Error Robust 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 in wireless sensor networks. We consider a wireless sensor network with both wireless link impairments and node failures. We investigate two performance metrics of the proposed image transport scheme: energy consumption and received image quality distortion. Simulation results show that the proposed image transport scheme improves the robustness to network errors at the expense of low energy overhead. This improvement is more noticeable in case of high node failure probability and long distance between the source and the destination. Our work also helps in understanding the tradeoffs between image quality distortion and energy consumption with different 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.**

I. Introduction

Recently, with the advance in image sensors [1], [2], there has been a growing interest in visual wireless sensors 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 fading phenomenon that causes channel errors. Unlike cellular networks or wireless local area networks (WLANs), the path between the source and the destination in wireless sensor networks normally contains multiple wireless links. 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 path. The goal of this paper is to present an image transport scheme that is able to improve 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 for 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 these methods 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 able to provide 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 coded image coefficients from different relaying nodes are combined along the path in order to reduce the bit errors caused by wireless link errors. In addition, forward error correction code is also applied on packets. The performance metrics of the proposed scheme we investigate in this work are the received image quality and the energy consumption of the image transport scheme. Through simulations, we show that there is indeed a robustness improvement compared to other schemes. This improvement is more noticeable in case of high node failure probability and long distance 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 in the underlying network) for our proposed scheme are also discussed.

The main contribution of this work is the design and simulated 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 [5], [7] 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 V). Furthermore, the improvements are attained 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 II, we discuss related issues and prior work in more detail. The model and assumptions are described in Section III. Section IV introduces the error robust image transport scheme. Simulations of the proposed scheme as well as other compared schemes are presented in Section V. We conclude the paper and discuss future research directions in Section VI.

II. 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 not benefit from the long time delay caused by retransmission. Furthermore, while the possible outcomes of receiving a data packet is 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 to protect an image bitstream against packet erasures by applying different FEC codes according to the importance of the bits to be protected. The 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 usage of FEC alone can not 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 scenario 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 [4], [5], [7] 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, loss probabilities) and informing the source node. While such assumption is reasonable for the routing layer in the networks investigated in prior work, it is not appropriate to have such requirement on the routing layer in wireless sensor networks due to the prohibitive 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 robustness algorithms for the transport of images, which is the focus of this paper, was not studied in [18].

III. 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 code and the energy consumption model.

A. Scenarios and Assumptions

We consider a densely deployed wireless sensor network which consists of 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 media access (TDMA) may be assumed). The transmission of packets is assumed to occur in discrete time. A node receives all packets heading to it during 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 routing layer, 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], [20]. Nodes are organized into one-hop clusters. A cluster head is selected in each cluster and maintains a membership list of its cluster. 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.

We choose the wavelet-based image compression method 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 are then quantized and coded to transmit as a bit stream. More details of wavelet image compression can be found in [21].

B. 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 is considered. In this paper, we do not consider the energy consumed in generating and compressing images at the source node which is not the focus of this paper. 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

$$MSE = \frac{1}{N^2} \sum_i \sum_j [x(i,j) - \hat{x}(i,j)]^2$$

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

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

to illustrate simulation results for a b-bits per pixel 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,

[1] Although there are some failure detection methods, the large overhead and long execution time are not suitable to visual monitoring and surveillance, which normally have low delay requirement. 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.

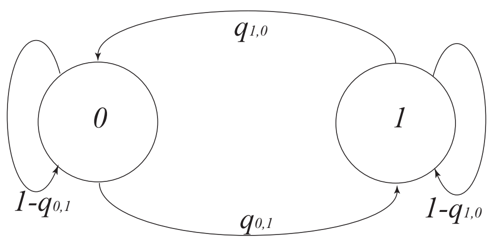

Fig. 1. A Markov chain model for transitions between "0" and "1" states. $q_{i,j}$ denotes the transition probability from state i to state j, $i, j \in \{0, 1\}$. The stationary probability of being in the state "0" is given as $P(0) = q_{1,0}/(q_{1,0} + q_{0,1})$.

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 actually 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 caused at the source.

C. Wireless Channel Error Model

The channel in every hop is modeled as an independent and identically distributed (IID) random bit error channel. Here, we employ a simple channel model, a two-state Markov channel model [22] as in Fig. 1. 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 transition probabilities between the good and bad states, and vice versa, respectively. The stationary probability of a channel being in the bad state is $P(bad) = \alpha/(\alpha + \beta)$. Thus, the average bit error probability of the channel is $P_e = P_b P(bad) + P_g(1 - P(bad))$. For our simulations, we used this model to independently generate error patterns for all links between nodes. In this paper, we interchangeably use a wireless *channel* and wireless *link*.

D. Node Failure Model

We also use a Markov model to model the node state. The off state is denoted "0" and the on state is denoted "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 the node does not change state in the middle of 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 [23]. 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 that 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 [24].

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 in tanks or large vehicles. For example, in [25], reliable nodes are deployed to construct a reliable routing path. Those reliable nodes usually are chosen as cluster heads due to their higher capabilities. 2) in case of homogeneous nodes, the clustering algorithm generally replaces a cluster head when its energy is depleted or it is not capable to be a cluster head anymore. Thus, the cluster heads are less likely to be unreliable under the circumstances we considered in this paper.

E. Error Correction Code

Error correction coding is required to provide reliable transmission given the possibility of channel errors. In this research, we use Reed-Solomon (RS) error correction code, which 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 be 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 the RS code can be found in [26].

F. Energy Consumption Model

In this study, we use a transceiver energy dissipation model similar to the one proposed in [27]. 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 energy consumed by the circuit per bit, d is the distance

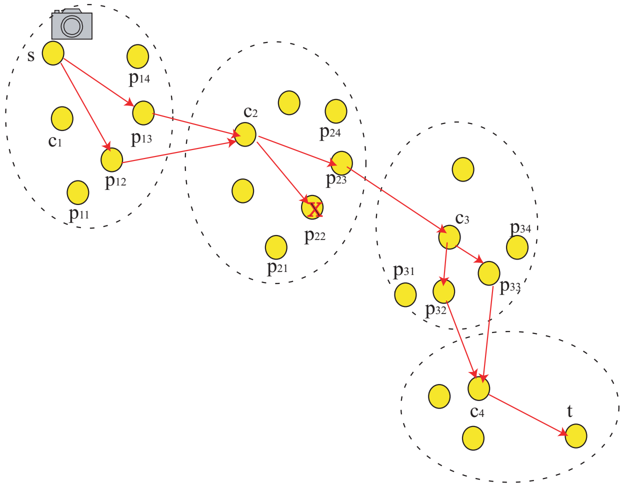

Fig. 2. Example of "in-network" diversity combining. The cluster head c_2 combines the packets from two nodes (p_{12} and p_{13}) using the diversity combining method. When forwarding a packet, c_2 sends it into multiple nodes (2 in this figure). The data sending to p_{22} and p_{23} is the same. Thus,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

between a wireless transmitter and a receiver, and 2 is the path loss parameter. We use the energy consumption model of RS codec proposed in [28]. 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 IV) per bit is estimated by [29]

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

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

A. 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 is 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 computes RS code for the data and generates two copies of a packet, then transmits them to relaying nodes (p_{12} and p_{13}). Those nodes run RS decoding algorithm on their received packets 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 algorithm to get multiple copies of image coefficients and combines them to get a new copy of image coefficients. c_2 also runs RS encoding algorithm on the combined results 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).[3]

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 $f \geq 1$, and the packet is forwarded to those nodes.

We use a combining method that is similar to one of the methods proposed in [17].[4] The method is described here for completeness. When the data containing the wavelet transformed coefficients are received after RS decoding, a decision is made as to whether to take the data 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 in case of receiving different coefficients. We demonstrated here using

[3]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 if the assumption is not true.

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

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.

B. FEC coding

Although combining packets can improve the image quality, the combining results may become worse when multiple packets are received with errors in case of high channel error probability P_e. Furthermore, the multiple hops on the path also make the situation worse by accumulating errors. Thus, our scheme employs FEC-based error protection.[5]

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 code table that will be used for error protection. Let $\mathcal{C} = \{k_1, k_2, \ldots, k_u\}$ be the set of RS codes with $k_1 > k_2 > \ldots > k_u > 0$. For the estimated channel error probability P_e, the node chooses the largest k_i such that $\|P_{\text{cor}}(n, k_i) - 1\| \leq \nu$ where ν is a determined value.

At each node, the FEC coding is applied. The data in every packet is encoded with RS code 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 a packet to correct bit errors then RS encoding the data 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. Once again, the principle of "in-network processing" is applied. 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 and still be combined even when the RS decoder can not fully correct all bit errors.

V. Simulations

In this section, we perform extensive simulations to measure the performance of our proposed image transport scheme. We describe our experimental methodology and list the parameters. Finally, we present and discuss the simulation results.

A. 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 code is applied in schemes (B) and (D) as in Section IV. Multiple relaying nodes in each cluster are included in scheme (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 scheme (C) and (D). In scheme (C), redundant packets are directly combined, while they are combined after RS decoding in scheme (D).

[5] 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 V-B.

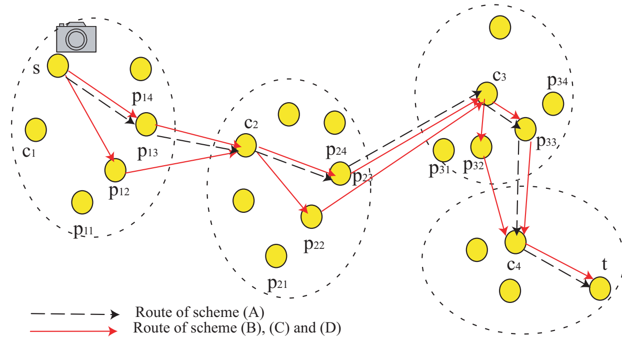

Fig. 3. An example of routes for four schemes. The difference between scheme (B) and (D) is that no diversity combining is conducted at the cluster heads in scheme (B). The difference between scheme (C) and (D) is that no FEC coding is conducted in scheme (C).

The parameters we 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 which 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. A fair comparison with previous multipath transport schemes [4], [5] is difficult because the multiple paths selected may not be the same. The multiple paths selected by previous schemes were assumed not 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 multiple relaying nodes scheme (B), (C) and (D), f is chosen to be 2 if not specified. Each data point in the figures presented below 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 parameters for channel coding and wireless channel model are chosen as follows. We use RS code with $m = 8$ bits per symbol. We fix $n = 255$ and choose $k = 223$ with the assumption that the channel error probability estimation at each node is 1×10^{-3}. To fairly compare schemes, the packet size is also chosen to be 255 for scheme (A) and (C) without RS coding. It is worth noting that the simulation is

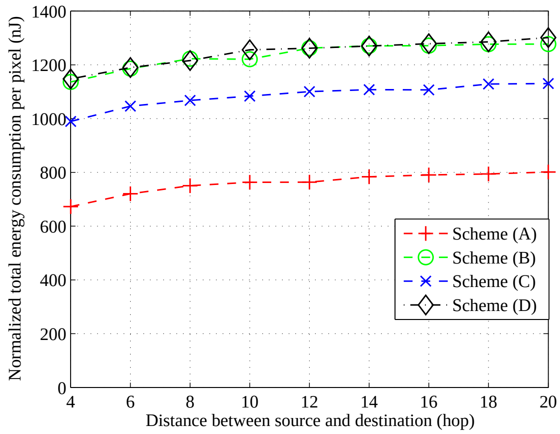

Fig. 4. Normalized total energy dissipation per pixel of four schemes versus distance between the source and the destination. $P_e = 1 \times 10^{-3}$, $P_{\text{off}} = 0.1$.

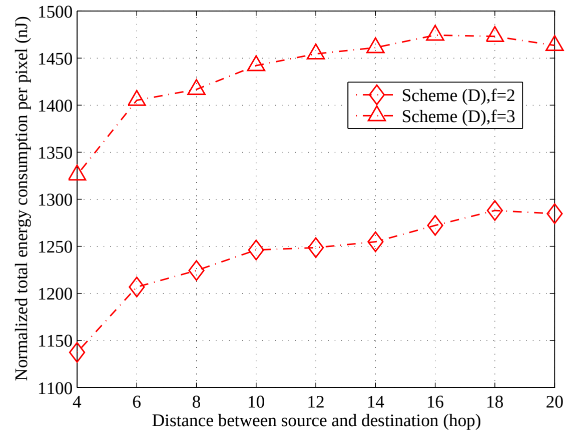

Fig. 5. Normalized total energy dissipation per pixel versus distance between the source and the destination for different f. $P_e = 1 \times 10^{-3}$, $P_{\text{off}} = 0.1$.

not intended to investigate the performance of FEC code 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 meters. After the deployment, the nodes organized into clusters according to the clustering algorithm [10]. The node communication radius d is fixed to be 10 m. In the node failure model in Section III-D, we fix the transition probability $\mu = 0.1$ and vary the value of the transition probability λ to have different stationary probabilities of a node in "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 (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 [27]. The values of the parameters of the RS encoding and decoding energy model (6) and (7) are computed for $RS(255, 223)$ code based on the models as in [28]. The value of η is $0.08 \times 10^{-9} Joule/bit$ and the value of θ is $0.21 \times 10^{-9} Joule/bit$. The energy consumption of diversity combining in scheme (C) and (D) is estimated by *JouleTrack* [29]. The experiment data in terms of energy expended by a StrongARM SA -1100 processor at 206Mhz is measured when running our combining algorithm on test image *Lena*. From the experiment, the value of δ in (8) is estimated to be $1 \times 10^{-9} Joule/bit$.

B. Results

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 V-A, we normalize the total energy consumption with respect to the number of nodes on the paths. For ease of presentation, we also normalize it with respect to the number of pixels of the image. It is observed that the difference between scheme (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 data and using FEC code. The energy cost of FEC coding is about 15% mainly because we use (255,223) RS code. The normalized total energy consumption of the proposed scheme is about 60% more than scheme (A) for moderate and long distance between the source and the destination (≥ 8 hops). The proposed scheme provides much better image quality as described in the next simulation results. To show the effect of f on the total energy consumption, we plot the simulation results of scheme (D) for different value of f in Fig. 5.

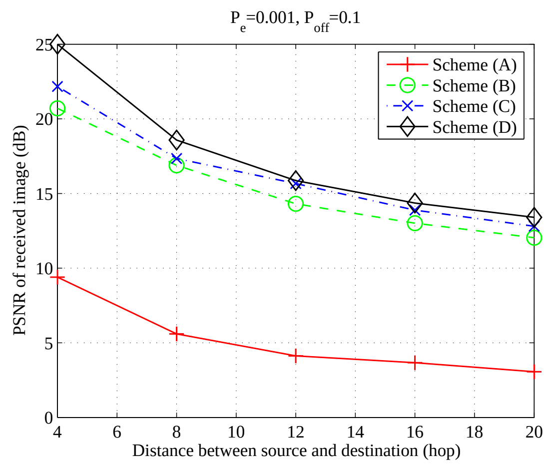

Fig. 6. Received image quality versus the distance between the source and the destination h. $P_e = 1 \times 10^{-3}$, $P_{\text{off}} = 0.1$.

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 Fig. 6, Fig. 7 and Fig. 8, respectively.

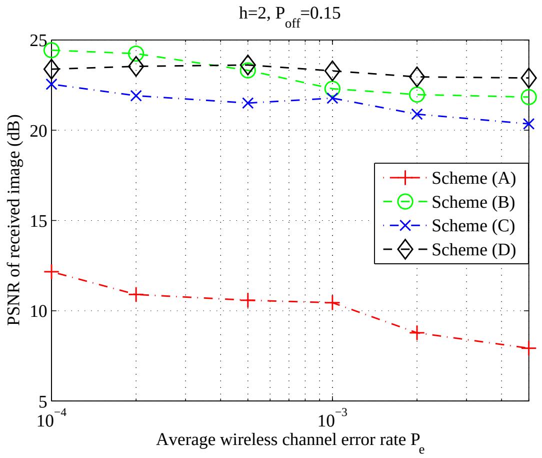

Fig. 7. Received image quality versus the average wireless channel error probability P_e. $h = 2$, $P_{\text{off}} = 0.15$.

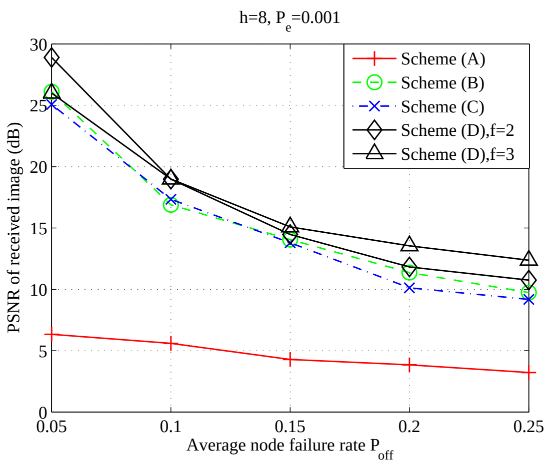

Fig. 8. Received image quality versus the average node failure probability P_{off}. $P_e = 1 \times 10^{-3}$, $h = 8$.

It is shown in these figures that scheme (A) is the most susceptible to network errors (link and node) and multiple hops. Imperfect channels and node failures will dramatically worsen the received image quality. Fig. 6 also shows that the path diversity and combining are effective to reduce the errors incurred by multiple hops.

Fig. 7 shows that scheme (D) provides up to $3dB$ 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 $1dB$ improvement is observed for large P_e when comparing scheme (B) with scheme (D).

In case of node failure (Fig. 8), the multiple copies of packets and combining are effective to provide up to $10dB$ 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 combining method on packets which in some case may worsen the results. Other combining rules will be investigated for future work.

We observed that the impact of node failure on received image quality is more severe than the impact of wireless channel error. 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 rate. From these figures, we 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 distance between the source and the destination. It is worth nothing that interleaving and error concealment are not applied in this paper, which can further improve both the perceptual image quality and PSNR value.

VI. Conclusion and Future Work

In this paper, we studied the problem of image transport in error prone wireless sensor networks. The design and evaluation of an error robust image transport scheme is presented. We use 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. Performance evaluation shows 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 work of image transport in wireless sensor networks is at early stage and many issues such as theoretical analysis of received image quality and energy consumption 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 selection algorithm may be needed.

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