On the Use of Clustering for Resource Allocation in Wireless Visual Sensor Networks

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ABSTRACT

The present study is focused on the problem of quality–driven cross–layer optimization of Direct Sequence Code Division Multiple Access (DS–CDMA) Wireless Visual Sensor Networks (WVSNs). We consider a centralized topology where each sensor transmits directly to a Centralized Control Unit (CCU), which manages the network resources. In real environments, the visual sensors view and transmit scenes with varying amount of motion. Thus, each recorded video has its individual motion characteristics. Our aim is to enable the CCU to jointly allocate the transmission power and source–channel coding rates for each WVSN node under certain quality–driven criteria and constant chip rate. We consider two approaches for the cross–layer optimization scheme. In the first, the optimal set of network resources is assigned to each node according to its individual motion characteristics. In the second approach, the nodes are partitioned into clusters according to the amount of motion in the recorded scenes. Then, all nodes within a cluster are assigned identical network resources. Both approaches result in mixed–integer optimization problems, which are solved with the Particle Swarm Optimization algorithm. Experimental results demonstrate the quality/complexity trade–off for the two approaches.

Keywords: Wireless Visual Sensor Networks, DS–CDMA, Cross–layer Optimization, Resource Allocation, Nash Bargaining Solution, Clustering, Particle Swarm Optimization, H.264/AVC.

1. INTRODUCTION

According to a recent study conducted by CISCO about the *Visual Networking Index* (VNI), mobile video has the highest growth rate of any application category measured within the forecast. The study predicts that mobile video traffic will exceed 50% of the total mobile data traffic in 2011 and will be approximately two-thirds of the global mobile data traffic by 2015.[1] Part of this mobile video technology are the *Wireless Visual Sensor Networks* (WVSNs) that offer a variety of multimedia services, including environmental monitoring, surveillance and automated tracking, among others. Traditional WVSNs with centralized topologies are comprised of low–weight, spatially distributed nodes equipped with visual sensors and a *Centralized Control Unit* (CCU). The nodes communicate only with the CCU over the network layer. The CCU applies channel– and source–decoding to obtain the received video from each node.

A significant issue that arises in WVSNs is the sharing of the network resources among the sensor nodes. Each node has different resource requirements (i.e., energy consumption or network resources), due to scenes of varying motion or texture that the visual sensors record and transmit. Moreover, each video data transmission has an imminent effect on the other nodes' transmissions due to interference, which degrades the received video quality. Furthermore, recent research has shown that wireless stations need to optimally adapt their multimedia compression and transmission strategies jointly across the protocol stack in order to guarantee a predetermined quality at the receiver.[2,3] Thus, a quality–driven joint allocation of network resources is necessary.

In previous WVSN cross–layer optimization schemes,[4–6] the classification of the nodes in groups according to the motion characteristics was proposed. The nodes were grouped into two general classes, namely high– and low–motion, with respect to the motion level of the recorded video sequences, which was considered the same for all nodes of the same class. Then, the power and network resources were allocated equally for all nodes within each class. In general, the idea of clustering in WVSNs has been mainly used for network organization and communication or energy efficiency purposes.[7,8] Clustering provides the advantage of scalability for large

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WVSNs, where multi–hop routings are required. In our paper, we use motion–based clustering as part of the proposed methodology in order to reduce the number of parameters in the resource allocation problem, thereby reducing its complexity.

In a real environment, the sensors monitor scenes with motion– and texture–varying content in most cases. Hence, it is important to consider these individual characteristics in the resource allocation. The idea of considering independent (and unclustered) wireless network nodes has gained ground in recent research works.[9–11] In Refs. 9, 10, only a small number of two or three cameras were considered. In our previous work,[11] we considered the individual characteristics of a 20–node WVSN, although our main goal was the improvement of the end–to–end video quality according to the recorded motion level.

The paper at hand extends our previous work by comparing it with another approach in terms of quality and complexity. More specifically, we study two approaches for the problem of network resource allocation among the nodes of a DS–CDMA WVSN. The first one considers the visual sensors as independent nodes with their individual motion amount, while the second one partitions the independent nodes into motion clusters. In the latter case, a simple, widely used partitional algorithm is used to divide the nodes into non–overlapping clusters. In both approaches, the reasonably realistic case of a 20–node WVSN is considered. Also, the nodes cooperate to find an optimal solution, in contrast to the model of Ref. 10 where the nodes were competing with each other on the resource allocation problem to achieve higher end–to–end video quality. Moreover, the quality/complexity trade–off of the two approaches in the problem of the joint transmission power and source–channel rate allocation is investigated and discussed.

The rest of the paper is organized as follows: Section 2 is devoted to the necessary background information in terms of the reference architecture of the considered WVSN. The corresponding problem is formulated in Section 3, along with descriptions of the two approaches, while brief presentations of the employed algorithms are provided in Section 4. Experimental results are reported and discussed in Section 5. Finally, the paper concludes in Section 6.

2. BACKGROUND INFORMATION

DS–CDMA is used in the physical layer, hence all nodes transmit over the same frequency. For a single bit transmission, L chips are transmitted by a node. Thus, each node, $k = 1, 2, \ldots, K$, is associated with a spreading code, s_k, which is a vector of length L. Namely, in order to transmit the i–th bit of a bitstream, node k actually transmits $b_k(i) \times s_k$, which is a vector of L chips with $b_k(i)$ assuming the values 1 or -1 according to the value of the transmitted bit.[4] We assume that the interference received from all other nodes at the node of interest can be modeled as additive white Gaussian noise.[12] The background and thermal noise are assumed to be negligible compared with the interference and, hence, they are ignored.

Each network node operates at a specific power level and a reduced power is received due to attenuation. In order to calculate the received power at the node of interest from the neighboring nodes, we adopt the two–ray ground propagation model. This model is appropriate for the considered WVSN, since it considers both the direct path and a ground–reflected propagation path between transmitter and receiver. The received power, $S_{\mathrm{r},k}$, at distance d from the transmitting node k is proportional to the transmission power and inversely proportional to the fourth power of the distance, i.e.:

$$S_{\mathrm{r},k} \propto \frac{S_k}{d^4},$$

and can be expressed as:

$$S_{\mathrm{r},k} = S_k \, G_{\mathrm{t}} \, G_{\mathrm{r}} \, \frac{h_{\mathrm{t}}^2 \, h_{\mathrm{r}}^2}{d^4}, \tag{1}$$

where S_k is the transmission power of node k in Watts; G_{t} and G_{r} are the antenna gains; and h_{t}, h_{r}, are the antenna heights of the transmitter and receiver, respectively.[13]

The received power in Watts from each node k in the CCU is given as follows:

$$S_{\mathrm{r},k} = E_k \, R_k, \tag{2}$$

where E_k is the energy–per–bit and R_k is the total bit rate. The total transmission bit rate for node k, can be expressed as the fraction of the source coding rate, $R_{\mathrm{s},k}$, to the channel coding rate, $R_{\mathrm{c},k}$, i.e.:

$$R_k = \frac{R_{\mathrm{s},k}}{R_{\mathrm{c},k}}, \qquad k = 1, 2, \ldots, K. \tag{3}$$

The source coding rate is expressed in bits/sec, while the channel coding rate is a dimensionless. Thus, the transmission bit rate is expressed in bits/sec.

The energy per bit to *Multiple Access Interference* (MAI) ratio is defined as:

$$\frac{E_k}{N_0} = \frac{S_{\mathrm{r},k}/R_k}{\sum\limits_{\substack{j=1\\ j\neq k}}^{K} S_{\mathrm{r},j}/W_{\mathrm{t}}}, \tag{4}$$

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. For the source coding of the captured video sequences, the H.264/AVC video coding standard is used. H.264/AVC design consists of two conceptual layers: the network abstraction layer (NAL) and the video coding layer (VCL). VCL is specified to efficiently represent the content of the video data and fulfill the design objective of enhanced coding efficiency. The NAL unit structure provides a generic form for use in both packet–oriented and bitstream–based systems.[14]

Moreover, *Rate Compatible Punctured Convolutional* (RCPC) codes are deployed for channel coding (see Ref. 15), and Viterbi's upper bounds are used for bit error probability estimation. Under the consideration of a constant spreading code length, L, and the constraint of identical chip rate, R_{chip}, for all network nodes, the transmission bit rate, $R_k = R_{\mathrm{chip}}/L$ in bits/sec, is correspondingly constant within the network. Under this constraint, and with the aim of achieving optimal end–to–end video quality, the network resources are allocated to the nodes by the CCU at the network layer.

In order to estimate at the encoder the expected video distortion for each node k due to lossy compression and channel errors, we assume the *Universal Rate Distortion Characteristics* (URDC):

$$E\{D_{\mathrm{s+c},k}\} = \alpha_k \left[\log_{10}\left(\frac{1}{P_{\mathrm{b}}}\right)\right]^{-\beta_k}, \tag{5}$$

where P_{b} is the bit error probability estimation, and parameters $\alpha_k, \beta_k > 0$ depend on both the motion level of the video sequence and the source coding rate.[16]

Experiments revealed that the values of α_k tend to be lower for low motion video, while getting higher as motion increases in the video sequences. This implies that the values of α_k can be used for the relative quantification of the motion level. In order to determine the values of α_k and β_k for each node at the encoder, we apply mean squared error optimization on several experimentally attained pairs $(E\{D_{\mathrm{s+c},k}\}, P_{\mathrm{b}})$. For the accurate estimation of the decoder distortion at the encoder, the recursive optimal per–pixel estimate (ROPE) is used.[17] Finally, the expected distortion, $E\{D_{\mathrm{s+c},k}\}$, for node k can be written as a function of the source coding and channel coding rates, $R_{\mathrm{s},k}$ and $R_{\mathrm{c},k}$, and the transmission powers of all nodes, $S = (S_1, S_2, \ldots, S_K)^\top$, i.e., it has the general form $E\{D_{\mathrm{s+c},k}\}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S)$.[4]

3. PROBLEM FORMULATION

Based on the framework described in the previous section, our work copes with the problem of determining the vectors of the source coding rate and channel coding rate:

$$R_{\mathrm{s}} = (R_{\mathrm{s},1}, R_{\mathrm{s},2}, \ldots, R_{\mathrm{s},K})^\top, \qquad R_{\mathrm{c}} = (R_{\mathrm{c},1}, R_{\mathrm{c},2}, \ldots, R_{\mathrm{c},K})^\top,$$

respectively, as well as the power level,

$$S = (S_1, S_2, \ldots, S_K)^\top,$$

so that a function of the overall end–to–end expected distortion, $f(E\{D_{\mathrm{s+c},1}\},\ldots,E\{D_{\mathrm{s+c},K}\})$, is minimized:

$$(R_{\mathrm{s}}^*, R_{\mathrm{c}}^*, S^*) = \arg \min_{R_{\mathrm{s}},R_{\mathrm{c}},S} f(E\{D_{\mathrm{s+c}}\}),$$

subject to the constraint of equal transmission bit rate, R_k, for all nodes.

This distortion–related function depends on the deployed optimization criterion. In order to successfully solve the aforementioned problem, we consider two approaches:

(1) ***Independent WVSN nodes***: In this approach, each node acts as individual with its own content– and time–varying video and transmission parameters. The network resources are individually assigned to each node and the delivered video quality is estimated.

(2) ***Clustered WVSN nodes***: In this case, we apply partitional k–means clustering according to the individual video content–related parameters. Consequently, each node is a member of a cluster represented by its center. The transmission parameters are allocated according to the centers of the clusters and they are used to estimate the delivered video quality of each node.

In both approaches, we employed three distortion–related optimization criteria. The first criterion is the *Minimization of the Average Distortion* (MAD), which results in the minimization of the average end–to–end video distortion among all nodes.[4] The second criterion is the *Minimization of the Maximum Distortion* (MMD), which focuses on the minimization of the maximum video distortion of the network.[4] The last criterion is the *Nash Bargaining Solution* (NBS),[5] derived from Game Theory, and performs a bargaining game among the nodes. Below, we formally describe each criterion in detail.

3.1 MAD Criterion

Given a total target bit rate, R_k, we determine the vectors of optimal source coding rates, R_{s}^*, channel coding rates, R_{c}^*, and powers, S^*, such that the overall end–to–end *average distortion*, $D_{\mathrm{ave}}(R_{\mathrm{s}}, R_{\mathrm{c}}, S)$, over all nodes is minimized:

$$(R_{\mathrm{s}}^*, R_{\mathrm{c}}^*, S^*) = \arg \min_{R_{\mathrm{s}},R_{\mathrm{c}},S} D_{\mathrm{ave}}(R_{\mathrm{s}}, R_{\mathrm{c}}, S), \tag{6}$$

where:

$$D_{\mathrm{ave}}(R_{\mathrm{s}}, R_{\mathrm{c}}, S) = \frac{1}{K}\sum_{k=1}^{K} E\{D_{\mathrm{s+c},k}\}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S),$$

subject to:

$$R_1 = R_2 = \cdots = R_K = R_k.$$

Obviously, the MAD criterion emphasizes on the average performance of the network, allowing some individual nodes to assume higher distortion values than the rest.

3.2 MMD Criterion

Given a total target bit rate, R_k, we determine the vectors of optimal source coding rates, R_{s}^*, channel coding rates, R_{c}^*, and powers, S^*, such that the overall end–to–end *maximum distortion* over all nodes is minimized:

$$(R_{\mathrm{s}}^*, R_{\mathrm{c}}^*, S^*) = \arg \min_{R_{\mathrm{s}},R_{\mathrm{c}},S} \max_k E\{D_{\mathrm{s+c},k}\}(R_{\mathrm{s}}, R_{\mathrm{c}}, S), \tag{7}$$

subject to:

$$R_1 = R_2 = \cdots = R_K = R_k.$$

The MMD criterion emphasizes on the minimization of the worst case, ensuring that all distortions will be upper bounded in reasonable ranges.

3.3 NBS Criterion

The NBS approach consists of playing a bargaining game where the network nodes have to negotiate, agree and jointly determine their parameters. It is sensible that a player (node) will join the game only if it is ensured that it will get at least as high a utility as it would get without cooperation. This is called the *disagreement point*, henceforth denoted as $dp = (dp_1, dp_2, \ldots, dp_K)^\top$.

Let the *utility function*, U_k, be the PSNR of the received video of each node k:

$$U_k = 10 \log_{10} \frac{255^2}{E\{D_{\mathrm{s+c},k}\}}, \tag{8}$$

where $E\{D_{\mathrm{s+c},k}\}$ is the expected video distortion for node k, given by Eq. (5). We define $\mathbf{U}$ as the feasible set of all possible utility allocations, $U = (U_1, U_2, \ldots, U_K)^\top$. Each member of $\mathbf{U}$ results from a different combination of source coding rates, channel coding rates and transmission powers for all nodes. Then, the NBS, which is denoted as $F(\mathbf{U}, dp)$, is a member of the feasible set that satisfies the following axioms:[18]

(i) *Feasibility*: $F(\mathbf{U}, dp) \geqslant dp$.

(ii) *Pareto Efficiency*: $y > F(\mathbf{U}, dp) \Rightarrow y \notin \mathbf{U}$.

(iii) *Invariance to Equivalent Utility Representations*: $F(\tau(\mathbf{U}), \tau(dp)) = \tau(F(\mathbf{U}, dp))$, for any given strictly increasing affine transformation $\tau()$.

(iv) *Independence of Irrelevant Alternatives*: If $dp \in \mathbf{Y} \subseteq \mathbf{U}$, then $F(\mathbf{U}, dp) \in \mathbf{Y} \Rightarrow F(\mathbf{Y}, dp) = F(\mathbf{U}, dp)$.

In order to find the NBS, we have to maximize the Nash Product (NP). Particularly, given a total target bit rate, R_k, we need to determine the utilities vector, U, such that NP is maximized, i.e.:

$$F(\mathbf{U}, dp) = \arg \max_{U} NP, \tag{9}$$

where:

$$NP = (U_1 - dp_1)^{bp_1} (U_2 - dp_2)^{bp_2} \cdots (U_K - dp_K)^{bp_K}, \tag{10}$$

with $bp_1, bp_2, \ldots, bp_K$, denoting the bargaining powers, subject to:

$$U_k - dp_k > 0 \quad \text{and} \quad \sum_{k=1}^{K} bp_k = 1.$$

Since the defined utility function of Eq. (8) depends on the expected end–to–end distortion, $E\{D_{s+c,k}\}$, it also depends on $R_{s,k}$, $R_{c,k}$ and S. This implies that Eq. (9) can be written as:

$$F(\mathbf{U}, dp) = F(R_{\mathrm{s}}^*, R_{\mathrm{c}}^*, S^*, dp) = \arg \max_{R_s, R_c, S} NP. \tag{11}$$

In our study, we assumed that $dp \in \mathbf{U}$ is the minimum acceptable PSNR, determined by the CCU operator. The bargaining powers, $bp = (bp_1, bp_2, \ldots, bp_K)^\top$, determine who is more advantaged by the rules in the bargaining game,[18] while the game rules are designed with no intention of favoring a node against the others. Hence, the bargaining powers are identical:

$$bp_k = \frac{1}{K}, \tag{12}$$

with $k = 1, 2, \ldots, K$, which means that the bargaining powers are equal for all K nodes.

4. EMPLOYED ALGORITHMS

In the following paragraphs, brief descriptions of the clustering algorithm as well as the PSO algorithm used in our experiments, are provided.

4.1 Clustering Algorithm

The general goal of clustering is to form groups of objects that are similar to each other and different from the objects in the other groups. For the clustering of the WVSN nodes in our study, we selected the k–means algorithm. This choice was dictated by its prototype–based operation that simply divides the objects, producing non–overlapping clusters, i.e., each object belongs to a unique cluster.[19]

An additional advantage of k–means is its linear complexity in all relevant factors, namely the number of iterations, I_C, the number of clusters, K, and the dimensionality, D, of the search space, i.e., $O(I_C \times K \times D)$. The k–means algorithm selects k points as initial centroids. Then, it iteratively computes each point's distance from the centroids, forming k clusters and recomputing the centroids. This loop ends when the centroids stop changing.

In the present work, we perform clustering of the WVSN nodes according to the motion level of the transmitting video sequences in the second approach. For this purpose, we exploit the computed parameters α_k and β_k for each node at the encoder since, as already mentioned, parameter α_k is a salient indication of the motion level. In order to compute the distance between any pair of parameters (α_k, β_k) and the centroids, we are using the Euclidean norm. Each formed cluster is represented at the resource allocation problem by its centroid. This results in a remarkable reduction of the number of optimization parameters, which is indispensable in real–time applications.

4.2 Particle Swarm Optimization

All the criteria described in previous sections produce global optimization problems. For these tasks, we employed a swarm intelligence algorithm, namely *Particle Swarm Optimization* (PSO). This choice was based on its ease of implementation, the provision of globally optimal solution(s) and its rapid convergence. Those characteristics satisfy the performance requirements in most WVSN applications.

PSO is an effective and computationally efficient optimization algorithm, inspired by the dynamics of socially organized groups of living organisms. It utilizes a population (called a *swarm*) of search points (called *particles*) that iteratively probe the search space with an adaptive velocity (position shift), locating the most promising regions with the ultimate goal of finding a global minimizer.[20] Also, each particle has an adaptable memory where it stores the best position it has ever encountered during its search, i.e., the position with the lowest function value.

Furthermore, the particles can communicate among them, sharing their memory information. This way, they can benefit by the findings of their mates. The communication is based on abstract schemes, which are usually 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.[21]

Putting it formally, let:

$$\min_{x \in X \subset \mathbb{R}^D} f(x),$$

be the minimization problem under consideration. Also, let:

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

be a swarm consisting of N particles, each one defined as a D–dimensional vector:

$$x_i \in X, \qquad i = 1, 2, \ldots, N,$$

where X is the search space. Let also v_i denote the corresponding velocity and $p_i \in X$ 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:[21,22]

$$v_i(t+1) = \chi\Big[v_i(t) + c_1 R_1\big(p_i(t) - x_i(t)\big) + c_2 R_2\big(p_{g_i}(t) - x_i(t)\big)\Big], \tag{13}$$

$$x_i(t+1) = x_i(t) + v_i(t+1), \tag{14}$$

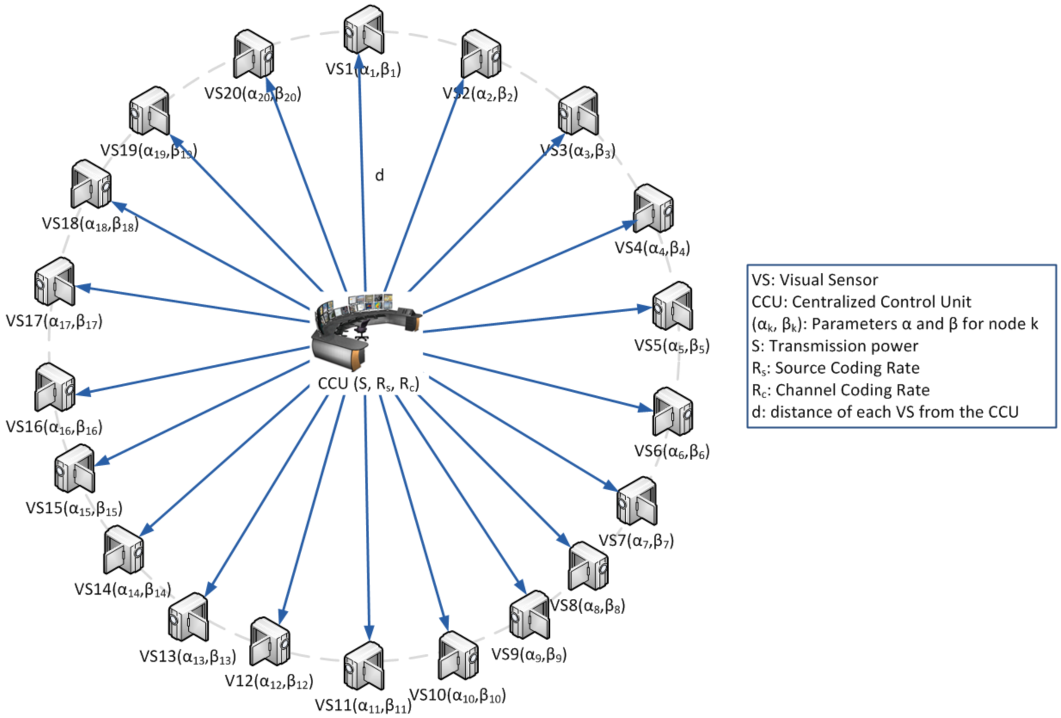

Figure 1. Considered WVSN topology for the experiments.

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.

Also, as already mentioned, the best position of each particle is updated each time it discovers a better one, until the global best position is achieved or a fixed number of iterations is reached:

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

The stability of PSO has been investigated by Clerc and Kennedy,[22] who proposed parameter values that probabilistically verify convergence towards solutions in the search space. From this study, the default parameter set:

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

was derived. Habitually, initialization of the particles is uniformly performed within the search space.

5. EXPERIMENTAL SETTING AND RESULTS

For the evaluation of our proposed approaches, we considered a number of test cases. Two of them were selected to be presented in the present study. The test cases aim to resemble reality, where each sensor node may record a scene of different motion. We considered a simple topology as depicted in Figure 1, where all nodes are equidistant from the CCU, having the same antenna gain (G_t, G_r) and height (h_t, h_r). Table 1 summarizes the parameter settings in our experiments. In all cases, the continuous transmission power levels were selected from the range $S = [0.5, 1.5]$ (in Watts). Regarding PSO, the particles were allowed to take continuous values for the position and velocity update, although they were rounded to the nearest integer for the evaluation of each particle. The default parameter set for the constriction coefficient and the acceleration parameters (cognitive and social) was used.

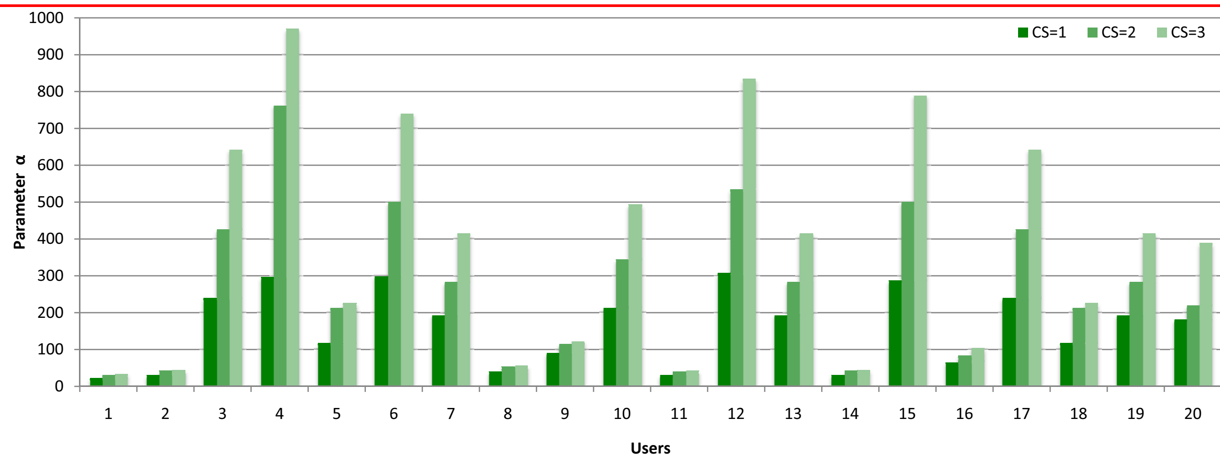

Figure 2. Random values of α_k for the three different coding sets (CS) for TC1.

Table 1. Parameter settings for the experiments.

Description	Parameter	Value
Number of WVSN nodes fig:powers	K	20
Motion Level		Random
Number of Clusters		3 (TC2)
Total Bandwidth	W_t	10 MHz
Total Transmission Rate	R_k	96 kbps
Valid Coding Sets for $(R_\mathrm{s}, R_\mathrm{c})$	CS	1–(32 kbps, 1/3), 2–(48 kbps, 1/2), 3–(64 kbps, 2/3)
Transmission Power	S_k	$[0.5, 1.5]$ (in Watts)
Antenna Heights	h_t, h_r	3 m
Antenna Gains	G_t, G_r	2 dB
Source Node to CCU Distance	d	120 m
Video Sequence Format		QCIF
RCPC Code Mother Rate		1/4
Link Layer Packet Size		400 bits
Disagreement Point	dp	24 dB
PSO Swarm Size	N	200 (TC1), 30 (TC2)
PSO Number of Iterations	$I_{\max}$	2000 (TC1), 500 (TC2)

Since PSO is a stochastic algorithm, for each problem instance we conducted 30 independent experiments to ensure the correctness of the results. During each experiment, the best detected solution was recorded. Our experiments confirmed that the resulting optimal resource allocation is not unique. In fact, there is a set of solutions, $(R_\mathrm{s}, R_\mathrm{c}, S)$, that satisfy the proposed optimization criteria. This is because the energy per bit to MAI ratio of Eq. (4) remains the same if all powers are multiplied by the same constant. Hence, in this case, only the nodes' power ratios, S_i/S_j, with $i, j = 1, 2, \ldots, K$, $i \neq j$, need to be determined in order to reach an optimal solution.

5.1 Test Case 1: Independent Nodes

Resembling a realistic simulation of a WVSN, we considered a first test case, henceforth denoted as TC1, of 20 visual sensors with different fields of view and variable motion. For this purpose, the parameters α_k and β_k were randomly assigned for each one of the 20 nodes, representing 20 different random motion levels. During experiments with well–known test sequences of various motion amounts, it has been noticed that motion levels

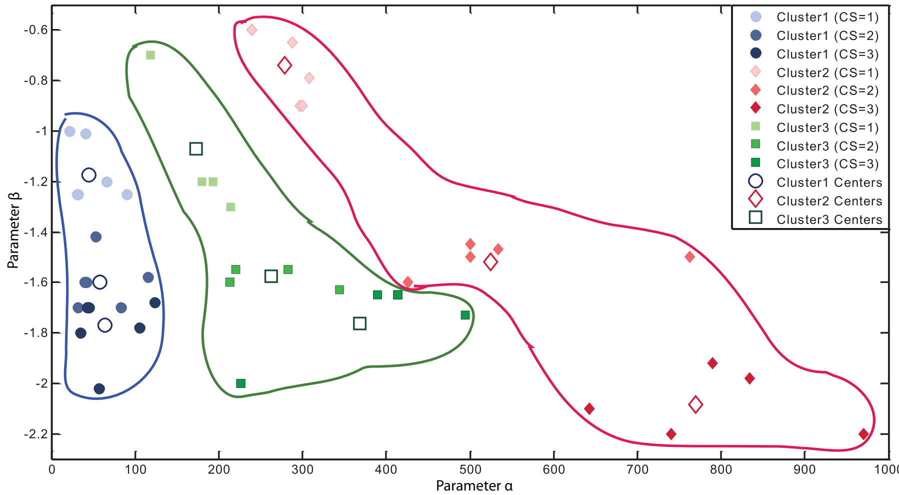

Figure 3. Clustering of the nodes based on the parameters α_k and β_k values for TC2.

affect α_k values, while β_k values lie within a narrow range. While the α_k ranges are distinguishable for videos with different amount of motion, the β_k ranges overlap.

Considering these properties, we defined a wide range for α_k values and randomly generated values within it for all nodes. The random values of α_k for the three different source and channel coding values in our experiments, are depicted in Figure 2. The corresponding values of β_k were determined accordingly, based on values of sequences with similar amount of motion. The dimension of the corresponding optimization problem for TC1 was $D = 40$.

5.2 Test Case 2: Clustered Nodes

In the second test case, henceforth denoted as TC2, the 20 nodes of TC1 were grouped into three clusters according to the sets of parameters α_k and β_k, using the k–means algorithm. As illustrated in Figure 3, for each of the clusters, three centers (pairs of (α_k, β_k) values) were produced. Each of the pairs was the representative cluster value for (α_k, β_k), for the three different cluster centers.

After determining the clusters' transmission power level and the source and channel coding rates, the corresponding PSNR values were calculated for each node of the cluster based on each node's (α_k, β_k). The corresponding optimization problem parameters were $D = 6$ in this case.

5.3 Discussion

Figure 4 shows the transmission power allocation, while Figure 5 shows the end–to–end video quality for all three criteria in both test cases. As we can see, for MAD and NBS the estimated PSNR values are very close, with the absolute differences being less than 1.0 dB. Yet, for some nodes it is higher than 1.0 dB. On the other hand, for the MMD criterion the difference of the estimated PSNR is higher and almost half of the nodes have higher than 1.0 dB absolute PSNR difference. This is due to the fact that during the network resource allocation, different source and channel coding rates may be assigned to the nodes. Consequently, a different pair of (α_k, β_k) is used for the PSNR estimation and the resulting value diverges.

Moreover, the results reveal that the NBS criterion allocates the transmission power among the nodes using the lowest power ratio, while the values in the two testing cases marginally differ. On the other hand, the other two criteria have the same power allocation for some nodes, however they diverge at a higher degree for others. The used criterion has to be decided with respect to the application requirements that may require to favor certain nodes according to the recorded video content. If the system requires the best possible quality for the low motion video sequences, then we recommend the NBS. Finally, for the case that the system requirements demand similar quality levels, we recommend the MMD deployment.

Figure 4. Comparison of the transmission power allocation for all three criteria in both test cases.

Comparing the employed source and coding rates in Figure 6, we can see that for the MAD and NBS criteria the CCU assigns the same values for both test cases. The selected values are 1 for (32 kbps, 1/3), 2 for (48 kbps, 1/2) and 3 for (64 kbps, 2/3), which means that higher error protection was required only when using the MMD criterion for TC1.

As far as the quality/complexity tradeoff of the different strategies is concerned, we shall consider several issues. Firstly, taking into account that the number of the particles and number of iterations both depend on the number of the WVSN nodes, PSO's complexity is directly related to the number of nodes included in the considered WVSN. This implies that TC1 has higher complexity than TC2. On the other hand, in TC2 the number of clusters regulates the complexity and the quality difference. This quality difference may be positive or negative as illustrated in Figure 5 and depends on the distance of each node's (α_k, β_k) values from its cluster's centroid, $(\alpha_{\text{centroid}}, \beta_{\text{centroid}})$.

Concerning the final decision on which approach is preferable according to the quality performance, it is easily derived that it exclusively depends on the considered application. Using clustering makes the system (computationally) less complicated, thus more time–efficient. However, it still fosters the danger of degrading the received video quality for some nodes. Therefore, the system's designer has to decide on the approach according to the system functional and non–functional requirements.

6. CONCLUSIONS

We investigated the idea of clustered and independent nodes in WVSNs, aiming at their efficient resource management. We assumed that in a 20–node WVSN each camera is monitoring a different field of view and, therefore, is recording and transmitting videos of various motion levels. We used three optimization criteria,

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
MAD -T.C.2	45,46	43,64	41,01	40,21	40,60	41,39	38,87	44,84	39,07	38,81	43,80	38,67	38,87	43,64	38,31	40,47	41,01	40,60	38,87	39,97
MAD - T.C.1	44,16	43,20	40,33	40,22	41,48	40,57	39,56	44,20	41,24	39,69	43,27	39,43	39,56	43,20	39,22	42,41	40,33	41,48	39,56	39,98

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
MMD - T.C.2	43,49	41,69	41,19	40,41	41,40	41,58	39,65	39,53	37,13	39,63	41,84	38,85	39,65	41,69	38,48	39,29	41,19	41,40	39,65	40,74
MMD - T.C.1	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15	40,15

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
NBS - T.C.2	46,94	45,05	40,76	39,95	39,93	41,13	38,22	46,51	40,46	38,12	45,20	38,44	38,22	45,05	38,09	41,94	40,76	39,93	38,22	39,31
NBS - T.C.1	47,07	45,20	39,95	39,71	42,13	40,44	38,64	46,89	41,68	38,84	45,32	38,19	38,64	45,20	37,81	43,88	39,95	42,13	38,64	39,40

Figure 5. Comparison of the PSNR for all three criteria in both test cases.

namely MAD, MMD and NBS. Owing to the assumption of continuous values for the transmission power and discrete values for the source and channel coding rates, the optimization problem is a mixed–integer one, which potentially renders PSO an appropriate choice for its solution.

The comparison of the two test cases (clustered/independent nodes) has shown the trade–off between quality and complexity. Overall, selecting the approach of clustering instead of having independent nodes offers the asset of a quicker optimal solution, at the possible cost of a reasonable quality decline for some nodes.

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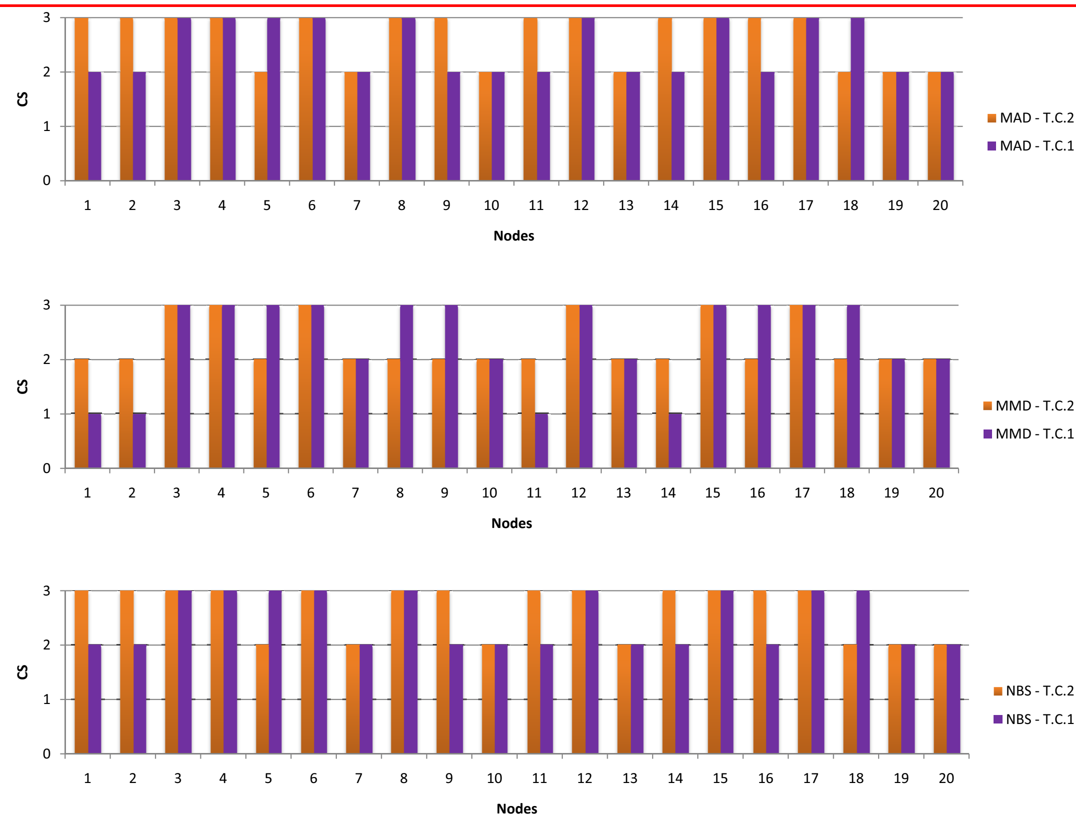

Figure 6. Comparison of the coding sets allocation for all three criteria in both test cases.

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