Link Quality Information Sharing by Compressed Sensing and Compressed Transmission for Arbitrary Topology Wireless Mesh Networks*

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SUMMARY We proposed to apply compressed sensing to realize information sharing of link quality for wireless mesh networks (WMNs) with grid topology. In this paper, we extend the link quality sharing method to be applied for WMNs with arbitrary topology. For arbitrary topology WMNs, we introduce a link quality matrix and a matrix formula for compressed sensing. By employing a diffusion wavelets basis, the link quality matrix is converted to its sparse equivalent. Based on the sparse matrix, information sharing is achieved by compressed sensing. In addition, we propose compressed transmission for arbitrary topology WMNs, in which only the compressed link quality information is transmitted. Experiments and simulations clarify that the proposed methods can reduce the amount of data transmitted for information sharing and maintain the quality of the shared information.

key words: *wireless mesh network, link quality, information sharing, compressed sensing, diffusion wavelets*

1. Introduction

A wireless mesh network (WMN) has the potential for autonomously constructed network infrastructures [2]–[5]. It is expected that WMNs will be used increasingly in various applications such as emergency communication systems during large-scale disasters and V2X networks for intelligent transport systems.

In a WMN, a node is connected to neighbor nodes by wireless links. The communication quality of the links depends on the wireless channel characteristics. Consequently, to manage WMNs effectively and/or to establish a path, it is important to know the link qualities. In the former case, some nodes collect link quality information and detect obstacle links. In the latter case, each node shares link quality information and selects the best or good path. Each node

can know the link qualities of its neighbor nodes but cannot know the link qualities of the entire network. An information sharing method is required for each node to know the link qualities of the entire network. Flooding is a typical method of sharing link quality information. In flooding, every node re-broadcasts all received packets. However this increases the number of transmitted packets and causes a broadcast storm problem [6]. For example, a link-state routing protocol uses the link quality information of the entire network to select paths. The optimized link state routing (OLSR) protocol [7] employs multipoint relay (MPR) flooding to reduce the number of nodes that rebroadcast packets, thereby reducing the packet load in the network making use of the network topology.

From a different viewpoint of making use of the network topology, we have proposed to apply compressed sensing [8]–[10] to realize information sharing [11]. The proposed method attempts to reduce the amount of the transmitting data by compressing the transmitting data of the link qualities rather than the number of the transmitting nodes. Compressed sensing employs a signal with sparse characteristics projected into low-dimensional space, and it compresses and obtains the information simultaneously. The original data are recovered from fewer samples by exploiting the sparsity as a prior knowledge of the original data. In [11], a grid topology WMN is assumed, and two-dimensional link quality information is mapped to two matrices of horizontal and vertical links. These matrices are projected to the sparse matrices by discrete cosine transform (DCT), and mapped to a vector. By applying compressed sensing and the gossip algorithm [12]–[15], this vector is compressed and shared by all nodes. Thus, our previously proposed method can reduce the amount of transmitting data instead of slightly degradation of the quality of the decoded data. However the previously proposed method can only be applied to a WMN with grid.

In this paper, we propose an information sharing method using compressed sensing for WMNs with arbitrary topology. For such WMNs, we introduce a link quality matrix, whose components represent the link qualities between all nodes. We extend a compressed sensing formula from a data vector to a data matrix and use diffusion wavelets [16] as a basis conversion for sparse representation of link quality. Diffusion wavelets is a multiresolution analysis technique

generalized for conventional wavelet transformation. Diffusion wavelets can be used to analyze the arbitrary discrete structure of a network by a wavelet basis taking account of network topology. Compressed sensing for networked data is proposed in [17]. In [17], a node (a vertex) has data, and all data in a network are represented by a vector. On the other hand, a link (an edge) has data, and all data are represented by a matrix in this paper. Moreover, it is easily estimated that data, e.g. temperature, sensed by nodes have spatial correlations, and it can be compressed by compressed sensing. However, the link quality is determined at not a node but a link between transmitting and receiving nodes. The link quality will have spatial correlation, but it is not verified whether the link qualities can be compressed by compressed sensing. In addition, we propose a compressed transmission method for a WMN with arbitrary topology by extending a previously proposed method [11]. We evaluate the performance of the proposed methods experimentally and through simulations. The experimental results clarify the effectiveness of the proposed methods in real environments. As an example of information sharing, we demonstrate the effect of path selection using the proposed methods in simulations. The contribution of this paper is as follows:

1. introduction of link quality matrix and proposal of the combination of the link quality matrix and compressed sensing using the diffusion wavelets by extending the compressed sensing formula of a matrix,
2. clarification of compression effect of link quality information in real environments by experimental results, and
3. evaluation of path selection using the proposed methods by simulations as an example of information sharing.

The remainder of this paper is organized as follows. The WMN and link quality model are explained in Sect. 2. The proposed information sharing methods based on compressed sensing are described in Sect. 3. The performance of the proposed methods is evaluated in Sects. 4 and 5. Conclusions are presented in Sect. 6.

2. Network Model and Link Quality Matrix

In this section, we describe the WMN model used in this paper and define the link quality matrix.

We assume an arbitrary topology WMN, i.e., nodes are located at arbitrary points in a target area. Nodes within communication range are connected by wireless links, and the quality of each link depends on the surrounding environment, such as weather conditions, communication interference, and obstacles between nodes. The qualities of nearby links will have a spatial correlation. Due to this spatial correlation among links, the sequence of link qualities will be projected to the sparse one by an appropriate transform.

Our past work assumed a grid topology WMN [11] where horizontally and vertically adjacent nodes are linked. Let the number of nodes in the WMN be N. Then, the qualities of horizontal and vertical links can be represented by $N \times (N - 1)$ and $(N - 1) \times N$ matrices, respectively. The adjacent components of horizontal link and vertical link matrices will have spatial correlations because they represent the qualities of adjacent links. Therefore, DCT can be used to convert the horizontal and vertical link matrices to sparse matrices, in which link quality information is concentrated in a few low-frequency components.

An arbitrary topology WMN cannot use horizontal and vertical link matrices because links are not distributed in a grid. We introduce a link quality matrix whose components indicate the link qualities between all nodes. Note that information sharing should be performed periodically before a significant change of link qualities in the network. Let $X(l)$ be the lth sample of the link quality matrix by the information sharing, where $X(l)$ consists of $N \times N$ components, and each component $x_{i,j}(l)$ indicates the link quality from node i to node j of the lth sample. This matrix can handle link asymmetry, i.e., link qualities $x_{i,j}(l)$ and $x_{j,i}(l)$ can have different values. The link quality $x_{i,j}(l)$ takes a small value if link quality is poor and approaches 0 when the link is disconnected.

3. Proposed Method

In this section, we propose an information sharing method using compressed sensing for a WMN with arbitrary topology. In the proposed method, the compressed sensing formula is extended from a data vector to a data matrix, and all nodes can share the link quality matrix by compressed sensing based on diffusion wavelets.

The proposed methods assume all nodes use the identical period of information sharing. In addition, each node has to know the total number of nodes. The total number of nodes can be known by [18], [19].

3.1 Application of Diffusion Wavelets

The link quality information of a grid topology WMN can be analyzed using conventional wavelet transformation and DCT. However, the link quality matrix of a WMN with arbitrary topology (Sect. 2) has spatially independent components; thus, conventional wavelet transformation cannot be used to analyze the link quality matrix. In this paper, we employ diffusion wavelets [16]. Using the diffusion wavelets basis, the link quality matrix may be projected to a sparse matrix, making use of the spatial correlation.

Here, it is assumed that each node knows the link quality of only its neighbor nodes. Diffusion wavelets use network topology as a priori knowledge, and then it cannot be used as it is under our assumption. As described in Sect. 2, the link quality matrix should be sampled periodically prior to significant change in link quality. Successive samples of the link quality matrices will have a time correlation. We construct a diffusion wavelets basis from the link quality matrix before one sample as a priori knowledge and use the basis for compressed sensing.

3.2 Information Sharing Method Using Compressed Sensing

In our previous work [11], sparse matrices of link quality information were mapped to a vector, and a compressed vector was derived by multiplying the random matrix. In this paper, the link qualities in the entire network represent the link quality matrix. Then, we extend compressed sensing formula from a vector to a matrix.

In the proposed method, compressed sensing of a matrix formula is represented as follows:

$$Y(l) = AX(l)A', \tag{1}$$

where A and A' are $K \times N$ and $N \times K'$ random matrices, respectively, and $Y(l)$ is a $K \times K'$ compressed matrix. By setting $K, K' \leq N$, the amount of link qualities can be reduced to $K \cdot K'/N^2$. The components $a_{i,j}$ and $a'_{i,j}$ of the random matrices A and A' take ± 1 randomly. The component $y_{i,j}(l)$ of the compressed matrix $Y(l)$ is expressed by

$$y_{i,j}(l) = a_{i,1}a'_{1,j}x_{1,1}(l) + \cdots + a_{i,N}a'_{N,j}x_{N,N}(l). \tag{2}$$

The component $y_{i,j}(l)$ is a linear combination of the link quality matrix components $x_{1,1}(l), \cdots, x_{N,N}(l)$.
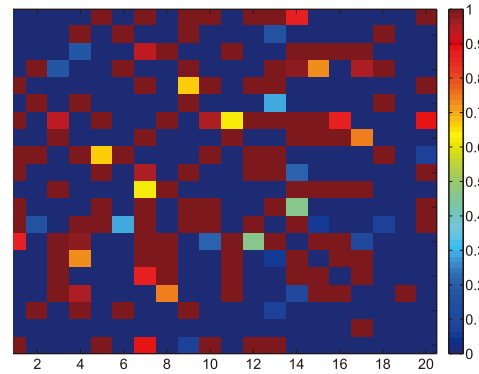
The gossip algorithm [12]–[15] can compress the link quality matrix and share the compressed matrix among all nodes simultaneously. Each component of the compressed matrix is derived by (2). Calculation of a component requires all link qualities $x_{1,1}(l), \cdots, x_{N,N}(l)$. However, each node only knows the qualities of its own links. Using the gossip algorithm, each node can derive the components of the compressed data matrix without gathering all link qualities [11]. First, node x knows the qualities of its own links $x_{x,j}(l)$ and $x_{i,x}(l)$ ($i, j \in \{1, \cdots, N\}$). Node x calculates $y_{i,j}(l)$ by setting the qualities of links other than its own to 0. Node x exchanges $y_{i,j}(l)$, and calculates the average value. By repeating this procedure, the average value approaches $(a_{i,1}a'_{1,j}x_{1,1}(l) + \cdots + a_{i,N}a'_{N,j}x_{N,N}(l))$, i.e., the $y_{i,j}(l)$ component of the compressed matrix. In this algorithm, every node has to share A and A'. For example, every node can share A and A' by generating pseudo-random numbers using the IP addresses of each node as a seed value [17].

After obtaining the compressed matrix $\hat{Y}(l)$, each node estimates a sparse matrix $\Theta(l)$. The link quality matrix is converted to the sparse matrix by diffusion wavelets. The sparse matrix $\Theta(l)$ is expressed by
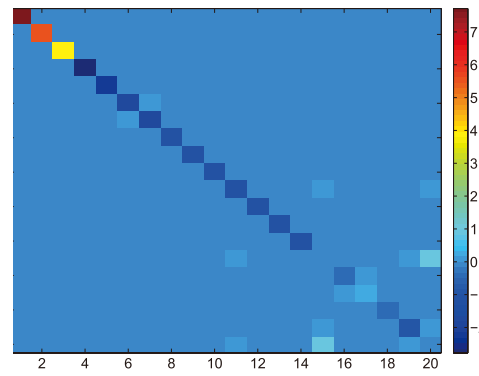
$$\Theta(l) = \Psi(l)X(l)\Psi^T(l), \tag{3}$$

where $\Psi(l)$ is a diffusion wavelets basis for the link quality matrix of the lth sample. Similar to compressed sensing of a vector, the sparse matrix is estimated by

$$\hat{\Theta}(l) = \arg\min_{\Theta(l)} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| \theta_{i,j}(l) \right|$$

(a) Before diffusion wavelets.

(b) After diffusion wavelets.

Fig. 1 Example of a link quality matrix.

$$subj.\, to\; \hat{Y}(l) = A\Psi^{-1}(l-1)\Theta(l)(\Psi^T(l-1))^{-1}A', \tag{4}$$

where $\theta_{i,j}(\ell)$ is the ith row and the jth column component of $\Theta(l)$. As described in Sect. 3.1, a diffusion wavelets basis is derived from the link quality matrix before one sample as a priori knowledge. The above estimation uses the diffusion wavelets basis derived from the estimated link quality matrix of the $(l-1)$th sample. From the estimated sparse matrix, the link quality matrix is derived by

$$\hat{X}(l) = \Psi^{-1}(l-1)\hat{\Theta}(l)(\Psi^T(l-1))^{-1}. \tag{5}$$

To improve the decoding accuracy of compressed sensing, we introduce a weight matrix W. Figure 1 shows an example of a link quality matrix before and after applying diffusion wavelets. As can be seen, diffusion wavelets concentrates values on the diagonal components of the sparse matrix. To make the estimated sparse matrix have the desired structure with large values for the diagonal components and small values for non-diagonal components [20], we modify (4) as

$$\hat{\Theta}(l) = \arg\min_{\Theta(l)} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \left| \theta_{i,j}(l) \right|$$

$$subj.\, to\; \hat{Y}(l) = A\Psi^{-1}(l-1)\Theta(l)(\Psi^T(l-1))^{-1}A', \tag{6}$$

where $w_{i,j}$ is the ith row and the jth column component of

the weight matrix W, expressed by

$$w_{i,j} = \begin{cases} 0 & (i = j) \\ 1 & (i \neq j) \end{cases}. \tag{7}$$

This weight matrix can minimize only the non-diagonal components by (6).

In the proposed method, nodes that try to get link quality information should perform diffusion wavelets for each sample. The calculation cost of diffusion wavelets is $O(N \log^2 N)$ [16], but this calculation is not huge because it is performed in an instant in simulations, described in Sect. 5.

3.3 Compressed Transmission

Similar to [11], we propose compressed transmission for WMNs with arbitrary topology. As described in Sect. 3.2, diffusion wavelets concentrates values on the diagonal components of the sparse matrix. Compressed sensing compresses and shares the link quality matrix by (1), while the compressed transmission transmits only the significant values, i.e., diagonal components and their adjacent components, in the sparse matrix. This idea is simple, but is not considered so far.

In the compressed transmission, the link quality matrix is converted to a sparse matrix by the diffusion wavelets basis derived from the link quality matrix before one sample, that is

$$\Theta(l) = \Psi(l-1)X(l)\Psi^T(l-1). \tag{8}$$

The diagonal components of the sparse matrix have large values, and the values of the other components approach 0. Then, the sparse matrix is compressed to the compressed vector by selecting the diagonal components and their adjacent components, as follows:

$$\begin{aligned} y(l) = {} & (\theta_{1,1}(l), \theta_{2,2}(l), \cdots, \theta_{N,N}(l), \\ & \theta_{1,2}(l), \theta_{2,1}(l), \theta_{2,3}(l), \theta_{3,2}(l), \cdots), \end{aligned} \tag{9}$$

where the size of the compressed vector is limited by K_{CT}, i.e., the compression ratio is K_{CT}/N^2. The detail procedure of selecting the components is described in Appendix. Each component of the compressed vector is derived by (8), i.e., it is a linear combination of the components of the link quality matrix; therefore, the compressed vector can be shared among all nodes using the gossip algorithm, as described in Sect. 3.2.

When each node obtains the compressed vector $\hat{y}(l)$, the sparse matrix is regenerated by

$$\hat{\Theta}(l) = \begin{bmatrix} \hat{y}_1(l) & \hat{y}_{N+1}(l) & 0 & \cdots & 0 \\ \hat{y}_{N+2}(l) & \hat{y}_2(l) & \hat{y}_{N+3}(l) & & \vdots \\ 0 & 0 & \ddots & & \vdots \\ \vdots & & & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & \hat{y}_N(l) \end{bmatrix}, \tag{10}$$

where $\hat{y}_i(l)$ is the ith component of $\hat{y}(l)$. Note that (10) represents $K_{CT} = N + 3$. In (10), the components not obtained from the compressed vector are set to 0. From the retrieved sparse matrix, each node obtains the estimated link quality matrix $\hat{X}(l)$ by (5).

Compressed transmission will yield good performance because only the dominant components of the sparse matrix can be transmitted. However, it requires the diffusion wavelets basis to compress the link quality matrix. On the other hand, compressed sensing requires random matrices but does not require the diffusion wavelets basis. Therefore, each node can compress the link quality matrix without knowledge of the network topology.

4. Experimental Evaluation

In this section, we evaluate the performance of our proposed methods by the measurement results of link qualities in a WMN testbed.

4.1 Evaluation Method

We use expected transmission count (ETX) [21] as link quality. ETX indicates the expected number of transmissions (including retries) required to transmit a packet successfully. ETX is calculated from a packet error rate. To measure the packet error rate, each node can use broadcast packets [18], i.e., each node needs not send proving or real unicast packets to investigate ETX even though for a poor link. The reciprocal value of ETX is employed so that the quality of a bad link approaches 0. First, the packet error rates of all links in the testbed are measured. The ETX of every link is calculated from the measured results, and a link quality matrix is derived using the calculated ETX. Here, we focus on evaluating the potential application of the proposed methods in a real environment. Note that some ideal conditions are assumed. The diffusion wavelets basis is calculated from the measured ETX itself. An ideal gossip algorithm is assumed, and each node obtains $\hat{Y}(l)$ and $\hat{y}_i(l)$ with no errors and retrieves $\hat{X}(l)$.

Figure 2 shows node locations in the testbed, and Table 1 shows node configurations and experimental parameters. The testbed consists of eight nodes, which are two DE2700 and six DE3100 barebone computers. A wireless LAN (WLAN) interface (IF) SX-PCEAN is mounted on each node. The Debian operating system is installed on each node, and a modified ath9k (math9k) [22] driver is used for the WLAN IF. This driver enables each node to set a fixed IEEE 802.11n compliant transmission rate. In addition, iperf [23] is used to send probe packets. The packet error rate is obtained from a math9k debug file system, which outputs the number of successes, i.e., the number of receiving ACKs, and the number of retried transmissions. On each link, the packet error rate is measured for 10 s. We use CVX [24] to calculate (6) and Diffusion Wavelets Code [25] for the basis construction of diffusion wavelets. We derive the root mean squared error (RMSE) between the estimated and measured
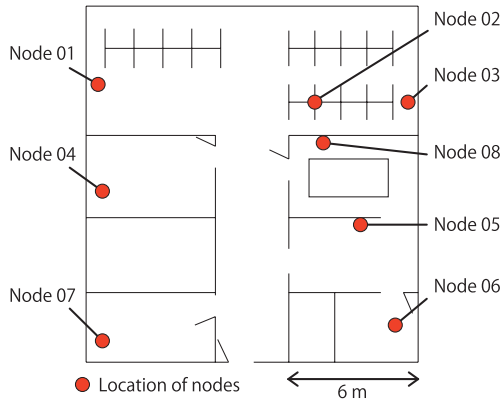
Fig. 2 Node locations in the testbed.

Table 1 Node configurations and experiment parameters.

Embedded PC	AOPEN DE2700/DE3100
Wireless LAN IF	Silex SX-PCEAN
Distributions	Debian 6.0.6
Kernel	linux 2.6.34
Wireless LAN driver	math9k [22]
Measurement tool	iperf 2.04
Number of nodes	8
Transmit power	20 dBm
Transmission rate	MCS 3 (54 Mbps)
Channel	36+40 ch (HT40)
Transport protocol	UDP
Packet size	1470 bytes
Measurement duration	10 s
Size of random matrices	$K = K' = 1, 2, 3, 4, 5, 6, 7, 8$
Size of compressed vector	$K_{CT} = K \cdot K'$
(compression ratio)	(2, 6, 14, 25, 39, 56, 77, 100%)
Number of experiments	4

Fig. 3 Experimental results of diffusion wavelets.

Fig. 4 Experimental results of RMSE of estimated 1/ETX.

link quality matrices with several compression ratios, where we set $K = K'$ and $K_{CT} = K \cdot K'$.

4.2 Experimental Results

First, we evaluate the degree of sparseness of the measured link quality matrix. Figure 3 shows all of the components of the link quality matrix before and after diffusion wavelets. Note that the values are sorted in descending order. Prior to using diffusion wavelets, approximately three-quarters of the components in the link quality matrix have non-zero values. On the other hand, after using diffusion wavelets, only some components take large values and one-half of the components approach 0. We confirm that diffusion wavelets can convert the link quality matrix to the sparse matrix.

Figure 4 shows the RMSE of the estimated 1/ETX on each link as a parameter of the compression ratio. A compression ratio of 100% means no compression of link quality information, and this case corresponds to the conventional methods. As can be seen, the RMSE increases as the compression ratio decreases. Compressed sensing without the weight matrix cannot estimate the link quality matrix accurately, while introducing the weight matrix can decrease RMSE significantly. If a RMSE of 0.2 is permitted, the
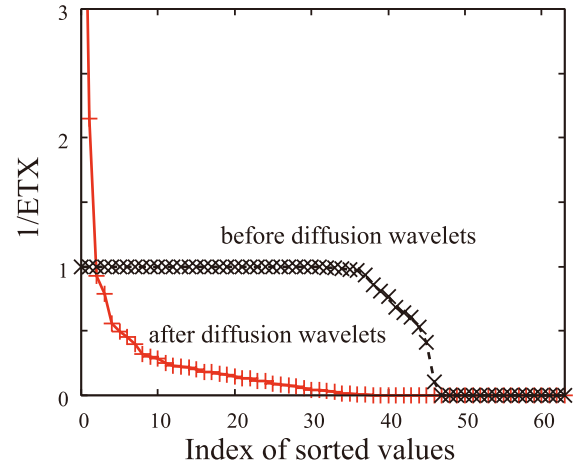
amount of the link quality matrix can be reduced to 25%. Furthermore, the compressed transmission can reduce the amount of the link quality matrix to 6%. The proposed methods are very effective at reducing the amount of data transmitted for information sharing. Note that RMSE still exists when the compression ratio is 100%. Even if the compression rate is 100%, the compressed sensing method or the compressed transmission method is carried out. The estimation process such as (4) causes estimation errors.

5. Simulated Evaluation

In this section, as an example of the information sharing of link quality, we apply the proposed methods to path selection in WMNs. Each node gathers the link qualities in the entire WMN and selects a path from a source node to a destination node using the obtained link quality information. We use ETX as the metric to select a path, and we evaluate the path ETX of the selected path, where the path ETX is the sum of ETX values of the links on the selected path. In this simulation, we consider errors to use the link quality matrix

Table 2   Simulation parameters.

Simulation area	$1.0\,\mathrm{km} \times 1.0\,\mathrm{km}$
Number of nodes	$N = 10, 20, 30, 40$
Location of source node	Lower left side
Location of destination node	Upper right side
Radio propagation model	Plane-Earth reflection
Height of node	$2.0\,\mathrm{m}$
Transmit power	$10\,\mathrm{dBm}$
Noise power	$-98\,\mathrm{dBm}$
Modulation scheme	BPSK
Packet length	100 bytes
Mobility model	Random walk model
Maximum moving speed	$0, 10, 20, 30\,\mathrm{km/h}$
Size of random matrices	$K = K' = \frac{N}{10}, \frac{2N}{10}, \frac{3N}{10}, \cdots, N$
Size of compressed vector	$K_{CT} = K \cdot K'$
(compression ratio)	$(1, 4, 9, 16, \cdots, 100\%)$
Time interval of samplings	$10\,\mathrm{s}$
Refresh cycle	$2, 5, 10, 15, 20$ samples

before one sample for the derivation of the diffusion wavelets basis. We also evaluate the performance degradation of the proposed method due to the movement of nodes.

5.1   Simulation Method

Table 2 summarizes the parameter values used in this simulation. In this simulation, a source node and a destination node are placed at the lower-left and upper-right sides of the simulation area, respectively. The other nodes are distributed randomly. We use the plane-earth reflection model [26] as a radio propagation model. In this model, receive power is determined by the transmit power, the distance between transmitting and receiving nodes, and the height of the transmitting and the receiving nodes. From the receive power and the given noise power, the signal-to-noise ratio (SNR) is obtained. We assume that the modulation scheme is BPSK, a wireless channel is an additive white Gaussian noise environment, and the packet length is 100 bytes. We can then derive the packet error rate as a parameter of the distance of each link. Under our simulation parameters, the distance with the packet error rate of 10% is 525 m. The ETX of each link is obtained from the packet error rate of each link.

The information sharing by the proposed methods is performed every 10 s. The random walk model [27] is assumed as a mobility model. During the sampling interval, each node moves in a random direction at a constant speed, which takes 0 to the given maximum moving speed randomly. For the derivation of the diffusion wavelets basis, we examine both ideal and actual cases. For the ideal case, the diffusion wavelets basis is calculated from the link quality (ETX) matrix of the current sample, i.e., the ideal basis is employed. The diffusion wavelets basis is calculated from the estimated ETX matrix before one sample in the actual case. In this case, errors in the estimation of the ETX matrix might increase cumulatively with repeated sampling. Then, we introduce a refresh cycle, in which every node sends the non-compressed ETX matrix once every refresh cycle. Similar to the experimental evaluation described in Sect. 4,
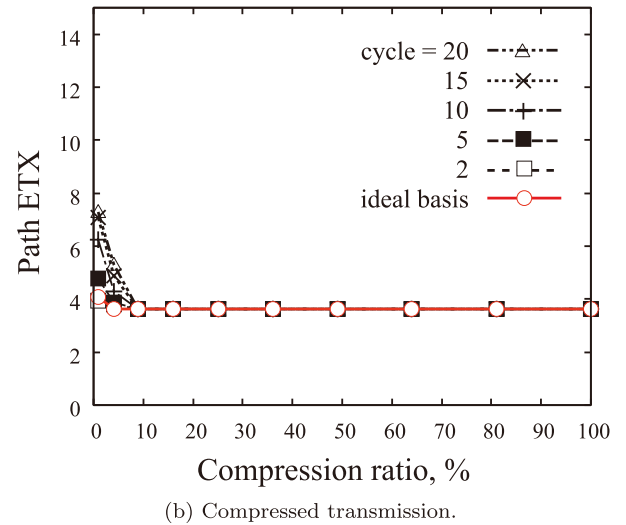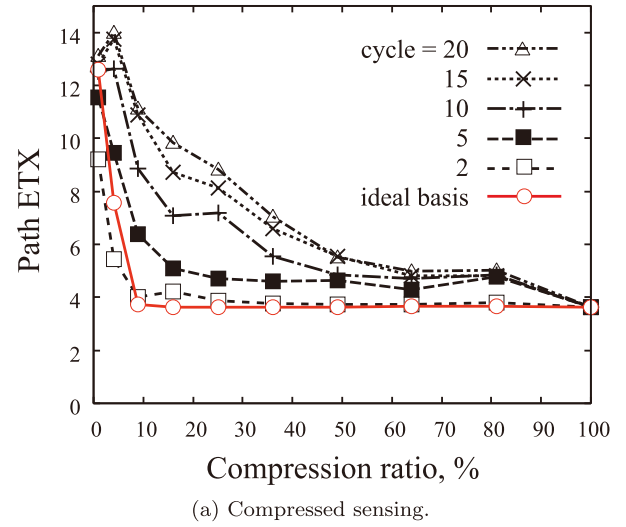

(a) Compressed sensing.

(b) Compressed transmission.

Fig. 5   Simulation results for path ETX when nodes are stationary and the refresh cycle is changed (the number of nodes is 20).

information sharing via the gossip algorithm is assumed to be performed in an ideal manner.

After each instance of information sharing, the source node selects a path to the destination node using the Dijkstra algorithm with the estimated ETX matrix. The Dijkstra algorithm selects a path with minimized path ETX. Note that we evaluate the actual path ETX of the selected path rather than the estimated in order to clarify the quality of the selected path.

5.2   Simulation Results

Figure 5 shows the simulation results for path ETX when all nodes are stationary and the refresh cycle is changed, where the number of nodes is 20. The path ETX indicates the quality of the selected path, i.e., smaller path ETX indicates better path quality. For compressed sensing, as shown in Fig. 5(a), the amount of the transmitting link quality matrix for the ideal basis can be reduced to 9% while path ETX is
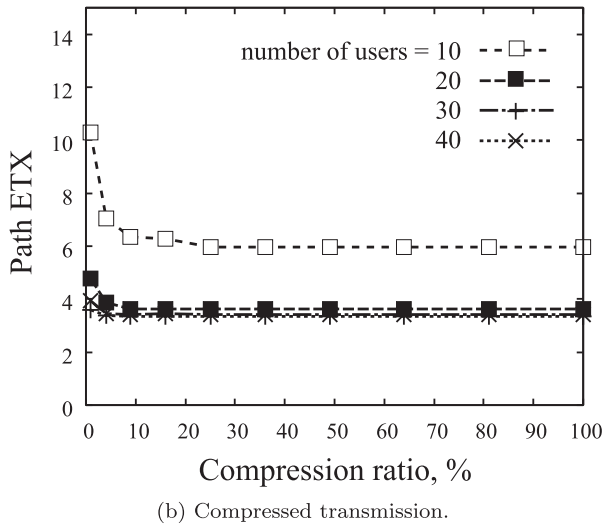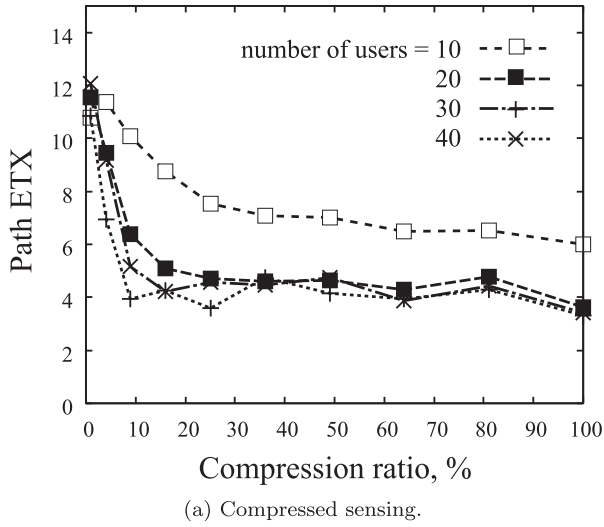
(a) Compressed sensing.

(b) Compressed transmission.

Fig. 6 Simulation results for path ETX when nodes are stationary and the number of nodes is changed (the refresh cycle is 5).

Fig. 7 Simulation results for path ETX with mobile nodes (the number of nodes is 20).

prevented from rising. For the actual case, the path ETX increases due to cumulative errors in the estimated link quality matrix even if no nodes move. When the refresh cycle is 5, the compression ratio can be reduced to 16%. The compression ratio required to keep the path ETX small increases as the refresh cycle becomes longer. Suppressing the increase of the path ETX requires frequent refreshes. For the compressed transmission, as shown in Fig. 5(b), the compression ratio can be decreased to 9% for both the ideal basis and actual cases. The compressed transmission is effective at reducing the amount of the transmitting link quality matrix. Note that the number of transmitting packets for gossip algorithm is discussed in [15]. When the total number of data is N^2, flooding requires the amount of transmitting packets of $O(N^2 \cdot N)$. On the other hand, gossip algorithm requires the amount of transmitting packets of $O(kN^2/\log^3 N)$, where k is equal to $K \cdot K'$ and K_{CT} for compressed sensing and compressed transmission, respectively. The amount of transmitting packets can be reduced by the proposed methods
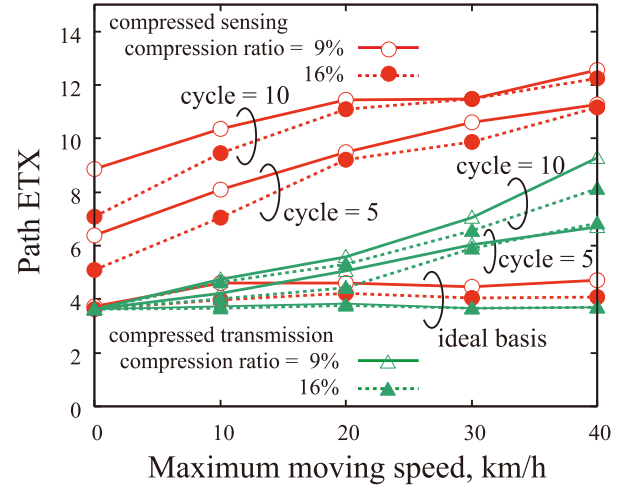
when the proposed method achieves the compression ratio of $N/(N^2/\log^3 N)$. If $N = 20$, this value is 11%.

Figure 6 shows the simulation results for path ETX when all nodes are stationary and the number of nodes is changed, where the refresh cycle is 5. From this figure, the compression ratio to prevent the path ETX from rising is smaller as the number of nodes increases. For the case of compressed sensing, the compression ratio to prevent the path ETX from rising is 16% for 20 nodes, while that is 9% for 40 nodes. As the number of nodes increases, the density of nodes becomes dense. Then, the spatial correlation among links becomes high and the efficiency of compressing the link quality matrix is improved.

Figure 7 shows the simulation results for path ETX as a parameter of the maximum moving speed of the nodes. For both compressed sensing and transmission, the path ETX for the actual case increases as moving speed increases because the basis derived from the link quality matrix before one sample contains more errors than the ideal basis. In this situation, the assumption that information sharing should be performed before a significant change of link qualities is not satisfied. Even if nodes are moving, the compressed transmission can keep the path ETX small.

6. Conclusions

In this paper, we have proposed information sharing methods using compressed sensing for arbitrary topology WMNs. For arbitrary topology WMNs, we have introduced a link quality matrix and a matrix formula for compressed sensing. Using the diffusion wavelets basis, both compressed sensing and compressed transmission can be achieved.

Our experimental results show that the proposed methods can reduce the amount of data transmitted for information sharing in real environments. In addition, simulations have shown that the proposed methods can reduce the size of the link quality matrix transmitted while maintaining path selection quality. Even if we consider environments in which

link quality fluctuates, compressed transmission can prevent degradation of the quality of the selected path while reducing the amount of the transmitted link quality matrix.

The proposed compressed sensing and transmission methods are effective for information sharing in arbitrary topology WMNs from the different viewpoint of the conventional methods such as the usage of the spatial correlation among link qualities. In addition, because the conventional method such as MPR flooding and our proposed method employ the different factors, network topology and spatial correlation, for reducing the information respectively, both methods can be used simultaneously.

Note that the overhead of our proposed methods on network performance is not evaluated because this paper focuses on the evaluation of the tradeoff between the reduction of transmitted data and the estimated error of link qualities. The evaluation of the overhead is treated as future work.

Acknowledgment

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Appendix: Selection Procedure for Compressed Transmission.

Let $y_i(l)$ be the ith component of $\boldsymbol{y}(l)$. In the compressed transmission, the sparse matrix is compressed to the compressed vector by selecting the diagonal components and their adjacent components, as follows:

$j = 1, k = 0$
for $i = 1$ to K_{CT} **do**
  if $k = 0$ **then**
    $y_i(l) = \theta_{j,j}(l)$
    $j = j + 1$
  else
    if $(i - N)\%2 = 1$ **then**
      $y_i(l) = \theta_{j+k,j}(l)$
    else
      $y_i(l) = \theta_{j,j+k}(l)$
      $j = j + 1$
    end if
  end if

if $j + k > N$ **then**
    $k = k + 1, j = 1$
end if
end for

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