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Online Data Transmission Reduction Scheme for Energy Conservation in Wireless Video Sensor Networks

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Abstract

Wireless Video Sensor Networks (WVSNs) are networks of low-cost, low-power camera sensor nodes. These nodes communicate locally and process information to meet an application's goal. WVSNs are extensively used in diverse monitoring applications, such as security, military, industrial, medical, and environmental monitoring. However, the transmission of large amounts of data collected by video sensor nodes in WVSNs poses challenges in terms of energy consumption, bandwidth usage, and network congestion. Reducing energy for processing and transmitting data in WVSNs is difficult due to the huge amount of sensed data in real-time. To address this issue, this paper proposes an Online Data Transmission Reduction Scheme (ODaTReS) for energy conservation in WVSNs. The data reduction by the ODaTReS is based on two phases: the sensing phase and the transmission phase. ODaTReS adapts the frame rate to limit the number of video frames captured during the sensing phase. It does this by using three efficient techniques: ORB (Oriented FAST and Rotated BRIEF), Brute-Force (BF) Matcher, and Grid-based Motion Statistics (GMS). During the transmission phase, we use an adaptive transmission threshold that is responsible for deciding whether to transmit the current captured frame or remove it. Several experiments are conducted to demonstrate the effectiveness of the ODaTReS. The proposed ODaTReS outperforms the FRABID method in terms of data reduction and energy consumption. The results reveal that ODaTReS reduced the transmitted data by 80%, compared to 43% for the FRABID method. This reduction in data transmission contributes to a decrease in the total energy consumed, which is reduced to 141.22 joules compared to the FRABID method, which consumes 173.16 joules of energy.

Keywords

Wireless Video Sensor Networks; Online Transmission Reduction; ORB Algorithm; GMS algorithm; Sensing data; Transmitted data Feature Extraction; Energy Consumption.

RESEARCH PAPER

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Abstract

Wireless Video Sensor Networks (WVSNs) are networks of low-cost, low-power camera sensor nodes. These nodes communicate locally and process information to meet an application's goal. WVSNs are extensively used in diverse monitoring applications, such as security, military, industrial, medical, and environmental monitoring. However, the transmission of large amounts of data collected by video sensor nodes in WVSNs poses challenges in terms of energy consumption, bandwidth usage, and network congestion. Reducing energy for processing and transmitting data in WVSNs is difficult due to the huge amount of sensed data in real-time. To address this issue, this paper proposes an Online Data Transmission Reduction Scheme (ODaTReS) for energy conservation in WVSNs. The data reduction by the ODaTReS is based on two phases: the sensing phase and the transmission phase. ODaTReS adapts the frame rate to limit the number of video frames captured during the sensing phase. It does this by using three efficient techniques: ORB (Oriented FAST and Rotated BRIEF), Brute-Force (BF) Matcher, and Grid-based Motion Statistics (GMS). During the transmission phase, we use an adaptive transmission threshold that is responsible for deciding whether to transmit the current captured frame or remove it. Several experiments are conducted to demonstrate the effectiveness of the ODaTReS. The proposed ODaTReS outperforms the FRABID method in terms of data reduction and energy consumption. The results reveal that ODaTReS reduced the transmitted data by 80%, compared to 43% for the FRABID method. This reduction in data transmission contributes to a decrease in the total energy consumed, which is reduced to 141.22 J compared to the FRABID method, which consumes 173.16 J of energy.

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1. Introduction

In the past, personal computers with an established Internet connection have served as the primary means of computation and communication. This form of communication technology is not expected to be used shortly. Instead, a new paradigm called wireless sensor networks (WSN) is emerging, where intelligent and communicative devices, equipped with sensing capabilities and wireless communication, form a network. This will represent the next generation of the Internet, sometimes referred to as the "Internet of Things" [1]. Inexpensive CMOS image sensors have made possible the development of WSN [2], known as "WVSN". All abbreviations and meanings are shown in Table 1. WVSNs are composed of several video sensor devices that are equipped with an audio system, a low-power battery, small video cameras, and a wireless transceiver [3]. These devices are small, inexpensive, simple, and have the ability to process visual data and transmit it to a sink in real time [4,5]. The integration of WVSN in various domains offers tremendous potential for enhanced data acquisition, analysis, and intelligent decision-making. The field

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Table 1. Abbreviation description.

WSNs	Wireless Sensor Networks
WVSNs	Wireless Video Sensor Networks
WMSNs	Wireless Multimedia Sensor Networks
ODaTReS	Online Data Transmission Reduction Scheme
FRABID	Frame Rate Adaptation Based on Image Difference Algorithm
BF	Brute-Force
ORB	Oriented FAST and Rotated BRIEF
GMS	Grid-based Motion Statistics
oFAST	Oriented FAST
BRIEF	Binary Robust Independent Elementary Features
RANSAC	Random Sample Consensus
FLANN-based Matche	Fast Library for Approximate Nearest Neighbors Matche
BF Matcher	Brute-Force Matcher
MR	Matching Ratio
Dict key, value	Dictionary with content (key, value)
MSE	Mean Square Error
VRE	Video Reconstruction Error
PSNR	Peak Signal-to-Noise Ratio
SRD	Shot Reconstruction Degree
CDnet	Change Detection.net benchmark
SVM	Support Vector Machine
SIFT	Scale-Invariant Feature Transform
CHs	Cluster Heads
BS	Base Station
CMOS	Complementary Metal Oxide Semiconductor

of environmental monitoring stands to greatly benefit from WVSN advancements [1]. These networks enable distributed nodes to detect and track moving targets using visual cues, empowering intelligent objects to capture periodic images and videos from the surrounding environment [6]. E.g., WVSN can be utilized on smart highways to proactively prevent accidents [7].

WVSNs have additional features and challenges beyond those of WSNs. Due to the small size of the sensors, limited resources on the video sensor node, and the large amount of multimedia data produced by multimedia applications, WVSNs have many resource limitations in terms of bandwidth, energy, memory, data rate, and processing power. Furthermore, processing this massive amount of data in WVSNs is more sophisticated because it necessitates high processing power and memory efficiency. On the other hand, visual data transmission depletes the most energy from the WVSN [8,9]. WSNs face numerous research challenges in the field of video transmission. Addressing these challenges requires effective data reduction strategies. In this paper, we present a novel approach to data reduction utilizing the ORB algorithm and adaptive thresholding. By leveraging these techniques, we aim to significantly reduce the amount of data transmitted in the network, thereby improving overall efficiency and optimizing resource utilization. Through this research, we contribute to the advancement of video transmission in WSN by providing an efficient solution to the existing challenges.

The following is a summary of our significant contributions to this work:

1). An online data transmission reduction scheme (ODaTReS) for energy conservation in WVSNs is proposed. The ODaTReS reduces the amount of data that needs to be sent in two phases: the sensing phase and the transmission phase. The main goal of these two phases is to reduce the number of transmitted frames by getting rid of redundant frames, save energy, and maintain an acceptable level of quality of received data at the sink.

2). In the sensing phase, ODaTReS uses frame rate adjustment to limit the number of sensed video frames per period. We propose an adaptive rate frame sensing approach by integrating three efficient techniques: ORB, BF Matcher, and GMS. These techniques are responsible for finding the matching ratio between each of the last two captured consecutive frames in the current period. The transmission phase will use this ratio to determine the frame transmission decision and adjust the frame capture rate of the video sensor accordingly. This will decrease the number of sensed frames per period and lower the required energy for the sensing activity inside the wireless video sensor node.

3). A frame transmission reduction approach is proposed that is joined with the frame rate adaptation in the ODaTReS. In this phase, the current captured frame transmission decision will be taken based on the matching ratio and the transmission threshold (α). We suggest using an adaptive transmission threshold to decide whether the currently captured frame should be sent or deleted. This threshold keeps the balance between the quality of the video and the amount of data sent. This enables the video sensor node to transmit only important frames. This lowers the amount of traffic, saves energy, and improves the performance of the WVSNs.

4). Numerous experiments were conducted on the Highway dataset using the Python programming language. To evaluate the performance of the proposed ODaTReS, a comparison was made with other existing data reduction strategies mentioned in Ref. [6]. The results demonstrate the superiority of ODaTReS in various aspects, including frame rate adaptation, data reduction, transmitted frame count, energy consumption, and video quality.

This paper is structured into five sections. Section 2 presents the relevant work in this particular field. In Section 3, the suggested ODaTReS approach is described. The experimental results are introduced and discussed in Section 4. In Section 5, the conclusion and some suggestions for further work are presented.

2. Related work

Due to their wide-ranging applicability, WVSNs have garnered significant research attention among various types of networks. WVSNs consist of numerous wireless nodes equipped with processors, power supplies, image sensors, and transceivers. These nodes collectively form a WVSN. To facilitate environmental and traffic monitoring, WVSNs have been introduced to capture visual information within the monitoring area [10]. Operating continuously, 24 h a day, 7 days a week, these WVSNs accumulate a substantial volume of data. For that reason, data generated during monitoring activities often exhibits gradual changes over time, leading to the inclusion of redundant information. To optimize performance, minimizing the amount of transmitted data becomes crucial. This optimization is particularly important in WSNs due to their limited energy resources and the energy-intensive nature of radio communication and sensing activities within these networks. By reducing the number of transmissions, significant reductions in energy consumption can be achieved, thereby extending the lifetime of WSNs [11]. In the literature, various methods have been proposed to address this energy consumption challenge in WVSNs. Most of these approaches either use scheduling, compressive sensing [12], or reduce the amount of transmitted data over the network using compression methods, Machine Learning [13], and reduction of similar data, such as strategies in Refs. [6,15], and [16].

2.1. Data reduction based on similar data

In this section, the focus is on reducing the amount of data transmitted by leveraging the similarity between consecutive video frames.

Matheen and Sundar [17] introduce the Fuzzy Criminal Search Ebola Optimization (FCSEO) algorithm as a new approach for selecting optimal cluster heads in a Wireless Multimedia Sensor Network (WMSN). The paper's primary goal is to reduce data redundancy and minimize energy consumption while improving the overall network lifetime. The proposed FCSEO algorithm tackles data redundancy by examining the overlap between the fields of view of different sensors. The main limitations of this work are related to accurately detecting overlap within the field of view and the challenges associated with the time consumption in selecting cluster heads based solely on energy levels.

Salim et al. [11] propose the STAFRA algorithm, which utilizes the L2-norm to compare consecutive frames and selectively transmits the difference image in cases of significant variations. The algorithm dynamically adjusts the frame rate of individual sensor nodes based on the occurrence of events in the area of interest over the last period. This will help reduce the number of sensed frames, which leads to energy savings. The author's experiments reveal that the size of the transmitted data in each period is reduced, in addition to reducing the execution time. However, limitations arise from employing JPEG lossy compression and transmitting only the image difference, hindering complete image reconstruction at the sink node. Building upon this work, Koteich et al. [6] introduce the FRABID algorithm, which employs the L1-norm to compare sensed frames with the last transmitted frame. Both STAFRA and FRABID focus on transmitting only the differential information, neglecting the complete image. Overcoming this limitation requires developing algorithms or techniques to reconstruct the original image by integrating the transmitted differential information with the last complete image received. By addressing this aspect, the efficiency and effectiveness of the overall system can be further improved. Typically, measuring image similarity involves either distance-based measurements or relative measurements, both of which can be time-consuming processes [16]. In our work, we propose the use of the ORB algorithm and adaptive threshold to selectively transmit only important frames, thereby reducing the number of sensed and sent frames and eliminating the need for additional techniques to process image differences at the coordinator. Wan et al. adopt spatiotemporal interest points to eliminate redundant video frames. When the spatiotemporal interest points remain unchanged, this means the frame is redundant [18]. The main drawback of this work is that it is similar to video summarization and is based on video frame extraction, which makes it not suitable for real-time applications.

In [19], Moallem et al. examined the relationship between image entropy and the distance between camera nodes and the target, as well as the angle between the main view line of the camera and the target. A formula was developed to quantify the relationship between image entropy and the number of bits needed to represent image pixel values. Building upon this, a node selection algorithm based on entropy was proposed. However, the limitations of this approach should be considered. The effectiveness of the proposed algorithm may depend on various environmental conditions and the specific application scenario.

Similar techniques were used by Yazici et al. [20]. The authors introduced a fusion-based framework for WVSNs to reduce data transmission in the network. Their approach involved object detection and classification in a three-layer system. In the first layer, an acoustic sensor was utilized. In practical scenarios, energy optimization was achieved by keeping the microphone and camera in sleep mode when no activity was detected in the monitored area. However, when a significant sound was detected by the acoustic sensor, the microphone was triggered and activated to capture audio data in the second layer. This layer employed multimedia sensors such as a video camera and an audio microphone. The activation of the camera was based on the activation of the microphone. Later the authors employed Support Vector Machine (SVM) and Scale-Invariant Feature Transform (SIFT) algorithms for object classification and the fusion layer. However, it should be noted that a limitation of their work was the high time consumption of the SIFT algorithm, which rendered it unsuitable for real-time applications. In contrast, the ORB algorithm was suggested as a more suitable alternative for real-time applications.

Liu et al. [21] proposed a method for reducing sensor node energy loss in WVSNs by extracting wildlife photos. Their approach involves utilizing the Hermite transform to extract image texture information and perform adaptive mean-shift clustering.

Singh et al. use barrier coverage instead of blanket coverage in video surveillance systems as a straightforward method to save energy. In blanket coverage, “the goal is to acquire a set configuration of sensor nodes to maximize the total area of detection”. Blanket coverage, when all pixels of all frames are delivered, is not energy efficient. So, the barrier coverage and grid coverage concepts can detect suspicious objects in the border zone [22]. The network's lifetime increases depending on the number of invasions if it only transmits frames with intrusions. The nodes will need to compute intrusion detection throughout the image. Communication energy is more significant than processing energy in WSN.

2.2. Data reduction based on two levels

Data aggregation is an intelligent method used in WSNs to collect data from multiple Sensor Nodes through intermediate nodes called Cluster Heads (CHs). This technique reduces the number of data packets transmitted to the central Base Station (BS), thereby optimizing network bandwidth utilization. In cluster-based WSN architectures, CHs consume more energy due to additional tasks such as intra-cluster data aggregation and transmission to the BS. Therefore, selecting suitable CHs is crucial for extending the network lifespan and optimizing energy consumption [23].

Jain and Kumar [23] produced an efficient method related to Dual-Prediction. Dual-Prediction is an approach that utilizes historical data to estimate future sensor readings by analyzing the moving trends in the data. This mechanism is implemented at both the sensor nodes and the BS, enabling them to make consistent predictions using the same prediction model and shared historical data. Dual-Prediction offers a data reduction technique by leveraging historical data and prediction models to estimate future sensor readings. While it provides benefits such as reduced data transmission and energy consumption, its effectiveness depends on the quality of historical data and synchronization between the nodes and the BS. By employing the Dual-Prediction, sensor nodes can avoid transmitting their sensed data to the base station if their predictions align with the base station's predictions. This leads to reduced data transmission and lower energy consumption in the network. In Ref. [23], the authors employ data reduction in sensor nodes and CH as well as a data prediction method in CH and BS. To further improve the network's live time, Tayeh et al. combine prediction-based data reduction with an adaptive sampling rate. His solution reduced energy use and extended the network's lifespan [24].

With the same research direction, the authors produce two-level data aggregation in Refs. [16,25]. Barathy and Dejey [16] produce work based on two levels of reduction, where the Patch Code Sequence (PCS) has been implemented by the local cluster head on non-overlapping patches to eliminate redundant data taken from the local cluster members. The master cluster head uses the HOSVD decomposition method for decoding images as the second level of aggregation. One of the main drawbacks of this approach is the lack of a defined strategy for selecting the cluster head and master cluster head in the network. The cluster head plays a crucial role in data aggregation and coordination within the cluster, while the master cluster head is responsible for aggregating data from multiple clusters and transmitting it to the base station. Without a clear selection strategy, the choice of cluster head and master cluster head may be arbitrary or based on simple heuristics, leading to suboptimal performance. The selection process should consider factors such as energy level, proximity to the base station, communication capabilities, and data aggregation capabilities.

3. The ODaTReS approach

This section introduces the proposed ODaTReS approach in more detail. A smart monitoring camera can transmit 25−30 frames per second to the sink to ensure smooth viewing. Since the monitoring involves 24-h video data collection, it provides long videos containing many redundant static frames, which require a lot of processing time and high bandwidth for transmission. To deal with this challenge, the ODaTReS presents a data reduction approach to reduce data redundancy with low power consumption in the video sensor node while maintaining the quality of the data. Fig. 1 shows the proposed ODaTReS approach that will be implemented at the level of the video sensor nodes. The ODaTReS approach performs two phases to achieve its goal: the sensing and transmission phases. The next subsections explain these phases in more detail.

3.1. The network model

The WVSN is composed of three primary levels: the WVSN, the coordinator, and the sink, as depicted in Fig. 2. In a wireless video sensor network, each sensor node gathers the necessary data, which consists of the frames in a video sequence. The sensor node then delivers the information to the coordinator that is responsible for the region of interest. The coordinator collects data from all sensors in its region and transmits it to the sink for analysis by the team in charge of this field.

In this paper, the proposed ODaTReS approach is based on this network architecture and implemented at each video sensor node in the WVSN. The main goal is to reduce the transmitted frames to the sink and decrease the energy consumption at the sensor node level while maintaining a suitable quality for the received frames at the sink.

3.2. Sensing phase

This phase can minimize the vast number of captured and transmitted frames by preventing video sensors from collecting duplicate or near-duplicate frames. This helps in reducing the sensing activity. To achieve the ODaTReS goal of reducing the number of sensed frames, we adapted the number of sensed frames based on three integrated efficient techniques: ORB, BF Matcher, and GMS to find the matching ratio and adjust the frame rate after stopping the frame capture. In each period p, the frame rate is adjusted based on the number of transmitted frames from the previous period. The integrated techniques have been used to achieve frame rate adaptation due to their ability to meet the demands of real-time analysis.

The ORB algorithm is built on an improved FAST algorithm. The ORB is an efficient approach for the extraction and description of features. Rublee and colleagues first proposed it in their ICCV 2011 work [26]. There are two parts to the ORB algorithm: the feature point extraction phase and the feature point description phase. The oFAST (Oriented FAST) is used for feature point extraction, while the Binary Robust Independent Elementary Features (BRIEF) descriptor is used for feature point description [27]. This descriptor shows feature points in binary form, which saves space and makes matching much faster.

The FAST algorithm is used to extract feature points (FP) in each frame, as shown in Fig. 3. After detecting feature points, the BRIEF algorithm will be used to compute feature descriptors. The nearby pixels' distinctive patterns are utilized to describe the feature point, known as a patch. The BRIEF descriptor (des), is used to convert frame patches into a binary feature vector. In brief, each feature point is described by a binary feature descriptor vector, which is a 128−512 bit string.

3.3. Feature matching

After completing the feature detection and description of the compared frames, the next step is to find the best candidate matches for every shared feature point between the two frames. The matching between the feature detector and descriptor includes determining the relationship between descriptors in images that show the same scene from various angles [29]. There are two extensively used matchers: the Brute-Force Matcher (BF Matcher) and the Fast Library for Approximate Nearest Neighbors Matcher (FLANN-based Matcher). These two matchers each have two distinct matching functions. Hamming distance calculations can be done quickly with the BRISK and ORB algorithms, which both use binary bit-string descriptors. Whereas SIFT and SURF use Euclidean distance between descriptors [30]. In this study, detection

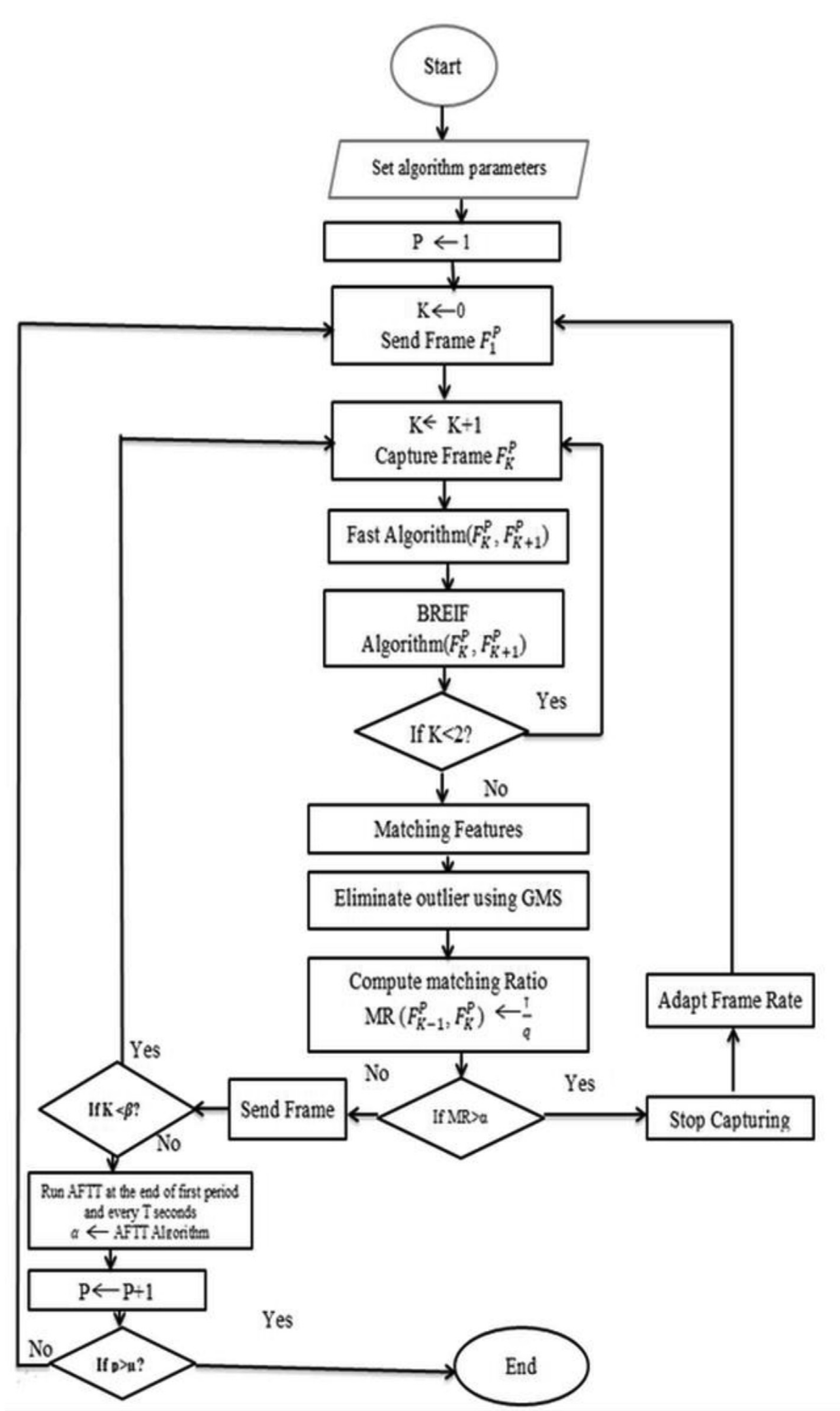

Fig. 1. The ODaTReS approach.

and extraction methods are integrated with the BF Matcher so that feature matching can be done quickly and accurately. The BF Matcher is simple. It compares the description of one feature in the first set to all other features in the second set and returns the closest. It uses Euclidean or Hamming distance, depending on the descriptors. Since ORB uses binary bit-string descriptors, the hamming distance

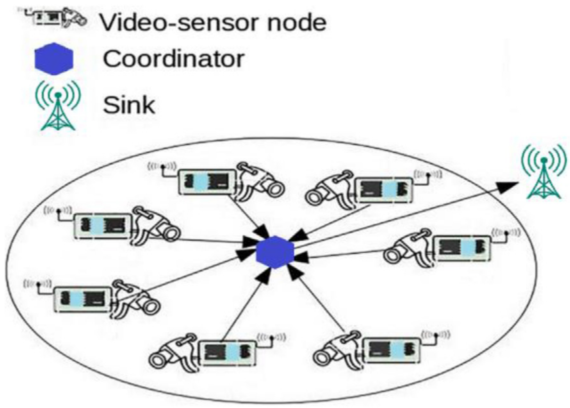

Fig. 2. The WVSN architecture.

between one point and all the other feature points is computed to find the nearest pair.

In each period p, after sending the first captured frame F_1^p to the sink, the next frame F_k^p will be captured. All paper symbols are shown in Table 2. As shown in Fig. 4, each current frame and a previously sent frame descriptor are compared using a descriptor matcher to determine the correspondence between descriptors in frames. Suppose the sequence of frames during the period p is $F^p = \{F_1^p, F_2^p, \ldots, F_k^p, \ldots F_\beta^p\}$. Consider an image frame F_{k-1}^p from which Γ feature point descriptors are extracted. Another image frame, F_k^p, shares the same set of defining features. Assuming that q out of Γ descriptors match, The Matching ratio (MR) is inspired by Ref. [28] and can be calculated as follows:

$$MR\left(F_{k-1}^p, F_k^p\right) = \frac{\Gamma}{q} \tag{1}$$

The MR between two frames is a real value between 0 and 1. If the matching ratio exceeds the adaptive threshold similarity value α, this reflects a high similarity between the compared frames. In this scenario, the capturing is stopped at this period to reduce the number of sensed frames; otherwise, the frame is transmitted to the sink. This frame is defined as a "critical frame" because it reflects the happening of an important event.

The ORB's correspondence may contain some mismatches among good matches. It's important to optimize matching information as quickly as possible. The GMS is used to filter incorrect matches in ODaTReS. The GMS is an ideal technique to differentiate between true and false matches with great computational efficiency and high-quality correspondence.

There are usually many mismatches among good matches. Therefore, it is essential to optimize matching information on time. We use GMS, which uses a grid-based solution for quick calculations and adds the smoothness restriction to a separation statistics framework. Existing approaches are sometimes too slow for real-time applications.

3.4. GMS: feature match filtering

The basic idea of GMS is to discriminate between true and false matches with high computational efficiency and quality correspondence. GMS works by counting the total number of matches in the neighborhood of each pair of matching points [31]. Extract Γ and Q feature points from a pair of frames $\{I_a, I_b\}$, each point has a matching probability independently from the other, with the probability of correct matching being t. By brute force matching, we get $\{\chi_1, \chi_2, \chi_3, \ldots, \chi_n\}$ [27,32]. All algorithm steps are shown in Algorithm 1.

To identify true and spurious correspondences, the authors in Ref. [27] assume that close pixels move

(a) **(b)**

Fig. 3. Feature Point Detection between Adjacent Frames: a) Frame i, b) Frame i+1.

Table 2. Symbols description.

Parameters	Meaning
F_k^p	Image frame number (k) in period (P)
q	Feature point descriptors
Γ	Feature point descriptors match between two frames
$\{I_a, I_b\}$	Pair of frames
$\{\chi_1, \chi_2, \ldots, \chi_n\}$	Matches set
$\lvert\chi ik\rvert$	number of matches between cells i_k, j_k
S_{ij}	Score of matching
ξ	Per-cell threshold
n_i	Total number of features in the 9-cell neighborhood
τ_i	Threshold
α	Transmission Threshold
T	Time slot
CF	Critical Frame
β	Number of frames per period
K	Number of sensed frames
P	Period
Key	Transmission thresholds
Value	Unique PSNR value for each transmission threshold
Len_dict	Dictionary length
$V = \{F_1, F_2, \ldots, F_{NF}\}$	Original Video
$V^* = \{F_1, F_2, \ldots, F_{NF}\}$	Reconstructed Video
H, W	Dimension of Frame
KF_t	Keyframe (important frame)
D	Distance function between two images
VS	Video shot
Diff	Difference between the two images
E, E_{radio}, E_{comp}	toral energy, radio energy for transmission, and energy for computation, respectively.
L_{Tx}, L_{Rx}	Electronic power for transmission and reception, respectively.
T_{Tx}, T_{Rx}	Operating time for transmission and reception of data, respectively.
V	voltage value required for transmission
Q_{add}, Q_{mul}, Q_{cmp}	Shift, multiplication, and comparison operations, respectively

together. It is logical, i.e., neighboring pixels have a high chance of settling on one rigid object or structure and have similar motions. Getting rid of outliers from matched features can be done in a probabilistic manner using the Random Sample Consensus (RANSAC), M-estimator Sample Consensus (MSAC), and Progressive Sample Consensus (PROSAC) methods. According to the experiment results in Ref. [32], GMS is superior to RANSAC.

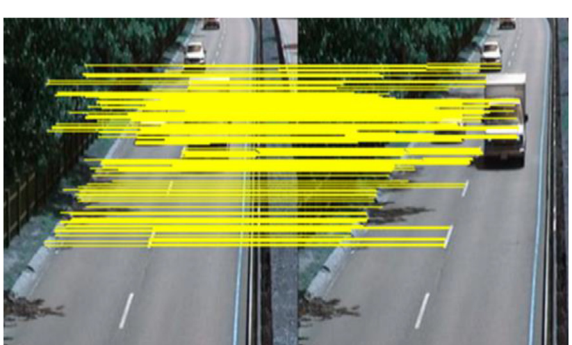

*Fig. 4. Frames Matching. *Special description of the title (dispensable).*

Algorithm 1: GMS Algorithm

Inputs: Pair of frames $\{I_a, I_b\}$, $\{\chi_1, \chi_2, \ldots, \chi_n\}$ *//feature points and matches set for pair of frames $\{I_a, I_b\}$*

Outputs: Inliers

For each feature in I_b, find its nearest neighbor in I_a.
Divide the pair of frames $\{I_a, I_b\}$ by G grids with non-overlapping cells i^k, j^k respectively, G=20*20.
For i = 1 to |G1|
  j = 1
  For k = 1 to |G2|
    If $|\chi_{ik}| > |\chi_{ij}|$ **Then** *//where $|\chi_{ik}|$ refers to the number of matches between cells i_k, j_k,*
      j = k
    End if
  End for
  $S_{ij} = \sum_{k=1}^{9} |x_{i^k, j^k}|$
  Set $\tau_i = \xi\sqrt{n_i}$, *//where n_i is the total number of features in the 9-cell neighborhood*
  If $S_{ij} > \tau_i$, **Then**
    Inliers = Inliers∪X_{ij}.
  End if
End for

3.5. Transmission phase

To reduce energy consumption, we must eliminate the redundant frames transmitted in WVSN. The first frame will be sent at the start of a new period p to maintain the influence of data in the sink. After comparing images according to the strategy explained in the previous section, we select to send only the critical frames from the sensed frames that have a matching ratio less than or equal to the adaptive transmission threshold value α. If the matching ratio exceeds the α, this reflects a high degree of similarity between the compared frames. In this case, we must stop capturing at this point and update the frame rate.

The new value for the adaptive transmission threshold value α is calculated at the end of the first period and then it will recompute every T time slot to be used in the next period during the transmission phase. In this paper, T is set to 30 s, and it can be changed according to the use of the application.

Algorithm 2: ODaTReS algorithm

1: **initialize: CF ← 0** // *CF is the Number of Critical Frames*
   β ← 30 // *β is the Number of Frames per period (30 fps)*
2: *While SensorEnergy > 0 and Sink Availability == True do:*
3: $\alpha = 0.5$
4: **For** every- period -p **do** // *every period 1 second*
5: K ← 0 // *K is the Number of Sensed Frames*
6: **While** K < β **do**
7: K ← K + 1
8: **If** K = 1 **Then**
9: Capture First Frame F_1^p
10: Send First Frame F_1^p to the Sink
11: Dictionary_psnr = {'0.4': 0, '0.5': 0, '0.6': 0, '0.7': 0, '0.8': 0, '0.9': 0}
12: $F_{K-1}^{p} \leftarrow F_1^p$
13: **Else**
14: Capture next Frame F_K^p
15: FP1, des1 ←orb.detectAndCompute(F_{K-1}^p) // *using ORB (FAST, BRIEF)*
16: FP2, des2 ← orb.detectAndCompute(F_K^p) // *using ORB (FAST, BRIEF)*
17: matches ← BFmatcher(des1, des2) // *using BF Matcher*
18: Call GMS Algorithm
19: Compute matching Ratio (MR) // *using Equation 1*
20: Update Energy of Video Sensor node // *energy required for computation*
21: **If** MR > α **Then**
22: Stop Capturing
23: **Else**
24: Send F_K^p to sink
25: Update Energy of Video Sensor node // *energy required for radio*
26: $F_{K-1}^{p} \leftarrow F_K^p$
27: CF ← CF + 1
28: **End if**
29: **End if**
30: **End while**
31: **If** (p = 1) or ((($(\frac{p}{T})$-($\left\lfloor (\frac{p}{T}) \right\rfloor$)=0) **Then**
32 Dictionary_psnr=Get_PSNR()
33: α ← Call AFTT Algorithm(Dictionary_psnr) // *AFTT = Adaptive Frame Transmission Threshold*
34: **End if**
35: **End for**
End While

Algorithm 2 shows the overall proposed ODaTReS approach that will be executed inside each video sensor node. In this algorithm, steps 1−8 involve parameter initialization and condition validation. Step 9 is related to trigger frame capture. Send a command or signal to the camera sensor node, instructing it to capture an image.

In step 10, send the first captured image to the sink. Steps 15−19 achieve the ORB, BF Matcher, and GMS techniques on each consecutive two frames to find the matching ratio. Steps 21−29 are used to decide on the current captured frame transmission using the matching ratio and the transmission threshold (α). We set an initial value for α equal to 0.5 in the first period. In step 32, call the Get_PSNR() function to get the PSNR value for each threshold in the key between the original frame for period p(OF^{p}) and the transmitted frame for period p ($TF^{p\,(k)}$) and save it in the dictionary $Dict_{key,\ value}$. The parameter key includes the threshold values 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9.

After that, we propose an algorithm to adapt this threshold to make the proposed ODaTReS decide whether the currently captured frame should be sent or deleted. This threshold keeps the balance between the quality of the video and the amount of data sent. This enables the video sensor node to transmit fewer frames, save energy, and improve the performance of the WVSNs. **Algorithm 3** refers to the Adaptive Frame Transmission Threshold (AFTT) algorithm.

Algorithm3: AFTT Algorithm

Inputs: Dictionary_psnr = {'0.4': x_1, '0.5': x_2, '0.6':x_3, '0.7': x_4, '0.8': x_5, '0.9': x_6}// represent as key, value ($Dict_{key,\ value}$)
Output: Adaptive_Threshold
1: **For** key_i, $value_i$ in $Dict_{key,\ value}$:
2: **If** $value_i < 30$
3: Remove $Dict_{keyi,valuei}$ *//delete the threshold that gives PSNR lower than 30 and corresponding PSNR*
4: **End if**
5: **Endfor**
6: Len_dict ← Length($Dict_{key,value}$)
7: **If** Len_dic = 0 then
8: Adaptive_Threshold←0.9
9: **else**
10: Adaptive_Threshold←Median($Dict_{key,value}$)
11: **End if**
12: **Return** Adaptive_Threshold

Threshold determination is critical in determining the number of critical frames that will be transmitted to the sink. If we are working under careful circumstances in which we need to catch even the smallest movement, we should set the threshold to its highest value, and vice versa. This leads to two facts: if the threshold is set to a high value, an excessive number of crucial frames will be sent, and many of these frames may be redundant. On the other hand, if the threshold is set to a too low value, the critical frames that are extracted do not accurately represent the video, and this will damage the video's quality. To find a balance between the quality of the retrieved video at the sink and the volume of transmitted frames on the network, the adaptive frame transmission threshold α will be used. The threshold value is determined according to the scenario under consideration. In the beginning, we set the value α to 0.5. Then, we execute Algorithm 3 at the end of the first period and after every T second to find the adaptive frame transmission threshold (α).

In Algorithm 3, steps 1−5 check the PSNR value for each threshold in the dictionary Dict $_{key,\ value}$. If the calculated PSNR is less than 30, the record in Dict $_{key,\ value}$ will be removed. In lossy image and video compression, the PSNR is typically between 30 and 50 dB, with higher values being preferable and an optimal bit depth of 8 bits. If the PSNR of a video is under 30 dB, it is generally considered to be of poor quality, whereas a PSNR of 40 dB or higher is considered to be of high quality [1,33]. Steps 7−12 are responsible for selecting the optimal frame transmission threshold and balancing between the number of transmitted frames and the quality of the video. The function Median Dict$_{key,\ value}$ will return the median threshold value according to PSNR values.

3.6. Computational complexity

This section examines the space and time complexities of the proposed ODaTReS approach. In Algorithm 2, the ORB algorithm (steps 15−17) has a time complexity equal to $\theta(Length(F^p))$ and requires storage equal to $\theta(Length(F^p)+Length(des))$ where $Length(F^p)$ and $Length(des)$ are the length of the frame and descriptor feature vector, respectively. Step 18 in Algorithm 2 uses Algorithm 1, which requires $\theta((Length(des))^2)$ both time and storage requirements. The AFTT Algorithm 3 takes $\theta(Length(F^p))$ of time complexity and storage.

Hence, the overall time complexity of Algorithm 2 is $\theta(\beta*(Length(F^p)+Length(des))^2))$ and it takes $\theta(Length(F^p)+(Length(des))^2))$ of storage, where β is the total number of frames per period that is fixed to 30.

Function Get_PSNR():

Inputs: OF^p: list of original frames during period p, $TF^{p(key)}$: list of transmitted frames during period p for different transmission thresholds key = {0.5, 0.6, 0.7, 0.8, 0.9}

1: For each key:
2: Value = Compute PSNR(OF^P,$TR^{p(k)}$)//*use equation 5.*
3: Dict($_{key}$) = value
Return Dict($_{key,\ value}$)

End Function

4. Performance evaluation

In this section, the proposed ODaTReS approach is assessed using the Python programming language based on a real dataset that is presented in the next subsection. The findings of the ODaTReS approach are compared to a well-known recent approach, the FRABID method [6] which has been reviewed in the literature.

4.1. Data set description

Change detection is a low-level video analytic task. In Ref. [34], authors established the change detection net (CDnet) benchmark in 2012, a video data set for change and motion detection. In this dataset, the author gives the current CDnet dataset, which includes 22 extra movies in 5 new categories. The 2014 CDnet features realistic, camera-captured indoor and outdoor videos, like the 2012 CDnet. Low-resolution IP cameras, consumer camcorders, Commercial PTZ cameras and near-infrared cameras were used to record these films. The Highway Dataset is continuous motion with a slight dynamic background for 57 periods, and the video is recorded as 1 s for each period. The video is captured at a frame rate of 30 frames per second (FRt = 30 fps). Table 3 refers to the recorded highway datasets.

Table 3. The recorded highway datasets.

Total Number of Frames	Critical Frame	Period	Frame Rate
1700	1300	57	30

4.2. Performance metrics

In this section, we will discuss the performance metrics that are used in the evaluation of the proposed ODaTReS approach. First, let us define two videos: the original video $V = \{F_1, F_2, ..., F_{NF}\}$ and the reconstructed video $V^* = \{F_1^*, F_2^*, ..., F_{NF}^*\}$.

4.2.1. Mean square error (MSE)

One of the important image quality evaluation techniques is the mean squared error (MSE), which is utilized to evaluate image quality without human interference [35].

$$MSE = \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} \left(F_{ij} - F_{ij}^*\right)^2 \tag{2}$$

where H and W are the dimensions of the original frame F and the reconstructed frame F*.

4.2.2. Video reconstruction error (VRE)

This metric is inspired by Ref. [36], where it can be used to calculate the quality of the reconstructed video as follows:

$$VER = \sqrt{\frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} \left(F_{ij} - F_{ij}^*\right)} \tag{3}$$

4.2.3. Peak signal-to-noise ratio (PSNR)

It is the ratio between the maximum achievable power and the noise that corrupts image representation. A high PSNR value indicates good image quality.

$$PSNR(x, y) = 10 \log_{10} \frac{\max^2}{MSE} \tag{4}$$

where max refers to the maximum pixel value in the image.

4.2.4. Validity measure

To limit the quantity of useless video content, keyframe extraction is performed. The original video's information quotient must be preserved in the created frame sequence. The output summary provided by the suggested method was validated using fidelity and shot reconstruction degree (SRD) ratings.

4.2.4.1. Fidelity measure. In this measure, each critical frame is compared to the frames in the original video sequence, and fidelity is used to provide a reasonable universal description of the video.

The set of an important frame extracted from the original video KF_t is defined as follows $KF_t = \{KF_1, KF_2, ..., KF_m\}$. A distance function (d) between any two image frames is defined as shown in Equation (6).

$$d(F_i, KF_t) = \min_d \{Diff(F_i, KF_t)\} \tag{5}$$

The Semi-Hausdrauff distance between KF and the video shot (VS) is as follows:

$$d(VS, KF) = Max(d(F_i, KF_t)) \tag{6}$$

High Fidelity means that the selected essential frames from the video sequence well describe its visual content.

4.2.4.2. Shot reconstruction degree (SRD). A video fidelity criterion must be defined to decide what information is significant and to be able to measure image fidelity. Based on how well a video shot retains motion dynamics, shot reconstruction degree (SRD) is used to choose the mainframes [37]. SRD is computed according to the below **Equation**.

$$SRD(V, KF) = \sum_{i=1}^{n} Sim\left(F_i, F_i^*\right) \tag{7}$$

Based on the work in Ref. [37], the chosen similarity measure, Sim (.), has been defined as a PSNR as follows.

$$Sim\left(F_i, F_i^*\right) = 10 \log_{10} \frac{255^2}{MSE} \tag{8}$$

4.2.5. Energy consumption

Energy consumption is one of the main challenges in WVSNs. In this paper, we employed the energy consumption model that is used in Ref. [38]. The energy consumption model for WVSN is calculated according to **Equation** 10. In this model, the WSN is equipped with a CC2420 radio transceiver and an ARM7TDMI microprocessor.

$$E = E_{radio} + E_{comp} \tag{9}$$

for

Where E_{radio} is computed as shown in the equation below:

$$E_{radio} = K.L_{TX}.V.T_{TX} + K.L_{RX}.V.T_{RX} \tag{10}$$

L_{Tx}, L_{Rx} Electronic power is required for radio transmission and reception, respectively. While T_{Tx}, T_{Rx} equivalent operating time is above 1 byte. The parameter V is the regular voltage supply during the transmission.

The values of these parameters are fixed in this model as found in Refs. [38,39] data sheets. The values of L_{TX}, L_{RX} T_{TX}, T_{RX}, and V are set to 17.4 mA, 19.7 mA, 3.2×10^{-5} s, 3.2×10^{-5} s, and 3.3 V respectively.

E_{comp} is calculated as follows.

$$E_{comp} = N_{add} \times Q_{add} + N_{mul} \times Q_{mul} + N_{cmp} \times Q_{cmp} \tag{11}$$

where the Q_{add}, Q_{mul}, and Q_{cmp} are fixed to 2.13 nJ, 6.39 nJ, and 2.13 nJ respectively.

4.3. Comparison results

This section provides an evaluation of the proposed ODaTReS approach in comparison to recent related work [6]. Multiple experiments were conducted, and the obtained results were meticulously analyzed and discussed to ensure a higher level of accuracy and reliability in assessing the effectiveness and efficiency of the ODaTReS approach.

4.3.1. Adaptive frame transmission

To maintain the smoothness of the video, the frame transmission threshold α is selected based on the PSNR quality metric while reducing the number of sensed and transmitted critical frames.

In Table 4, we tested the proposed ODaTReS approach against different fixed values for α (0.4, 0.5, 0.6, 0.7, 0.8, and 0.9).

The result shows the similarity between each pair of consecutive frames in each period is greater than 0.5; therefore, only the first frame in each period will be sent in the case of α (0.4 and 0.5). This forms 3% of the sensed data in each period. This ratio increases with the increase of α value, and once we reach 0.9, the result shows the video will be sent in a ratio that reaches 100%.

As a result, the increased value of the α leads to an increase in the transmitted frames and reduces the percentage of frame reduction per period. Therefore, it is necessary to choose a transmission threshold α such that I strike a balance between the data reduction and the quality of the received video at the sink. In this paper, we propose an algorithm (see Algorithm 3) to adapt the transmission threshold α per period and achieve a balance between the number of transmitted frames and the quality of received video at the sink.

Table 4. The number of sensed frames, sent frame, sent frame ratio, and the data reduction ratio.

Parameters	FRABID	ODaTReS
Total	1700	1700
sensed	971	386
Sent	963	336
sent ratio	57%	20%
Reduction ratio	43%	80%

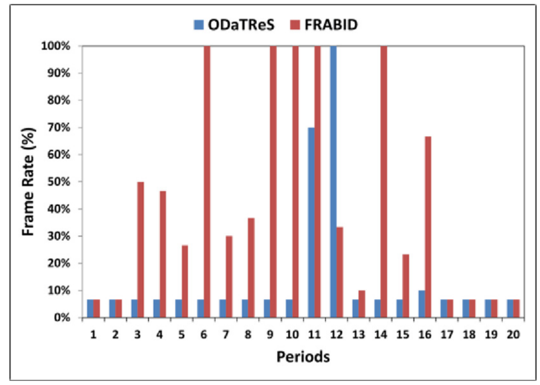

Fig. 5. Frame rate adaptation.

4.3.2. Frame rate adaptation

This experiment investigated the frame rate adaptation per period inside the video sensor node. Fig. 5 refers to the frame rate adaptation in the video sensor node.

It can be observed that the proposed ODaTReS approach changed the frame rate dynamically per period according to the similarity of the sensed frames and based on the ORB algorithm.

In Fig. 5, the average adapted frame rate over all periods for ODaTReS and FRABID is 15% and 43%, respectively. We conclude from these results that the proposed ODaTReS approach outperforms the other methods in improving the sensing activity by reducing the sensed frames.

4.3.3. Data reduction

A data reduction approach in the video sensor node is necessary to reduce the amount of sent data while the critical frame is maintained. Eliminating redundant data has an impact on reducing the power consumption of these devices. The simulation is done using a video called “Highway”. Table 5 shows the number of sensed frames, sent frame ratio, and data reduction ratio of the proposed

Table 5. Sensor Node Behavior with Different Threshold α

Tested Threshold							
Parameters	0.4	0.5	0.6	0.7	0.8	0.9	α
Transmitted Frames No.	57	57	79	566	1340	1700	336
Sensed Frames No.	124	114	136	609	1355	1700	386
Sent Frames Ratio	3%	3%	5%	33%	79%	100%	20%
Reduction Ratio	97%	97%	95%	67%	21%	0%	80%

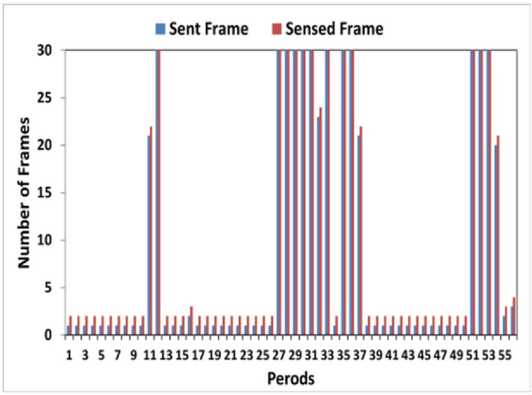

Fig. 6. Sent frames in each period.

ODaTReS approach compared with the FRABID method. It can be seen from the results in Table 5 that the ODaTReS approach sent 20% of frames to sink, compared to 57% for the FRABID methods. In addition, the ODaTReS reduced the transmitted data by 80% compared to 43% for the FRABID method, respectively. Hence, the comparison results show that the proposed ODaTReS approach outperforms the compared method in terms of data reduction and transmitted data ratio. Fig. 6 shows the number of frames sent in each period.

4.3.4. Data quality

Data quality is an essential issue in WVSNs since the end user relies on it to make accurate decisions. The quality of the data can be measured using various metrics such as accuracy, precision, completeness, and consistency. The critical frames in the input video can be detected, and all the duplicate frames will be removed. The sudden events in the measurements might be lost if the frame rate is dropped for a specified time. As a result, the estimation of these non-processed irregular data may overtake the intended

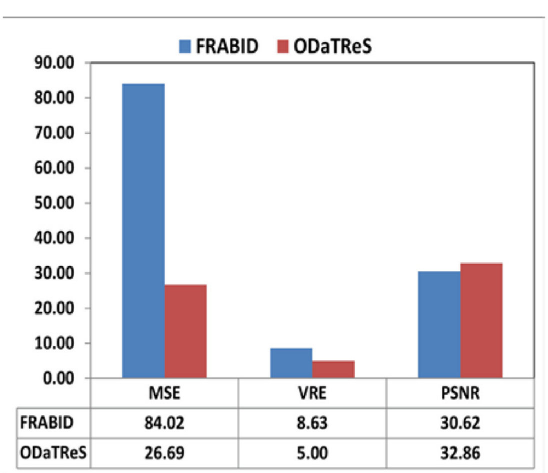

Fig. 7. Comparison based on average video quality.

error level. In this experiment, the impact of the frame rate adaptation of the proposed ODaTReS approach is evaluated based on the three data quality metrics (VRE, MSE, and PSNR). Fig. 7 refers to the data quality evaluation vs. frame number using the average values of MSE, VRE, and PSNR over the whole video.

It can be observed from Fig. 7 that the ODaTReS approach introduces better results than the compared method in terms of PSNR, VRE, and MSE. The ODaTReS approach achieves a higher accuracy rate while eliminating the huge redundant frames inside the video sensor node.

4.3.5. Validity measure

The ability of the mainframe set to recreate the original contents. The output summary provided by the suggested method was validated using fidelity and SRD ratings. With a maximum SRD value, you can make sure that the shot's motion dynamics are maintained.

The other video frames are interpolated from the mainframes. Reconstructing the original frames determines the system's reduction ability. The difference between the interpolated frames and the original video frames is calculated using the frame-matching ratio. The proposed ODaTReS approach is evaluated using these fidelity and SRD measures. Table 6 shows the validity measures: in both terms, an average of SRD and an average of fidelity in comparison with other methods. It can be seen from Table 6 that the proposed ODaTReS approach introduces better results than the FRABID method in terms of average SRD and average fidelity.

4.3.6. Energy consumption

In this experiment, we will investigate the amount of energy consumed by the proposed ODaTReS approach in comparison with the FRABID method, where ODaTReS uses the energy consumption model presented in Section 6.2 that was used by Ref. [38] to evaluate the energy consumption inside the video sensor node. This study takes into account both the processing and transmission energy requirements. The ODaTReS detects 386 frames with a resolution of 240 × 320 (76.800 pixels). On the same dataset, FRABID detected 971 frames. In ODaTReS, to compare two frames, we compare each pixel in two frames. In ODaTReS, to compare two frames, we compare

Table 6. The validity measures: Average of SRD and average of fidelity.

Methods	SRD	Fidelity
FRABID	30.62	1.95
ODaTReS	32.86	3.67

Table 7. Energy consumption (in Joules).

Parameters	FRABID	ODaTReS
Energy consumption	157.5	131.84
Energy Radio	15.66	9.38
Total	173.16	141.22

each pixel in two frames. The ODaTReS is made up of two comparisons. Table 7 shows the energy consumed by ODaTReS and FRABID. For instance, the energy consumed for the proposed ODaTReS computation is calculated as follows:

$$E_{comp} = 336 \times 320 \text{ x } 240 \times (2 \times Q\_cmp) + 336 \times Q\_cmp$$

$$E_{comp} = 336 \times 320 \text{x} 240 \times (2 \times 2.13) + 336 \times 2.13 = 131.84\,J$$

On the other hand, the energy consumed for computation in FRABID is calculated as follows:

$$E\_comp = 963 \times 320 \text{ x } 240 \times (1 \times Q\_add) + 963 \times Q\_cmp = 157.5\ J$$

Regarding the energy consumption model's computation part, the proposed ODaTReS approach sends 336 frames, which is equal to 4.87 MB, while FRABID sends 963 frames, equivalent to 8.13 MB of data.

For ODaTReS, the consumed energy for radio transmission is calculated as follows:

$$E_{radio} = 4.87 \times 1024 \text{ x } 1024 \times 17.4 \times 10^{-3} \text{ x } 3.3 \times 3.2 \times 10^{-5} = 9.38$$

And for FRABID:

$$Er_{adio} = 8.13 \times 1024 \text{ x } 1024 \times 17.4 \times 10^{-3} \text{ x } 3.3 \times 3.2 \times 10^{-5} = 15.66$$

From the results presented in Tables 7 and it can be observed that the proposed ODaTReS approach outperforms the FRABID method in terms of the consumed energy of processing and transmission. ODaTReS consumes less energy in total (energy of processing + energy of transmission) compared to FRABID. This increase in performance will extend the lifetime of WVSN while maintaining suitable data quality.

5. Conclusion and future works

WVSNs face challenges in reducing energy consumption due to the large amount of real-time sensed data they process and transmit. Moreover, the extraction of important frames from real-time videos poses computational challenges, making it computationally expensive to identify and extract visual information. To address these issues, this paper proposes an Online Data Transmission Reduction Scheme (ODaTReS) for energy savings in WVSNs. The ODaTReS approach achieves two phases. First, the sensing phase by which ODaTReS adapts frame rate to limit the number of captured video frames using three efficient techniques: ORB, BF Matcher, and GMS. In the transmission phase, we use an adaptive transmission threshold that is responsible for deciding whether to transmit the current captured frame or remove it. Several experiments are conducted to demonstrate the effectiveness of the ODaTReS. ODaTReS significantly eliminates redundant frames, reduces the number of sensed and transmitted frames to the sink, and maintains the data quality in WVSNs. The simulation results prove that the proposed ODaTReS improves the performance of the WVSN by reducing the sensed frames by 60.24%, decreasing the sent frames by 20%, decreasing the consumed energy by 18.5%, and maintaining the data quality in comparison with the FRABID method. In future studies, we intend to explore compression techniques to further reduce the size of the entire image before transmitting it to the next level of the network. This will contribute to enhancing the efficiency and effectiveness of WVSNs.

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