Resource Management in Visual Sensor Networks using Nash Bargaining Solution in Generalized Fading

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Abstract— **In this paper we consider the problem of resource management for a Direct Sequence Code Division Multiple Access (DS-CDMA) wireless Visual Sensor Network (VSN) in a generalized fading environment. In a VSN application, the primary goal is ensuring that maximum video quality is achieved in spite of the prevailing network resource constraints. The Nash Bargaining Solution (NBS) was used in determining the transmission power and source and channel coding rates for each node. The nodes in the network negotiate in order to determine their transmission parameters. 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. Particle Swarm Optimization (PSO) is used to solve the mixed-integer optimization that arises. The analysis was carried out for a myriad of wireless multipath fading environments using a unified moment generating function (MGF) approach.**

Keywords **— visual sensor network, cross layer optimization, Nash bargaining solution, game theory, multipath fading, particle swarm optimization, moment generating function.**

I. Introduction

Present day service demand requires that wireless systems should be able to support heterogeneous types of data (audio, images, video) at different data rates. However, wireless video communications suffer from several network resource constraints such as bandwidth, energy and computational complexity limitations. The performance of a wireless Visual Sensor Network (VSN) can be affected by the bit rate available for video transmission. This work focuses on wireless Direct Sequence Code Division Multiple Access (DS-CDMA) VSN. Challenges involved in wireless VSN include bandwidth and power limitations, problems due to channel conditions such as multipath fading, interference and background noise.

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. The goal of this paper is to coordinate the behavior and performance of each individual node of a VSN with the aim of optimizing the overall performance of all the nodes, in terms of video quality.

We shall employ game theory as a means of dynamically managing the available network resources for optimum performance.

Previous research in this field focuses on the important issue of controlling power consumption in VSN [1, 2, 3]. However, solutions presented in [1, 2] 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 [4, 5, 6]. Though more often than not, wireless communication systems are affected by multipath fading channels. In previous work, the authors did not consider multipath fading environment, only AWGN channel environments were considered. Hence, there is a need to have proper characterizations of the available solutions in a generalized fading environment. We employed a Moment Generating Function (MGF) approach which has a lower computational complexity compared to other methods for fading environment analysis; in addition to that, it can be easily generalized as long as the MGF of the fading environment exist.

In this paper, the cross-layer resource allocation scheme is based on the Nash Bargaining Solution (NBS) from game theory. Previous research work has been able to show that the NBS provided a better result than the *Minimization of the Average Distortion* (MAD) and the *Minimization of the Maximum Distortion* (MMD) [4]. Resources are allocated by the NBS based on negotiations between the nodes, coordinated by the centralized control unit. 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 discrete values, whereas the transmission power is allowed to take value from a continuous set. Hence, the resulting optimization problem is a mixed-integer problem, and it is solved using the Particle Swarm Optimization (PSO) [7].

The remainder of the article is organized as follows; in Section II, we discuss the system model and derive the expected distortion expression under fading environment. The node clustering and optimization framework is presented briefly in Section III. Selected computational results are

1*Visiting scientist under a National Research Council Research Associateship Award at the Air Force Research Laboratory.Approved for Public Release; Distribution Unlimited: 88ABW-2012-3512, 20 June 2012 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 visual sensor networks. The technique assumes that three different layers (physical, data link, and application) cooperate with each other for network performance optimization, in terms of video quality. Transmission powers are determined at the physical layer; optimal channel coding rates are selected at the data link layer, while compression rates are chosen at the application layer. The Centralized Control Unit (CCU) coordinates collaboration among the layers by communicating with all nodes on the network in order to request changes in transmission parameters.

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 $k = 1, 2, ..., K$. $R_{s,k}$ 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:

$$\frac{E_k}{N_0} = \frac{S_k / R_k}{\sum_{j \neq k}^{K} S_j / W_t}, \qquad k = 1, 2, ..., K \tag{1}$$

where $N_0/2$ 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 H.264/MPEG-4 AVC video coding standard was used to encode the videos captured at the source nodes. Since severe video degradation can result from errors in the transmitted compressed video, channel coding is required to provide system resistance/immunity to channel errors. In this paper, channel coding is achieved by using the Rate Compatible Punctured Convolutional (RCPC) codes [8]. RCPC codes are families of codes that can be decoded with the same Viterbi decoder. The Viterbi upper bound for bit error probability, P_b is:

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

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 Binary Phase Shift Keying (BPSK) scheme, P_d is:

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

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.

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. Changes in the network resources may be requested by the CCU of the nodes, therefore it is expedient for the CCU 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:

$$E[D_{s+c,k}] = \alpha \left[\log_{10}\left(\frac{1}{P_b}\right)\right]^{-\beta} \tag{4}$$

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. Rather than calculating the URDCs based on experimental results for every possible P_b, we calculated the expected distortion for a few packet loss rates associated with specific bit error rates using experiments and then use the model given in (4).

It is worth mentioning here that limitations exist concerning the total available bit rate that can be used by each node for both source and channel coding. Each node should transmit data with the same maximum bit rate. It therefore implies that the source coding rate and channel coding rate are interdependent.

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, $S = (S_1, S_2, ..., S_K)^{\mathrm{T}}$ of all nodes participating in the network.

$$E[D_{s+c,k}](R_{s,k}, R_{c,k}, S) = \alpha \left[\log_{10}\left(\frac{1}{\frac{1}{P}\sum_{d=d_{free}}^{\infty} c_d Q\left(\sqrt{\frac{2dR_c E_k}{N_0}}\right)}\right)\right]^{-\beta} \tag{5}$$

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

Fading Channel

The expected distortion in a BPSK modulation scheme for each node can be evaluated under a multipath fading environment. In fading channels where the channel gain changes within a symbol period or where interleaving occurs, the average error probabilities should be used instead of (3). Using the identity in [10], given by:

$$Q\left(\sqrt{2\gamma}\right) \approx 0.5a_1 e^{-b_1\gamma} + 0.5c_1 e^{-2b_1\gamma} \tag{6}$$

where $a_1 = 0.2938,\ b_1 = 1.0483,\ c_1 = 0.5070$

the union bound for P_d given in (3) can be shown as:

$$P_d \approx 0.5a_1 e^{-b_1\gamma} + 0.5c_1 e^{-2b_1\gamma} \tag{7}$$

where $\gamma = dR_c E_k / N_0$

The above expression is a very good approximation for P_d [10]. Moreover, the above expression is in a desirable exponential form, and averaging over fading distribution is simply the Laplace Transform of the applicable pdf, i.e.,

$$\begin{aligned}\overline{P_d} &= \int_0^\infty P_d f_\gamma(\gamma)d\gamma \\ &\approx 0.5a_1\phi_\gamma(b_1) + 0.5c_1\phi_\gamma(2b_1)\end{aligned} \tag{8}$$

where $\phi_\gamma(s)$ is the moment generating function. It is interesting to note that even in different fading environments; the expression in (8) is very close to the actual result.

The moment generating function of different fading distribution can be expressed in general form as [11]

$$F(A,B,C) = \left(\frac{A}{A+s\gamma}\right)^C \exp\left(\frac{-Bs\gamma}{A+s\gamma}\right) \tag{9}$$

For instance, using the parameters in Table 1, the moment generating function for a Nakagami fading channel will be expressed as

$$\phi_\gamma(s) = \left(\frac{m}{m+s\gamma}\right)^m$$

TABLE 1. MGF PARAMETERS

	A	B	C
Rayleigh	1	0	1
Nakagami	m	0	m
Rice	1+K	K	1

Therefore, it follows that the expression for the expected distortion $E[D_{s+c,k}]$ for node k under multipath fading environment can be obtained by simply replacing the P_d expression of (3) which was used in (5) with the expression derived in (8).

$$E[D_{s+c,k}](R_{s,k}, R_{c,k}, S) = \alpha\left[\log_{10}\left(\frac{1}{\frac{1}{P}\sum_{d=d_{free}}^{\infty} c_d \overline{P_d}}\right)\right]^{-\beta} \tag{10}$$

III. NODE CLUSTERING AND OPTIMIZATION FRAMEWORK

To characterize the notion of heterogeneous data, one group of node cluster captures videos with high levels of motion whereas the other group cluster captures video with low levels of motion or relatively stationary fields. Hence, after node clustering and taking into consideration the constraint, 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, $R_{s+c,low}$ represents 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) [12], which is based on game theory. In NBS, the nodes tries to find the Nash equilibrium based on the bargaining power of each node and the disagreement point.

Nash Bargaining Solution

The bargaining solution that fulfils the following axioms [13] for the feasible set **U** and the disagreement point *dp* is known as the Nash Bargaining Solution (NBS).

1. a) *Individual Rationality (IR):* $F(U, dp) \geq dp$
   b) *Pareto Optimality (PO):* $U_k > F(U, dp) \Rightarrow U_k \notin U$
2. *Invariance to Affine Transformations (*INV*)*: Given any strictly increasing affine transformation τ(.) then $F(\tau(U), \tau(dp)) = \tau(F(U, dp))$
3. *Independence of Irrelevant Alternative (IIA):* If $dp \in Y \subseteq U$ then $F(U,dp) \in Y \Rightarrow F(Y,dp) = F(U,dp)$

The first axiom states that the solution should lie in the bargaining set. The second axiom implies the invariance to affine transformations, which means that the solution is not affected by an affine transformation scaling of the utility function or the disagreement point.

The NBS is the solution that maximizes the Nash product:

$$F(U,dp) = \arg\max_{U \geq dp} \prod_{k=1}^{K}\left(U_k - dp_k\right)^{a_k} \tag{11}$$

such that $\sum_{k=1}^{K} a_k = 1, \quad a_k \geq 0,$ for each node *k*.

a_k is the *bargaining power* of each node and shows the advantage of each player in the game. A higher bargaining power implies the player has more advantage and vice versa. Since we are considering node grouping (clustering) into high- and low-motion class of nodes, the vectors of utility and disagreement points for the motion classes become $U = (U_h, U_l)^T$ and $d = (d_h, d_l)^T$, respectively. Therefore considering the node classes, the Nash product given earlier becomes

$$F(U,dp) = \arg\max_{U \geq dp}\left(U_h - dp_h\right)^{a_h}\left(U_l - dp_l\right)^{a_l} \tag{12}$$

such that $a_h + a_l = 1$.

The utility function, U_k, constitutes a measure of relative satisfaction for each user. In our problem, it is defined equivalent to the PSNR:

$$U_k = 10\log_{10}\left(\frac{255^2}{E\left[D_{s+c,k}\right]}\right) \text{ for a node } k = 1, 2, \ldots, K.$$

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, the provision of optimal global solution, and its quick convergence. These are essential characteristics for optimality in several wireless VSN applications.

IV. Computational Results

We considered a VSN comprising of 100 nodes, clustered in two motion classes. The bit error probabilities that were used for the calculation of expected video distortions 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. The RCPC codes used for channel coding had a mother code rate ¼. Since the total bit rate constraint is R_k = 96 kbps, the following are the available source-channel coding rate pairs ($R_{s,k}$, $R_{c,k}$):

$$\left(R_{s,k}, R_{c,k}\right) \in \left\{(32kbps, 1/3), (48kbps, 1/2), (64kbps, 2/3)\right\}$$

Subscript k represents the class of nodes (high, low). The transmission power S can take continuous values from 5.0 to 15.0 measured in Watts. The disagreement point dp = (28,28).

For the implementation of the NBS, two assumptions were made concerning the bargaining powers. The first approach consider 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.

The bandwidth, W_t is chosen to be 100 MHz and the disagreement point dp is taken to be $(28, 28)^T$ dB. The result listed in Table 2 is for the n.NBS criterion for AWGN channel, while Table 3 result is for Nakagami fading channel (with fading index m=3), and Table 4 is for a Rice fading channel (with the Rice fading index K=5). Similar results were obtained for the c.NBS criterion as well.

TABLE 2.

N.NBS for various node distributions, R_k = 96 kbps, W_t = 100 MHz, $dp = (28,28)^T$dB (AWGN Channel)					
Node Distribution	$R_{c,high}$	$R_{c,low}$	S_h/S_l	$PSNR_h$	$PSNR_l$
90 - 10	2/3	1/2	1.4691	41.8039	46.9773
70 - 30	2/3	1/2	1.4641	42.3367	47.4992
50 - 50	2/3	1/2	1.4583	42.901	48.0508
30 - 70	2/3	1/2	1.4517	43.4985	48.6334
10 – 90	2/3	1/2	1.4445	44.1312	49.2485

TABLE 3.

N.NBS for various node distributions, R_k = 96 kbps, W_t = 100 MHz, $dp = (28,28)^T$dB (Nakagami Channel, m=3)					
Node Distribution	R_{ch}	R_{cl}	S_h/S_l	$PSNR_h$	$PSNR_l$
90 - 10	1/3	1/3	1.6994	26.7766	33.4653
70 - 30	1/3	1/3	1.6884	26.9114	33.7543
50 - 50	1/3	1/3	1.6775	27.0515	34.0496
30 - 70	1/3	1/3	1.6666	27.1977	34.3531
10 – 90	1/3	1/3	1.6558	27.3513	34.667

TABLE 4.

N.NBS for various node distributions, R_k = 96 kbps, W_t = 100 MHz, $dp = (28,28)^T$dB (Rice Channel, K=5)					
Node Distribution	R_{ch}	R_{cl}	S_h/S_l	$PSNR_h$	$PSNR_l$
90 - 10	1/3	1/3	2.2021	25.1814	30.6481
70 - 30	1/3	1/3	2.1712	25.3102	31.0093
50 - 50	1/3	1/3	2.144	25.4453	31.3669
30 - 70	1/3	1/3	2.12	25.589	31.7276
10 – 90	1/3	1/3	2.0987	25.745	32.0992

Fig. 1 and Fig. 2 illustrated the performance of the NBS under different channel condition. Fig. 1 is the plot for the n.NBS criterion while Fig. 2 is the corresponding plot for the c.NBS criterion. As expected the system performed better under AWGN channel condition in comparison to the multipath fading environment. The low motion class always result into higher PSNR compared to the high-motion class.

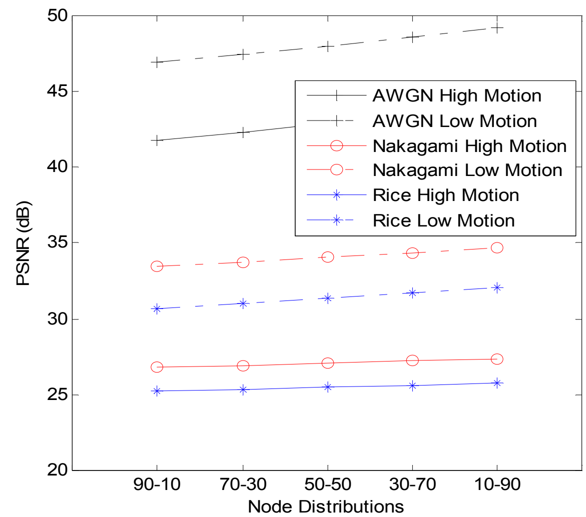

Fig. 1. PSNR under different channel condition using n.NBS

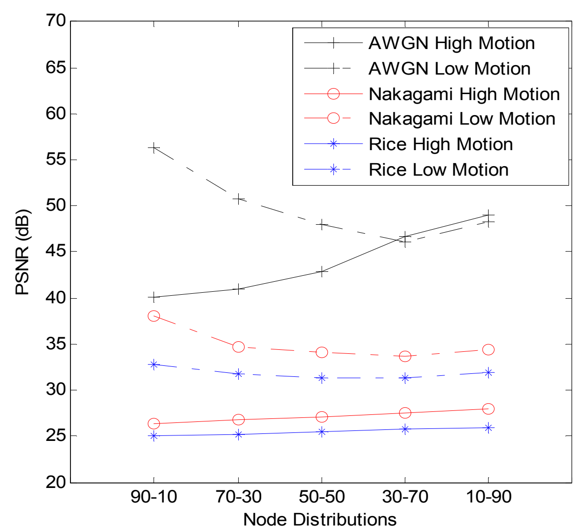

Fig. 2. PSNR under different channel condition using c.NBS

Fig. 3 shows a plot of the power ratios for the two schemes under different fading environments. It can be seen that the power ratio stays relatively constant across all node distributions considered for the n.NBS criterion regardless of the fading environment whereas there is significant changes in the power ratios for the c.NBS criterion for different node distributions.

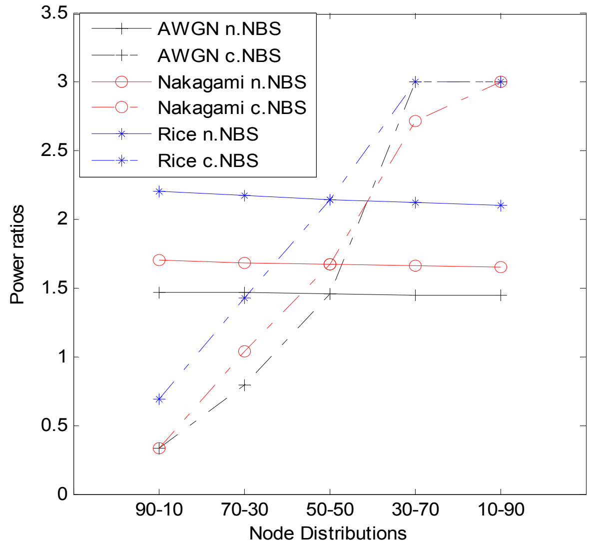

Fig. 3. Power ratios for n.NBS and c.NBS

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 multi-rate wireless DS-CDMA VSN. We have been able to derive required equations for adequate characterization and analysis in multi-path fading environment using the moment generating function approach. Previous research work either only considered AWGN channel or derived cumbersome equations for analysis. Our results revealed that fading should be an important consideration in developing algorithms meant for airborne communications, since there are significant differences between the outputs at the application layer (measured with the Quality of Service metric, Peak Signal to Noise Ratio (PSNR)) under AWGN channel conditions, in comparison to more realistic fading environments. Our MGF approach provides a simple and generalized method for analysing the VSN in multipath fading environment.

References

[1] T.H. Hu and M. M. K. Liu, “A new power control function for multirate ds-cdma systems,” *IEEE Trans. on Communications,* vol. 47, no. 6, pp. 896 – 904, 1999.

[2] C. W. Sung and W. S. Wong, “Power control and rate management for wireless multimedia cdma systems,” ,” *IEEE Trans. on Communications,* vol. 49, no. 7, pp. 1215 – 1226, 2001.

[3] S. Misra, M. Reisslein, and G. Xue, “A survey of multimedia streaming in wireless sensor networks,” *IEEE Communications Survey Tutorials,* vol. 10, no. 4, pp. 18-39, 2008.

[4] L. P. Kondi and E. S. Bentley, “Game-theory based cross-layer optimization for wireless DS-CDMA visual sensor networks,” in *Proc. IEEE International Conference on Image Processing,* Hong Kong, 2010.

[5] E. S. Bentley, L. P. Kondi, J. D. Matyjas, M. J. Medley, and B. W. Suter, “Spread spectrum visual sensor networks resource management using an end-to-end cross layer design,” *IEEE Transactions on Multimedia,* 2011.

[6] K. Pandremmenou, L. P. Kondi, and K. E. Parsopoulos, “Optimal power allocation and joint source-channel coding for wireless DS-CDMA visual sensor networks,” in *Proc. SPIE Electronic Imaging Symposium (Visual Information Processing and Communication II),* San Francisco, CA, 2011.

[7] K. E. Parsopoulos and M. N. Vrahatis, “Particle swarm optimization and intelligence: Advances and applications,” *Information Science Publishing,* (IGI Global), 2010.

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

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

[10] O. Olabiyi, and A. Annamalai, “ASER Analysis of Cooperative Non-Regenerative Relay Systems over Generalized Fading Channels,” *Proc. IEEE ICCCN’11,* Maui, Aug. 2011.

[11] A. Annamalai, and C. Tellambura, “An MGF-Derivative based Unified Analysis of Incoherent Diversity Reception of M-ary Orthogonal Signals over Fading Channels,” *Proc. IEEE Vehicular Technology Conference*, pp. 2404 - 2408, Oct. 2001.

[12] Pandremmenou, K.; Kondi, L.P.; Parsopoulos, K.E.; , "Optimal power allocation and joint source-channel coding for wireless DS-CDMA visual sensor networks using the Nash Bargaining Solution," *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on* , vol., no., pp.2340-2343, 22-27 May 2011.

[13] K. Binmore, Playing for Real: A text on Game Theory. Oxford University Press, 2007.