},M})^\top$
are the vectors of received power, source coding rate and channel coding rate of source nodes $k = 1, 2, \dots, K$ and relay nodes $m = 1, 2, \dots, M$, respectively. The type of the function $f(.)$ is different for each one of the deployed optimization criteria.

Assuming that $Pb_{h,k}$ is the bit error probability for hop h and the source node k, then the end–to–end bit error probability across an H–hop path for k is:

$$Pb_k = 1 - \prod_{h=1}^{H} (1 - Pb_{h,k}). \tag{2}$$

In conjunction with Eq. (2), the expected distortion due to lossy compression and channel errors is given by the model used in [9]:

$$E\{D_{\text{s+c},k}\} = \alpha_k \left[\log_{10} \left(\frac{1}{1 - \prod_{h=1}^{H} (1 - Pb_{h,k})} \right) \right]^{-\beta_k} \tag{3}$$

where parameters $\alpha_k > 0$ and $\beta_k > 0$ depend on the motion level of the transmitted video sequence and the source coding rate and may vary in time. Values of α_k for high motion video sequences are generally greater than those for low motion video sequences [5]. These parameters are determined using mean square optimization from a few ($E\{D_{\text{s+c},k}\}$, Pb_k) pairs and the $E\{D_{\text{s+c},k}\}$ values are estimated at the encoder using the *Recursive Optimal Per–pixel Estimate* (ROPE) model [10]. As an estimate of the bit error probabilities for the transmitting node n at the h–th hop (after channel decoding), we use the Viterbi upper bound for RCPC codes, which is

$$Pb_{h,n} = \frac{1}{2P} \sum_{d=d_{\text{free}}}^{\infty} c_d \text{erfc} \left(\sqrt{d R_{\text{c},n} \left[\frac{E_n}{I_0 + N_0} \right]} \right) \tag{4}$$

where P is the period of the used code, d_{free} is the free distance of the code, c_d is the information error weight, and erfc(.) is the complementary error function given by $\text{erfc}(z) = \left(2 \int_z^{\infty} \exp(-t^2) dt\right)/\sqrt{\pi}$.

For the minimization of the distortion, three priority–based optimization criteria are used. The first two criteria are based on the

Criterion Name	Bargaining Power per Source Node
e.NBS	$bp_k = 1/K$
w.NBS	$bp_k = \alpha_k / \sum_{j=1}^{K} \alpha_j; j = 1, 2, \ldots, K$

Table 1. Bargaining powers for the e.NBS and w.NBS criteria.

Nash Bargaining Solution from Game Theory, which allocates resources as a result of the bargaining game among the nodes, while the last criterion minimizes a weighted aggregation of the distortions of the videos of all nodes. These criteria result in global optimization problems that are resolved by the Particle Swarm Optimization (PSO) algorithm, an effective and efficient algorithm with linear complexity to both the number of the iterations and utilized particles [11].

3.1. Nash Bargaining Solution

Each node can achieve a better video quality by joining the game instead of avoiding cooperation, under the guarantee that it can get a minimum video quality if negotiations fail (disagreement point dp) [12]. As utility function U_k we used the PSNR of the received video of each node k, given by: $U_k = 10 \log_{10}(255^2/E\{D_{\text{s+c},k}\})$. Due to the fact that $E\{D_{\text{s+c},k}\}$ depends on the source coding rate, the channel coding rate and the received power, the defined utility function depends on the same parameters, as well.

Based on the Nash Bargaining Solution we define the bargaining game as a pair $(\mathbf{U}, dp)$, where the *feasible set* $\mathbf{U} \subseteq \mathbb{R}^K$ is the set of all possible allocations resulting from different combinations of the vectors of the received power from all nodes $S^{\text{rec}} = (S^{\text{rec}}_{\text{S},1}, \ldots, S^{\text{rec}}_{\text{S},K}, S^{\text{rec}}_{\text{R},1}, \ldots, S^{\text{rec}}_{\text{R},M})^\top$, the source coding rates of the source nodes $R_{\text{s}} = (R_{\text{S},1}, \ldots, R_{\text{S},K})^\top$ and the channel coding rates $R_{\text{c}} = (R_{\text{c,S},1}, \ldots, R_{\text{c,S},K}, R_{\text{c,R},1}, \ldots, R_{\text{c,R},K})^\top$ for all nodes, and $dp \in \mathbb{R}^K$ is the vector of all the disagreement points, namely $dp = (dp_1, \ldots, dp_K)^\top$. The Nash Bargaining Solution can be written as a function $F(.)$ of $\mathbf{U}$ and dp. It satisfies four axioms, which guarantee that it is *feasible*, *Pareto optimal*, *invariant to affine transformations*, and *independent from irrelevant alternatives* [12]. The Nash Bargaining Solution can be found by maximizing the Nash Product:

$$F(\mathbf{U}, dp) = \arg\max_{U} (U_1 - dp_1)^{bp_1} (U_2 - dp_2)^{bp_2} \ldots (U_K - dp_K)^{bp_K}, \tag{5}$$

subject to the constraints: $(U_k - dp_k) > 0$ and $\sum_{k=1}^{K} bp_k = 1$.

The minimum acceptable PSNR ($dp \in \mathbf{U}$) depends on the QoS requirements of the application and can be determined by the system designer. The bargaining power bp_k of each node indicates the advantage it has in the bargaining game; a node with a higher bargaining power is favored by the rules of the bargaining game compared to a node with a lower bargaining power. Based on the bargaining powers, two criteria are formulated as shown in Table 1. The e.NBS criterion assumes that all bargaining powers are equal, while the w.NBS criterion assigns to each source node a motion–related bargaining power. With w.NBS the resources are allocated according to the motion level of the source nodes as it is reflected by parameters α_k, so that a source node with higher motion level has a higher bargaining power [5].

Test Case 1								
	C1		**C2**		**C3**		**C4**	
Criterion	PSNR(dB)	CS	PSNR(dB)	CS	PSNR(dB)	CS	PSNR(dB)	CS
e.NBS	32.5422	3	40.5000	3	33.7773	2	33.8292	2
w.NBS	39.1853	3	28.9987	1	29.8229	1	30.1971	1
MWAD	36.7435	3	30.4577	1	32.6942	2	32.9295	2
Test Case 2								
	C1		**C2**		**C3**		**C4**	
Criterion	PSNR(dB)	CS	PSNR(dB)	CS	PSNR(dB)	CS	PSNR(dB)	CS
e.NBS	30.2792	3	39.1806	3	32.8663	2	32.9030	2
w.NBS	33.6779	3	28.9038	1	31.3255	2	31.6311	2
MWAD	33.4342	3	29.5509	1	31.6767	2	31.9092	2

Table 2. PSNR and Source and Channel Coding Rates per Test Case.

3.2. Minimization of the Weighted Aggregation of Distortions (MWAD)

According to this criterion, we form a function that expresses the weighted aggregation of the expected distortion of all source nodes. The objective is to determine the vectors of the received power S^{rec} from all nodes, the source coding rates R_{s} for the source nodes and the channel coding rates R_{c} for all nodes, so that this function is minimized. To put it formally:

$$(R^*_{\text{s}}, R^*_{\text{c}}, S^{\text{rec}\,*}) = \arg\min_{R_{\text{s}}, R_{\text{c}}, S^{\text{rec}}} \sum_{k=1}^{K} w_k E\{D_{\text{s+c},k}\}, \tag{6}$$

where $w_k = \alpha_k / \sum_{j=1}^{K} \alpha_j$ (with $\sum_{k=1}^{K} w_k = 1$) is the weight for each source node k. The weights in our work are tuned according to parameters α_k, which reflect the motion level of each recorded video. Hence, high motion nodes have a higher priority in the minimization of their distortion, and as a result in the enhancement of the delivered video quality.

4. EXPERIMENTAL RESULTS

In the considered WVSN, we assume that neighboring visual sensors monitor the same area. Due to this assumption, the 20 nodes are organized in four clusters of the same cardinality $\{C1, C2, C3, C4\}$. As the CCU is out of the transmission range of the source nodes, four relay nodes $\{R1, R2, R3, R4\}$ retransmit the received videos of each cluster to the CCU as shown in Fig. 1. Interference exists among the nodes in the clusters as they transmit their videos to their corresponding relay node. Moreover, the relay nodes interfere with each other when they retransmit videos to the CCU. The five nodes of each cluster transmit video sequences of the same motion level, thus the (α_k,β_k) parameters within a cluster's nodes are assumed to be equal and invariant in time. In order to evaluate the performance of our method, several cases with different motion amounts per cluster and various levels of power spectral density of background noise N_0 have been tested. Two of them are presented as they distinctly demonstrate the effectiveness of the priority–based criteria for different visual sensors resource requirements. In Test Case 1, N_0 is equal to 0 pW/Hz, while in Test Case 2 it is equal to 1 pW/Hz. In both test cases, the nodes of cluster $C1$ transmit high motion videos while the nodes of cluster $C2$ transmit low motion videos and the nodes of clusters $C3$ and $C4$ transmit different medium motion videos. The notions “low”, “medium” and “high” motion are used for video sequences of similar motion levels with “Akiyo”, “Salesman” and “Foreman” QCIF video sequences of 15 fps, respectively.

The range of $[100, 500]$ mW is used for the transmission powers of all source nodes and the range $[100, 5000]$ mW for the relay nodes. For all links, the total bandwidth W_t is 5 MHz. For the

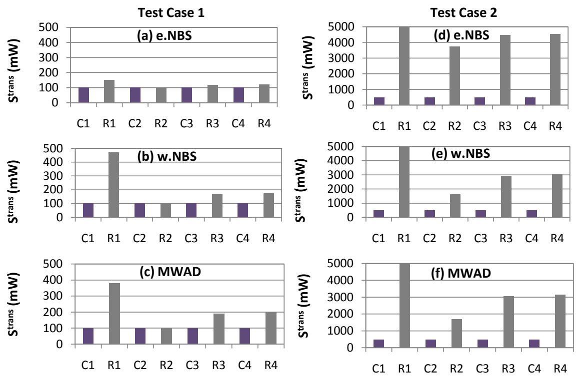

Fig. 2. Allocated Transmission Power per Test Case.

source nodes in clusters, the valid source and channel coding rate set is $CS \in \{1 : (32\text{kbps}, 1/3), 2 : (48\text{kbps}, 1/2), 3 : (64\text{kbps}, 2/3)\}$ and the transmission bit rate R_k is equal to 96 kbps. For the relay nodes the transmission bit rate R_m is 480 kbps and the channel coding rate is set to 2/3. RCPC codes with mother rate 1/4 are used and the size of the link layer packets is 400 bits. A number of 30 independent experiments were conducted for each criterion. Our experiments have shown that the PSO algorithm performs efficiently for all employed criteria and both test cases using a number of parameters equal to 12, a number of particles equal to 80 and a maximum number of iterations equal to 500.

Table 2 depicts the achieved PSNRs and the allocated CS of all the optimization criteria in each test case. In both test cases, e.NBS offers the lowest PSNR to high motion nodes whereas the low motion nodes have the highest PSNR. Both w.NBS and MWAD generally achieve to enhance the PSNRs according to the motion level, i.e. they offer better quality to nodes that transmit high motion video. Nonetheless, MWAD treats more fairly the low and medium motion nodes as it offers higher PSNR than w.NBS can achieve. More specifically, in the first test case, if w.NBS is used, the high motion nodes have a gain of 2.4418 dB in comparison with the case that MWAD is used; the low and medium motion nodes have a gain of 1.4590–2.8713 dB when MWAD is employed. In the second test case, low and medium motion nodes have a gain of 0.2781–0.6471 dB if MWAD is used. This criterion achieves higher average PSNR compared to w.NBS. Also, observing Table 2, it can be pointed out, that in both test cases, w.NBS and MWAD choose the source and channel coding rate combination that offers the highest available source coding rate to the high motion nodes. On the contrary, a higher channel coding rate is preferred for the low and medium motion nodes.

As far as the transmission power allocation is concerned (Fig. 2), in both test cases and with every criterion, the transmission powers of the relay nodes are in accordance with the motion level of the transmitted video sequences. Namely, the transmission powers for the relay nodes of the clusters with high motion nodes are higher than the transmission powers of the relays of low and medium motion clusters. Moreover, considering the background noise results in higher transmission power demand for all nodes in order to keep the bit error rate probability per hop low and maintain high quality.

5. CONCLUSIONS

In this paper, a cross–layer resource allocation scheme for multihop DS–CDMA WVSN is proposed. Two priority–based criteria that allocate the resources with respect to the motion level of the recorded video scenes are proposed and compared. w.NBS maximizes the distortion–related Nash Product by using motion–based bargaining powers, while MWAD minimizes the weighted aggregation of the expected end–to–end video distortions by using motion–based weights. The e.NBS criterion is the Nash Bargaining Solution with equal bargaining powers. The conducted experiments have illustrated that both priority–based criteria achieve their goal even in the case that the background noise is considered, resulting in higher video quality (in terms of PSNR) for the source nodes that view scenes of high motion compared to e.NBS. However, MWAD achieves higher average PSNR, whereas w.NBS demands lower transmission power.

6. REFERENCES

[1] S. Betz and H.V. Poor, “Energy efficiency in multi-hop CDMA networks: A game theoretic analysis considering operating costs,” in *Proc. IEEE Intern. Conf. on Acoustics, Speech and Signal Processing*, 2008, pp. 2781–2784.

[2] M. Meghji and D. Habibi, “Transmission power control in multihop wireless sensor networks,” in *Proc. Third Intern. Conf. on Ubiquitous and Future Networks*, 2011, pp. 25–30.

[3] J. N. Al-Karaki and A. E. Kamal, “Routing techniques in wireless sensor networks: a survey,” *IEEE Wireless Communications*, vol. 11, no. 6, pp. 6–28, 2004.

[4] P. Jayachandran and T. Abdelzaher, “Bandwidth allocation for elastic real-time flows in multihop wireless networks based on network utility maximization,” in *Proc. Intern. Conf. on Distributed Computing Systems*, 2008, pp. 849–857.

[5] A. V. Katsenou, L. P. Kondi, and K. E. Parsopoulos, “Resource management for wireless visual sensor networks based on individual video characteristics,” in *Proc. IEEE Intern. Conf. on Image Processing*, 2011, pp. 149–152.

[6] Y. S. Chan and J. W. Modestino, “A joint source coding-power control approach for video transmission over CDMA networks,” *IEEE Journ. on Selected Areas in Communications*, vol. 21, no. 10, pp. 1516–1525, 2003.

[7] T. S. Rappaport, *Wireless Communications: Principles and Practice*, Prentice Hall PTR, 1996.

[8] J. Hagenauer, “Rate-compatible punctured convolutional codes (RCPC codes) and their applications,” *IEEE Trans. on Communications*, vol. 36, no. 4, pp. 389–400, 1988.

[9] E. S. Bentley, L. P. Kondi, J. D. Matyjas, M. J. Medley, and B. W. Suter, “Spread spectrum visual sensor network resource management using an end-to-end cross-layer design,” *IEEE Trans. on Multimedia*, vol. 13, no. 1, pp. 1377–1380, 2011.

[10] R. Zhang, S. L. Regunathan, and K. Rose, “Video coding with optimal inter/intra-mode switching for packet loss resilience,” *IEEE Journ. on Selected Areas in Communications*, vol. 18, no. 6, pp. 966–976, 2000.

[11] K. E. Parsopoulos and M. N. Vrahatis, *Particle Swarm Optimization and Intelligence: Advances and Applications*, Information Science Publishing (IGI Global), 2010.

[12] K. Binmore, *Playing for Real: A Text on Game Theory*, Oxford University Press, 2007.