RESOURCE MANAGEMENT FOR WIRELESS VISUAL SENSOR NETWORKS BASED ON INDIVIDUAL VIDEO CHARACTERISTICS

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ABSTRACT

We propose a novel approach for the optimized network resource management of a Direct Sequence Code Division Multiple Access (DS-CDMA) visual sensor network. The visual sensors monitor different scenes of varying motion levels, thus different network resources need to be allocated to each sensor. For each recorded scene, our approach considers its individual content-related parameters, in contrast with previous methods that group the sensors according to the amount of motion present in the scene and assign the same transmission parameters to all members of a group. Cross-layer optimization is used across the physical, link and application layers. Based on quality-driven criteria (under the constraint of constant chip rate), we allocate to each node a suitable continuous power level, a discrete source coding rate and a discrete channel coding rate. The resulting problem is solved using the Particle Swarm Optimization algorithm. Experimental results demonstrate the performance and efficiency of each criterion.

Index Terms— Cross-layer Optimization, Visual Sensor Network, Nash Bargaining Solution, DS–CDMA, Particle-Swarm Optimization

1. INTRODUCTION

The present work focuses on wireless Direct Sequence Code Division Multiple Access (DS–CDMA) Visual Sensor Networks (VSN). VSN provide a variety of multimedia services like environmental monitoring, surveillance, automated tracking, etc. Wireless VSN comprise two parts: a) low-weight distributed nodes that are equipped with video cameras and b) a centralized control unit. The nodes communicate with the centralized control unit over the network layer. The centralized control unit applies channel and source decoding to obtain the received video from each node. A significant issue that the control unit has to deal with is the resource allocation among the nodes. Having a network of sensors that are monitoring different scenes means that each sensor has different resource requirements. Besides this, the issue of interference to the transmission of the other nodes and the degradation of the received video quality arises. Owing to all these, a joint strategy for the optimal allocation of network resources (transmission power, source coding and channel coding rate) is demanded in order to maintain good end-to-end video quality.

In previous cross-layer optimization schemes [1, 2, 3], the classification of the nodes into two classes, low-motion and high-motion, was performed according to the amount of motion in the scenes they are imaging. Thus, the power and network resources were allocated equally for all sensors within each class. In our work, we consider

each node as individual and not as part of a class, with its own time-varying video and transmission parameters, requesting a fair resource allocation.

In this paper, we propose the use of the Nash Bargaining Solution (NBS) from Game Theory as an optimization criterion. The NBS has been used before in video transmission, as in [2, 4]. In [2], it was used for the cross-layer optimization of a DS–CDMA visual sensor network with partitioning of the nodes into two classes, low-motion and high-motion, according to the amount of motion in the scene they were imaging. All bargaining powers for both classes were considered equal. In [4], the NBS was used in video streaming for the problem of allocating the total bit rate among a few video nodes. Two assumptions were made for the assignment of the bargaining powers to each user: a) using equal bargaining powers and b) using different bargaining powers, which affects the resource allocation tradeoffs. The different bargaining powers were assigned using an algorithm that aims to achieve similar quality levels at the cost of overall system performance. In the present work, a novel content-aware version of NBS is introduced. A weight that is tuned according to the motion level is assumed for each user resulting in different bargaining powers, and not necessarily equal as considered in previous works [2].

Furthermore, the transmission power is allowed to take continuous values within a reasonable prespecified range [3], instead of assuming only specific discrete values as in [1, 2]. The source coding rate and the channel coding rate can assume only discrete values. Due to the fact that the resulting optimization problem is a mixed-integer problem, a stochastic optimization technique is deployed, the Particle Swarm Optimization (PSO) [5].

The rest of the paper is organized as follows. In section 2, the basic architecture of the considered VSN is described. The proposed optimization criteria are detailed in section 3. The experimental results are presented in section 4, and conclusions are drawn in section 5.

2. CONSIDERED DS–CDMA VSN

In the physical layer, DS–CDMA is used, where all nodes transmit on the same frequency. For a single bit transmission, L chips are transmitted by a node, hence each node k is associated with a spreading code s_k (vector of length L). This means, that in order to transmit the i-th bit of a bitstream, node k actually transmits $b_k(i)s_k$, which is a vector of L chips with $b_k(i)$ taking the values 1 or -1 according to the value of the transmitted bit [1]. As in [6], we assume that the interference received from all other nodes at the node of interest can be modeled as additive white Gaussian noise. Background and thermal noise are considered negligible compared with the interference and reasonably ignored. Assuming that the VSN comprises K nodes, each user k operates at power level $S_k = E_k R_k$ in Watts, where E_k is the energy-per-bit, and $R_k = R_{s,k}/R_{c,k}$ with $k = 1, 2, ..., K$,

is the total bit rate used for source and channel coding ($R_{s,k}$ is the source coding rate and $R_{c,k}$ the channel coding rate for node k). Then, the energy per bit to Multiple Access Interference (MAI) ratio becomes

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

where $N_0/2$ is the two sided noise power spectral density due to MAI in Watts/Hertz, and W_t is the total bandwidth in Hertz.

The H.264/AVC video coding standard is used for the source coding of the captured videos. For channel coding, Rate Compatible Punctured Convolutional (RCPC) codes are deployed [7], and Viterbi's upper bounds are used for bit error probability estimation.

The network resources are allocated to the nodes by the centralized control unit at the network layer. This control unit manages the nodes and may request changes in the transmission parameters (transmission power, source coding and channel coding rate) with the aim to achieve optimal performance, under the constraint that the chip rate R_{chip} is the same for all nodes. Since we assume that the spreading code has the same length L for all nodes and the transmission bit rate is $R_k = R_{chip}/L$, the constraint on R_{chip} corresponds to a constraint on R_k.

3. PROPOSED METHOD

Our work considers and proposes an efficient method for solving the following problem; given the constraint that imposes the same transmission bit rate R_k to all nodes, determine for each node k the source coding rate $R_{s,k}$, the channel coding rate $R_{c,k}$ and the power level S_k, so that a function of the overall end-to-end expected distortion $E\{D_{s+c,k}\}$ is minimized. This distortion related function depends on the deployed criterion. The first criterion results in the minimization of the average end-to-end distortion (MAD) among all nodes of the network, whereas the second focuses on the minimization of the maximum distortion (MMD). Both criteria have been proposed and tested in our previous work [1, 3], for the case where the nodes were partitioned into classes according to the motion. The third and fourth criterion derive from Game Theory and exploit the bargaining concept to provide an effective network resource tradeoff among multiple nodes. The VSN optimal performance depends on the application requirements, which determine the "fairness" of the network resource allocation, and hence the preferable criterion.

In order to estimate the expected video distortion due to lossy compression and channel errors for each user k, we assume the following model, as in [8]:

$$E\{D_{s+c}, k\} = a \left[\log_{10} \left(\frac{1}{P_b} \right) \right]^{-b}, \tag{2}$$

where P_b is the bit error probability, and parameters a ($a > 0$) and b ($b > 0$) depend on the amount of motion of the video sequence and the source coding rate. Particularly, a values tend to be low for a low motion amount in video sequences, and are increasing as motion gets higher. This means that the values of parameter a are a salient metric for the motion level. Parameters a and b are determined using mean square optimization from a few ($E\{D_{s+c,k}\}$,P_b) pairs. The $E\{D_{s+c,k}\}$ values are estimated at the encoder using the recursive optimal per-pixel estimate (ROPE) proposed in [9].

3.1. Criteria based on the Nash Bargaining Solution

We next describe the criteria that are based on the Nash Bargaining Solution [10]. Each node joins the bargaining game with the aim

of achieving, through cooperation with other nodes, a higher utility than what it could achieve if it were to operate selfishly, without cooperation. Clearly, each node would agree to cooperate only if the utility it would get was at least as high as what it would get without cooperation. The utility each node can get without cooperation is the *disagreement point (dp)*.

Let the *utility function* U_k be the PSNR of the received video:

$$U_k = 10 \log_{10} \frac{255^2}{E\{D_{s+c,k}\}}, \tag{3}$$

where $E\{D_{s+c,k}\}$ is the expected video distortion for node k (where $k = 1, \ldots, K$, with K being the number of nodes). Both U_k and $E\{D_{s+c,k}\}$ depend on the source coding rate $R_{s,k}$ and channel coding rate $R_{c,k}$ of node k, and the transmission powers S_k of all nodes ($k = 1, \ldots, K$) [1].

We define the *feasible set* $\mathbf{U}$ as the set of all possible utility allocations $U = (U_1, U_2, \ldots, U_K)$, which can be achieved using the available choices of transmission power, source coding rate, and channel coding rate for each node. The Nash bargaining solution $F(\mathbf{U}, dp)$ is a member of the feasible set that satisfies the following axioms [10]:

- $F(\mathbf{U}, dp) \geq dp$
- $y > F(\mathbf{U}, dp) \Rightarrow y \notin U$
- Given any strictly increasing affine transformation $\tau(.)$, $F(\tau(U), \tau(dp)) = \tau(F(\mathbf{U}, dp))$.
- If $dp \in Y \subseteq U$, then $F(\mathbf{U}, dp) \in Y \Rightarrow F(Y, dp) = F(\mathbf{U}, dp)$.

It can be shown that, in order to find the Nash bargaining solution $F(\mathbf{U}, dp)$, we have to maximize the Nash Product. Given a total target bit rate R_k we determine the vectors of optimal source coding rates $\underline{R_s^*}$, channel coding rates $\underline{R_c^*}$, and powers $\underline{S^*}$, such that the Nash Product is maximized:

$$F(\mathbf{U}, dp) = \arg \max_U (U_1 - dp_1)^{bp_1} (U_2 - dp_2)^{bp_2} \ldots (U_K - dp_K)^{bp_K} \tag{4}$$

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

In the present work, we assume that $dp \in \mathbf{U}$ is the minimum acceptable PSNR and is determined by the system designer. The bargaining powers bp are assigned according to the rules of the bargaining game and show which player (node) is more advantaged. Based on the bargaining powers, we consider two different criteria:

1. *e.NBS Criterion*: We assume that all nodes are treated *equally*. Thus, the bargaining powers are equal to $1/K$ for all K nodes.

2. *c.NBS Criterion*: We propose the assignment of *content-related* bargaining powers to the nodes.

Particularly for c.NBS, the resource allocation can be determined based on the available resources and the video content characteristics (level of motion) of the participating nodes. The latter characteristic is represented by the bargaining power of each user. A salient metric for the level of motion in a video sequence is parameter a from the deployed rate-distortion model from equation (2). The higher the motion level in a video sequence is, the higher the value of parameter a and vice versa. Thus, for the c.NBS criterion, let us define the bargaining power of each node k as the fraction:

$$bp_k = \frac{a_k}{\Sigma_{k=1}^K a_k} \tag{5}$$

under the constraint: $\Sigma_{k=1}^{K} bp_k = 1$. This implies that the higher the motion level of a user is, the higher its bargaining power is.

3.2. Employed Optimization Algorithm

Particle Swarm Optimization (PSO) is a stochastic optimization algorithm that draws inspiration from the social dynamics of living organisms. It utilizes a population (called a *swarm*) of search points (called *particles*) that iteratively move within the search space with an adaptive velocity (position shift), locating the most promising regions [11]. Each particle has a memory where it stores the best position it has ever encountered during its movement, i.e., the position with the lowest function value. Also, the particles can exchange information based on abstract communication schemes. These schemes can be represented by graphs where nodes correspond to particles and interconnections represent communication links among them. The form of such a scheme is called the *neighborhood topology*, and it has a crucial impact on the information flow within the swarm [5].

Let $\mathcal{S} = \{x_1, x_2, \ldots, x_N\}$ be a swarm consisting of N particles, each one defined as an n–dimensional vector, $x_i \in \mathbb{S}$, $i = 1, 2, \ldots, N$, where $\mathbb{S}$ is the search space. Let also v_i denote the corresponding velocity and $p_i \in \mathbb{S}$ the best position of the i–th particle. If t denotes the current iteration of the algorithm, then the velocity and current position of x_i are updated according to the equations [5, 12]:

$$
\begin{aligned}
v_i(t+1) &= \chi\Big[v_i(t) + c_1 R_1\big(p_i(t) - x_i(t)\big) + \\
&\quad + c_2 R_2\big(p_{g_i}(t) - x_i(t)\big)\Big], \quad (6) \\
x_i(t+1) &= x_i(t) + v_i(t+1), \quad (7)
\end{aligned}
$$

where χ is a parameter called the *constriction coefficient*; c_1, c_2 are positive acceleration parameters called *cognitive* and *social* parameter, respectively; and R_1, R_2 are vectors with components uniformly distributed in the range $[0, 1]$. All vector operations in Eqs. (6) and (7) are performed componentwise. Also, the best position of each particle is updated as soon as it discovers a better one.

Clerc and Kennedy [12] studied the stability of PSO, proposing parameter values that promote convergence of the algorithm towards the most promising solutions in the search space. Based on this study, the default set of parameters is defined as, $\chi = 0.729$, $c_1 = c_2 = 2.05$. Its efficiency and the minor required implementation effort, rendered PSO one of the most popular intelligent optimization approaches. Up–to–date, PSO accounts a vast number of applications in science and technology, with impressive results [5].

4. EXPERIMENTAL RESULTS

For the evaluation of our proposed criteria, we have considered several testing cases, of which two have been chosen to be presented. The first one is designed as an example to demonstrate the tradeoffs involved using each of the proposed criteria. It assumes a VSN with three nodes that view a low, medium and high motion scene represented by the "Akiyo", "Salesman" and "Foreman" QCIF video sequences of 15 frames/s, respectively. The second testing case has been created with the aim to remain close to reality, where each camera node may record a different motion scene, and therefore a and b parameters have been randomly assigned for each node. Particularly, video sequences with various motion levels have been considered and a range from the the lowest motion to the highest has been

	Users	1.Foreman	2.Akiyo	3.Salesman
MAD	**S (Watts)**	9.6097	5.0000	7.6583
	CS	3	3	3
	PSNR (dB)	39.3569	41.1732	39.7637
MMD	**S (Watts)**	11.2150	5.0000	8.6920
	CS	3	3	3
	PSNR (dB)	39.9345	39.9345	39.9345
e.NBS	**S (Watts)**	8.1560	5.0000	6.9390
	CS	3	3	3
	PSNR (dB)	38.5607	42.2113	39.8105
c.NBS	**S (Watts)**	15.0000	5.0000	8.3580
	CS	3	1	3
	PSNR (dB)	42.3753	36.5033	37.9800

Table 1. Testing Case 1: Comparison of Power Allocation and PSNR results per tested criteria for three nodes.

defined for both a and b. It has been noticed that motion levels affect a values the most, while b values are moving within a narrow range. Therefore, we have defined the wide range for a values, generated randomly a values for all nodes, and according to those we assigned a corresponding b value.

The continuous power levels were selected from the range $\mathbf{S} = [5.0000, 15.0000]$ Watts. We assumed Binary Phase Shift Keying (BPSK) modulation and RCPC codes with mother rate $1/4$ as in [7]. The link layer packet size is 400 bits and the target bit rate R_k was selected to be 96 kbps. The total bandwidth W_t was different for each testing case. The valid source and channel coding set (CS) for all nodes is $CS \in \{1 : (32kbps, 1/3), 2 : (48kbps, 1/2), 3 : (64kbps, 2/3)\}$. In the PSO algorithm implementation, the discrete parameters were allowed to take continuous values for the position and velocity update, although they were rounded to the nearest integer for the evaluation of the particle. Since PSO is a stochastic algorithm, for each problem instance we conducted 30 independent experiments. The swarm size and the number of iterations depend on the considered testing case, and the algorithm performance was assessed on average. During each experiment, the best detected solution was recorded. It should be pointed out that the optimal power allocation is not unique. From Eq. (1) it can be seen that E_k/N_0 does not change if all powers are multiplied by the same constant. This is due to the fact that background and thermal noise were assumed to be negligible. Thus, only the optimal power ratio can essentially be determined. In our results, we have normalized the powers so that the lowest allocated power is equal to 5.0000 Watts.

Table 1 depicts the four criteria performance on the three nodes case. The channel bandwidth for this case was set to 1 MHz. The number of the PSO problem parameters is six, the maximum number of iterations per experiment was set to 500 for the first testing case, and the used swarm size was 30. We can see from the video quality point of view that MAD and e.NBS favor the low motion sequence, while c.NBS gives priority to the higher motion levels. MMD achieves the same quality level for all three nodes. On the other hand, from the power allocation point of view, we have to point out that the e.NBS allocates lowest total power to the nodes in comparison to the other three criteria. The c.NBS assigns the highest total power and this is considered as the "cost" of achieving higher quality for the higher motion nodes.

In testing case 2 the number of nodes increases to 20, thus the PSO problem parameters are now 40. The maximum number of PSO iterations per experiment was set to 2000, and the used swarm size was selected to be 200. The bandwidth for this case was set to 10 MHz. Figure 1 (c) depicts the randomly selected motion levels for CS=3. The parameter a values and the motion level are directly re-

lated, i.e. the higher the value of *a* is, the higher the motion level of the video sequence is. Figures 1 (a) and 1 (b) draw the four criteria performance on the 20 randomly selected video sequences case. A first observation of the experimental results for testing case 2 shows that the performance of all four criteria is in line with the results from testing case 1. Another observation is that the power levels assigned to each user are in accordance with the motion levels for all criteria. Moreover, e.NBS assigns lower power levels for all nodes except for the low motion nodes. On the other hand, c.NBS increases the power of the high motion nodes, which are favored. Concerning the quality performance of the criteria, we have to say that the "fairness" has to be decided with respect to the application requirements from the system designer. If the system requires the best possible quality for the high motion video sequences, then the recommended criterion is c.NBS. If the opposite is required, then we recommend using the e.NBS criterion. Finally, for the case that the system requirements demand similar quality levels, we recommend the deployment of the MMD criterion.
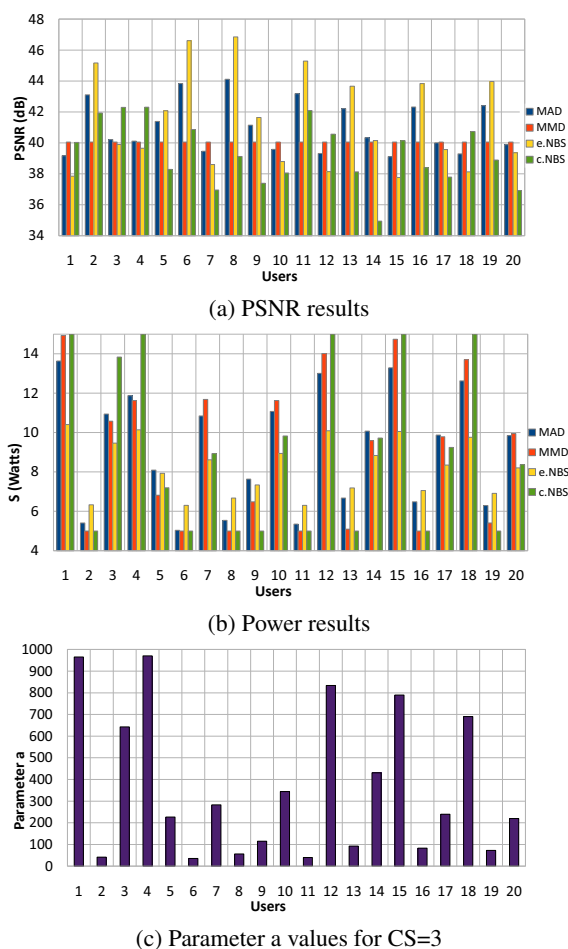

(a) PSNR results

(b) Power results

(c) Parameter a values for CS=3

Fig. 1. Testing Case 2: Comparison of Power Allocation and PSNR results per tested criterion for 20 random nodes.

5. CONCLUSIONS

We have presented a resource allocation method for DS–CDMA VSN using two criteria based on the NBS and two other optimization

criteria, MAD and MMD. Our approach moves beyond the state-of-the-art for mainly two reasons. First, the visual sensors are not grouped according to the amount of motion of the scene they are imaging and their individual video content related parameters are considered instead. Second, assigning bargaining powers according to the motion level of each recorded video sequence, is a type of content-aware "fairness" and should be useful in many applications. The experimental results have proved that the relative appropriateness and fairness of the used criteria has to be decided by the system designer based on the application requirements.

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