

Allocation Optimale des Ressources pour la Maximisation de la Durée de Vie des Réseaux de Capteurs Multimédias Sans Fil[†]

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De nos jours, les caméras sans fil sont largement déployées dans divers domaines d'application tels que les domaines commerciaux et militaires. Cependant, dans un tel réseau, les données capturées sont généralement volumineuses et nécessitent un traitement local, entraînant ainsi un besoin énergétique élevé. Par conséquent, le problème le plus important consiste à trouver un équilibre entre le niveau de compression de la vidéo au niveau de la source et la qualité de cette dernière exigée par l'utilisateur final, tout en maximisant la durée de vie du réseau. À cette fin, nous proposons un algorithme distribué qui considère le problème d'allocation des ressources dans un réseau de capteurs vidéo sans fil. Par opposition aux approches existantes, notre algorithme, est fourni pour trouver un tel compromis quelle que soit la configuration initiale du réseau. Outre, le problème d'optimisation formulé prend en considération le changement dynamique des capacités des liens.

Keywords: Réseaux de Capteurs Multimédias Sans Fil, Optimisation, Compression, Qualité vidéo, Maximisation de la durée de vie, Algorithme distribué.

1 Introduction

In order to take advantage of the benefits they can offer, WMSNs are used in a large number of real applications in several domains, such as home automation, elderly person assistance, advanced health care delivery. For instance, according to a recent report from *Tractica* [Tra15], the tele-health video consultation would increase from 20 to 950 million \$ from 2014 to 2020, respectively. These new applications involve the capture, the process and the delivery of not only scalar data but also multimedia content which consequently poses new research challenges.

At the sink, where data is consumed, some applications may require high visual quality in order to perform complex processing operations (e.g., face recognition) whereas other applications can accept lower visual quality (e.g., presence detection). On the other side, delivering high data rates (*i.e.* high visual quality) will draw down the resources of nodes, as the latter are driven by batteries. From that, a **trade-off** between the desirable visual quality at the sink and the network resources consumption has to be found, in order to prolong the network lifetime. Therefore, we propose a **fully distributed approach** that is able to derive the optimal encoding power and source rate at each video node in a way to meet the network constraints (limited link's bandwidth) on one hand and to prolong the network lifetime on the other hand.

To overcome the limitations of previously proposed approaches, we propose a novel approach that is able to : **a)** Find the optimal encoding power and source rates allocations which maximize the network lifetime independently of any networks settings. **b)** Our proposal handle a **dynamic change of links capacity**, in order to avoid both : (1) data losing (2) and low network connectivity. **c)** In order to evaluate the effectiveness of our proposal, we have implemented, in addition to our approach, the one, named *DQLM* [GLB09], in which, and unlike our solution, the capacity of the existing links were **fixed** and the solution is **semi-distributed**. Simulation results show that our approach increases the network lifetime by 4 times compared to *DQLM* solution, which demonstrates the effectiveness of our proposal.

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2 Network model

We consider a network composed of a set \mathcal{N} of video nodes and a sink. Let $\mathcal{V} \subset \mathcal{N}$ be the set of the video sensor. Each video sensor $h \in \mathcal{V}$ transmits the multimedia content to the sink. All the possible paths are stored into a sequence \mathcal{L} of links.

Under the oriented graph assumption, let a_{il} (with $\mathcal{N} * \mathcal{L}$ length) denotes the matrix of link information, in which 1 presents an outgoing traffic, -1 presents an incoming traffic. Moreover, the outgoing links (resp. with incoming links) are represented with a_{il}^+ matrix (resp. with a_{il}^- matrix), whose elements are defined by : 1 if l is an outgoing link (resp. with an incoming link) and 0 otherwise. Each video sensor h generates data traffic R_h , and transmits this latter with respect to the link rate x_{hl} . Thus, the flow is conserved at each node as follows : $\eta_{hi} = R_h$ if i is the generator of the traffic, $\eta_{hi} = -R_h$ if i is the sink and 0 otherwise.

Video coding power (P_{sh}) : We used the power-rate-distortion (P-R-D) analytical model presented in [HLG09] $P_{sh} = \left(\frac{\ln(\sigma^2) - \ln(D_h)}{\gamma * R_h} \right)^{\frac{2}{3}}$, P_{sh} is the power needed for compression, σ^2 is the average input variance, D_h is the encoding distortion, and γ is the encoding efficiency coefficient and R_h is the source rate.

Transmission and reception powers : we used the power consumption model presented in [HLG09] for data transmission and reception powers, respectively, as follows : $P_{ti} = \sum_{l \in \mathcal{L}} a_{il}^+ * (\alpha + \beta d_l^{n_p}) * y_l$, $P_{ri} = c^r * \sum_{l \in \mathcal{L}} a_{il}^- * y_l$, where y_l corresponds to the aggregate rate transmitted through link l , α and β are transmit electronics parameters, d_l is the distance between the transmitter and the receiver, n_p is the path-loss exponent. We define $c_l^s = (\alpha + \beta d_l^{n_p})$ to simplify the notation, that will be used in the rest of the paper. c^r is the radio receiver energy consumption cost. However, each node has a maximum transmission power P_{tmax} , (resp. reception power P_{rmax}), that it can't exceed to sent (resp. to receive) data.

In fine, the total energy consumption of node i is : $P_i = P_{sh} + P_{ti} + P_{ri}$.

We note that each node i is given with an initial energy provision, denoted B_i . Hence, the lifetime of each node is : $T_i = B_i / P_i$.

In this paper, we rely on critical applications in which the energy depletion of the first node leads to the death of the network. More formally, the network lifetime T_{net} is defined as : $T_{net} = \min_{i \in \mathcal{N}} B_i / P_i$.

Channel capacity (C_l) : it changes depending on both, noise power and data rates perceived at the receiver, and can be formulated, using the Shannon's theorem (1984), as the following : $C_l = W \log_2 \sqrt{1 + \frac{P_{rl}}{N_0 W}}$ $\forall l \in \mathcal{L}$, where W is a measure of the width of a range of frequencies (measured in Hertz), P_{rl} is the reception power, and N_0 is the additive white Gaussian noise.

2.1 Problem formulation and Solution

Taking into account the aforementioned constraints, the optimization problem can be formulated as follows :

$$\begin{aligned}
 & \underset{(R,x,P_s,q)}{\text{minimize}} \sum_{i \in \mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_h R_h^2 + \delta_p \sum_h P_{sh}^{8/3} \\
 & \text{subject to} \sum_{l \in \mathcal{L}} a_{il} x_{hl} = \eta_{hi} \quad \forall h \in \mathcal{V} \quad \forall i \in \mathcal{N}, \rightarrow \text{the flow conservation at each node} \\
 & \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \leq D_h \quad \forall h \in \mathcal{V}, \rightarrow \text{the P-R-D model} \\
 & P_{sh} + P_{ti} + P_{ri} \leq q_i B_i \quad \forall i \in \mathcal{N}, \rightarrow \text{the power consumption formulation} \\
 & \sum_{i \in \mathcal{N}} a_{il} q_i = 0 \quad \forall l \in \mathcal{L}, \rightarrow \text{ensures the convergence of the system} \\
 & \sum_{h \in \mathcal{V}} x_{hl} \leq W \log_2 \sqrt{1 + \frac{P_{rl}}{N_0 W}} \quad \forall l \in \mathcal{L}, \rightarrow \text{data sent on each link should not exceed } c_l \\
 & \sum_{l \in \mathcal{L}} a_{il}^+ P_{tl} \leq P_{tmax} \quad \forall i \in \mathcal{N}, \rightarrow P_{tl} \text{ should not exceed the maximum transmission power } P_{tmax} \\
 & \sum_{l \in \mathcal{L}} a_{il}^- P_{rl} \leq P_{rmax} \quad \forall i \in \mathcal{N}, \rightarrow P_{rl} \text{ should not exceed the maximum reception power } P_{rmax} \\
 & x_{hl} \geq 0, R_h \geq 0, P_{sh} > 0, q_i > 0. \rightarrow \text{ensures that the variables remains positive}
 \end{aligned} \tag{1}$$

Before going further, let us discuss the objective function ($\sum_{i \in \mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_h R_h^2 + \delta_p \sum_h P_{sh}^{8/3}$). $q_i = 1/T_{net}$ is the inverse lifetime of the network, and was integrated to ensure a fully distributed resolution. Such an integration must be followed by the fourth constraint (*i.e.*, $\sum_{i \in \mathcal{N}} a_{il} q_i = 0$ ($\forall l \in \mathcal{L}$)) in order to ensure the convergence of the system. On the other hand, to ensure a strict convexity of the system, we have introduced powers (*i.e.*, 2, 2 and 8/3) for each of R_h , x_{hl} and P_{sh} , respectively. Then, to keep their impact as minimal as possible on the objective function, a small quadratic regularization terms (*i.e.*, δ_r , δ_x and δ_p) were introduced.

Let us now discuss the resolution of such an optimization problem. Lagrangian Dual based methods [PC06] can be used to solve such a problem. Thus, the Lagrangian function for the optimization problem (1) can be written as below :

$$\begin{aligned}
 L(R, x, P_s, q, \eta, v, \lambda, w, \Gamma, \zeta, Z) = & \sum_{i \in \mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_h R_h^2 + \delta_p \sum_h P_{sh}^{8/3} \\
 & + \sum_{h \in \mathcal{V}} \sum_{i \in \mathcal{N}} u_{hi} (\sum_{l \in \mathcal{L}} a_{il} x_{hl} - \eta_{hi}) + \sum_{h \in \mathcal{V}} v_h \left(\frac{\ln(\sigma^2/D_h)}{\gamma P_{sh}^{2/3}} - R_h \right) \\
 & + \sum_{i \in \mathcal{N}} \lambda_i (P_{sh} + \sum_{l \in \mathcal{L}} a_{il}^+ c_l^s x_{hl} + c^r \sum_{l \in \mathcal{L}} a_{il}^- x_{hl} - q_i B_i) + \sum_{l \in \mathcal{L}} w_l (\sum_{i \in \mathcal{N}} a_{il} q_i) \\
 & + \sum_{l \in \mathcal{L}} \Gamma_l \left(\sum_{h \in \mathcal{V}} x_{hl} - W \log_2 \sqrt{1 + \frac{(c^r \sum_{h \in \mathcal{V}} x_{hl})}{N_0 W}} \right) + \sum_{i \in \mathcal{N}} Z_i (\sum_{l \in \mathcal{L}} a_{il}^+ c_l^s \sum_{h \in \mathcal{V}} x_{hl} - P_{imax}) \\
 & + \sum_{i \in \mathcal{N}} \zeta_i (\sum_{l \in \mathcal{L}} a_{il}^- c^r \sum_{h \in \mathcal{V}} x_{hl} - P_{rmax}).
 \end{aligned} \tag{2}$$

For any $h \in \mathcal{V}$, $i \in \mathcal{N}$, and $l \in \mathcal{L}$, and where u_i , v_h , $\lambda_{h,i}$, w_l , Γ_l , Z_i and ζ_i are the Lagrange multipliers associated with the different constraints of the optimization problem.

Following the subgradient method [BNO⁺03], the different Lagrange multipliers can be iteratively calculated, as follows :

$$\begin{aligned}
 u_{hi}^{k+1} = & u_{hi}^k - \theta^k (\eta_{hi}^k - \sum_{l \in \mathcal{L}} a_{il} x_{hl}^k); & v_h^{k+1} = & \max \left\{ 0, v_h^k - \theta^k \left(R_h^k - \frac{\ln(\sigma^2/D_h)}{\gamma (P_{sh}^k)^{2/3}} \right) \right\}; \\
 \lambda_i^{k+1} = & \max \{ 0, \lambda_i^k - \theta^k (q_i^k B_i - P_{ri}^k - P_{ri}^k) \}; & w_l^{k+1} = & w_l^k + \theta^k \sum_{i \in \mathcal{N}} a_{il} q_i^k; \\
 Z_i^{k+1} = & \max \{ 0, Z_i^k - \theta^k (P_{imax} - \sum_{l \in \mathcal{L}} a_{il}^+ P_{il}^k) \}; & \zeta_i^{k+1} = & \max \{ 0, \zeta_i^k - \theta^k (P_{rmax} - \sum_{l \in \mathcal{L}} a_{il}^- P_{rl}^k) \}; \\
 \Gamma_l^{k+1} = & \max \left\{ 0, \Gamma_l^k - \theta^k \left(W \log_2 \sqrt{1 + \frac{P_{hl}^k}{N_0 W}} - \sum_{h \in \mathcal{V}} x_{hl}^k \right) \right\},
 \end{aligned} \tag{3}$$

where θ^k represents the step size and given by : $\theta^k = \rho/k^{1/2}$, where $\rho > 0$ and $k > 0$.

It can be observed that the functions to be used are differentiable, and thus, can be computed in only one step as follows :

$$\begin{aligned}
 R_h^k = & \max \left\{ 0, \frac{v_h^k}{2\delta_r} \right\}; \\
 q_i^k = & \max \left\{ \epsilon, \frac{-(\sum_{l \in \mathcal{L}} a_{il} w_l - \lambda_i B_i)}{2} \right\}; & P_{sh}^k = & \max \left\{ \epsilon, \left(\frac{-3\lambda_h^k + \sqrt{(3\lambda_h^k)^2 + 64\delta_p \cdot v_h^k / \gamma \cdot \ln(\sigma^2/D_h)}}{16\delta_p} \right)^{\frac{3}{5}} \right\} \\
 x_{hl}^k = & \max \left\{ 0, \frac{-1}{2\delta_x} (\sum_{i \in \mathcal{N}} u_{hi}^k a_{il} + c_l^s \sum_{i \in \mathcal{N}} \lambda_i^k a_{il}^+ + c^r \sum_{i \in \mathcal{N}} \lambda_i^k a_{il}^- + \Gamma_l^k + c_l^s \sum_{i \in \mathcal{N}} Z_i^k a_{il}^+ + c^r \sum_{i \in \mathcal{N}} \zeta_i^k a_{il}^- - \frac{c^r \Gamma_l^k}{2N_0 \ln 2}) \right\}.
 \end{aligned}$$

2.2 Simulation Results

Let us now study the network lifetime of the proposed fully distributed solution under the dynamic change of the links capacity. To ensure the effectiveness of our solution, we have also implement the *DQLM* solution [GLB09] (unlike our solution, in [GLB09] the capacity of the existing links were fixed and the solution is semi-distributed) in OMNET++, by using the topology in figure 1-(a) (heavily borrowed from [GLB09]).

2.2.1 Energy cost

Figure 1-(c) shows the requirement in terms of battery, where we have taken the nodes with the highest battery consumption, spent to ensure an optimal power and rate allocation. Namely, node1 for *DQLM* node3

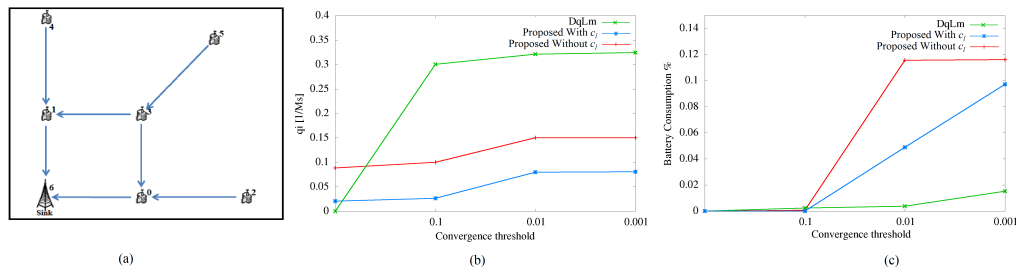


FIGURE 1: (a) Network Topology, (b) Network lifetime inverse comparison and (c) Battery Consumption Comparison

for our proposed solution with dynamic change of links capacity, as well as the node5 for also our proposal but this time without applying the links capacity. We can observe that, our proposed solution, with the dynamic change of links capacity, ensures the lesser battery consumption compared to the solution without applying the dynamic change of the links capacity.

Regarding the *DQLM* solution, we can observe that there is a difference compared to our proposal with dynamic change of links capacity. This difference can be explained by the fact that the *DQLM* solution is semi-distributed, while our solution is fully distributed. Therefore, our solution requires more time to converge, and hence more energy consumption compared to *DQLM* (especially in a such topology, where there is a minor communication between the different sensor nodes).

2.2.2 Network Lifetime

Let us recall that the main objective of this paper is to maximize the network lifetime, by finding the optimal power and rate trade-off, while ensuring the desired video quality at the destination. Thus, to calculate the network lifetime we can simply inverse the q_i variable. Figure 1-(b) shows that our approach maximizes the network lifetime by 4 times compared to the *DQLM* solution, and by 1.8 times compared to the solution without applying the links capacity.

3 conclusion

In this paper, we propose a fully distributed approach that is able to find an optimal trade-off between the desirable visual quality at the sink and the network resources consumption, while ensuring the maximization of the network lifetime. In order to evaluate the effectiveness of our proposal, we have implemented, the *DQLM* algorithm proposed in [GLB09]. Simulation results show that our approach increases the network lifetime by 4 times compared to *DQLM* solution, and this independently of any networks settings.

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