Optimal Power Allocation and Joint Source–Channel Coding for Wireless DS–CDMA Visual Sensor Networks

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ABSTRACT

In this paper, we propose a scheme for the optimal allocation of power, source coding rate, and channel coding rate for each of the nodes of a wireless Direct Sequence Code Division Multiple Access (DS-CDMA) visual sensor network. The optimization is quality-driven, i.e. the received quality of the video that is transmitted by the nodes is optimized. The scheme takes into account the fact that the sensor nodes may be imaging scenes with varying levels of motion. Nodes that image low-motion scenes will require a lower source coding rate, so they will be able to allocate a greater portion of the total available bit rate to channel coding. Stronger channel coding will mean that such nodes will be able to transmit at lower power. This will both increase battery life and reduce interference to other nodes. Two optimization criteria are considered. One that minimizes the average video distortion of the nodes and one that minimizes the maximum distortion among the nodes. The transmission powers are allowed to take continuous values, whereas the source and channel coding rates can assume only discrete values. Thus, the resulting optimization problem lies in the field of mixed-integer optimization tasks and is solved using Particle Swarm Optimization. Our experimental results show the importance of considering the characteristics of the video sequences when determining the transmission power, source coding rate and channel coding rate for the nodes of the visual sensor network.

Keywords: Visual sensor networks, DS–CDMA, Cross–layer optimization, Resource allocation, Joint source–channel coding, H.264, Rate compatible punctured convolutional codes, Particle Swarm Optimization

1. INTRODUCTION

Sensor networks have been a very active research topic during the last few years. Most of the previous work has focused on networks that transmit one–dimensional signals, such as seismic data, temperature, etc. Visual sensor networks are concerned with the transmission of visual data (images or video). The transmission of visual data is more challenging due to the higher required bit rates and the delay constraints that are in place for real–time video transmission.

In this paper, we consider a *Direct Sequence Code Division Multiple Access Visual Sensor Network* (DS–CDMA VSN), where we assume that the nodes in the network are deployed to survey a large area and are equipped with a video camera. Some of the nodes are imaging a relatively stationary field, while others are imaging scenes with a high level of motion. In a DS–CDMA VSN, low–motion scenes can be source encoded at a lower bit rate, thus a larger bit rate may be used for channel coding. Therefore, nodes that image such scenes can afford to use a lower transmission power. It is important for a node to transmit data at low power, since it both increases battery life and reduces interference to the transmissions of the rest of the nodes. Actually, increasing the transmission power of a node improves the quality of the transmitted video, but it also degrades the video quality of the other nodes due to the increased interference. This effect can be alleviated by properly determining the transmission parameters of all nodes, such that the resulting distortions adhere to the application requirements. Hence, the necessity for a joint optimization of the parameters of all nodes becomes evident.

The nodes communicate directly with a centralized control unit, which performs channel and source decoding to obtain the received video from each node. The control unit transmits information to the nodes in order to request changes in transmission parameters, such as source coding rate, channel coding rate, and transmission power. For example, it can request that the video of specific nodes be transmitted at a lower picture quality and bit rate, if the content of the video is deemed of secondary importance.

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We propose an optimization scheme that determines the transmission power, source coding rate, and channel coding rate for each sensor node, under constraints for the transmission bit rate. Two optimization criteria are considered: one that minimizes the average video distortion of the nodes without considering fairness issues among the nodes, and one that minimizes the maximum distortion among the nodes, in order to be fair. In Ref. 1 and 2, a simple version of this problem, where the transmission power was only allowed to take values from a finite discrete set, was solved. In the present work, the transmission power was allowed to take continuous values within a reasonable prespecified range, while the source coding rate and channel coding rate can assume only discrete values. Thus, the problems were modeled as mixed–integer optimization tasks.

Deterministic mixed–integer programming approaches can be used to tackle such problems. However, such methods usually require the existence of derivatives and they are sensitive to the initial conditions provided by the user. For this reason, a computational intelligence optimization algorithm, namely Particle Swarm Optimization (PSO), was employed to solve the aforementioned problems. The stochastic nature of PSO, as well as its ability to efficiently work in highly–complex environments with uncertainties (see Ref. 3), relieves the user from the burden of presenting an appropriate initialization to the algorithm. The obtained results justify the usefulness of PSO in tackling optimal resource allocation problems in wireless DS–CDMA VSNs.

The rest of the paper is organized as follows: in Section 2, we describe the basic architecture of the considered wireless VSN that utilizes DS–CDMA. In Section 3, the proposed optimal resource allocation schemes that minimize either the average video distortion of all nodes or the maximum distortion among the nodes, are presented along with the PSO algorithm. Experimental results are presented and discussed in Section 4, and the paper concludes in Section 5.

2. VISUAL SENSOR NETWORKS

We next describe the basic architecture of the considered wireless VSNs. At the physical layer, DS–CDMA is used, while for the source and channel coding, the H.264 and *rate compatible punctured convolutional* (RCPC) codes are used, respectively.

2.1 Direct Sequence Code Division Multiple Access

In DS–CDMA, all nodes (users) transmit on the same frequency. In order to transmit a single bit, a node actually transmits L "chips". Thus, each node, k, is associated with a spreading code (signature sequence), s_k, which is a vector of length L. Therefore, in order to transmit the i–th bit of a bit stream, node k actually transmits the vector:

$$\left[b_k(i)\, s_k\right],$$

which consists of L chips, and $b_k(i)$ is either 1 or -1, depending on the value of the transmitted bit. The node of interest suffers interference from the other nodes. It is reasonable to assume that the interference can be approximated by *additive white Gaussian noise* (AWGN).[4]

The node of interest, k, has an associated power level, S_k, in Watts, defined as:

$$S_k = E_k\, R_k, \qquad (1)$$

where E_k is the energy–per–bit, and R_k is the transmitted bit rate in bits per second. Assuming that thermal noise is negligible compared to the interference, the energy–per–bit to multiple–access–interference ratio becomes:

$$\frac{E_k}{N_0} = \frac{\frac{S_k}{R_k}}{\sum_{j\neq k}^{K} \frac{S_j}{W_t}}, \qquad k = 1, 2, \ldots, K, \qquad (2)$$

where $N_0/2$ is the two–sided noise power spectral density due to *multiple access interference* (MAI) in Watts/Hertz; S_j is the power of the interfering node j (in Watts); and W_t is the total bandwidth (in Hertz).[4]

2.2 Source Coding

In our model, we assumed that the video captured by the nodes of the network is compressed using the H.264/AVC video coding standard. This design covers a *video coding layer* (VCL), and a *network abstraction layer* (NAL). The VCL is specified to efficiently represent the content of the video data. It consists of a hybrid of temporal and spatial prediction, in conjunction with transform coding. The NAL is specified to format that data and provide header information in a manner appropriate for conveyance by the transport layers or storage media.

All data are contained in NAL units, each of which contains an integer number of bytes. A NAL unit specifies a generic format for use in both packet–oriented and bitstream systems. The format of NAL units for both packet–oriented transport and bitstream delivery is identical, except that each NAL unit can be preceded by a start code prefix in a bitstream–oriented transport layer.

2.3 Channel Coding

Regarding the channel coding, we used RCPC codes,[5] which allow the utilization of Viterbi's upper bounds on the bit error probability, P_b, defined as:

$$P_b \leqslant \frac{1}{P} \sum_{d=d_{\text{free}}}^{\infty} c_d P_d, \tag{3}$$

where P is the period of the code; 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.[5]

An AWGN channel with *binary phase–shift keying* (BPSK) modulation has a probability:

$$P_d = Q\left(\sqrt{2dR_c \frac{E_k}{N_0}}\right), \tag{4}$$

where R_c is the channel coding rate, and E_k/N_0 is the energy–per–bit normalized to the single–sided noise spectral density (measured in Watts/Hertz). The Q-function refers to the tail probability of the standard Gaussian distribution and it is related to the complementary error function, as follows:

$$Q(x) = \frac{1}{2}\text{erfc}\left(\frac{x}{\sqrt{2}}\right), \tag{5}$$

where:

$$\text{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} \exp\left(-t^2\right) dt.$$

We can now discuss the estimation of the expected video distorion, in the next section.

2.4 Expected Video Distortion

The expected video distortion for a node is due to both the lossy compression and the channel errors; hence, it shall depend on the corresponding bit error rate. We utilized *universal rate–distortion characteristics* (URDC),[6] which express the expected distortion as a function of the bit error rate, P_b, after channel decoding.

In accordance to the work in Ref. 7, we assumed the following model for the expected video distortion of the k–th user:

$$E[D_{s+c,k}] = \alpha \left[\log_{10}\left(\frac{1}{P_b}\right)\right]^{-\beta}, \tag{6}$$

where, $\alpha > 0$ and $\beta > 0$, such that the squared approximation error is minimized. Thus, instead of calculating the expected distortion based on experimental results for every possible value of P_b, we experimentally computed the expected distortion for a few bit error rates. Then, we used the model described in Eq. (6) to approximate the distortion for other bit error rates. The parameters α and β depend on the video sequence and source coding rate.

Substituting Eq. (5) into Eq. (4), Eq. (4) into Eq. (3), and finally Eq. (3) into Eq. (6), it can be shown that the expected distortion, $E[D_{s+c,k}]$ for the k–th node is a function in its source and channel coding rates, $R_{s,k}$ and $R_{c,k}$, respectively, and in the transmission powers of all nodes, $S = (S_1, S_2, \ldots, S_K)^\top$. Thus, the expected video distortion can be written as $E[D_{s+c,k}](R_{s,k}, R_{c,k}, S)$.

3. THE CONSIDERED OPTIMAL RESOURCE ALLOCATION PROBLEMS

In the following paragraphs, we formulate the corresponding resource allocation problems for the two considered criteria.

3.1 Problem Formulation

In order to determine the expected video distortion, we need to determine the source coding rate, channel coding rate and transmission power for each node. Let K be the number of nodes in the network, grouped into M *motion classes* according to the amount of motion in the scenes they are imaging. In our model, we assume that $M = 2$, namely there are two classes of nodes. The first class consists of high–motion nodes, while the second class contains low–motion nodes. Each class has its own set of parameters α and β.

The quantities that need to be determined for each class of nodes are the vectors:

$$\begin{aligned} R_s &= (R_{s,\text{high}}, R_{s,\text{low}})^\top, \\ R_c &= (R_{c,\text{high}}, R_{c,\text{low}})^\top, \\ S &= (S_{\text{high}}, S_{\text{low}})^\top, \end{aligned}$$

where $R_{s,\text{high}}$, $R_{c,\text{high}}$ and S_{high}, are the source coding rate, channel coding rate and transmission power, respectively, for the high–motion nodes, while $R_{s,\text{low}}$, $R_{c,\text{low}}$ and S_{low}, are the corresponding values for the low–motion nodes. Moreover, we assume that the transmission powers can take real values within a predetermined range, i.e.:

$$S_{\text{high}}, S_{\text{low}} \in \mathbf{S} = [s_{\min}, s_{\max}] \subset \mathbb{R},$$

while the source coding rates and the channel coding rates can take values from two predefined discrete sets, $\mathbf{R_s}$ and $\mathbf{R_c}$, respectively:

$$R_{s,\text{high}}, R_{s,\text{low}} \in \mathbf{R_s}, \qquad R_{c,\text{high}}, R_{c,\text{low}} \in \mathbf{R_c}.$$

Obviously, increasing the size of $\mathbf{R_s}$ and $\mathbf{R_c}$ increases the search space (and consequently the problem's difficulty) considerably.

We considered two optimization criteria in order to tackle the problem of optimal resource allocation among the nodes of a wireless DS–CDMA VSN. The constraint for both criteria is that the chip rate, R_{chip}, shall be identical for all nodes. Assuming that the spreading code length, L, is the same for all nodes, a constraint on the chip rate corresponds to a constraint on the transmission bit rate R_k, for a node k, as follows:

$$R_k = \frac{R_{\text{chip}}}{L}. \tag{7}$$

Equivalently, we can impose a constraint on the bit rate instead of the chip rate (i.e., $R_k = R_{\text{budget}}$, for all k). Since it holds that:

$$R_k = \frac{R_{s,k}}{R_{c,k}}, \tag{8}$$

the source coding rates and the channel coding rates share the same transmission bit rate. The quantities $R_{s,k}$ and $R_{c,k}$ take values from the finite discrete sets, $\mathbf{R_s}$ and $\mathbf{R_c}$, respectively. If we assume that R_k is fixed, it follows that the pairs, $(R_{s,\text{high}}, R_{c,\text{high}})$ and $(R_{s,\text{low}}, R_{c,\text{low}})$, take values from a finite discrete set, $\mathbf{R_{s+c}}$. Clearly, the cardinalities of the sets, $\mathbf{R_s}$, $\mathbf{R_c}$, and $\mathbf{R_{s+c}}$, shall be equal. In the following, the subscript k refers to the k–th node, which may be a high–motion or a low–motion node.

The First Considered Critetion

In the first considered criterion, the goal is to determine the optimal source coding rates, R_s, channel coding rates, R_c, and powers, S, given a total target bit rate, R_{budget}, such that the overall end–to–end distortion, $D_{\text{ave}}(R_s, R_c, S)$, over all nodes is minimized, i.e.:

$$\begin{aligned} \{R_s, R_c, S\} &= \arg\min_{R_s, R_c, S} D_{\text{ave}}(R_s, R_c, S), \\ \text{subject to} &\qquad R_1 = R_2 = \cdots = R_K = R_{\text{budget}}, \end{aligned} \tag{9}$$

where R_k is defined as in Eq. (8). The function, $D_{\text{ave}}(R_s, R_c, S)$, is defined as:

$$D_{\text{ave}}(R_s, R_c, S) = \frac{1}{K} \sum_{k=1}^{K} E[D_{s+c,k}](R_{s,k}, R_{c,k}, S). \tag{10}$$

We will refer to this criterion as the *Minimum Average Distortion* (MAD).

The Second Considered Critetion

The second considered criterion that is used to allocate resources to the nodes in the network, minimizes the maximum distortion among all the nodes. According to it, given a total target bit rate, R_{budget}, we need to determine the optimal vectors of source coding rates R_s, channel coding rates, R_c, and powers, S, such that the maximum distortion among all the nodes, $D_{\max}(R_s, R_c, S)$, is minimized, i.e.:

$$\begin{aligned} \{R_s, R_c, S\} \;&=\; \arg \min_{R_s, R_c, S} D_{\max}(R_s, R_c, S), \\ \text{subject to} \qquad & R_1 = R_2 = \cdots = R_K = R_{\text{budget}}, \end{aligned} \tag{11}$$

where R_k is defined as in Eq. (8), and $D_{\max}(R_s, R_c, S)$ is defined as follows:

$$D_{\max}(R_s, R_c, S) = \max_k E[D_{s+c,k}](R_{s,k}, R_{c,k}, S). \tag{12}$$

This criterion retains fairness for all nodes, in the sense that always the worst distortion of the network is minimized. We will refer to this criterion as the *Minimum Maximum Distortion* (MMD).

The transmission powers take values from a continuous set, whereas the combination of source coding rate and channel coding rate assumes values from a finite, discrete set. Thus, the resulting optimization problems are of mixed–integer type, and they are solved by using the Particle Swarm Optimization algorithm, which is described in the following section.

3.2 The Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is a population–based, stochastic optimization algorithm.[3,8] Its dynamic is governed by fundamental laws encountered in swarms in nature hence it is categorized as a swarm intelligence algorithm. PSO exploits a population (called a *swarm*) of search points (called *particles*) to probe the search space. Each particle moves in the search space with an adaptable *velocity* (position shift), retaining a *memory* of the best position it has ever visited. In minimization problems, such positions have the lowest function values. The velocity is adapted based on information coming from the particle itself as well as from the rest of the swarm. More specifically, each particle assumes a "neighborhood" that consists of some other particles. The best position ever attained by any member of the neighborhood is then communicated to the particle and influences its velocity's update.

To put it formally, let:

$$\min_{x \in V \subset \mathbb{R}^n} f(x),$$

be the minimization problem under investigation. Then, a swarm to tackle this problem consists of N particles:

$$\mathcal{S} = \{x_1, x_2, \ldots, x_N\},$$

which are n–dimensional vectors:

$$x_i = (x_{i1}, x_{i2}, \ldots, x_{in})^\top \in V, \qquad i = 1, 2, \ldots, N.$$

The velocity of the i–th particle:

$$v_i = (v_{i1}, v_{i2}, \ldots, v_{in})^\top,$$

as well as its best position:

$$p_i = (p_{i1}, p_{i2}, \ldots, p_{in})^\top \in V,$$

are also n–dimensional vectors. If t denotes the current iteration of the algorithm, then the best position is defined as:

$$p_i(t) = \arg \min_{s\in\{0,\ldots,t\}} f(x_i(s)).$$

The neighborhoods of the particles are usually defined based on their indices. The most common neighborhood topology is the "ring" topology, where the neighborhood of a particle consists of all particles with neighboring indices. Thus, a neighborhood of radius m of x_i is defined as the set of indices:

$$NB_i = \{i-m, i-m+1, \ldots, i, \ldots, i+m-1, i+m\},$$

where index 1 is assumed to follow immediately after N. The best particle in the neighborhood of x_i, is the one with the smallest funcion value and it is denoted as p_{g_i}. Thus,

$$p_{g_i} = \arg \min_{s\in NB_i} f(p_s).$$

If the cardinality of each particle's meighborhood is equal to the swarm size, N, then the whole swarm is considered as the neighborhood of each particle, and we denote this model as *gbest PSO*. On the other hand, if strictly smaller neighborhoods are used, i.e., $m < N/2$, then we obtain the *lbest PSO* model.

The difference between the two models lies in the rate of information flow among the particles. In the gbest PSO model, a new best position is communicated immediately in the next iteration to all particles. This results in a rapid convergence of all particles towards the best positions discovered in the first iterations. However, this is accompanied by rapid loss of divergence in the swarm, which may foster the danger of premature convergence to suboptimal solutions (local minima). On the other hand, in the lbest PSO model, a new best position discovered by a particle is communicated only to particles belonging in its neighborhood. Thus, the information flows slower in the swarm, thereby providing to the rest of the particles the opportunity to discover a possibly better solution. Obviously, the lbest PSO model has slower convergence but it retains higher levels of effectiveness than the gbest one.

The velocity and position of x_i are updated according to the equations:[3, 9]

$$v_i(t+1) = \chi\Big[v_i(t) + c_1R_1\big(p_i(t) - x_i(t)\big) + c_2R_2\big(p_{g_i}(t) - x_i(t)\big)\Big], \quad (13)$$

$$x_i(t+1) = x_i(t) + v_i(t+1), \quad (14)$$

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. (13) and (14) are performed componentwise. The best position of a particle is updated as soon as a better position (i.e., one with lower function value) is discovered by the particle, i.e.:

$$p_i(t+1) = \begin{cases} x_i(t+1), & \text{if } f(x_i(t+1)) \leqslant f(p_i(t+1)), \\ p_i(t), & \text{otherwise.} \end{cases}$$

Clerc and Kennedy[9] 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:

$$\chi = 0.729, \quad c_1 = c_2 = 2.05.$$

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.[3]

4. EXPERIMENTAL RESULTS

In order to evaluate the proposed criteria for the optimal resource allocation among the nodes of the network, we conducted a number of experiments on real video data, some of which are presented here. We assumed two motion classes ($M = 2$). Thus, nodes were divided into high–motion nodes and low–motion nodes, depending on the amount of motion in the scenes they were imaging. The "Foreman" video sequence was used to represent high–motion nodes, whereas the "Akiyo" video sequence was used to represent low–motion nodes. Therefore, two sets of URDC curves were needed, one for each level of motion. Specifically, two sets of parameters α and β were required in Eq. (6), one for each video sequence.

The characteristics were obtained for both video sequences at a frame rate of 15 frames/s. The data points that were used to obtain the parameters α and β, were determined by corrupting the video stream with packet errors based on a bit error rate, P_b, decoding the corrupted video bit stream with the H.264/AVC codec, calculating the distortion, repeating this experiment 300 times and then taking the average distortion. This process was followed twice, once for the "Foreman" and one for the "Akiyo" video sequence, and for all source coding rates of interest.

We assumed BPSK modulation and RCPC codes with mother rate 1/4 from Ref. 5. Also, two different target bit rate constraints were considered, namely $R_{\text{budget}} = 96000\,\text{bits/s}$ and $R_{\text{budget}} = 144000\,\text{bits/s}$, with bandwidths of $W_t = 20\text{MHz}$ and $W_t = 15\text{MHz}$. The set of admissible source coding rates and corresponding channel coding rates for the two different bit rates, were as follows:

$$R_{\text{budget}} = 96000\,\text{bits/s} \;\rightarrow (R_{s,k}, R_{c,k}) \in \;\{(32\,\text{kbps}, 1/3), (48\,\text{kbps}, 1/2), (64\,\text{kbps}, 2/3)\}\,, \tag{15}$$

$$R_{\text{budget}} = 144000\,\text{bits/s} \rightarrow (R_{s,k}, R_{c,k}) \in \;\{(48\,\text{kbps}, 1/3), (72\,\text{kbps}, 1/2), (96\,\text{kbps}, 2/3)\}\,. \tag{16}$$

The power levels assumed values from the range, $\mathbf{S} = [5.0, 15.0]$ (representing Watts).

Regarding PSO, a swarm of $N = 20$ particles was used under the ring topology of radius $m = 1$. Each particle consisted of four unknowns, namely the two continuous transmission powers (one for each class of nodes) and the discrete source coding rate and channel coding rate. In our 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. The default PSO parameter values reported in Section 3.2, were also adopted in our study. Since PSO is a stochastic algorithm, its performance is assessed on average over a number of experiments. Thus, for each problem instance we conducted 30 independent experiments. PSO was allowed to execute 500 iterations at each experiment, and the best detected solution was recorded.

Our experiments confirmed that there is no unique optimal solution to our optimization problems. In fact, PSO was able to detect a number of different solutions (in the 30 runs per problem instance) that all achieved the optimum value for both (average and minimax) distortion minimization criteria. This is a consequence of the fact that the ratio, E_k/N_0, in Eq. (2) does not change if all powers are multiplied by the same constant, assuming that the thermal noise is negligible and the AWGN is entirely due to interference provided by the nodes. Thus, we can find the optimal ratio, $S_{\text{high}}/S_{\text{low}}$, rather than specific values for the powers. Nevertheless, the optimal source and channel coding rates are unique.

Tables 1 through 8 report the solutions obtained for the MAD and MMD criteria, for the following cases:

(a) 90 high–motion users and 10 low–motion users,

(b) 70 high–motion users and 30 low–motion users,

(c) 50 high–motion users and 50 low–motion users,

(d) 30 high–motion users and 70 low–motion users,

(e) 10 high–motion users and 90 low–motion users,

High	$(R_{s,\text{high}},R_{c,\text{high}})$	S_{high}(W)	Low	$(R_{s,\text{low}},R_{c,\text{low}})$	S_{low}(W)	$PSNR_{\text{high}}$(dB)	$PSNR_{\text{low}}$(dB)
90	(48 kbps, 1/2)	9.8451	10	(32 kbps, 1/3)	5.0000	28.2705	31.2943
70	(48 kbps, 1/2)	15.0000	30	(32 kbps, 1/3)	7.6069	29.2296	32.2581
50	(64 kbps, 2/3)	15.0000	50	(32 kbps, 1/3)	7.0428	30.9419	32.8537
30	(64 kbps, 2/3)	8.6240	70	(64 kbps, 2/3)	5.0000	31.3844	35.1131
10	(64 kbps, 2/3)	10.7080	90	(64 kbps, 2/3)	5.9845	32.9787	36.7642

Table 1. Optimal resource allocation for the MAD criterion for various distributions of high–motion and low–motion users and a target bit rate of 96000 bits/s and bandwidth 20MHz.

High	$(R_{s,\text{high}},R_{c,\text{high}})$	S_{high}(W)	Low	$(R_{s,\text{low}},R_{c,\text{low}})$	S_{low}(W)	$PSNR_{\text{high}}$(dB)	$PSNR_{\text{low}}$(dB)
90	(48 kbps, 1/2)	15.0000	10	(32 kbps, 1/3)	5.7234	28.3919	28.3919
70	(64 kbps, 2/3)	13.4344	30	(32 kbps, 1/3)	5.0000	29.7737	29.7737
50	(64 kbps, 2/3)	13.0847	50	(32 kbps, 1/3)	5.0000	31.6114	31.6114
30	(64 kbps, 2/3)	12.6814	70	(32 kbps, 1/3)	5.0000	33.4049	33.4049
10	(64 kbps, 2/3)	13.3488	90	(64 kbps, 2/3)	5.0000	35.7218	35.7218

Table 2. Optimal resource allocation for the MMD criterion for various distributions of high–motion and low–motion users and a target bit rate of 96000 bits/s and bandwidth 20MHz.

High	$(R_{s,\text{high}},R_{c,\text{high}})$	S_{high}(W)	Low	$(R_{s,\text{low}},R_{c,\text{low}})$	S_{low}(W)	$PSNR_{\text{high}}$(dB)	$PSNR_{\text{low}}$(dB)
90	$(32kbps,1/3)$	15.0000	10	$(32kbps,1/3)$	10.1943	26.4203	31.1773
70	$(32kbps,1/3)$	11.2833	30	$(32kbps,1/3)$	7.4632	26.7595	31.6151
50	$(48kbps,1/2)$	9.8262	50	$(32kbps,1/3)$	5.0000	27.7762	30.7930
30	$(48kbps,1/2)$	9.8485	70	$(32kbps,1/3)$	5.0000	29.0488	32.0672
10	$(64kbps,2/3)$	10.5000	90	$(32kbps,1/3)$	5.0000	31.4521	33.3203

Table 3. Optimal resource allocation for the MAD criterion for various distributions of high–motion and low–motion users and a target bit rate of 96000 bits/s and bandwidth 15MHz.

High	$(R_{s,\text{high}},R_{c,\text{high}})$	S_{high}(W)	Low	$(R_{s,\text{low}},R_{c,\text{low}})$	S_{low}(W)	$PSNR_{\text{high}}$(dB)	$PSNR_{\text{low}}$(dB)
90	$(32kbps,1/3)$	15.0000	10	$(32kbps,1/3)$	6.7090	26.5321	26.5321
70	$(32kbps,1/3)$	12.3831	30	$(32kbps,1/3)$	5.0213	27.1521	27.1521
50	$(48kbps,1/2)$	13.1570	50	$(32kbps,1/3)$	5.0000	28.5991	28.5991
30	$(64kbps,2/3)$	13.2312	70	$(32kbps,1/3)$	5.0000	30.7191	30.7191
10	$(64kbps,2/3)$	12.7296	90	$(32kbps,1/3)$	5.0000	32.5542	32.5542

Table 4. Optimal resource allocation for the MMD criterion for various distributions of high–motion and low–motion users and a target bit rate of 96000 bits/s and bandwidth 15MHz.

with a target bit rate of 96000 bits/s and 144000 bits/s, and a bandwidth of 20MHz and 15MHz. In all cases, $K = 100$ nodes were assumed in the network. Each line in the tables corresponds to a different allocation of the nodes between high–motion and low–motion nodes. The high–motion nodes' source–channel coding rate, transmission power and PSNR are represented by, $(R_{s,\text{high}}, R_{c,\text{high}})$, S_{high}, and $PSNR_{\text{high}}$, respectively, while $(R_{s,\text{low}}, R_{c,\text{low}})$, S_{low}, and $PSNR_{\text{low}}$, represent the same parameters for the nodes that image low–motion. The number of high–motion nodes is given under the column denoted as "High", while the number of low–motion nodes is given under the column "Low".

From Table 1 for the MAD criterion, we can see that minimizing the average distortion among all nodes favors the low–motion nodes, which always have a higher PSNR than the high–motion nodes. On the other hand, Table 2 reveals that minimizing the maximum distortion among the nodes leads to equal distortions (and PSNR) between low–motion and high–motion nodes. Thus, we can infer that the MMD criterion provides a fair solution for both classes of nodes. However, for the MMD criterion we observe that the PSNR was increased compared to the MAD criterion for the high–motion nodes, while it decreased for the low–motion nodes, especially when the high–motion nodes heavily outnumber low–motion nodes. Therefore, from one point of view the MMD criterion is equally fair for both node classes since it assigns to each motion class exactly the same PSNR. From the other point of view, we can say that the high–motion nodes are more advantaged compared to low–motion nodes, since the PSNR of the low–motion nodes decreases significantly. In all cases, low–motion nodes require a lower trasmission power than high–motion nodes. This shows the importance of considering the characteristics

High	$(R_{s,\text{high}}, R_{c,\text{high}})$	S_{high}(W)	Low	$(R_{s,\text{low}}, R_{c,\text{low}})$	S_{low}(W)	$PSNR_{\text{high}}$(dB)	$PSNR_{\text{low}}$(dB)
90	$(48kbps, 1/3)$	15.0000	10	$(48kbps, 1/3)$	10.1822	25.7146	29.3730
70	$(48kbps, 1/3)$	15.0000	30	$(48kbps, 1/3)$	9.9501	26.3744	30.0843
50	$(48kbps, 1/3)$	7.7429	50	$(48kbps, 1/3)$	5.0000	27.1339	30.9033
30	$(48kbps, 1/3)$	15.0000	70	$(48kbps, 1/3)$	9.3816	28.0306	31.8707
10	$(72kbps, 1/2)$	15.0000	90	$(48kbps, 1/3)$	7.7859	30.3384	32.7780

Table 5. Optimal resource allocation for the MAD criterion for various distributions of high–motion and low–motion users and a target bit rate of 144000 bits/s and bandwidth 20MHz.

High	$(R_{s,\text{high}}, R_{c,\text{high}})$	S_{high}(W)	Low	$(R_{s,\text{low}}, R_{c,\text{low}})$	S_{low}(W)	$PSNR_{\text{high}}$(dB)	$PSNR_{\text{low}}$(dB)
90	$(48kbps, 1/3)$	9.2654	10	$(48kbps, 1/3)$	5.0000	25.8461	25.8461
70	$(48kbps, 1/3)$	9.8197	30	$(48kbps, 1/3)$	5.0000	26.8316	26.8316
50	$(48kbps, 1/3)$	10.5707	50	$(48kbps, 1/3)$	5.0000	28.0450	28.0450
30	$(48kbps, 1/3)$	11.6677	70	$(48kbps, 1/3)$	5.0000	29.6328	29.6328
10	$(72kbps, 1/2)$	15.0000	90	$(48kbps, 1/3)$	6.3505	32.3213	32.3213

Table 6. Optimal resource allocation for the MMD criterion for various distributions of high–motion and low–motion users and a target bit rate of 144000 bits/s and bandwidth 20MHz.

High	$(R_{s,\text{high}}, R_{c,\text{high}})$	S_{high}(W)	Low	$(R_{s,\text{low}}, R_{c,\text{low}})$	S_{low}(W)	$PSNR_{\text{high}}$(dB)	$PSNR_{\text{low}}$(dB)
90	$(48kbps, 1/3)$	15.0000	10	$(48kbps, 1/3)$	11.2265	22.7828	26.2144
70	$(48kbps, 1/3)$	15.0000	30	$(48kbps, 1/3)$	11.0044	23.4145	26.8932
50	$(48kbps, 1/3)$	15.0000	50	$(48kbps, 1/3)$	10.7484	24.1375	27.6703
30	$(48kbps, 1/3)$	15.0000	70	$(48kbps, 1/3)$	10.4476	24.9842	28.5810
10	$(48kbps, 1/3)$	15.0000	90	$(48kbps, 1/3)$	10.0856	26.0090	29.6841

Table 7. Optimal resource allocation for the MAD criterion for various distributions of high–motion and low–motion users and a target bit rate of 144000 bits/s and bandwidth 15MHz.

High	$(R_{s,\text{high}}, R_{c,\text{high}})$	S_{high}(W)	Low	$(R_{s,\text{low}}, R_{c,\text{low}})$	S_{low}(W)	$PSNR_{\text{high}}$(dB)	$PSNR_{\text{low}}$(dB)
90	$(48kbps, 1/3)$	11.0000	10	$(48kbps, 1/3)$	6.9700	22.9148	22.9148
70	$(48kbps, 1/3)$	15.0000	30	$(48kbps, 1/3)$	9.0465	23.8711	23.8711
50	$(48kbps, 1/3)$	15.0000	50	$(48kbps, 1/3)$	8.4876	25.0406	25.0406
30	$(48kbps, 1/3)$	9.6410	70	$(48kbps, 1/3)$	5.0000	26.5537	26.5537
10	$(48kbps, 1/3)$	12.3251	90	$(48kbps, 1/3)$	5.6041	28.7266	28.7266

Table 8. Optimal resource allocation for the MMD criterion for various distributions of high–motion and low–motion users and a target bit rate of 144000 bits/s and bandwidth 15MHz.

of the video sequence (low– vs high–motion) when determining the optimal transmission powers.

The same conclusions can be drawn by examining Tables 3 through 8 for the corresponding criteria. Furthermore, when the bit rate is set to 144000 bits/s (Tables 5 through 8), and for the same bandwidth value, the source–channel coding rates for both node classes for the MAD criterion are the same with the corresponding values for the MMD criterion, for the various node allocations (of course, the powers are different). Tables 7 and 8 show that all the pairs of source–channel coding rates for both node classes and for both optimization criteria are the same. Namely, the high–motion class and the low–motion class compress their video at the lowest source coding rate, using more bits for channel coding.

Moreover, from the above tables we can see that increasing the target bit rate while keeping the bandwidth constant results in a decrease of the PSNR for both node classes and for all node allocations. This is due to the fact that the transmitted energy per bit decreases, as we can see from Eq. (2). Thus, from Eq. (4), the P_d value increases and, from Eq. (3), the bit error rate, P_b, also increases. Alternatively, the same occurs by decreasing the bandwidth while keeping the target bit rate constant.

Finally, since high–motion nodes transmit their data with higher transmission power compared to low–motion nodes, it is reasonable that the E_k/N_0 ratio from Eq. (2) decreases more when the number of high–motion nodes is larger than the number of low–motion nodes. Thus, the PSNR for both node classes increases as we move down the MAD and MMD tables, since the number of high–motion nodes decreases and simultaneously the number of low–motion nodes increases.

5. CONCLUSIONS

In the present work, we solved the problem of optimal resource allocation among the nodes of a wireless DS–CDMA VSN. We assumed continuous values for the transmission powers and discrete values for the source coding rates and channel coding rates. This mixed–integer optimization problem was solved using Particle Swarm Optimization algorithm. The performance of our proposed scheme was assessed on two optimization criteria. The one minimizes the average distortion of all nodes, while the other minimizes the maximum distortion among the nodes. Our experimental results showed that the MAD criterion favors always the low–motion nodes assigning them a greater PSNR compared to high–motion nodes, while the MMD criterion considers fairness between both node classes assigning them equal PSNR at all node allocations.

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