A Secure Distributed Algorithm for Network Lifetime Maximization and Video Distortion Minimization in Wireless Multimedia Sensor Networks

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ABSTRACT

In this paper, we investigate a joint performance optimization on network lifetime and video distortion for wireless multimedia sensor network (WMSN). Considering the tradeoff between minimum video distortion and maximum network lifetime, a multi-objective cross-layer optimization framework is proposed, which not only optimizes network lifetime but also achieves optimal video quality, where the source encoding rate and link rate are jointly optimized. In addition, a secret scheme that couples secret sharing and multipath routing is developed to provide reliable security. Finally, a video distortion model, including source rate and link rate is specially studied. Decentralized algorithms are realized using a subgradient method to solve the multi-objective optimization problem. Experimental results demonstrate the optimal tradeoff performance. We also illustrated that the proposed scheme can achieve greater network lifetime and much less video distortion compared to existing distributed algorithms.

Keywords

Cross-layer optimization, wireless multimedia sensor network (WMSN), convex optimization.

1. INTRODUCTION

Wireless multimedia sensor networks (WMSNs) consist of distributed sensors that communicate with each other through wireless channels. WMANs are a category of WSN in that each sensor is prepared with video capture and processing components. WMSNs enable an wide range of applications such as multimedia surveillance, emergency response, environmental tracking, and advanced health care delivery [2]. Each video sensor has a camera component to capture the video and a processing component to compress the video. The multimedia sensors usually have a mesh network topology, and they interconnect with each other over a limited transmission range. The video is collected and encoded at the source sensor node and then is sent to a destination node for additional analysis and decision making.

Over the previous years, optimization strategies have been developed to deal with numerous issues in wireless networks. In [9], the authors studied two classes of distributed rate control algorithms for wireless networks. Convex optimization is used to maximize utility for resource allocation in networks [10]. Cross-layer optimization for wireless ad hoc networks was introduced in [11], [12]. A scheme based on optimizing the routing scheme and the source rate concurrently was suggested in [13]. Joint optimization of source coding, routing, and resource allocation in wireless sensor networks was developed in [14]. Network lifetime maximization for traditional wireless sensor networks has been broadly investigated in the previous years. In [15], the authors suggested a routing scheme to maximize the network lifetime. To solve lifetime maximization problem, a distributed algorithm was suggested using the dual decomposition and the subgradient method [16]. A distributed algorithm was developed to enhance the lifetime of a WMSNs by jointly optimizing the routing scheme, source rates, encoding powers [17]. A scheme was proposed to solve the lifetime maximization problem with a distributed algorithm based on the dual decomposition and the subgradient method [18].

The tradeoff between network lifetime and video quality has been extensively investigated. In [3], a scheme for energy minimization was proposed by testing its tradeoff with video encoding. In [4], an optimization technique was designed to control the network flow with lifetime constraint. An optimization scheme for WMSNs to accomplish resource allocation together with network lifetime maximization was developed [5]. A power minimization and rate allocation scheme was suggested, where the main objective was to achieve optimal rate allocation and guarantee minimum power consumption [6]. The scheme successfully accomplished an optimal tradeoff between lifetime and video distortion. Video distortion along with network flow performance optimization for different video rate is considered [7]. The objective of the framework is to perform the optimal rate-distortion tradeoff by joining the inter-layer dependencies among network layers as constraints. An adaptive solution for joint source and channel rate is suggested, with considering link rate and video encoding [8]. The suggested frameworks in [7] and [8] can both performed optimal tradeoff between video quality and resource allocation. However, both of schemes did not succeed in enhancing the network lifetime. Moreover,

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the schemes that enhance network lifetime and video quality do not accomplish optimal resource allocation. Therefore, it is necessary to design a proper technique to perform optimal tradeoff among network sources, video quality and lifetime. The issues related video quality, network lifetime and resource optimization were investigated disjointedly in literature

To tackle the above limitations of present schemes, we have suggested a multi-objective distributed optimization schemes that achieve optimal video quality tradeoff with network lifetime while maximizing resource utilization.

Another significant issue in WMSNs is security. When the nodes deployed in a hostile surroundings, they are subject to compromise. Normally, it is not economically desirable to make the sensor nodes tamper proof that means when a node is attacked, all the secrets saved in that node with cryptographic keys can be extracted too, which put the information relayed by that at risk. Recently, a number of secure routing schemes have been developed to address the secure routing problem in wireless networks. In [1], the author proposed a secure protocol for reliable data delivery (SPREAD) for the end-to-end message delivery in WSNs. Instead of using the single shortest path to route the data from one node to the other, SPREAD splits a message into multiple shares using the secret sharing scheme. The SPREAD idea was shown to be effective in improving the security. In [19] , to secure the data transmission in wireless network, each path frequently transmits a reliability rating that is calculated by the ratio of the successful packet deliveries to unsuccessful packet deliveries over that path.

The remainder of this paper is structured as follows: Section 2 presents the network model and its associated specifications. Section 3 states the tradeoff problem of minimizing video distortion and maximizing network lifetime as multi-objective optimization problem. A distributed algorithm for joint rate allocation, share allocation, distortion minimization, and network lifetime maximization is suggested. Experimental results are illustrated in Section 4. Finally, we conclude our paper in Section 5.

2. MODELS

2.1 A threshold Secret Sharing

A threshold secret sharing scheme with a threshold (Q, J) divides a secret packet into J shares and requires the knowledge of a certain number Q (threshold) of shares to reconstruct the original image. Any less than the threshold number of shares D give its holder no larger chance of retrieving the secret than what an outsider who knows nothing at all about the secret sharing system. Table I sums up the major notation used in this paper. Table 1 sums up the major notations used in this paper.

2.2 Share Allocation Scheme

Assume that we have assigned m disjoint paths to deliver Q shares to the destination node. According to the shares allocation scheme [1], in order to achieve the required security level, the number of shares allocated to $m-1$ must be less than $Q-1$ shares. In such a case an unauthorized users must compromise all the m paths before he/she can disclose the message. However, the drawback of this scheme is that the disjoint paths have to be determined before the shares are transmitted

Table 1: Major notations used in this paper

V	the set of nodes
L	the set of links
D_t	the transmission range
$d_{i,j}$	distance between node \$i\$ and \$j\$
c_l	link capacity
SNR	the Signal to Noise Ratio
α	the path loss exponent
N	the power spectral density of the noise
W	the system bandwidth
γ	the coding gain
A	node-link incidence matrix
S	the source rate
f_l	the link flow
Q	The secret sharing threshold number
R	The shares set
s	The share rate
m	The number of disjoint paths
Z	A share-link matrix
p_{E-E}	The end-to-end packet loss rate of a share \$r\$
d	The expected distortion of the constructed video
Re	The expected received rate (throughput) at the receiver
T_{net}	The lifetime of a network
E_i,E_{ti},E_{ri}	The node initial energy, the energy required to transmit one bit, and and the energy required to receive one bit respectively

2.3 Network Model

We consider a static wireless network an model it as an undirected graph $G(V, L)$ where V is the set of nodes, and L is the set of links. Let D_t be the transmission range. Two nodes i and j are connected if the distance between them $d_{i,j}$ is less than D_t. We assume that the total capacity of the wireless link between two nodes i and j is defined by c_l and is derived as follows [20]:

$$c_l = \frac{w}{2}\left[1 + \gamma\ SNR_l\right] \tag{1}$$

Where SNR is the Signal to Noise Ratio between the nodes i and j and can be written as follows:

$$SNR_l = \frac{d_{i,j}^{-\alpha}}{WN} \tag{2}$$

α denotes the path loss exponent, N represents the power spectral density of the noise, W is the system bandwidth, and γ is the coding gain. It is also assumed that the transmission power is equal at all nodes. In the following, we will assume that the nodes are static with $\alpha = 2$.

The network topology can be represented by its node-link incidence matrix A

$$\begin{cases} 1 & \text{if } l \text{ is an outgoing link from nod } i \\ 0 & \text{otherwise} \\ -1 & \text{if } l \text{ is an incoming link from node } i \end{cases} \tag{3}$$

The relationship between node i and its outgoing links can be described with a matrix A^+

$$a_{il}^+ = \begin{cases} 1 & \text{if l is an outgoing link from nod i} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The relationship between node i and its incoming links can be described with a matrix A^-

$$a^-_{il} = \begin{cases} 1 & \text{if l is an outgoing link from nod i} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

We assume a standard medium access control (MAC) protocol is used to address the interference issue. Each sensor node $i\,(\forall i \in N)$ is capable of capturing and encoding the video, and then producing data with a source rate s (data traffic here represents a defined number of Group of pictures (GOPs)). To secure this data traffic, a secret sharing algorithms is applied on the data traffic to produce Q number of shares, each share with a source rate s. To deliver these shares safely, they must be sent to the destination according to the allocation scheme as we mentioned in the previous section.

Let S and f_l denote source rate and the link flow respectively. The link flow cannot exceed the capacity c_l of the link. When a secret sharing is applied, the packet is divided into J number of shares denoted by set R. Each share with a source rate s and $|R| = Q$. The packet can be reconstructed by a threshold number of shares no less than Q.

A flow must fulfill the restriction that the traffic flow into a node equals the traffic flow out of it, except if it is a source node which has only outgoing flow, or sink, which has only incoming flow.

$$\sum_{l\in\mathbf{L}} A_{il} f_l = \beta_i = \begin{cases} \sum_{r\in R} s_r & \text{if } i \text{ is the source node} \\ 0 & \text{otherwise} \\ -\sum_{r\in R} s_r & \text{if } i \text{ is the destination node} \end{cases} \tag{6}$$

2.4 Video Distortion Model

The expected distortion of the reconstructed video is determined by the expected throughput. The higher the throughput a receiver receives the higher quality it can reconstruct. The empirical Rate-Distortion $(R-D)$ model is used to represent the distortion d [21]. We extend this model to characterize the distortion relationship for the prioritized coded video with protection redundancy. It is given by

$$d = D_0 + \frac{\Theta_0}{Re + \Phi_0} \tag{7}$$

where d is the expected distortion of the constructed video, Re is the expected received rate (throughput) at the receiver, D_0, θ_0 and α are model parameters which can be found using data fitting techniques.

Therefore, the expected video distortion can be represented by :

$$\begin{aligned} d &= D_0 + \frac{\Theta_0}{S(1 - \sum_{l\in L} p_l \frac{f_l}{S}) + \Phi_0} \\ &= D_0 + \frac{\Theta_0}{(S - \sum_{l\in L} p_l f_l) + \Phi_0} \end{aligned} \tag{8}$$

In secret sharing when a share lose one element such as pixel, it results in losing Q pixels in the reconstructed image, therefore the expected distortion of the reconstructed video becomes

$$d = D_0 + \frac{\Theta_0}{(\sum_{r\in R} s_r - \sum_{l\in L} Q p_l f_l) + \Phi_0} \tag{9}$$

2.5 Network lifetime

The lifetime of a network T_{net} is defined as the time when the first sensor runs out of its energy. Assume that each sensor i has an initial energy E_i and a lifetime of T_i, the lifetime of the network is defined as $T_{net} = min_{i\in N} T_i$ which is equal to the following equation

$$T_{net} = \min_{i\in N}\left(\frac{Ei}{E_{ti}\sum_{l\in L} a^+_{il} f_l - E_{ri}\sum_{l\in L} a^-_{il} f_l}\right) \tag{10}$$

Where E_{ti} and E_{ri} denote the energy required to transmit one bit and the energy required to receive one bit respectively.

3. PROBLEM FORMULATION

3.1 Optimization Problem

Several important issues are considered: the share source rate; the routing scheme; and the network lifetime and video distortion. These issues are interrelated. The link rate must not be higher than the link capacity, which is not independent on the transmitting or receiving power. Furthermore, the link rate allocation is related to the source rate.

The main objective of this work is to maximize the network lifetime. On the other hand, the key issue for video transmission is how to obtain a good video quality at the destination. To achieve this, we should reduce the end-to-end video distortion at the destination node, i.e., $min\ d$. It is clear from (9) that a larger throughput at a receiver leads to a smaller distortion. Thus, we need to maximize the throughput $\left(\sum_{r\in R} s_r - Q\sum_{l\in L} f_l P_l\right)$. Minimizing the total video distortion and maximizing the network lifetime can be performed as constrained minimization problems. Thus, the tradeoff between two optimization problems can be expressed as a multi-objective programming problem.

$$\begin{aligned} &\text{maximize}_{s,f}\left(T_{net} + \left(\sum_{r\in R} s_r - Q\sum_{l\in L} f_l P_l\right)\right) \\ &\text{subject to} \\ &\sum_{l\in L} a_{il} f_l \le \beta_i \quad \forall\ i \in N \\ &\sum_{l\in L} a^+_{il} f_l \le \sum_{r\in R} s_r \Delta_i \quad \forall\ i \in N \\ &T_{net} = \min_{i\in N}\left(\frac{Ei}{E_{ti}\sum_{l\in L} a^+_{il} f_l - E_{ri}\sum_{l\in L} a^-_{il} f_l}\right) \\ &0 \le f_l \le c_l \quad \forall\ l \in L \\ &s_r \ge 0 \qquad \forall\ r \in R \end{aligned} \tag{11}$$

The first constraint represents the flow conservation at each node $i \in N$. The second constraint is used to ensure the each node must not pass more than where $\Delta_i \in R^{N\times 1}$, $\Delta_i = [1, 1/x, 1/x..., 0]^T$. Here we assume x is the minimum cut of a network. The fourth constraints describes the energy constraint on each node. The node total energy must be higher than the The product of energy cost rate and lifetime.

Replacing variable to $g = \frac{1}{T}$, we end up with the following linear programming formulation

$$
\begin{aligned}
&\text{maximize}_{(s,f)} \left(\frac{1}{g} + \left(\sum_{r\in R} s_r - Q\sum_{l\in L} f_l P_l\right)\right)\\
&\text{subject to}\\
&\sum_{l\in L} a_{il} f_l \le \beta_i \quad \forall\, i \in N\\
&\sum_{l\in L} a_{il}^{+} f_l \le \sum_{r\in R} s_r \Delta_i \quad \forall\, i \in N\\
&\left(E_{ti}\sum_{l\in L} a_{il}^{+} f_l - E_{ri}\sum_{l\in L} a_{il}^{-} f_l\right) \le g E_i\\
&0 \le f_l \le c_l \quad \forall\, l \in L\\
&s_r \ge 0 \quad \forall\, r \in R
\end{aligned} \tag{12}
$$

3.2 Distributed Algorithm

This optimization formulation cannot be solved in a decentralized fashion, because the value of g needs to be transmitted to each node in the network [16]. To solve this optimization in decentralized manner, we need to give each node a local variable g_i. Minimization g is equivalent to the minimization of $\sum_{I\in N} g_i^2$.

$$
\begin{aligned}
&\text{minimize}_{(g,s,f)} \left(\sum_{i\in N} g_i^2 - \left(\sum_{r\in R} s_r - Q\sum_{l\in L} f_l P_l\right)\right)\\
&\text{subject to}\\
&\sum_{l\in L} a_{il} f_l \le \beta_i \quad \forall\, i \in N\\
&\sum_{l\in L} a_{il}^{+} f_l \le \sum_{r\in R} s_r \Delta_i \quad \forall\, i \in N\\
&\left(E_{ti}\sum_{l\in L} a_{il}^{+} f_l - E_{ri}\sum_{l\in L} a_{il}^{-} f_l\right) \le g E_i\\
&0 \le f_l \le c_l \quad \forall\, l \in L\\
&s_r \ge 0 \quad \forall\, r \in R
\end{aligned} \tag{13}
$$

The dual decomposition is used to solve this formulation in a distributed fashion [24]. However, since objective function (16) is not strictly convex in flow rate link and shares source rates. We need to append a regulation term to the objective function. Quadratic regulation term is added for each link rate variable and source rate variable to force the objective function to be strictly convex. Then the optimization problem becomes

$$
\text{minimize}_{(g,s,f)} \left(\sum_{i\in N} g_i^2 - \left(\sum_{r\in R} s_r - Q\sum_{l\in L} f_l P_l\right) + \sum_{r\in R} \delta s_r^2 + \sum_{l\in L} \delta f_l^2\right) \tag{14}
$$

By forcing $\delta\,(\delta > 0)$ to be close enough to 0, we can make the solution of the objective in (14) close to the optimal solution in (11). Now the optimization problem is strictly convex, therefore CVX can be easily used to solve it [23].

By introducing Lagrange multipliers for the four constraints at each sensor node, the Lagrangian of the optimization can be expressed by:

$$
\begin{aligned}
L\left(g,s,f,\lambda_i,u_i,v_i\right) = &\sum_{i\in N} g_i^2 - \left(\sum_{r\in R} s_r - Q\sum_{l\in L} f_l p_l\right) +\\
&\sum_{r\in R} \delta s_r^2 + \sum_{l\in L} \delta f_l^2 + \lambda_i\left(\sum_{l\in L} a_{il} f_l - \beta_i\right) +\\
&u_i\left(\sum_{l\in L} a_{il}^{+} f_l - \sum_{r\in R} s_r \Delta_i\right) +\\
&v_i\left(E_{ti}\sum_{l\in L} a_{il}^{+} f_l - E_{ri}\sum_{l\in L} a_{il}^{-} f_l - g_i E_i\right)
\end{aligned} \tag{15}
$$

Then the objective function of the dual problem is expressed by

$$
D\left(\lambda_i,u_i,v_i\right) = \min_{g,s,f} \quad L\left(g,s,f,\lambda_i,u_i,,v_i\right) \tag{16}
$$

and the dual problem is

$$
\begin{aligned}
&\max \ D(\lambda_i,u_i,v_i)\\
&\qquad s.t\\
&\qquad \lambda_i \ge 0, u_i \ge 0, v_i \ge 0
\end{aligned} \tag{17}
$$

The subgradient method is used to solve the objective function in (17). The subgradient converges to the optimal solution if the step size $\xi^k\left(\xi^k > 0\right)$ are chosen such that

$$
\lim_{k\to\infty} \xi^k = 0, \sum_{k=1}^{\infty} \xi^k = \infty \tag{18}
$$

The dual variables λ_i, u_i and v_i at (k+1) iterations are calculated by

$$
\lambda_i^{k+1} = \lambda_i^k - \xi^k\left(\beta_i - \sum_{l\in L} a_{il} f_l\right) \tag{19}
$$

$$
u_i^{k+1} = u_i^k - \xi^k\left(\sum_{r\in R} s_r\Delta_i - \sum_{l\in L} a_{il}^{+} f_l\right) \tag{20}
$$

$$
v_i^{k+1} = v_i^k - \xi^k\left(gE_i - E_{ti}\sum_{l\in L} a_{il}^{+} f_l + E_{ri}\sum_{l\in L} a_{il}^{-} f_l\right) \tag{21}
$$

By knowing the dual variables, the primal variables can be calculated as shown below.

$$
g_i^k = \min_{g_i>0} \quad \left(g_i^2 - v_i g_i E_i\right) \tag{22}
$$

$$
s_r^k = \min_{s_r>0} \quad \left(-s_r - \lambda_i\beta_i - s_r\sum_{i\in N} u_i\Delta_i + \delta s_r^2\right) \tag{23}
$$

$$
\begin{aligned}
f_l^k = \min_{f_l>0} \quad &\left(f_l\sum_{i\in N} a_{il}\lambda_i + f_l\sum_{i\in N} a_{il}^{+} u_i + Qf_l p_l\right.\\
&\left. + v_i\left(f_l\sum_{i\in N} a_{il}^{+} E_{ti} - f_l\sum_{i\in N} a_{il}^{-} E_{ri}\right) + \delta f_l^2\right)
\end{aligned} \tag{24}
$$

The proposed algorithm is totally distributed. Each node calculates the primal variables the variable g_i, the share source rate s_r and the link rate f_l for each node, by the utilizing dual variables of itself and its neighboring nodes. The dual variables and the primal variables converge to their optimal values simultaneously. The message exchange is only needed within the one-hop neighbors; therefore the communication overhead is reduced significantly

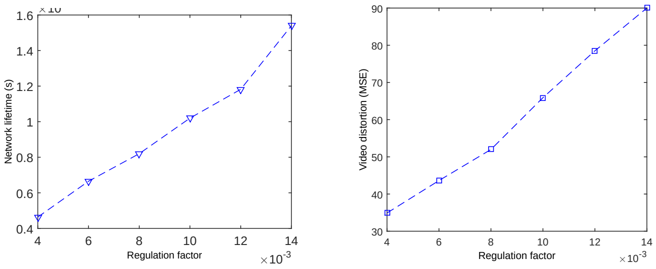
4. SIMULATION RESULTS

In this section, we present performance results of the proposed distributed solution for the network lifetime and distortion optimization in WMSNs. We consider a WMSN with 11 nodes distributed in a square region of 500 m ÃŮ 500 m. Node 11 is the destination node, and node 1 is source node. Each node has a maximum transmission range of 50 m. Video sequence "Foreman" in common intermediate format (QCIF) is utilized in the simulations. The source node encodes the video, and then the secret sharing scheme with a threshold $(Q = 6, J = 6)$ is applied on each 16 GOPs of this video to generate number of shares. The step size we use in our algorithm is $\xi^k = \mu/k$, where $\mu = .30$. The bandwidth of each link is set to 12 MHz according to [14]. In order to incorporate the effect of noise and interference, we choose the SNR of each link to be 15 dB. Also we set E_i,E_{ti}, and E_{ri} to be $5.0MJ$, $0.5J/Mb$, and $0.25/Mb$ respectively. All the optimization problems were solved with cvx software.

The maximum network lifetime and the maximum video distortion can be achieved by solving the optimization problem (11) with the centralized algorithm. A regulation factor is introduced to solve the optimization problem in a distributed manner. The proposed distributed scheme distributed the computation burden between all the nodes with a small efficiency loss in contrast to the centralized schemes. The effect of regulation factor δ on the tradeoff between collected video distortion minimization and the network lifetime maximization is presented in Fig.1. Fig.1(a) and Fig.1(b) illustrate the effect of the regulation factor δ on the average video distortion and the network lifetime. We can notice that as regulation factor δ increases, the resultant optimal network lifetime increases with an increase in the video distortion. In contrast, the network lifetime increases and the video distortion drops as the regulation factor δ increases.

The proposed scheme is compared with the Distributed Algorithms for Network Lifetime Maximization (DALT) in [17]. DALT is a distributed scheme operate by maximizing the lifetime, and the quality of the reconstructed video is prescribed. For have a fair comparison, we assume the initial power of all the sensor nodes in both schemes is equal. The network lifetime is defined as the lifetime of the node that exhausts its power first. By changing the average packet loss rate of each wireless link from 2% to 28%, the network lifetime and the average video distortion for both algorithms are presented in Fig.2(a) and Fig.2(b). It can be noticed that, once the average packet loss rate increments, the average video distortion increments, and the network lifetime diminishes. The reason behind this is as follows: When the packet loss rate of a link increases, the number of required packet should be sufficient to mitigate the packet loss rate. However, as presented in Fig.2(d), both schemes provide almost the same network lifetime. Also as shown in Fig 2(c), the proposed algorithm can achieve lower video distortion, because the proposed scheme works by minimizing the collected video distortion and maximizing the network lifetime simultaneously.

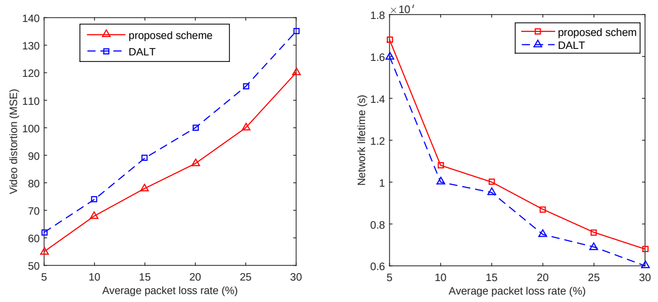
To examin the security performance of the scheme, we must see how the scheme is capable of allocating the shares and developing disjoint paths. We compared the proposed scheme with (SPREAD)[1]. In SPREAD, the secret data is split into a number of shares and these shares are sent over disjoint paths so that even if some paths are compromised, the overall message becomes secret. Thus, the issue here is about how to discover disjoint paths and distribute the shares between these paths according to share allocation scheme [1]. A secret sharing threshold $(Q = 6, J = 6)$ is used. The main observation worth highlighting here is that the two schemes achieve almost the same performance as illustrated in Fig.3 where the network flows are represented as a graph, where the thickness of an edge is proportional to the amount of flow on the corresponding wireless link. The proposed scheme discovers the possible disjoint paths without using any route discovery algorithms. An unauthorized user has to compromise the two disjoint path before he discloses the packet. The scheme also effectively manages the traffic allocation in a network for load balancing.



(a)

(b)

Figure 1: The effect of regulation factor δ on (a) the network lifetime, (b) the average video distortion



(a)

(b)

Figure 2: The comparison of the proposed algorithm with DALT (a) average video distortion, (b) network lifetime

(a) (b)

Figure 3: The comparison of the proposed algorithm with SPREAD (a) proposed algorithm,(b) SPREAS scheme

5. CONCLUSION

In this paper, we have investigated the network lifetime maximization and video distortion minimization problem in wireless multimedia sensor networks. By jointly optimizing the source rates and flow rates, a distributed algorithms is formulated to resolve the tradeoff issue between the network lifetime maximization and video distortion minimization using a subgradient method. The secret sharing is used to provide security by applying a constraint on the shares flow. By simulations, we examined the convergence of the proposed scheme, and illustrated that the proposed algorithm can provide security and an optimal performance compared to existing distributed schemes.

6. ACKNOWLEDGEMENT

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