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Error resilient image transport in wireless sensor networks

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Abstract

In this paper, we propose an "in-network" diversity combining scheme for image transport over wireless sensor net-works. We consider a wireless sensor network with both wireless link impairments and node failures. We analyze two per-formance metrics of the proposed image transport scheme: energy consumption and received image quality distortion. Our analysis models key aspects of the network including forward error correction, path diversity, and the multi-hop nature of ad-hoc networks. The channel model used is a two-state Markov model describing errors on the bit level. We also use a two-state Markov model of node transitions between an "on" and "off" state. Reed–Solomon coding is used for forward error correction. Theoretical and simulation results show the robustness improvement. This work also helps in understanding the tradeoffs between image quality distortion and energy consumption as a function of various network parameters such as the number of hops between the source and the destination, the average channel error rate, and the average node failure rate.

Keywords: Diversity combining; Forward error correction; Image transport; Sensor networks

1. Introduction

Recently, with the advance in image sensors [1,2], there has been a growing interest in visual wireless sensor networks for a variety of applications, including active monitoring, target tracking and remote surveillance [3]. However, wireless sensor networks pose a great challenge to image transport. The wireless links between nodes are susceptible to wireless channel fading, which causes channel errors. Unlike cellular networks or wireless local area networks, the path between the source and the destination in wireless sensor networks normally contains multiple wireless links (hops). Thus, transmission errors in wireless sensor networks are more frequent and severe than those in wireless networks with single hop routes between nodes. In addition, node failures are very common to sensor networks. The nature of wireless sensor networks makes the problem of image transport far more challenging when compared to image transport in a more predictable wired or even wireless networks with single hop paths. The goal of this paper is to present an

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image transport scheme that is capable of improving the robustness of image quality in spite of the wireless channel impairments and sensor node failures.

To protect the data against transmission errors, redundancy is commonly used. Redundancy takes two forms; spatial and temporal. Spatial redundancy replicates the data in a system. Transport over multiple paths through a network and the use of forward error correction (FEC) codes are examples of spatial redundancy. Automatic repeat request (ARQ) is an example of temporal redundancy. Unlike delay tolerant applications, image surveillance may not benefit from retransmission-based error recovery due to the additional delay incurred. Therefore, we focus on spatial redundancy for visual sensor networks in this paper.

Several methods have been proposed to improve the robustness of image transport in the literature. Forward error correction-based methods for image transmission have received wide interest because of their efficiency in combating wireless channel errors. However, FEC-based methods do not address node failures where the whole packet is lost. Multipath transport that utilizes independent (or highly uncorrelated) transmission paths has also been explored for fault-tolerance. Recently, several interesting proposals on delivering image and video over multihop wireless networks using multiple paths have been introduced in [4,5]. However, these methods are not very practical for resource constrained sensor networks, since they require setting up multiple paths between the source and the destination a-priori and continuously monitoring and reporting path information to the source node. Further, the effect of node failures is not considered in [4,5], nor is the energy consumption discussed.

In this work, we present an image transport scheme that is capable of providing an image of acceptable perceptual quality at the receiver in spite of the channel impairments and node failures. Specifically, we propose an "in-network" diversity combining scheme which takes advantage of path diversity to achieve better performance. When sending a packet, multiple relaying nodes are chosen to provide redundancy against random node failures. Multiple copies of the coded image coefficients from different relaying nodes are combined along the path in order to reduce the wireless channel bit errors. In addition, forward error correction coding is applied on packets. The performance metrics of the proposed scheme are the received image quality and the energy consumption of the image transport scheme. Through theoretical analysis, we show that there is indeed a robustness improvement compared to other schemes. This improvement is more noticeable in case of higher node failure probability and larger number of hops between the source and the destination. Some performance related factors (the number of hops, the average channel error rate and the average node failure rate) are also discussed. The theoretical analysis is validated against simulations.

The main contribution of this work is the design and analytical as well as simulation-based evaluation of a new image transport scheme that is suitable for wireless sensor networks. The key features of this scheme are:

- The proposed scheme applies the concept of "in-network processing" [6]. Error robustness to network errors is improved by combining the image data *as it flows through the nodes*. Compared with previous multipath transport approaches [7,5] which split data at the source and combine data from different paths only at the final destination, in our scheme, the cluster heads on the paths are able to recover lost packets and further correct bit errors by combining packets. There is a noticeable image quality improvement when compared against state-of-the-art image transport schemes (detailed in Section 6). Furthermore, the improvements are achieved at low energy consumption.
- When compared with other state-of-the-art image transport schemes, our diversity scheme is simple and can be implemented with limited additional complexity by extending existing multipath routing and clustering protocols [8–10].

The rest of the paper is organized as follows. In Section 2, we discuss related issues and prior work in more detail. The model and assumptions are described in Section 3. Section 4 introduces the error robust image transport scheme. The analytical results are presented in Section 5. Simulations of the proposed scheme as well as simulations of a selected set of schemes representing prior work are presented in Section 6. We conclude the paper and discuss future research directions in Section 7.

2. Related work

Up to our knowledge, there has been little work on the design of reliable image transport for wireless

sensor networks. Although there is considerable amount of research on reliable transport in wireless sensor networks, the current approaches of reliable transport may not be suitable for images. PSFQ [11] and RMST [12] are two known reliable transport protocols for wireless sensor networks. Both of them are based on NACK and utilize ARQ for reliable data transport. As mentioned earlier, visual sensor networks may be adversely affected by the additional time delay caused by retransmission in ARQ schemes. Furthermore, while the possible outcomes of receiving a data packet are limited, in the sense that the packet is either successfully received or not, the characteristics of image offer a wide continuum of solutions in terms of improving the received image quality.

Error protection in image transport is well understood in conventional networks (e.g., Internet and cellular networks). Several methods have been proposed to improve the error robustness of image transport. These techniques essentially trade-off energy versus quality; either through error correction coding or multiple path transport.

Forward error correction allows recovery from error by incorporating controlled redundant data. FEC-based unequal error protection (UEP) for image transport has achieved wide interests for its efficiency in combating wireless link errors [13–16]. In [14], given the packet loss rate, the algorithms use FEC coding to protect an image bitstream against packet erasures by applying different FEC codes according to the importance of the bits to be protected. Multiple description coding (MDC) combined with UEP is proposed in [15] which is based on a rate-distortion optimization technique using Lagrange multipliers. To transmit JPEG2000 coded images over binary symmetric channels, the authors in [16] proposed an UEP algorithm for layered source coding based on Lagrangian optimization. These algorithms attempt to find the best FEC codes that maximize the expected reconstructed picture quality at the receiver. Obviously, the use of FEC coding alone cannot address the problem of node failures where the whole packet is lost. Furthermore, the performance of these error control methods in terms of energy consumption and received image quality in a multihop wireless network has not been investigated yet.

Multipath transport has been studied in the past in both wired and wireless networks. It has mainly been used to increase aggregate capacity, load balancing and fault-tolerance. Recently, several interesting proposals on delivering image and video over wireless networks using multiple paths have been introduced. In [17], a wavelet domain diversity combining method is proposed to combat link errors during image transmission over wireless channels. The work in [17] does not consider multihop scenarios since it considers a wireless network with only one hop between the source and the destination.

Multipath transport for images has also been investigated, although less extensively, for multihop wireless networks. The work in [7] applied multipath transmission in combination with UEP for progressive image coding. The problem of allocating packets to multiple paths is investigated to minimize the power consumption and end-to-end image distortion. The authors in [7] focused on how to allocate traffic to multiple end-to-end routes. The performance of such transport scheme is not discussed. A similar approach using multipath routing and MDC is proposed in [4] to enhance the network robustness to wireless link errors. However, it requires continuous monitoring of path quality at each hop and reporting this information to the source node which makes it hard to be utilized in sensor networks. A system of transporting video over multihop networks using multipath transport and multiple stream coding is investigated in [5]. Although it provided some very useful insights, all schemes (feedback based reference picture selection scheme, layered coding with selective ARQ scheme and multiple description motion compensation coding scheme) considered there are based on the motion compensated prediction technique which is only applicable to video, and consequently are not suitable for still images.

We believe it is necessary to discuss why the multipath transport schemes mentioned above are not suitable for sensor networks. First, in previous works, multipath transport is mainly used to combat wireless link errors through path diversity. Node failures, which may be common in sensor networks, are not considered. Second, previous multipath transport schemes which use end-to-end error control typically split data at the source and combine data from different paths at the destination. However, the intermediate nodes are unaware of errors inside packets. Thus, the errors accumulate as the packet travels towards the destination (i.e., error propagation). Our scheme utilizes "in-network processing" principle by in-network

diversity combining. Third, current multipath transport schemes [7,4,5] for multihop wireless networks require setting up multiple paths between the source and the destination a-priori. Further, these methods also assume continuously monitoring the paths with a set of quality of service parameters (e.g., bandwidth and loss probabilities) and informing the source node. While such assumption is reasonable for the routing layer in the networks investigated in prior work, it may not be appropriate to have such a requirement on the routing/aggregation function in wireless sensor networks due to the possibly prohibitively large energy cost. Fourth, in previous works, special image coding schemes are required at the source node (e.g., multiple description coding [4], multiple stream coding [5] or unequal error protection coding [7]).

Our previous work [18] considered algorithms for distributed image compression as a means to overcome the computation and/or energy limitation of individual nodes by sharing the processing of tasks. Error resilience algorithms for the transport of images, which is the focus of this paper, was not studied in [18].

3. Modeling

In this section, we describe the assumptions, the scenarios considered in this paper, the performance metrics of interest and the system model: the wireless channel error model, the node failure model, the error correction coding and the energy consumption model.

3.1. Scenarios and assumptions

We consider a densely deployed wireless sensor network which includes camera-equipped nodes. Every camera-equipped node can respond to an image query by generating a raw image (e.g., a snapshot of its sensing area) and compressing the raw image using an image compression algorithm before transmitting this image to the destination (sink). When sending an image query, the destination node specifies the desired image quality.

We make the following assumptions:

- All nodes have the same radio range d.
- Each node can estimate its channel error probability.
- Each node switches between *on* and *off* state independently. No dynamic node failure detection service is available in the network.[1]
- The communication environment is assumed to be contention-free (e.g., a media access scheme such as time division multiple access (TDMA) may be assumed). What strongly motivates us to make this assumption is the availability of contention-free MAC algorithms for sensor networks in the literature. For example, TDMA based MAC is proposed in [20]. In [21], a protocol is proposed to support collision avoidance. The transmission of packets is assumed to occur in discrete time. A node receives all packets addressed to it during a receiving interval unless the sender node is in "off" state.[2]
- A cluster based routing mechanism is assumed to be in place. Since our proposed image transport scheme interacts closely with the routing/aggregation function, we briefly describe the basic functions of a cluster-based routing protocol as follows. A more detailed description of clustering and cluster-based routing can be found in [10,22]. Nodes are organized into one-hop clusters. A cluster head is selected in each cluster and maintains a membership list of its cluster nodes. Every node knows its cluster head. Every cluster head knows the path(s) to its neighboring clusters as well as the path(s) to the sink. When a node becomes the source, it asks its cluster head for the relaying nodes. It is worth noting that these are the standard functions of cluster-based routing, we do not require any additional function from the network layer.

We choose wavelet-based image compression as the source coding scheme in this study since it is more robust to transmission and decoding errors, and also facilitates progressive transmission of images. Typically, wavelet-based image compression involves computing the two-dimensional wavelet decomposition of the source image to get low and high frequency subbands. The wavelet coefficients

[1] Although there exist some failure detection methods in the literature, the incur overhead and long execution time which may not be suitable for visual monitoring and surveillance, which normally have low delay requirements. For example, periodical broadcast is used in a cluster to acquire the status of every node and a node failure is detected after the analysis of the replies to the broadcast from all nodes [19].

[2] In practice, a timeout mechanism can be applied. A node waits some time before processing and forwarding the packets.

are then quantized, coded and transmitted as a bit stream. More details of wavelet image compression can be found in [23].

3.2. Performance metrics

The first performance metric in this paper is the *energy consumption* of the transport scheme. Particularly, the energy consumed in FEC encoding and decoding as well as the energy consumed in sending and receiving packets are considered. In this paper, we do not consider the energy consumed in generating and compressing images at the source node, as well as the energy consumed in clustering and routing, which are not the focus of this paper. Based on the assumption of contention-free MAC, the energy consumption in accessing the channel is also neglected.[3] We do take into account the energy cost of the combining algorithm in our scheme. Clearly, the total energy consumption is proportional to the number of nodes on the path(s) from the source to the destination. For this reason, we *normalize the total energy consumption* of the proposed image transport scheme with respect to the number of nodes on the paths from the source to the destination in order to meaningfully measure the energy cost.

The second performance metric is the image quality distortion. The image quality is measured as the Mean-Squared-Error (MSE) which is defined as $\mathrm{MSE} = \frac{1}{N^2}\sum_i\sum_j[x(i,j) - \hat{x}(i,j)]^2$ for an $N \times N$ image where $x(i,j)$ is the pixel value of the reconstructed image from the output of the source node's image encoder, $\hat{x}(i,j)$ is the pixel value of the reconstructed image at the destination. Since Peak Signal-To-Noise Ratio (PSNR) is a measure more common in the image coding community, we also use

$$\mathrm{PSNR} = 10\log_{10}\frac{(2^b-1)^2}{\mathrm{MSE}} \tag{1}$$

to illustrate simulation results for a b-bits gray scale image.

The traditional approaches for measuring image quality distortion compare the input image of the source's encoder against the output image of the destination's decoder. Here, we measure image quality distortion based on the *output* image of the source's encoder and the output image of the destination's decoder. The reason is as follows. Clearly, the overall image quality distortion depends on the image source codec, and the transport network. The overall MSE is a superposition of two distortion types; the distortion caused by signal compression at the codec and the distortion caused by the errors in the network. Our scheme's main objective is reduction of errors in the network and hence we do not consider the distortion at the source.

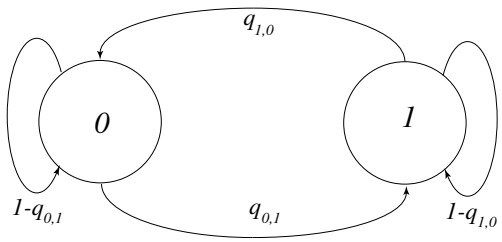

Fig. 1. A Markov chain model for transitions between "good" and "bad" states. $q_{i,j}$ denotes the transition probability from state i to state j, $i, j \in \{0, 1\}$. The stationary probability of being in state "0" is given by $P(0) = q_{1,0}/(q_{1,0} + q_{0,1})$.

3.3. Wireless channel error model

Here, we employ a two-state Markov channel model as in Fig. 1, which has been proved to provide a good approximation for both, slow fading (successive samples are correlated) and fast fading (successive samples are almost independent) wireless channels [24]. The two states of the model are denoted "1" (good) and "0" (bad). While in the good state, the bits are received incorrectly with probability P_g; and while in the bad state, the bits are received incorrectly with probability P_b. For this model it is assumed that $P_g \ll P_b$. Let $\alpha = q_{1,0}$ and $\beta = q_{0,1}$ denote the transition probabilities between the good and bad states, and vice versa, respectively. The steady-state probability of a channel being in the bad state is $P(\mathrm{bad}) = \alpha/(\alpha + \beta)$. Thus, the average bit error probability of the channel is $P_e = P_b P(\mathrm{bad}) + P_g(1 - P(\mathrm{bad}))$. For the simulations, we used this model to independently generate error patterns for all links[4] between nodes.

[3] In the case a contention-based MAC is used in the network, and since there is energy overhead in accessing the channel no matter what the transport scheme is used, the relative ratio of energy consumption of different transport schemes we show in Section 6.2 are expected to hold.

[4] In this paper, we interchangeably use a wireless *channel* and wireless *link*.

3.4. Node failure model

We also use a Markov model to model the node state. The *off* state is denoted by "0" and the *on* state is denoted by "1", as illustrated in Fig. 1. The stationary probability of a node being in the "off" state is given by $P_{\text{off}} = \lambda/(\lambda + \mu)$, where $\lambda = q_{1,0}$ and $\mu = q_{0,1}$ denote transition probabilities between on and off states, and vice versa, respectively. In the off state, all packets sent to the node are lost regardless of the wireless channel state. It is also assumed that a node does not change state during the transmission of a packet.

We believe that a discussion of using the Markov node failure model is necessary. There are two reasons. In one scenario, sensor nodes are placed into sleep or off mode during idle periods to save energy consumption [25]. Thus, each sensor is characterized by two operational states; active and sleep. In the active state the node is fully working and is able to transmit/receive data, while in sleep state it cannot take part in the network activity. Another scenario is when a node runs out of its battery, the node goes into recharge mode and eventually it comes back. A similar model is also used in [26].

We assume that the cluster heads on the path are reliable during the transmission. A discussion of this assumption is necessary. There are two intuitive reasons: (1) Cluster heads are more reliable than other nodes in some sensor network designs proposed in the literature. For instance, in a battlefield, low-powered sensors may be deployed in the field, with high-powered, reliable, and secure nodes located on tanks or large vehicles. For example, in [27], reliable nodes are deployed to construct a reliable routing path. Those reliable nodes are usually chosen as cluster heads. (2) In case of homogeneous nodes, the clustering algorithm generally replaces a cluster head when its energy is depleted or it is not capable of continuing to be a cluster head. Thus, the cluster heads are less likely to be unreliable under the circumstances considered in this paper.

3.5. Error correction coding

Error correction coding is required to provide reliable transmission given the possibility of channel errors. In the algorithms proposed here, Reed–Solomon (RS) error correction coding is used. RS coding is widely used for image communication. The error correction capability of an RS code depends on the coding redundancy. Let RS(n, k) be the code under consideration, where n is the block size in number of symbols and $k < n$ is the number of information symbols. Let m denote the number of bits in each symbol. Any combination of $t_c = \lfloor (n-k)/2 \rfloor$ symbol errors out of n can be corrected. Then the probability of a correctable packet transmission over one hop, P_{cor}, is given by

$$P_{\text{cor}} = \sum_{i=0}^{t_c} \binom{n}{i} P_s^i (1 - P_s)^{n-i}, \tag{2}$$

where the symbol error probability P_s is related to the bit error probability P_e by

$$P_s = 1 - (1 - P_e)^m. \tag{3}$$

A more general and detailed description of RS codes can be found in [28].

3.6. Energy consumption model

In this study, we use a transceiver energy dissipation model similar to the one proposed in [29]. The energy consumed in transmission per bit is

$$E_{\text{TX}} = \epsilon_e + \epsilon_a d^2 \tag{4}$$

and the energy consumed in reception per bit is

$$E_{\text{RX}} = \epsilon_e, \tag{5}$$

where ϵ_a is the energy dissipated in Joules per bit per m^2, ϵ_e is the energy consumed by the circuit per bit, d is the distance between a wireless transmitter and a receiver, and 2 is the path loss parameter. We use the energy consumption model of the RS codec proposed in [30]. The energy consumed in RS encoding is

$$E_{\text{RSE}} = \eta, \tag{6}$$

and the energy consumed in RS decoding is

$$E_{\text{RSD}} = \theta, \tag{7}$$

where η and θ are the energy dissipated for RS encoding and decoding per information bit, respectively. The energy spent in combining two packets (detail in Section 4) per bit is estimated by [31]

$$E_{\text{COM}} = \delta. \tag{8}$$

4. Image transport scheme

In this section, we describe how the proposed image transport scheme provides resilience to errors that may occur on the paths from the source to the destination. Our proposed image transport scheme

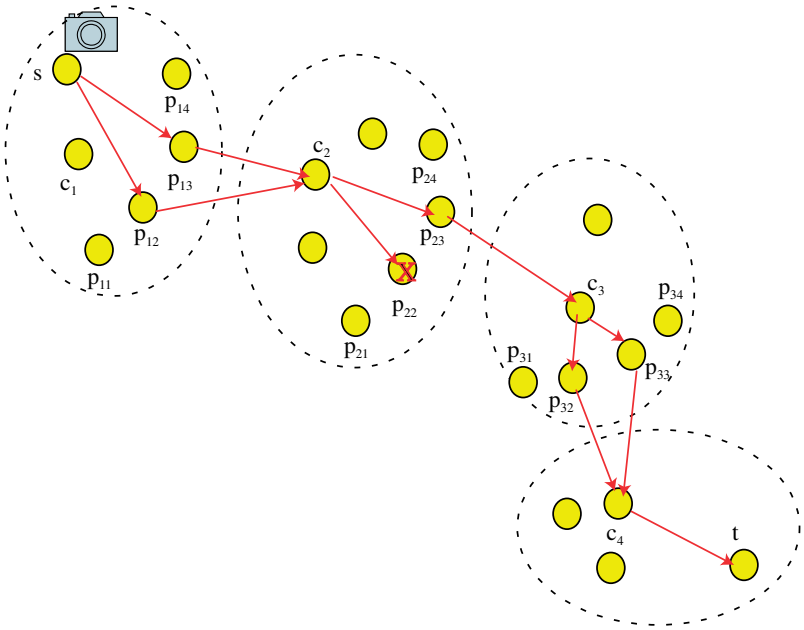

Fig. 2. Example of "in-network" diversity combining. The cluster head c_2 combines the packets from two nodes (p_{12} and p_{13}) using the diversity combining method. When forwarding a packet, c_2 sends it to multiple nodes (2 nodes in this figure). The data sent to p_{22} and p_{23} is the same. Thus, a copy of the packet can be received even if node p_{22} fails.

has two main components: (i) diversity by using multiple relaying nodes and (ii) FEC coding of each packet. Both provide spatial redundancy though at different levels; replicating packets is at packet level while FEC coding is at bit level. The main operations of our proposed scheme are described in more detail in the following sub-sections.

4.1. In-network diversity combining

In "in-network" diversity combining, multiple copies of the same packet are generated in the network. They are forwarded through different paths, and, at certain intermediate nodes (cluster heads), multiple copies are combined, processed, and then multiple copies of the result are retransmitted. For ease of illustration, we describe these operations in more detail using an example as shown in Fig. 2.

After the captured image data are wavelet transformed, the source s queries its cluster head c_1 for the route to the destination. c_1 selects multiple nodes (p_{12} and p_{13}) in the cluster as the relaying nodes then informs s. s RS encodes the data and then transmits it to relaying nodes (p_{12} and p_{13}). Those nodes run RS decoding algorithm on the received packet to correct bit/symbol errors. Then those nodes also run RS encoding algorithm to re-generate the packets and send to the next cluster head c_2. After receiving the packets, c_2 runs RS decoding to get multiple copies of the image coefficients and combines them to get a new copy. c_2 also runs RS encoding algorithm on the combined result and sends multiple copies of the packet to selected relaying nodes (p_{22} and p_{23}). In case of node failure (p_{22}), a copy of the packet can still be received at cluster head c_3. This procedure may continue on c_3 and its following clusters until the final image reaches the destination (sink) node t. The relaying nodes on the paths are not merely "relaying" (i.e., store-and-forward), but also processing the data (i.e., store-process-forward).[5]

The proposed path diversity algorithm randomly chooses the relaying nodes within a cluster. At a given cluster head c, let $N(c)$ denote the set of member nodes of c. When a packet reaches the cluster head c, f nodes are randomly chosen from $N(c)$ where $f \geqslant 1$, and the packet is forwarded to those nodes.

[5] It should be noted that, as shown in Fig. 2, the route from the source to the destination is a single path at the cluster head level. This is because we assume that the cluster heads do not fail. Diversity at the cluster head level may be required in case of unreliable cluster-heads.

We use a combining method that is similar to one of the methods proposed in [17].[6] The method is described here for completeness. When the data containing the wavelet transformed coefficients is received and RS decoded, a decision has to be made, when the results differ, as to whether to take the result from the first node, the second node, or from a combination of both. Depending upon the state of the two channels, through which the two copies of data are received, the data may contain the same values for many of the coefficients. The coefficients from the two copies are compared. If the received coefficient values are the same, it assumes that the value is correct and selects the coefficient from either node. Usually, the values of data within a small block do not vary significantly based on the assumption that a small block of an image is generally smooth. Thus, for data of low-frequency subbands, if the coefficient values at position (i, j) are different, the cluster head compares a 3×3 block of coefficients surrounding (i, j) from both nodes. The coefficients from the two blocks are grouped into a total of 18 values. Then the median value is chosen as the coefficient to be placed at that location (i, j). While for subbands in the high-frequency, where most of the coefficients have magnitudes close to zero, the coefficient with the minimum absolute value is chosen and placed in the final combined result. The preceding discussion is related to combining results from two nodes. In case of more than two nodes, in this paper, the combining method is used recursively, e.g., combining the first two packets, then combine the results of first two with the third packet, and so on.

4.2. FEC coding

Although combining packets can improve the image quality, the combining results may degrade in case of high channel error probability P_e. Furthermore, the existence of multiple hops on the path also worsen the situation by accumulating errors. Thus, our scheme employs FEC-based error protection.[7]

The determination of the error correction capability of an RS code is described as follows. It is assumed that each node computes a set of RS codes and stores this in a code table that will be used for error protection. Let $\mathscr{C} = \{k_1, k_2, \ldots, k_u\}$ denote the set of RS codes with $k_1 > k_2 > \cdots > k_u > 0$. For an estimated channel error probability P_e, a node chooses the largest k_i such that $\|P_{cor}(n, k_i) - 1\| \leqslant v$ where v is a predetermined value.

At each node, the FEC coding is applied. The data in every packet is RS encoded before transmission and each packet is RS decoded when received. For a regular node (not cluster head), the FEC coding procedure has two steps: RS decoding to correct bit errors then RS encoding to form a new packet to be forwarded. While at a cluster head, "in-network" diversity combining as described in the previous section is inserted between those two steps. Unlike previous approaches, in our scheme, the function of FEC coding is placed at each node instead of only at the source and the destination.

It is also worth mentioning that a packet is not discarded but rather is combined even when the RS decoder cannot fully correct all bit errors. The explanation for this is that even if a packet is not fully correct, it still contains some useful information, which can be utilized by the diversity combining scheme to improve the final image quality. This fact can be observed later in Section 6.2 when comparing performance of different image transport schemes.

5. Analysis

In this section, we analyze two performance metrics of the proposed image transport in a multihop wireless network; energy consumption and received image quality, both are defined in Section 3.2.

Prior to deriving expressions for performance metrics, we establish some notations. Let h denote the number of hops along the shortest path between the source and the destination. Let $a = \lfloor h/2 \rfloor$. Then $a + 1$ is approximately the number of clusters along the path.[8] Thus, to simplify our analysis, we use the following approximation:

$$h \approx 2a + r, \quad r = \begin{cases} 0 & h \text{ is odd,} \\ 1 & h \text{ is even.} \end{cases} \tag{9}$$

[6] The diversity combining method is for wavelet transformed coefficients without entropy coding.

[7] The "in-network" diversity combining can be applied without FEC coding, which complements the image transport scheme. The effect of FEC coding is shown in Section 6.2.

[8] $a + 1$ is exactly the number of clusters along the path if two adjacent clusters always communicate via the gateway nodes that are one hop away from these two cluster heads.

5.1. Energy consumption

In this sub-section, we calculate the energy consumption of the proposed transport scheme. Based on the description of the proposed scheme, image transport is performed progressively from cluster to the next. At each cluster, the cluster head c_i (the source s in case of the first cluster) will send a packet to f nodes. The energy cost of RS encoding and sending one packet to a relaying node is given by

$$E_1 = m(nE_{\mathrm{TX}} + kE_{\mathrm{RSE}}). \tag{10}$$

If a relaying node is not in "off" state, it will receive and forward the packet to the next cluster head c_{i+1}. The average energy cost associated with this process is given by

$$E_2 = m(1 - P_{\mathrm{off}})(nE_{\mathrm{RX}} + kE_{\mathrm{RSD}} + kE_{\mathrm{RSE}} + nE_{\mathrm{TX}}). \tag{11}$$

In case a relaying node is not "off", the cluster head c_{i+1} will receive the packet. The average energy consumption is given by

$$E_3 = m(1 - P_{\mathrm{off}})(nE_{\mathrm{RX}} + kE_{\mathrm{RSD}}). \tag{12}$$

Thus, the energy consumption of transmitting a packet from c_i to c_{i+1} with f intermediate nodes is given by

$$E_4 = f(E_1 + E_2 + E_3). \tag{13}$$

In case of receiving multiple packets, the cluster head c_{i+1} will also combine them with energy cost given by

$$E_5 = \sum_{j=2}^{f} \binom{f}{j} P_{\mathrm{off}}^{f-j}(1 - P_{\mathrm{off}})^j (j-1)mkE_{\mathrm{COM}}. \tag{14}$$

Combining (13) and (14), the energy consumption to transmit a packet between two clusters is

$$E_{\mathrm{clus}} = E_4 + E_5. \tag{15}$$

We use A_{i+1} to denote the event that a packet is received at the cluster head c_{i+1} where $i = 1, \ldots, a$. For a specific packet, there are f relaying nodes that forward the packet within a cluster. The packet will be sent from cluster head c_i and received by cluster head c_{i+1} unless all f relaying nodes are in "off" state. Thus, the probability that a packet is received at cluster head c_{i+1} given that it is received at cluster head c_i is given by

$$P[A_{i+1}|A_i] = 1 - P_{\mathrm{off}}^f, \quad i = 2, \ldots, a. \tag{16}$$

Given that there are $a + 1$ clusters and there are r hops before the last cluster head (i.e. the one closest to the destination) as in (9), combining (15) and (16),

$$E_{\mathrm{total}} = \sum_{i=1}^{a} (1 - P_{\mathrm{off}}^f)^{i-1} E_{\mathrm{clus}} + (1 - P_{\mathrm{off}}^f)^{a-1} rE_{\mathrm{last}}, \tag{17}$$

where E_{last} is the energy consumption of the last hop which is given by

$$E_{\mathrm{last}} = m(nE_{\mathrm{TX}} + kE_{\mathrm{RSE}} + KE_{\mathrm{RSD}} + nE_{\mathrm{RX}}). \tag{18}$$

The total number of nodes which send and receive a packet is given by

$$N = 1 + r + \sum_{i=1}^{a} (1 - P_{\mathrm{off}}^f)^{i-1} [1 + f(1 - P_{\mathrm{off}})]. \tag{19}$$

Finally, the total energy consumption of the proposed scheme is

$$E_{\mathrm{overhead}} = \frac{E_{\mathrm{total}}}{N}. \tag{20}$$

5.2. Image quality

In this analysis we focus on the image quality distortion caused by the transmission errors. Similar to the derivation of energy cost in Section 5.1, we start by looking at the transmissions within one cluster. Within a cluster, every packet will travel two hops with RS channel encoding and decoding at each hop. The probability that a packet is incorrectly received at cluster head c_{i+1} through one intermediate node given that it is correct at cluster head c_i is given by

$$P_1 = P_{\mathrm{off}} + (1 - P_{\mathrm{off}})(1 - P_{\mathrm{cor}}^2). \tag{21}$$

Similarly, the probability that a packet is incorrectly received at cluster head c_{i+1} through f intermediate nodes given that it is correct at cluster head c_i can be described by

$$P_{\mathrm{c}} \approx \sum_{i=0}^{f} \binom{f}{i} P_{\mathrm{off}}^i [(1 - P_{\mathrm{off}})(1 - P_{\mathrm{cor}}^2)]^{f-i}. \tag{22}$$

The approximation comes from the combining method used in this paper, which causes the residual packet error rate P_{c} after combining multiple packets to be dependent on the characteristics of the encoded image. Intuitively, the image quality distortion is related to P_{c}, since an increased number of

error packets will also increase the image pixel errors.

For a given image and given image compression implementation, it can be shown that the quality distortion that is introduced in the transmission between two clusters, denoted by D_c, can be expressed as [32]

$$D_c = gP_c, \tag{23}$$

where g is an empirically estimated parameter for a given image codec implementation.[9] Note that the linear relation is only valid for low residual error rates, i.e., $P_c < 0.1$. The given linear relation is sufficient for relevant operation conditions if reasonable image quality is required. Given that there are a combining operations and r hops from the last cluster head to the destination, the image quality distortion, denoted by D_n, can be derived from (23) as

$$\begin{aligned} D_n &= aD_c + rg(1 - P_{cor}) \\ &= g[aP_c + r(1 - P_{cor})]. \end{aligned} \tag{24}$$

6. Simulations

In this section, we perform extensive simulations to measure the performance of our proposed image transport scheme and validate the analytical results. We describe our experimental methodology and list the parameters. Finally, we present and discuss the simulation results. The simulator is built using MATLAB.

6.1. Simulation parameters and methodology

To evaluate the performance of our proposed scheme and compare with previous schemes, four transport schemes are simulated; (A) no error protection, (B) multiple relaying nodes with FEC coding but without combining, (C) multiple relaying nodes with combining but without FEC coding, and (D) our proposed image transport scheme. RS coding is applied in schemes (B) and (D) as in Section 4. Multiple relaying in each cluster is performed in schemes (B), (C) and (D). In scheme (B), in case of receiving multiple packets, the cluster head just chooses one of them to mimic the behavior of previous multipath transport such as [4,5]. Diversity combining is included in schemes (C) and (D). In scheme (C), redundant packets are directly combined, while they are combined after RS decoding in scheme (D).

The parameters that are varied in order to assess their impact on the performance of the transport schemes are: the number of hops h between the source and the destination, the average channel error probability P_e and the average node failure probability P_{off}. In each run, a source and a destination that are h hops apart are randomly chosen and one test image is sent from the source to the destination. Then a route is chosen for the source–destination pair which is used in scheme (A). A slightly different (randomly chosen relaying nodes between adjacent cluster heads) route is used in scheme (B), (C) and (D). An example of the routes for the four schemes is shown in Fig. 3. An exact comparison with previous multipath transport schemes [4,5] is difficult because the multiple paths selected may not be the same. The paths selected by previous schemes were assumed not to have common nodes along the route. While in our proposed transport scheme, common nodes along multiple paths are required. The same route is still used for all "multipath transport" schemes to facilitate the comparison. The source, the destination and the cluster heads on the paths are in the "on" state in each run. For the schemes that employ multiple relaying (schemes (B), (C) and (D)), $f = 2$ if not otherwise specified. Each data point in the simulation figures represents an average of 10 runs with identical choice of h, P_e and P_{off}, but different source–destination pair.

The simulation is done on test image *Lena* of size 512×512 pixels with 8 bits per pixel. The source images are decomposed to one level using the wavelet transform. Then the wavelet coefficients are uniformly quantized to 8 bits per pixel. Similar trends are observed for other values not reported here (for space considerations).

The value of g in (23) is estimated as follows. We use a subset of measurement points to match the model to experimental data. In theory, any two measurement points are sufficient to match g. More formally, we measure two distortion values D_c, for known values of h and P_c (calculated according to (22)). Then we obtain the corresponding values for g from (24) using numerical minimization.

The parameters for the channel coding and the wireless channel model are chosen as follows. We use an RS code with $m = 8$ bits per symbol. We fix $n = 255$ and choose $k = 223$ with the assumption that the channel error probability estimate at each

[9] Section 6.1 describes how to estimate g by experiments.

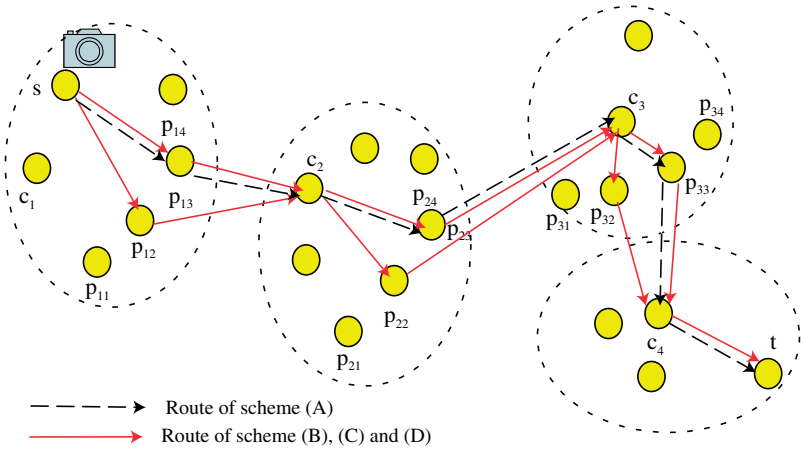

Fig. 3. An example of routes for four schemes. The difference between schemes (B) and (D) is that no diversity combining is conducted at the cluster heads in scheme (B). The difference between schemes (C) and (D) is that no FEC coding is conducted in scheme (C).

node is 1×10^{-3}. To fairly compare schemes, the packet size is also chosen to be 255 for schemes (A) and (C). It is worth noting that the simulation is not intended to investigate the performance of FEC codes over wireless channels, which itself has an extensive literature. For simplicity, in the simulation, we choose $P_g = 0$ and $P_b = 1$. We fix $\beta = 1/8$ and vary α to get different channel error probabilities P_e.

The network parameters are selected as follows. We consider a network with 1000 nodes randomly placed in an area of 160×160 m. After the deployment, the nodes organize into clusters according to the clustering algorithm described in [10]. The node communication radius d is fixed at 10 m. For the node failure model described in Section 3.4, $\mu = 0.1$ and vary the value of λ to generate different stationary probabilities of the "off" state P_{off}.

The values of the energy model parameters are chosen as follows. The values of the parameters of the wireless communication energy model in (4) and (5) are the typical values $\epsilon_a = 100 \times 10^{-12}$ Joule/bit/m^2 and $\epsilon_e = 50 \times 10^{-9}$ Joule/bit as in [29]. The values of the parameters of the RS encoding and decoding energy model in (6) and (7) are computed for RS(255, 223) code based on the models in [30]. The value of η is 0.08×10^{-9} Joule/bit and the value of θ is 0.21×10^{-9} Joule/bit. The energy consumption of diversity combining in schemes (C) and (D) are estimated by *JouleTrack* [31]. The experiment data in terms of energy expended by a StrongARM SA-1100 processor at 206 MHz is measured when running our combining algorithm on test image *Lena*. From the experiment, the value of δ in (8) is estimated to be 1×10^{-9} Joule/bit.

6.2. Results

6.2.1. Energy consumption

The comparisons between the normalized total energy dissipation of the four schemes are shown in Fig. 4. We examine the energy consumption with respect to the distance between the source and the destination for a given P_{off} (similar trends are observed for other values of P_{off}). As mentioned in Section 6.1, we normalize the total energy consumption with respect to the number of nodes on the paths. For ease of presentation, we also normalize

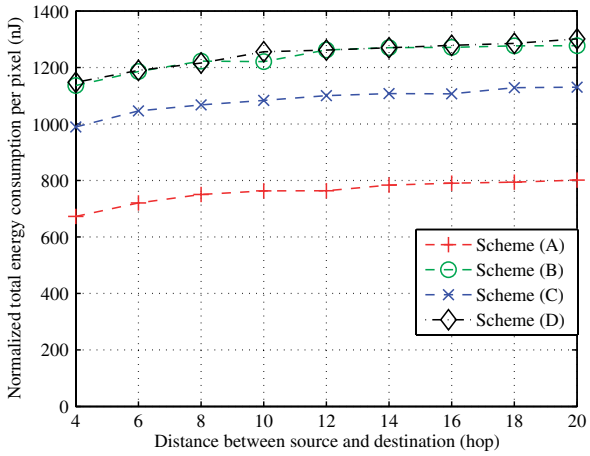

Fig. 4. Normalized total energy dissipation per pixel of the four schemes versus distance between the source and the destination: $P_e = 1 \times 10^{-3}$, $P_{off} = 0.1$.

it with respect to the number of pixels of the image. It is observed that the difference between schemes (B) and (D) in terms of the normalized total energy consumption is very small. Thus, the effect of diversity combining itself on the total energy consumption is small compared to sending multiple copies of the data and using FEC code. The energy cost of FEC coding is about 15% mainly because we use (255, 223) RS coding. The normalized total energy consumption of the proposed scheme is about 60% more than scheme (A) for moderate and long distances between the source and the destination ($\geqslant 8$ hops). The proposed scheme provides much better image quality as described in the next simulation results. To validate our theoretical analysis, Fig. 5 plots the theoretical results E_{overhead} from (20) of scheme (D) against the simulation results for different value of f. A close match between the analytical and simulation results is observed.

6.2.2. Received image quality

The received image quality in terms of PSNR of four schemes under different values of h, P_e and P_{off} are shown in Figs. 6–8, respectively. We also plot the analytical results of scheme (D) in each figure. For each figure, we first estimate g using two points of the experimental data. Then D_n is calculated according to (24). The PSNR values of D_n are calculated as in (1). It is shown that scheme (A) is the most susceptible to network errors (link and node) and increase in number of hops between source and sink. Imperfect channels and node failures will

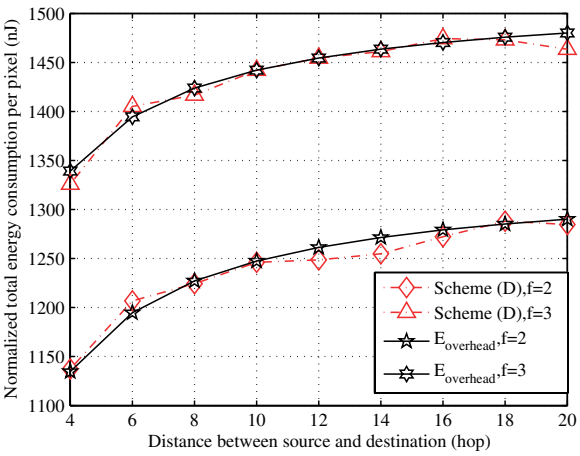

Fig. 5. Validation of the theoretical analysis of the normalized total energy dissipation. $P_e = 1 \times 10^{-3}$, $P_{\text{off}} = 0.1$. E_{overhead} is calculated according to (24).

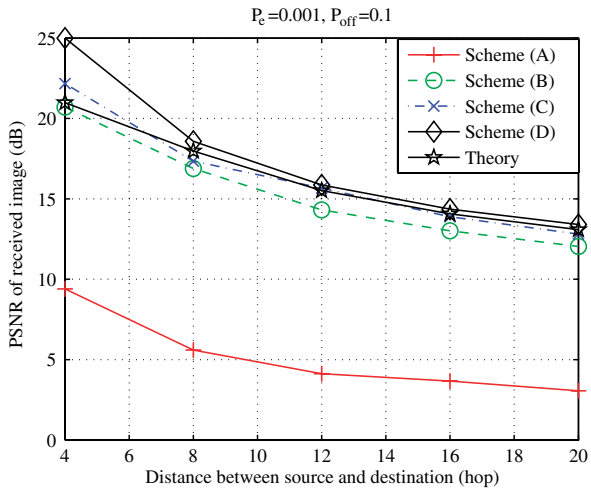

Fig. 6. Received image quality versus the distance between the source and the destination h: $P_e = 1 \times 10^{-3}$, $P_{\text{off}} = 0.1$.

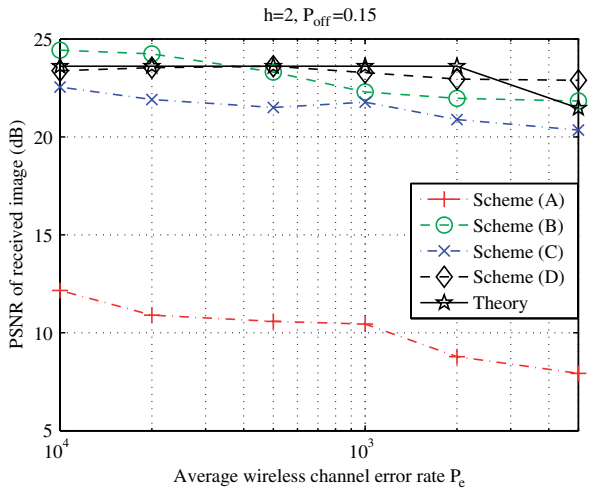

Fig. 7. Received image quality versus the average wireless channel error probability P_e: $h = 2$, $P_{\text{off}} = 0.15$.

dramatically worsen the received image quality. Fig. 6 also shows that the path diversity and combining are effective in reducing the errors incurred by the increase in the number of hops.

Fig. 7 shows that scheme (D) provides up to 3 dB improvement over scheme (C) for large P_e, due to the use of RS coding. The effect of combining can also be observed in Fig. 7. About 1 dB improvement is observed for large P_e when comparing scheme (B) with scheme (D). As mentioned before, the linear relation between D_n and P_c is valid for small P_c. This fact can also be seen in Fig. 7. The discrepancy between the theoretical results and simulation

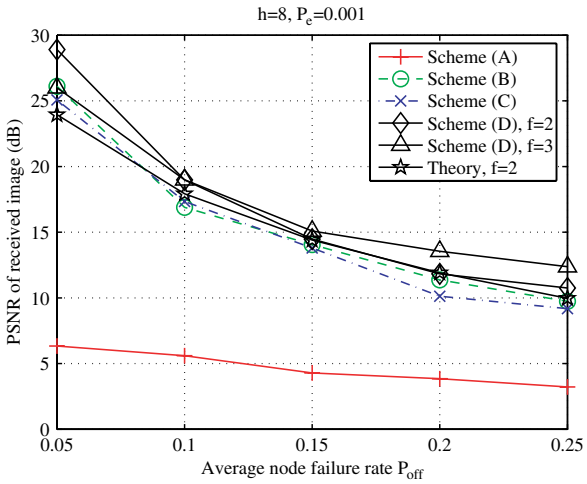

Fig. 8. Received image quality versus the average node failure probability P_{off}: $P_{\text{e}} = 1 \times 10^{-3}$, $h = 8$.

results increase for large P_{e} where P_{c} is no longer small enough (recall that the analytical results are valid only for small P_{c}).

In case of node failure (Fig. 8), sending multiple copies of the packets and using the combining scheme are effective to provide up to 10 dB better image quality compared with scheme (A). We also show the effect of f on the received image quality in Fig. 8. The quality improvement of $f = 3$ compared to the case of $f = 2$ is more noticeable for large P_{off}. It is observed that the image quality of $f = 3$ is lower than the results of $f = 2$ for small P_{off}. An intuitive reason is that we recursively apply the combining method on packets which in some cases may worsen the results. Other more sophisticated combining rules could be used (but may require additional computational power that may not be available for sensor nodes).

We observed in these simulations that the impact of node failure rate on the received image quality is more severe than the impact of wireless channel errors. Thus, the path diversity is more important than FEC coding in wireless sensor networks with node failures. The FEC coding and diversity combining are more effective for high wireless channel error rates. From these figures we also observe that our proposed image transport scheme is more robust to network errors compared to other schemes. Furthermore, performance degradation is also hardly influenced by the increase in the distance between the source and the destination (sink). It is worth noting that interleaving and error concealment are not applied in this paper, which can further improve both the perceptual image quality and PSNR value.

7. Conclusion and future work

We studied the problem of image transport over error prone wireless sensor networks. The design and evaluation of an error resilient image transport scheme is presented. It uses a combination of forward error correction coding, multiple relaying nodes, and in-network diversity combining to achieve robustness to both link errors and node failures. The combining method proposed here exploits some of the properties of the wavelet transform to improve the perceptual quality of the received image. The proposed scheme is simple and easy to implement. Analytical results and simulations show that this scheme can greatly improve image quality at the destination in case of link impairments and node failures.

To the best of our knowledge, this is the first work to consider error robust image transport in wireless sensor networks. The results obtained in this research may have several practical applications. An application for the case of error redundant protocol design could be the selection of the amount of the redundancy such that the energy cost is bounded by some given constant for a required quality. We believe that the research of image transport over wireless sensor networks is at early stage and many issues require further investigation. Several aspects of our future research are combining methods for entropy coded coefficients and unequal error protection, which may be integrated to further improve the received image quality. We also plan to take into account scenarios where the wireless link error rates vary widely with time. In such environment, adaptive FEC algorithms may be needed.

References

[1] A.E. Gamal, Trends in CMOS image sensor technology and design, in: Proceedings of IEEE International Electron Devices Meeting, San Francisco, CA, 2002.

[2] M. Rahimi, D. Estrin, R. Baer, H. Uyeno, J. Warrior, Cyclops, image sensing and interpretation in wireless networks, in: Proceedings of the 2nd International Conference on Embedded Networked Sensor Systems, ACM Press, 2004, p. 311.

[3] A.E. Gamal, Collaborative Visual Sensor Networks, 2004. Available from: <http://mediax.stanford.edu/projects/cvsn.html>.

[4] N. Gogate, D. Chung, S.S. Panwar, Y. Wang, Supporting image/video applications in a multihop radio environment using route diversity and multiple description coding, IEEE Transaction on Circuits and Systems for Video Technology 12 (9) (2002) 777–792.

[5] S. Mao, S. Lin, S.S. Panwar, Y. Wang, E. Celebi, Video transport over ad hoc networks: multistream coding with multipath transport, IEEE Journal on Selected Areas in Communications 21 (10) (2003) 1721–1737, Special Issue on Recent Advances in Wireless Multimedia.

[6] D. Estrin, Sensor network research: emerging challenges for architecture, systems, and languages, in: C. Norris, J.J.B. Fenwick (Eds.), Proceedings of the 10th International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS-X), 10 of ACM SIGPLAN Notices, vol. 37, ACM Press, New York, 2002, pp. 1–4.

[7] T. Stockhammer, P. Leelapornchai, Progressive image transmission applying multipath routing in mobile ad hoc networks, in: Proceedings of IEEE International Conference on Image Processing (ICIP), Rochester, NY, 2002.

[8] D. Ganesan, R. Govindan, S. Shenker, D. Estrin, Highly-resilient, energy-efficient multipath routing in wireless sensor networks, SIGMOBILE Mob. Comput. Commun. Rev. 5 (4) (2001) 11–25.

[9] A. Srinivas, E. Modiano, Minimum energy disjoint path routing in wireless ad-hoc networks, in: Proceedings of the 9th Annual International Conference on Mobile Computing and Networking, ACM Press, 2003, pp. 122–133.

[10] O. Younis, S. Fahmy, Distributed clustering in ad-hoc sensor networks: a hybrid, energy-efficient approach, in: Proceedings of the IEEE Infocom, IEEE, Hong Kong, China, 2004. Available from: <http://www.ieee-infocom.org/2004/Papers/13_5.PDF>.

[11] C.-Y. Wan, A.T. Campbell, L. Krishnamurthy, PSFQ: a reliable transport protocol for wireless sensor networks, in: Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications, ACM Press, 2002, pp. 1–11.

[12] F. Stann, J. Heidemann, RMST: reliable data transport in sensor networks, in: 1st IEEE International Workshop on Sensor Net Protocols and Applications (SNPA), Anchorage, Alaska, USA, 2003.

[13] P.G. Sherwood, K. Zeger, Error protection for progressive image transmission over memoryless and fading channels, IEEE Transactions on Communications 46 (12) (1998) 1555–1559.

[14] A. Mohr, E. Riskin, R. Ladner, Unequal loss protection: graceful degradation of image quality over packet erasure channel through forward error correction, IEEE Journal on Selected Areas in Communications 18 (6) (2000) 819–828.

[15] K.-W. Lee, R. Puri, T. Kim, K. Ramchandran, V. Bharghavan, An integrated source and congestion control framework video streaming in the Internet, in: Proceedings of Infocom, Tel-Aviv, Israel, 2000.

[16] T. Chu, Z. Liu, Z. Xiong, X. Wu, Joint UEP and layered source coding with application to transmission of JPEG-2000 coded images, in: Proceedings of Globecom, 2001, pp. 2306–2309.

[17] L.C. Ramac, P.K. Varshney, A wavelet domain diversity method for transmission of images over wireless channels, IEEE Journal of Selected Areas in Communications 18 (6) (2000) 891–898.

[18] H. Wu, A.A. Abouzeid, Energy efficient distributed image compression in resource-constrained multihop wireless networks, Computer Communications 28 (14) (2005) 1658–1668.

[19] A.T. Tai, K.S. Tso, W.H. Sanders, Cluster-based failure detection service for large-scale ad hoc wireless network applications, in: Proceedings of the International Conference on Dependable Systems and Networks (DSN), Florence, Italy, 2004.

[20] G. Pei, C. Chien, Low power TDMA in large wireless sensor networks, in: Proceedings of IEEE MILCOM 2001, vol. 1, 2001, pp. 347–351.

[21] W. Ye, J. Heidemann, D. Estrin, An energy-efficient MAC protocol for wireless sensor networks, in: Proceedings of the IEEE Infocom, USC/Information Sciences Institute, IEEE, New York, NY, USA, 2002, pp. 1567–1576. Available from: <http://www.isi.edu/ohnh/PAPERS/Ye02a.html>.

[22] S. Bandyopadhyay, E.J. Coyle, An energy-efficient hierarchical clustering algorithm for wireless sensor networks, in: INFOCOM, 2003.

[23] C.A. Christopoulos, T. Ebrahimi, A.N. Skodras, JPEG2000: the new still picture compression standard, in: Proceedings of the 2000 ACM Workshops on Multimedia, ACM Press, Los Angeles, CA, 2000, pp. 45–49.

[24] M. Zorzi, R.R. Rao, L.B. Milstein, On the accuracy of a first order Markov model for data block transmission on fading channels, in: Proc. IEEE ICUPC'95, 1995, pp. 211–215.

[25] A. Sinha, A. Chandrakasan, Dynamic power management in wireless sensor networks, IEEE Design and Test of Computers 18 (2) (2001) 62–74.

[26] C.-F. Chiasserini, M. Garetto, Modeling the performance of wireless sensor networks, in: Proceedings of the IEEE Infocom, IEEE, Hong Kong, China, 2004. Available from: <http://www.ieee-infocom.org/2004/Papers/06_1.PDF>.

[27] Z. Ye, S.V. Krishnamurthy, S.K. Tripathi, A framework for reliable routing in mobile ad hoc networks, in: Proceedings of the IEEE Infocom, IEEE, San Francisco, CA, 2003.

[28] S. Lin, D.J. Costello, Error Control Coding: Fundamentals and Applications, Prentice-Hall, Englewood Cliffs, NJ, 1983.

[29] E. Shih, S.-H. Cho, N. Ickes, R. Min, A. Sinha, A. Wang, A. Chandrakasan, Physical layer driven protocol and algorithm design for energy-efficient wireless sensor networks, in: Proceedings of the Seventh Annual International Conference on Mobile Computing and Networking (MOBICOM-01), ACM Press, 2001, pp. 272–287.

[30] S. Appadwedula, M. Goel, N.R. Shanbhag, D.L. Jones, K. Ramchandran, Total system energy minimization for wireless image transmission, Journal of VLSI Signal Processing Systems 27 (1/2) (2001) 99–117.

[31] A. Sinha, A. Chandrakasan, JouleTrack—a web based tool for software energy profiling, in: Design Automation Conference, 2001, pp. 220–225. Available from: <http://www-mtl.mit.edu/research/anantha/jouletrack/JouleTrack/index.html>.

[32] K. Stuhlmüller, N. Färber, M. Link, B. Girod, Analysis of video transmission over lossy channels, IEEE Journal on Selected Areas in Communications 18 (6) (2000) 1012–1032.