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Prioritization Scheme of Wireless Visual Sensor Network for Sewage Treatment Surveillance

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Abstract. Accuracy and survivability are the two primary problems in wireless visual sensor networks (WVSNs) for surveillance application subject to very limited resources. To overcome the frangibility, in this paper, we present a low-cost joint prioritization framework for processing and transmitting microscopic image data in WVSNs of sewage treatment system. Firstly, an improved fast visual background extraction (Vibe) algorithm is put forward to rapidly detect moving microorganisms in wastewater, which play an important role in judging the quality of wastewater treatment. Then, each image macro block is classified into different priority levels according to the object detection results and our designed central weighted criteria based on Gaussian function and user empirical value. Finally, a cognitive routing protocol depending on data priority levels is proposed to keep good balance between energy consumption and transmission delay. Experiment results show the efficiency and effectiveness in terms of salient object detection and resource utilization of our scheme. Compared with other state-of-the-art approaches, the proposed method significantly extends the entire network lifespan with less transmission delay.

Keywords: data prioritization, dynamic routing, object detection, wireless visual sensor network

1 Introduction

WVSNs have presently become as a popular kind of intelligent system and widely applied into various monitoring or surveillance domains, such as patient monitoring and remote security surveillance et al. For these applications, people equip the cameras on several sensor nodes and place them on preselected locations in their interesting regions. In case of any abnormal event, these cameras capture images and transmit them to the sink node via other sensor nodes without cable infrastructure. Therefore, it also has attracted considerable concerns in sewage treatment system recently [1]. Many recent studies have confirmed that the statistical properties of microorganisms in sewage, such as their population, abundance and activities play a key indicative role in quality judgement of wastewater treatment [2]. Thus, developing micro-image sensors and wireless intelligent networks in sewage system have significant potential to allow the real-time observation of treatment process and influence the timely control decision making as well. Despite the existence of numerous ideas for many practical monitoring applications, there are also several challenges in the actual implementation of WVSNs.

WVSNs work with very limited resources. The practical surveillance system based on WVSNs consists of numerous sensor nodes, and the on-board battery power of each sensor node is so finite that

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every individual node lifespan directly influences the entire monitoring network life. Further, these numerous sensor nodes require extensive bandwidth to transmit their raw video streams, but it has been confirmed that wireless transmission is already on the verge of its energy efficiency limit [3]. Moreover, huge volume of visual data collected by each sensor node also poses a critical energy consumption hurdle for sink node (SN) to detect and analyze anomalies events, which severely weaken the discern intelligence of surveillance system.

Robustness is another important consideration for wireless surveillance system. In real monitoring environment, various unpredictable situations would often happen those may be natural disasters, human invasion, or technical failure. Although multiple sensor nodes deployment and collaborative share surveillance data can ensure full visual access to the interesting regions and minimize the energy consumption of every sensor node at the same time, it also introduces the visual over-coverage problem, which produces massive redundant video data. Processing and transmitting these redundant data causes unnecessary resource waste in WVSNs. Meanwhile, if more sensor nodes need transmit video data in the network, the probabilities of packet collision and transmission delay increase obviously.

Therefore, the real surveillance system based on WVSNs must have four crucial requirements. They are accurate anomaly detection, efficient resource utilization, great system robustness and acceptable transmission delay. In this study, we present a low-cost untied prioritization scheme for multiple visual sensor wireless networks in sewage surveillance. Our scheme includes two aspects as image data prioritization and wireless transmission prioritization. In phase of image data prioritization, the sensor nodes detect and extract indicative microorganisms and categorize object image data into different importance levels. In phase of wireless transmission prioritization, we describe a cognitive dynamic routing protocol based on former ranking strategy of image content to keep a better balance between resource consumption and reliable transmission.

The main contributions of this paper can conclude as follows:

(1) We propose an entire prioritization frame for multiple visual sensor-based intelligent sewage surveillance system, which aggregates the minimum data processing and wireless communication.
(2) A region-based Vibe model is presented for fast motion object detection. The extracted indicative microorganisms from huge volume of useless backgrounds efficiently reduce the bandwidth requirements.
(3) Flexible cognitive-based data transmission ensures to keep good balance among multiple network performances by dynamically selecting the most appropriate channel.

We organize the rest of the paper as: a fast indicative microorganism detection algorithm is introduced in Section II. Section III describes the strategy of optimization ranking for every object macro block. The detailed dynamic routing protocol based on data prioritization levels is presented in Section IV. Some experiment and comparison results are demonstrated in Section V. Finally, Section VI draws the conclusions of this study.

2 Related Work

To overcome the limitations of WVSNs, recent literatures have focused on such aspects as image data optimization and wireless collaborative transmission. The fundamental concern of visual data handling in WVSNs is image coding, especially compression coding. Lee, Kim, Rahimi, Estrin and Villasenor [4] have constructed the baseline of famous JPEG comparisons which achieve the trade-offs in terms of energy consumption, computational cost and image quality. Another further trade-off method is distributed source coding (DSC) [5] that can balance the computational load on different sensor nodes. However, fragility of compressed data makes it hard to complete survive via lossy wireless channels. Real test experiments [6] have demonstrated that at least 14% of the JPEG 2000 coded image data are unrecoverable in a 2-hop transmission. By independently compressing the tiny 2×2 macro-blocks and utilizing interleaving encoded macro-blocks, Duran-Faundez, Lecuire and Lepage [7] propose a novel compression method to cope with fragility of traditional ones. Kaddachi et al. [8] describe image compression-based specialized hardware in their recent works. They reach significant goals in terms of processing speed and energy consumption. However, the energy costs of these methods are still very higher than application requirements. Moreover, because of the limited available memory of sensor nodes, compression computation is not possible for full images.

Another optimization approach is data ranking. Many researchers have realized that in real surveillance videos, humans tend to pay more attentions to motion objects, especially the saliency-based motion objects rather than the background [9]. Therefore, Lei, Wu, Feng, Hu and Hou [10] propose to allocate more resources to influential sections of image sequences reducing energy and bandwidth consumption. In general, moving object detection approaches mainly include frame difference, background subtraction and optical flow. In addition, saliency-based motion detection also causes wide concerns recently. Hu, Leou and Hsiao [11] use filtered optical flow and temporal difference imaging to achieve the salient motion targets. Lim, Chan, Monekosso and Remagnino [12] employ a dense optical flow algorithm to estimate the salient irregular or abnormal motions. But it is pity that their algorithm cannot accomplish individually tracking of each target and autonomous learning of prior objects. Almost all of the object detection methods mentioned above is based on the pixels of video frames, so they often fail in cases with dynamic background. Further, the computation cost is also hard to satisfy the real-time requirement of most surveillance system. But the mechanisms of salient motion detection bring a better enlightenment for the effective transmission of semantically significant data in resource-constrained WVSNs.

Spectrum aware opportunistic routing (SAOR) has attracted more attentions than other routing protocols in WVSNs recently, which can change the transmission path dynamically, following the current network conditions, and making it suitable with fast variation of spectrum availability. One of SAOR algorithm is proposed [13]. This study utilizes an opportunistic link transmission metric, considering the various delays of link access, packet queueing and delivering. Another advanced work named MSAOR (multichannel spectrum aware opportunistic routing) is described [14], which introduces channel access probability to represent the opportunistic channel link and effectively improves the performance of SAOR algorithm in 3-node network. Petros, Periklis and Dimitrios [15] propose a cognitive unicast routing protocol for wireless sensor networks which can achieve good energy efficient utilization. Petros, Periklis and Dimitrios [16] make full use of the cognitive radio to prevent packet collisions. Costa, Guedes, Vasques and Portugal [17] present a cognitive routing mechanism based on sensing relevancies of source nodes, which are applicable for time-critical applications in WVSNs.

Joint optimization scheme has also attracted considerable attention in recent years for automated wireless video surveillance. An available wireless video transmission system is proposed [18], which is based on salient region segmentation. The system can dynamically prioritize each image packet by a cost effective algorithm. However, it only thinks about single visual sensor node streams, and cannot provide any reliable transmission solution for high priority data. Irfan, Muhammád, Waleed and Sung [19] put forward a visual data prioritization frame in both single and multi-camera wireless networks based on salient motion detection. The frame can offer reliable transmission for high priority image data, but fail to consider the working load of relay nodes on reliable path and the whole network lifespan.

Therefore, we present a low-cost joint optimization scheme with indicative microorganism detection and a flexible image content-based dynamic routing to keep better balance between accurate detection, resource consumption and reliable transmission in WVSNs for sewage surveillance.

3 Fast Object Detection

Background subtract is almost the most common method for moving object detection, in which Vibe is regarded as a very fast one can be applied into real-time wireless networks. This samples-based algorithm can assure a smooth exponentially decaying lifespan for the samples in image background model by using a type of random selection policy [20]. However, Vibe is still a pixel-based method and it cannot integrate the image region information into background model, which results in its severe fragilities to noise disturbance and high computation consumption. Therefore, in this section, a region-based Vibe algorithm is presented to construct background model for fast microorganism detection.

3.1 Preliminary Segmentation

There are plenty of image segmentation approaches. An efficient graph-based one is proposed recently [21]. Inspired by this, we firstly transform each frame of microscopic video sequences to a graph with vertexes and edges. Thus, the image pixels are equivalent to the graph vertexes, and the edge values can be obtained by the differences of neighboring vertexes. Then, classic Kruscal algorithm is utilized to segment raw video frame into different divisions in nearly linear time. Finally, an adaptive threshold based on Ostu algorithm is designed for the graph edges to improve the segmentation effect. Once one edge value exceeds this threshold, it will be excluded from the graph edge set, which can considerably reduce the numbers of graph edges and compute cost for image preliminary partition.

3.2 Region Initialization

According to the preliminary region segmentation in micro-video frames mentioned above, each statistical mean value $\overline{I_R}$ of all the pixels in this region is calculated and then every pixel in the region is reinitialized as follows:

$$I_{x_{new}} = \alpha\, I_X + (1-\propto)\, \overline{I_R} \tag{1}$$

These pixel values are going to be utilized to construct and update the background model for moving object detection.

3.3 Region Classification

(1) For each input pixel I_{x_new}, we compute the minimal and the second minimal Euclidean distances d_1 and d_2 respectively in all the samples picked out by traditional pixel-based Vibe initialization approach.
(2) Assume the pixel values in every region satisfy the normal distribution, the probability of occurrence for pixel I_{x_new} in one region can be defined as:

$$w_x = \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-(I_{x-new} - \overline{I_R})^2}{2\sigma^2} \right) x \in R \tag{2}$$

(3) The accumulated weighted distance d_R of region R can be calculated as:

$$d_R = \frac{\sum w_x (\propto d_1 + (1-\propto) d_2)}{\sum w_x} x \in R \tag{3}$$

(4) According to the distance d_R and presupposed different thresholds, the region R can be easily classified as foreground, background and undetermined:

$$L(R) = \begin{cases} \text{background} & d_R < \beta_1 \\ \text{forground} & d_R > \beta_2 \\ \text{undetermined} & \text{others} \end{cases} \tag{4}$$

3.4 Object Detection

Based on the results of region classification step, all the pixels of video frames in one specific region achieve the same label, microorganism object or not. Only those pixels in undetermined region are necessary to be further identified by traditional pixel-based Vibe algorithm as [20].

4 Image Ranking Strategy

In this paper, we only allocate available channel link to useful image data transmitting towards sink node for abnormal monitoring, which can efficiently improve the wireless network resource utilization. The object detection results are blocked and ranked into different crucial levels for subsequent distinguished transmission as follows:
(1) We introduce Gaussian function and Euclidean distance function to define the central weighted variable:

$$\alpha = e^{\left(\left\| \sqrt{\frac{(x-x_c)+(y-y_c)^2}{\theta}} \right\| \right)^{\tau}} \tag{5}$$

Where, (x_c,y_c) is the central position of current frame image, and $\theta = c \times \sqrt{(\frac{W}{2})^2 + (\frac{H}{2})^2}$, in which W and H are the height and width of the image respectively.

(2) At time t, the salient prioritization ρ_i^t of current frame captured by sensor node i is designed as below:

$$\rho_i^t = (\alpha \times SM_i^t) \times \mu_i \tag{6}$$

Where, $\mu_i \in [0,1]$ is a preset empirical value by expert users to determine the importance degree of the monitoring region of sensor node i. SM_i^t is related with the detected objects area of the ith sensor node.

(3) Based on salient prioritization ρ_i^t and different presupposed thresholds, object detection results are ranked into different optimization levels:

$$L_k = \begin{cases} 0 & \rho_i^t \le \gamma_1 \\ 1 & \gamma_1 < \rho_i^t \le \gamma_2 \\ 2 & \rho_i^t \ge \gamma_2 \end{cases} \tag{7}$$

The priority levels are mapped into every data macro block, which is designed as 8 x 8. Then every packet in WVSNs has 66 bytes, where macro offset values occupies 2 bytes.

5 Cognitive Routing Protocol

Inspired by the theory of reactive opportunistic routing, a cognitive-based dynamic routing protocol is proposed in this section, which closely relevant to the crucial levels of data contents. The core concept of this protocol instructs to activate the best routing discovering only when very important data appears. Moreover, each source node selects its relay node of next hop by overall considering energy efficiency, transmission delay and error rates in its neighbor domain, which can ensure the important data with higher optimization levels arrive the sink node accurately and timely.

5.1 Network Address and Initialization

Each sensor node in our WVSNs has a unique network address, which is based on its location and the distance to sink node. According to the network addresses of any node i and sink node s, a delivery criterion can be locally obtained by broadcast method on counting the smallest number of hops. If a new sensor node takes part in the network, it can acquire its network address by means of its neighbor nodes. If a different source node joins or an existing node leaves, the network addresses of the other nodes remain unchanged. Only as the sink node changes, the broadcast procedure happens again.

The sink node initiates the connection to one source node by flooding a packet toward its candidate nodes that are on the edge of its maximum transmitting distance. Then, each intermediate sensor node forwards the packet to its own candidate nodes. When the source node receives the packet, it can calculate the delivery hops to the sink node by different routes and estimate the energy required for each hop. After that, it drops the packet. In this way, every sensor node in the network achieves its necessary data delivery information.

5.2 Channel Model

In wireless network, the packet error rate (PER) cannot be avoided for any sensor node to transmit any type of packet through any link channel. For more realistically simulating the damaged wireless channel in real application, we employ BPSK (binary phase shift keying) approach to define PER as [16]:

$$P\widehat{E}R(i) = 1 - \left(1 - Q(\frac{\sqrt{2P_t(i) \cdot \widehat{G}(i)}}{\delta_n^2})\right)^V \tag{8}$$

Here, P_t is the transmission power, V is the length of data, and δ_n^2 is the noise power. Additionally,

$$Q(x) = \frac{1}{\sqrt{\pi}} \cdot \int_{\frac{x}{\sqrt{2}}}^{\infty} e^{-t^2} dt \tag{9}$$

$$\widehat{G}(i) = A \cdot \widehat{D}_s(i)^{-n} \tag{10}$$

Where, A is a constant, $\widehat{D}_s(i)^{-n}$ reflects the distance between sender node s and its next hop node i. n represents the loss component of wireless channel. In above formula, P_t is very crucial to energy consumption and completely connectivity for overall wireless network. If P_t is too high, it will cause energy waste and increase the signal conflict probability among the adjacent sensor nodes. In the meantime, it also will enhance the numbers of relay nodes. On the contrary, if P_t is too low, it will restrict network connectivity, so that it will depend on increasing sensor nodes to accomplish the transmission task, which result in the whole network delay. Therefore, in this paper, we design different *PER* requirements for different data priority levels, then allocate distinguish and more reasonable transmission power for each sensor node in WVSNs.

5.2 Packet Levels

After processing as step 4, the data's crucial level information is inserted into each packet, which is very useful for other relay nodes to understand the importance of this packet. A packet with a higher crucial level, a more reliable and less hops path will be pitched on to send it. When various data with different levels are necessary to deliver simultaneously, the lower level data have to wait. Besides, if there is no or little communication flows in WVSNs, each sensor node sends location packet to sink node periodically, which makes it easy to record the update of all sensor nodes' location and amount in the network. We define the priority level of location packet as 0. The details of packet ranking mechanism are described as:

Table 1. Packet ranking mechanism

Levels	Mechanism Description
L_k=0	Not important. No important packet should be transmitted immediately.
L_k=1	Little important. The packet should be transmitted immediately, but it can tolerate some delay.
L_k=2	Very important. The packet should be transmitted immediately with minimum delay. All the other packetes have to wait.

5.3 Packet Transmission

There are four kinds of packets in our cognitive routing protocol which are DATA, ACK, RTS and CTS packet respectively. RTS is the packet of request of send and CTS is the packet of clear to send. Each type of packet is restricted by packet error rate (*PER)*. When one sensor node need send data packet, it firstly makes a RTS/CTS handshake with its adjacent nodes or candidate nodes to discover an available channel, then flooding a RTS packet to wait the first response.

Depending on the current network condition and the distances between different sensor nodes, several relay nodes can receive the RTS packet from sender. Suppose the node k receives RTS packet, and it does not have other packets with higher priority levels to deliver, the back-off time for node k sending CTS packet can be defined as follows:

$$T_{backoff} = ((\overline{L} - L_k) \times \log(D)) \times B_0 + SIFS \times B_1 \tag{11}$$

Where, $\overline{L}$ is the evaluated mean value of all packet priority levels in sewage surveillance system according to the ranking strategy as mentioned previously. D describes the distance between node i and node k. SIFS represents short inter-frame space. B_0 and B_1 are two fixed constants.

When node k detects an available channel C_i, it will send CTS response packet through this channel, otherwise, it will continue wait. While node i successfully receives the first response packet from node k, it will send image data packets through the same channel C_i immediately, and neglect the other CTS responses from other sensor nodes in the meantime. After that, node i will wait for the ACK packet from node k.

From this transmission scheme, we can see that the selection criterion of next relay node in WVSNs is not only associated with the sensor nodes location, but also closely relevant to the data priority levels. When a packet has low crucial level, the node closest to the sender will acquire a minimum of back-off time, which will lead to more jumps for this packet transmitting to the sink node. Inversely, if a packet has higher crucial level, the edge relay node can be picked out near the sender's maximum transmission range, that will obviously reduce the entire transmission delay.

Furthermore, we can see that in the proposed protocol, there are simple handshake and acknowledge mechanisms to make sure the reliable data transmission. Because each relay node executes the similar operation, subsequent packets can select diverse channel and path according to current network conditions and data priority levels. This just embodies the core idea of the proposed cognitive routing protocol.

5.4 Collision Avoidance

In our routing protocol, we make full use of the cognitive radio to avoid network collisions inspired by Petros et al. [15-16]. Because the radio can access a group of channels, we utilize two other frequency tones different from data channel frequency for sensing and polling respectively. When a sensor node need deliver a packet, it firstly senses for an available channel and then broadcasts a polling tone. All of the other nodes in the range of this source node can detect the polling tone and autonomously decide whether to join the transmission according to its own condition. If one node decides to participate in, it will forward a polling tone to the nodes surrounding it. By this means, spectrum interference is prevented.

6 Experiment and Analysis

Our simulation platform is under OpenCV2.3.1 and Matlab.R2015a with Inter Core i5 2.45GHz CPU, 4GB RAM and 64bits Window 7 OS. The resolution of microscopic video image is 600×400.

6.1 Experiments on Object Detection

In the fast microorganism detection algorithm, relevant parameters are respectively set as follows: $\propto = 0.75$, $R = 20$, $\beta_1 = 16$, and $\beta_2 = 32$. Furthermore, we calculate five most common used metrics [2] to describe the detection performance, which are *Precision*, *Recall, F-measure*, *PWD*, and Average Processing Rate (*AVR*). *Precision* represents the ratio of the accurately detected objects based on *Ground Truth* to the total objects. *Recall* describes the ratio of accurately detected objects to the total objects in *Ground Truth*. *F-measure* can be regarded as a concordant mean value of former two. And *PWD* is the percentage of wrong detection.

Four state-of-the-art object detection approaches [2] are utilized to compare with our proposed method. Some of experiment results are presented in Fig. 1, Table 2 and Table 3. From these figure and tables, we can clearly see that our algorithm has achieved better subjective and objective detection effects. Especially, it obtains optimum balance between detection quality and processing rate. The main reason may due to the proposed method makes full use of the advantages of graph-based image segmentation and Vibe background subtract model, while other state-of-the-art methods are all based on image pixels, which are very sensitive to noise and interference.

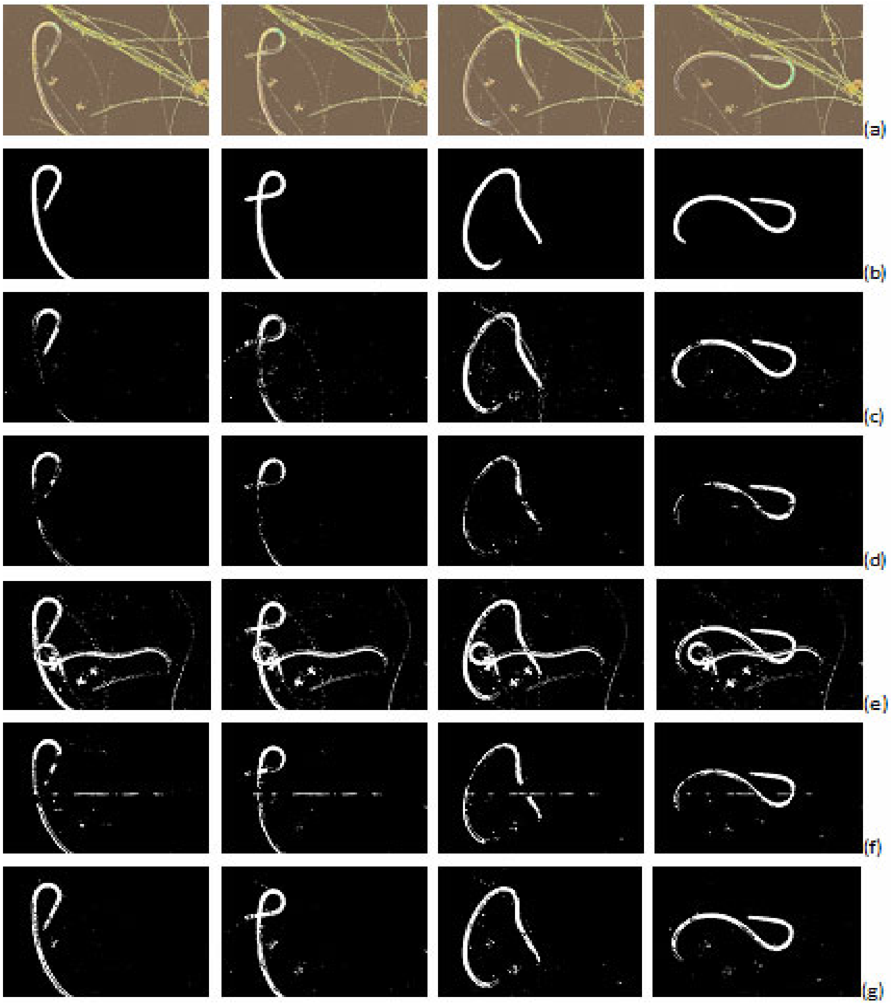

Fig. 1. Microorganism detection results on (a) Original sequences, (b) Ground Truth, (c) MoG, (d) CB, (e) SOBS, (f) Vibe, and (g) Our method

Table 2. Comparison of different algorithms

	Precision	Recall	F-measure	PWD
MoG	0.9241	0.7026	0.7980	2.5730
CB	0.9779	0.4927	0.6442	3.7830
SOBS	0.5344	0.9384	0.6773	6.6084
Vibe	0.8488	0.6763	0.7518	3.2425
Ours	0.9560	0.9762	0.9659	1.4993

Table 3. Average processing rate (AVR)

	MoG	CB	SOBS	Vibe	Ours
AVR (s/f)	0.0791	0.0544	0.0802	0.0275	0.0396

6.1 Experiments on Cognitive Routing

In this simulation, 300 sensor nodes are randomly distributed into a 100×100 (m^2) domain. The wireless communication parameters are listed in following Tab.4, which are selected based on IEEE 802.15.4. Additionally, each sensor node supposes to have two pairs of 1.5V AA batteries with 2Ah capacity, so that anyone of these sensor nodes possess about 22J initial energy (Energy(J) =capacity(Ah)× voltage(V)×time(s) [22]). Fig. 2 has demonstrated the comparison results of entire network lifespan under different node distribution densities between the proposed cognitive routing and traditional fixed routing protocol, the latter delivers all the packets towards the destination node through the same best chosen or fixed prearranged path [19].

Table 4. Simulation parameters of wireless network

Parameters	Value	Unit
DATA/RTS/CTS/ACK Packet	66	byte
SIFS	10	us
P_t	15	mW
Maximum Deliver Range	10	m
Bit Rate	250	kbps
B_0	10^{-5}	/
B_1	8	/

Fig. 3 to Fig. 5 have demonstrated the average end-to-end transmission delay of packet with different importance levels. Three groups of 1000 packets with three different levels are selected out to transmit from one source sensor node to the sink node in different density network. From these figures, we can see that our dynamic routing performs obviously better than fixed routing for high-level packets. The main reason should due to the opportunistic feature of our protocol, which manages to deliver the packets over any available link with less hop numbers by taking advantage of broadcast characters. Although the performance of proposed routing is not as well as the fixed one for low-level packet, our dynamic protocol can conserve energy for transmitting high-level packets by selecting those not often used nodes to deliver low-level packets. Hence, it can balance the network energy consumption and prolong the network lifespan efficiently.

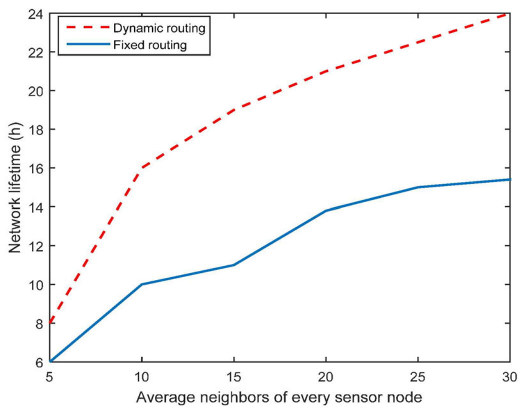

Fig. 2. Network lifespan comparison

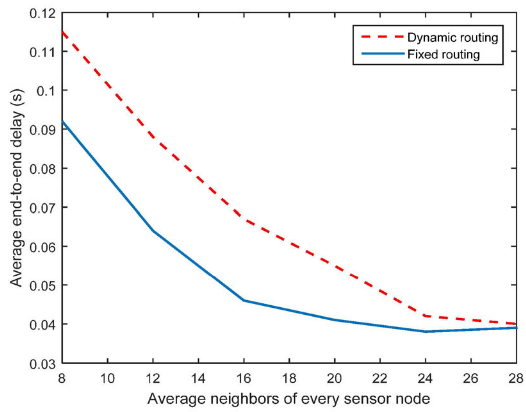

Fig. 3. Average transmission delay with level 0

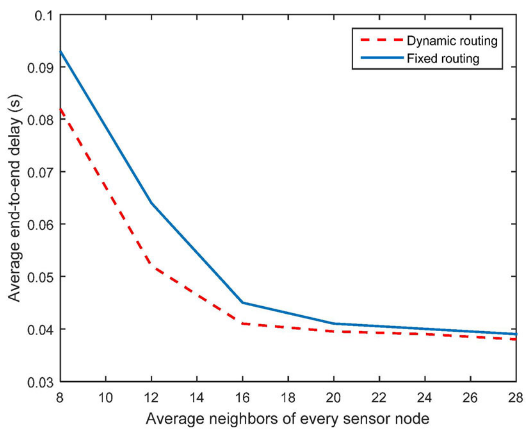

Fig. 4. Average transmission delay with level 1

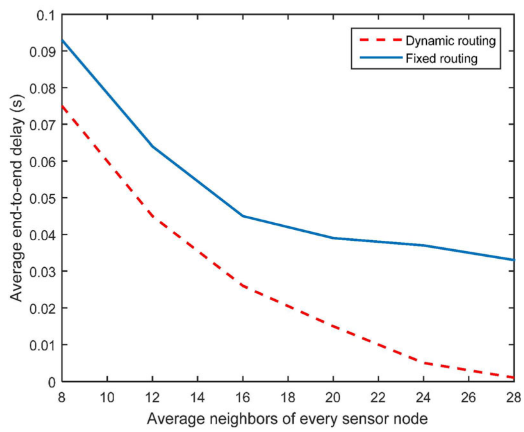

Fig. 5. Average transmission delay with level 2

7 Conclusion

In this paper, we propose a joint prioritization frame for microscopic video data processing and transmitting in WVSNs for wireless surveillance in wastewater treatment system. The scheme mainly includes three sections. The first one is a region-based Vibe algorithm for fast microorganism detection from complicated sewage background. The second one is a data prioritization ranking mechanism based on object detection results, and the last one is a cognitive dynamic routing protocol, whose relay selection criterion combines both location information and packet priority levels. It has shown by amounts of simulation that the proposed joint prioritization scheme not only detects salient microorganisms in sewage more efficiently and effectively, but also extends the whole network lifespan up to 30% and achieves less end-to-end transmission delay for the most significant packets than the other approaches.

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