Energy Conserving Forepart Detection Scheme with Dynamic Compressive Measurements Based on Compressive Sensing for WVSN

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Abstract

WVSN is severely constricted to energy, as it deals with video data. The major activities that consume more energy in WVSN are the local data processing and transmission. Among these two, data transmission consumes more energy. Hence, a mechanism to reduce the energy consumption during data transfer is required and this issue is addressed by compressive sensing. This paper presents an energy conserving scheme that extracts the forepart from the background scene. The compressive measurements are dynamically computed by this work, which reduces the overhead and energy consumption. This work selects minimal yet, optimal compressive measurements and forwards it to the destination side. The destination side rebuilds it with the help of CoSaMP algorithm. The performance of the proposed approach is tested in terms of forepart detection accuracy and energy consumption analysis. The proposed approach shows better results and outperforms the existing approaches.

Keywords: WVSN, Energy consumption, Compressive measurement

1 Introduction

Due to the advancement of technology, several real-time applications are presented to the society for improvising the quality of life. The real-time applications are claimed to be successful only when better accuracy rates with reasonable speed is proven. In order to improve the quality of service and the standard of the application, several changes are incorporated to the existing technologies. On that front, the Wireless Sensor Networks (WSN) are tailored with respect to the requirements of the application. Wireless Visual Sensor Networks (WVSN) is one among many kinds of network and it has gained substantial research interest due to its wider applicability. Usually, the WVSN is employed for real-time intelligent systems.

A WVSN is composed of numerous wireless nodes, which are packed with a processor, power back-up, image sensor and transceiver [1-2]. The nodes of this network sense and share the data with the Base Station (BS) or the powerful sink node, which is meant for processing the data locally. As WVSN is based on WSN, the basic characteristics such as distributed environment, wireless communication and energy restriction are inherited to it. The major functionality deviation of WVSN from WSN is the capability of environment sensing. The sensor nodes of WVSN capture the environment in three different dimensions in the place of normal one. Hence, WVSN is usually employed in environment monitoring and surveillance based applications.

The sensor nodes of WVSN take the video of the specific area and forward the captured video to the processing unit by means of relay nodes. The underlying point here is that it is unnecessary to transmit the video to the processing unit, unless some variation or change is involved in the video. This idea conserves energy, which in turn helps in maximizing the lifetime of the network. At this juncture, the concept of Compressive Sensing (CS) comes into picture. The CS technique accumulates and forwards the mandatory components (X) instead of the entire Y samples [3]. Though the complete samples are not forwarded, the CS ensures the better data recovery. This is achieved by computing the sparsity degree of the signal.

The sensor node of WVSN takes the video of a scene and performs CS for computing the sampling measurements. The so computed sampling measurements are forwarded to the destination and the video is rebuilt by the recovery algorithm. This work is based on the utilization of immobile cameras, such that the background is the same at all times. Hence, in order to conserve energy the background part of the video can be subtracted. In other words, the foreground of the video can easily be processed, which is the target of

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any application. This work employs flexible background subtraction technique for extracting the foreground objects.

Additionally, the foreground objects are detected by considering the CS sampling measurements and a threshold based mechanism is proposed. This threshold helps in extracting the foreground sampling measurements, which are then treated by the Compressive Sampling Matching Pursuit (CoSAMP) algorithm for rebuilding the targeted objects. Some of the contributions of the proposed approach are as follows.

- This work conserves energy, as the background of the video is subtracted.
- The proposed approach can make the data rate of the video flexible with respect to the scene.
- The count of sample measurements are fixed dynamically based on the theory of cross validation.
- This work is evaluated in terms of object detection accuracy, energy required to forward videos and so on. The proposed approach shows better results.

The rest of this article is systematized as follows. The recent review of literature with respect to compressive sensing is discussed in section 2. The proposed methodology is elaborated in section 3 and the performance of the proposed approach is evaluated in section 4. The conclusions of the proposed approach are finally presented in section 5.

2 Review of Literature

This section reviews the related literature with respect to compressive sensing in WVSN.

In [4], a parking lot occupancy detection system is proposed by utilizing WVSN. This system analyses the video and performs compression. This system is claimed to be flexible and can be utilized in the environment with multiple camera nodes. However, this work suffers from computational complexity. A relevance based approach for multi-sink mobility is presented for smart city application by WVSN in [5]. This work presents an algorithm for effective localization of several mobile sinks over the roads and streets. This approach increases the data transmission rate by placing the mobile sink node closer to the source nodes with better sensing relevance. Yet, this work consumes more energy to attain the task.

In [6], an energy efficient low bit rate image compression is presented in wavelet domain for image sensor networks. This work proposes a new approximation band transform algorithm and it works by extracting and encoding the image approximations by means of fixed-point arithmetic. This idea conserves the energy of resource constrained sensor networks, but the work is complex. The sensing, coding and transmission functionalities of visual sensor networks for smart city applications are modeled by means of fuzzy based approach in [7]. This work configures the activities of the sensors such as sensing, coding and transmission in a dynamic way by utilizing different parameters. This work suffers from computational and storage overhead.

An energy efficient image compressive transmission scheme is proposed for wireless camera networks in [8]. This work states that this work can extract the regions of interest, controls the quality of image and carries out better image communication. The performance of this approach is tested in terms of image quality, execution time and energy consumption and observed to be satisfactory. In [9], an energy efficient image transmission scheme for wireless multimedia sensor networks is presented on the basis of block based compressive sensing. The encoding algorithm of CS measurements is proposed by considering Bernoulli measurement matrix. The performance of the proposed approach is tested in terms of energy consumption and image quality. This work involves computational overhead and consumes more time.

In [10], an image coding scheme based on compressive sampling is presented for visual communication. This work encodes the image by performing polyphase down-sampling. Additionally, the local random convolutional kernel is utilized before the process of down-sampling. These measurements are utilized for preserving the features with greater frequency and to remove redundancy. This work suffers from time complexity. An efficient image coding and transmission system based on scrambled block compressive sensing is presented in [11]. This work employs scrambled block compressive sampling for performing image measurement by means of a sensing operator. This is followed by the execution of progressive non-uniform quantization and the progressive non-local low-rank reconstruction is utilized at the decoder side. This work is computationally complex and suffers from memory overhead also.

In [12], a Discrete Cosine Transform (DCT) based multi-focus image fusion scheme is presented for VSN. The fusion system mainly focuses on the Alternating Current (AC) coefficients computed in the DCT domain. This method is claimed to prove better image quality and minimal energy consumption. A clustering based data compression scheme based on k-means algorithm is proposed for wireless imaging sensor networks in [13]. This work compresses the images by means of k-means algorithm by considering the colour of image pixels and the image is compressed. However on the negative side, this work consumes more time to get processed. A survey on sensor coverage, visual data acquisition, processing and transmission is presented in [14].

An adaptive compressed sensing rate assigning algorithm based on standard deviation of the image blocks for wireless image sensor network is presented in [15]. In this work, all the image blocks are fixed with a static sampling rate. Additionally, an adaptive sampling rate is passed into all the blocks, such that greater sampling rates are allotted to blocks that are minimal compressible. Finally, the fixed and the adaptive measurements are considered together to form the final measurements. The performance of this work can be enhanced further with dynamic measurements.

In [16], an adaptive compressive sensing for tracking the targets in WVSN based surveillance is presented. The adaptive compressive sensing can achieve greater compression rates with respect to the sparsity nature of different datasets. This work is difficult to process and involves computational complexity. In addition to this, it is unnecessary to compress the whole image; instead the relative blocks that contain the target can alone be compressed. The image compression algorithms for wireless multimedia sensor networks are reviewed in [17].

In [18], a video compressed sensing framework is presented for wireless multimedia sensor networks by utilizing a combination of several matrices. This work utilizes the combination of Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) for performing compression. This work is proven to be better than Gaussian matrix.

Inspired by these works, this article intends to present an energy efficient compressive sensing algorithm for WVSN. This work concentrates on energy efficiency, better compression rates with high image quality. The working principle of the proposed approach is presented in the following section.

3 Proposed Compressive Sensing Algorithm for WVSN

This section elaborates the working principle of the proposed compressive sensing algorithm along with the overall flow of the approach.

3.1 Overall Flow of the Proposed Approach

The main focus of this work is to enhance the energy efficiency of the energy stringent WVSN, which in turn improves the lifetime of the network. Additionally, the proposed approach focuses on better compression rate, yet quality of the compressed image is concentrated. The first and foremost goal of this work is to reduce the energy consumption of the sensors. The overview of the work is depicted in Figure 1.

Usually, the sensors involved in WVSN consume more energy during the local data manipulation and transmission, yet these operations are inevitable. The energy consumption of these activities can be reduced by eliminating the static background, which makes sense that the background does not need to be processed. This idea conserves energy both in data processing and transmission activities.

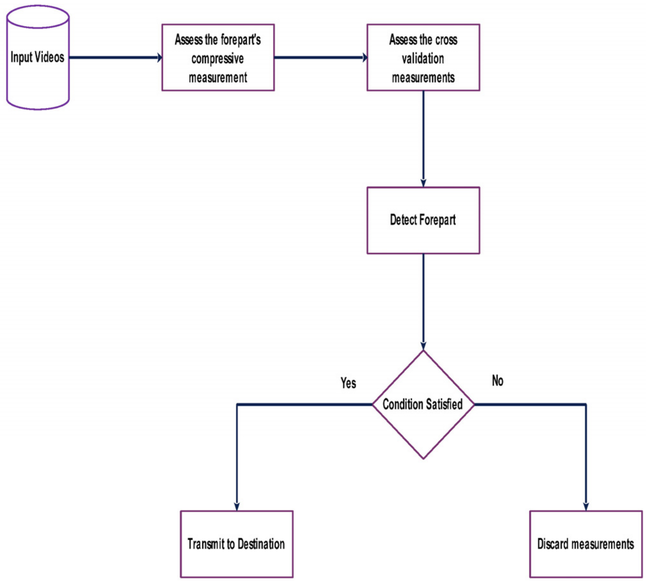


Figure 1. Overall flow of the work

The objectives are attained by decomposing the work into three phases such as background subtraction, forepart detection and rebuilding. The initial phase attempts to eliminate the background of the video, as this work is based on immobile cameras. The forepart detection phase attempts to detect the real objects being present in the video. As the forepart of the video frames is extracted, it is easy to process further and is transmitted. The destination side utilizes CoSaMP for rebuilding the frames. The following sections present all the above stated phases in detail.

3.2 Forepart Detection under the Scenario of Dynamic Compressive Measurements

In this work, the term adaptability represents varying compressive measurements. The main reason for considering variable compressive measurements is that it is complex to estimate the sparsity of videos. When the cameras are immobile, the background is the same for all video frames. Hence, it is unnecessary to process or transmit the background unnecessarily, as it consumes more energy and time as well. The increased time consumption leads to performance degradation and on the other hand, excessive energy consumption results in shorter lifetime of the network. In order to deal with both these issues, it is better to eliminate the background being present in the video frames, which leads to both energy and time conservation.

Consider an image i_{tp} that is made up of both background (bg_{tp}) and forepart (fg_{tp}) as represented in eqn.1.

$$i_{tp} = fg_{tp} + bg_{tp} \quad \textbf{(1)}$$

However, this work considers the same background for all the video frames. This work permits different compressive measurements for varying time periods *tp*. The changing measurement rates are obtained by measurement matrices for every *tp*, which is represented as follows.

$$\delta_{tp} \in \mathbb{M}^{R_{tp} \times c} \quad \textbf{(2)}$$

Where $\delta \in \mathbb{M}^{c \times c}$ is formed by choosing the entities from partial Fourier matrices. Hence, δ_{tp} is formed by considering the initial R_{tp} rows of δ and column. The compressive measurement of the forepart is assessed as shown below.

$$k_{tp}^{fg} = \delta_{tp} fg_{tp} \quad \textbf{(3)}$$

Consider $k^{bg} = \delta bg$ is multivariate Gaussian variable that is random and is denoted by

$$k^{bg} \sim N(\mu^{bg}, \Sigma) \quad \textbf{(4)}$$

$$\mu = \frac{1}{ob} \sum_{x=1}^{ob} k_x^{bg} \quad \textbf{(5)}$$

From the equations (1) and (4), the following equation is obtained.

$$k_{tp}^{bg} \sim N(k_{tp} - \mu_{tp}^{bg}, \Sigma) \quad \textbf{(6)}$$

Where $\mu_{tp}^{bg} \in \mathbb{M}^{R_{tp}}$ is constructed by utilizing the initial R_{tp} rows of μ^{bg} and k_{tp}^{fg} is represented as

$$k_{tp}^{fg} = k_{tp} - \mu_{tp}^{bg} \quad \textbf{(7)}$$

Let $\{i_{tp}\}_{tp=0}^{\infty}$ represent the intensities of the gray-scale video frames that are the part of video and *tp* denotes the time period that is discrete by nature. The compressive measurements are then assessed by means of

$$k_{tp} = \sigma_{tp} i_{tp} \quad \textbf{(8)}$$

The cross validation of the image's forepart is also estimated as follows.

$$\gamma fg_{tp} = \gamma i_{tp} - \mu_{\gamma}^{bg} \quad \textbf{(9)}$$

μ_{tp}^{fg} is the equivalent background assessment. As the count of measurements of this work is dynamic, the time period is taken into account. Hence, the R_{tp} is chosen such that $k_{tp}^{fg} \in \mathbb{M}^{R_{tp}}$ ensures perfect dimension that can guarantee

$$fg_{tp} = \Delta(k_{tp}^{fg}, \delta_{tp}) \quad \textbf{(10)}$$

The value of fg_{tp} strictly depends on the sparsity and the R_{tp}. Yet, the sparsity cannot be finalized before the process of sensing and hence, it cannot be utilized while choosing R_{tp}. This problem is addressed by setting the upper value to the sparsity (st_{tp}), such that $s \geq st_{tp}$ for all time periods and $R_{tp} = R$ at all tp. Δ attains a stable compression ratio.

Conversely in certain cases, the value of *s* is greater than st_{tp}, by showing vast difference. The greater estimation of st_{tp} results in the accumulation of more measurements, which do not minimize the reconstruction faults. Hence, the value of R_{tp} can be as smaller than *R*, such that the compression rate can be maximized, without affecting the quality of the forepart of the video frame. The proposed algorithm is presented as follows.

The estimation of st_{tp} is rough and this estimate is referred as p_t, which is known by the system before the process of sensing. With the value of p_t, this phase can select better R_{tp}. Before the initiation of sensing, it is taken that $st_{tp} = p_t$ and the p_t is altered in the subsequent time periods. When the value of p_t is greater than st_{tp}, then it is these are meant for rebuilding process on the destination side.

Proposed Algorithm

Input : Videos
Output : Forepart detection
Begin
Assess k_{tp}^{fg} *from the compressive measurements by (7);*
Assess cross validation measurements by (9);
Detect forepart by (10);
If $(p_t \geq st_{tp})$
  Transmit to the destination;
Else
  Discard the measurements;
End if;
// Destination
Rebuild by CoSaMP;
End;

On the contrary, when the value of p_t is lesser than st_{tp} then the measurements are not transmitted to the destination. This idea reduces the requirement of measurements to detect the entity being present in the video frame, which in turn reduces the energy consumption and improves the lifetime of the network.

3.2 Rebuilding by CoSaMP

At the destination, the CoSaMP algorithm is executed for rebuilding. This algorithm is a popular iterative algorithm and recovers the signal based on the Restricted Isometry Property (RIP). Though the working principle of CoSaMP is the same as OMP algorithm, the CoSaMP algorithm controls the process of search in all the iterations and includes a coordinate, while removing the useless coordinates.

In order to rebuild the signal, the measurement vector mv is solved by considering the measurement matrix and the sparse signal with k non-zeroes. The approximation of the signal is found out with the greater coordinates in every iterative step. The measurements are upgraded until the signal is built completely. As the measurement matrix is crisp, the time consumption for rebuilding is minimal and reasonable [19].

4 Results and Discussion

The proposed approach is simulated in Matlab environment on a stand alone computer with 8 GB RAM. The proposed approach is analysed by utilizing different video streams downloaded randomly. The size of the video frame is 288×352, the sparsity and the compressive measurements are dynamic. The value of δ is permuted row-wise by discrete Fourier transform matrix in a random fashion. The γ entities are presented by discrete Bernoulli distribution between 0 and 1. The performance of the proposed work is evaluated in terms of forepart detection accuracy, precision, recall, F-measure and energy consumption. Besides this, the potential of dynamism in terms of compressive measurements is justified. The performance of the proposed work is compared against [20-21] and [22]. Some of the sample input frames are depicted in Figure 2. Figure 3 to Figure 6 present the results attained by [20-22] and the proposed approach. From the attained results, it is evident that the proposed work shows better results than the existing approaches.

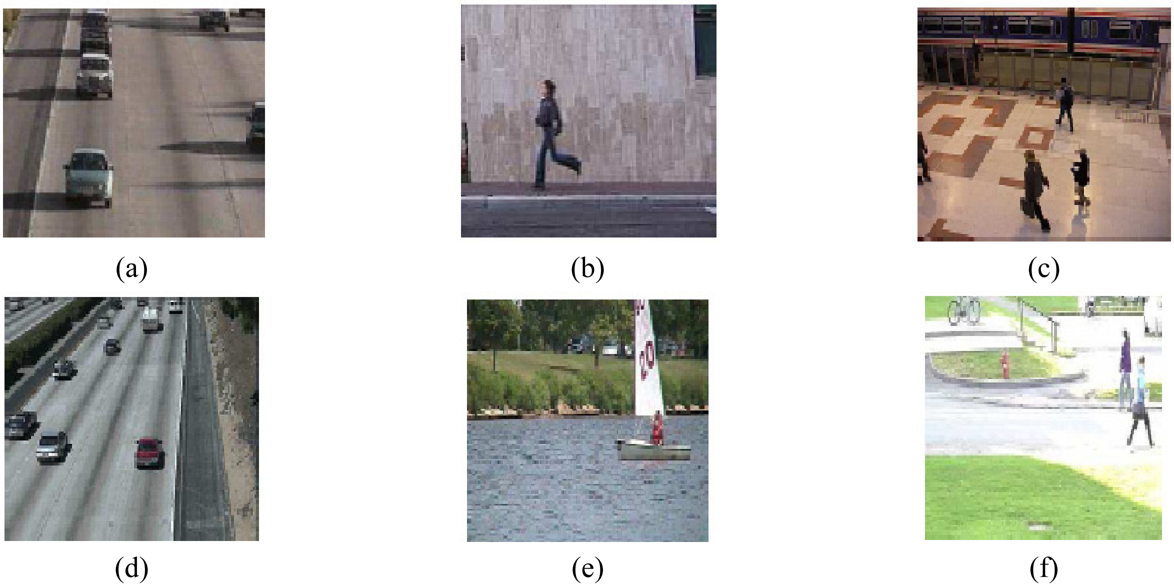


Figure 2. (a) to (f) Sample input frames

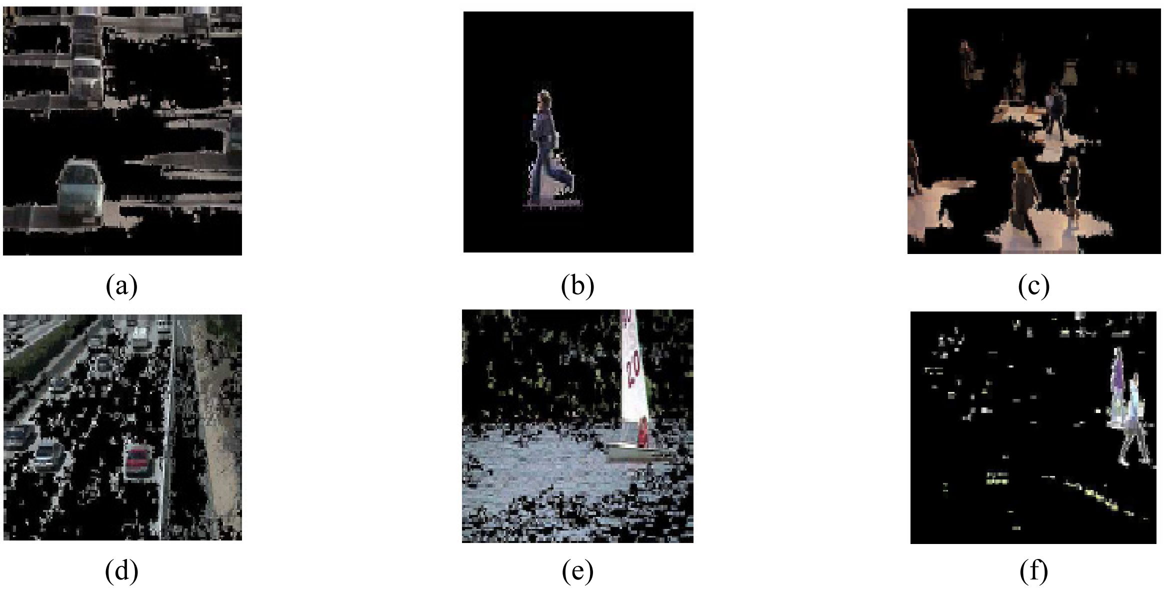
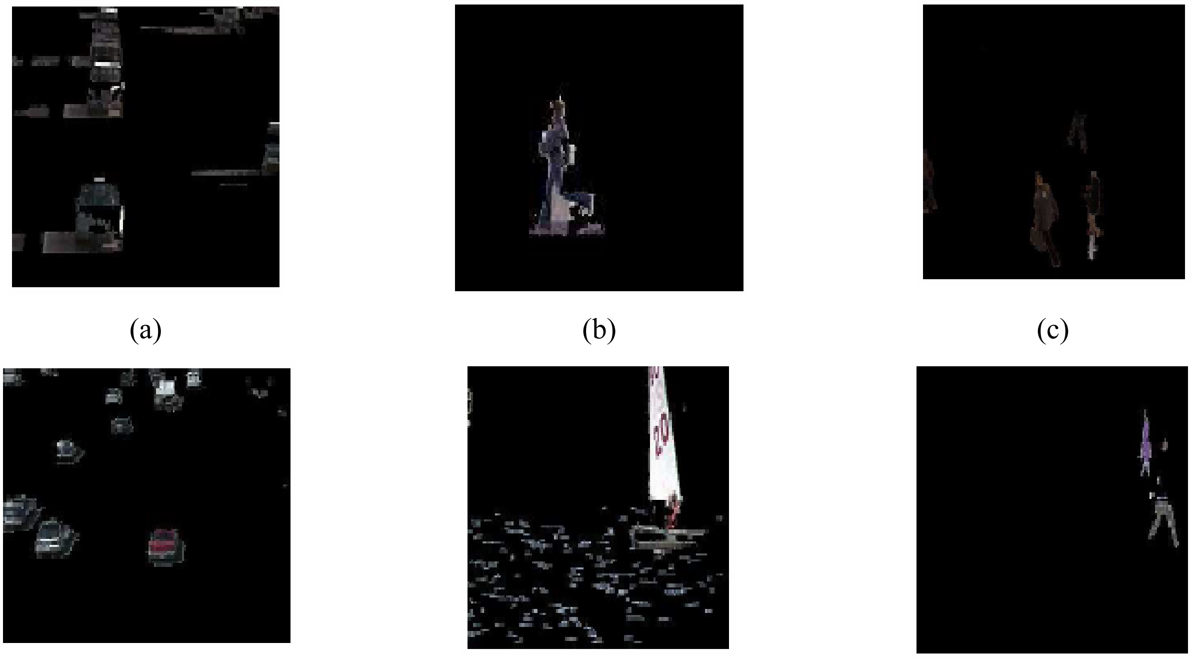


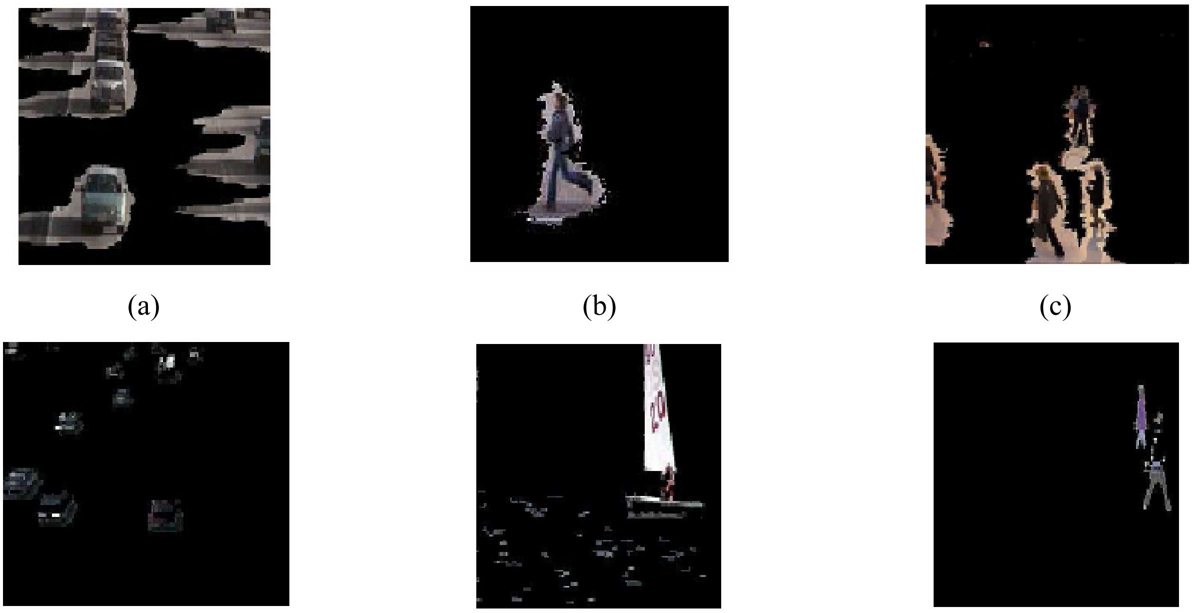
Figure 3. Results attained by [20] w.r.t input frames in Figure 2



(a) (b) (c)

(d) (e) (f)

Figure 4. (a) to (f) Results attained by [21] w.r.t the input frames in Figure 2



(a) (b) (c)

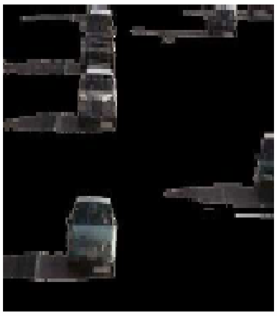
(d) (e) (f)

Figure 5. (a) to (f) Results attained by [22] w.r.t the input frames in Figure 2

4.1 Effectiveness of Forepart Detection

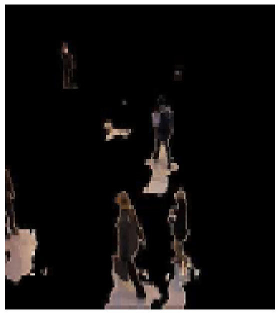
This section attempts to evaluate the forepart detection accuracy rate of the proposed approach in terms of precision, recall and F-measure. The ground truths of the input videos are manually computed. The above stated performance measures are standard measures, which can effectively determine the efficiency of the approach. The precision is the ratio of the total number of correctly classified foreground pixels to the total number of classified pixels.

On the other hand, recall rate is the total number of correctly classified pixels by the total actual pixels of the forepart. While the precision measure checks the correctness, the recall measure checks the reliability of the approach. Both these performance measures together are utilized for computing the F-measure and the average results are tabulated in Table 1.

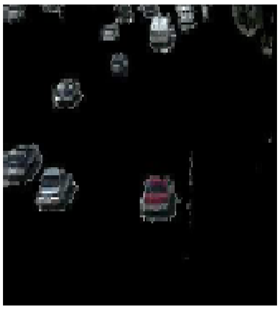


(a)

(b)



(c)



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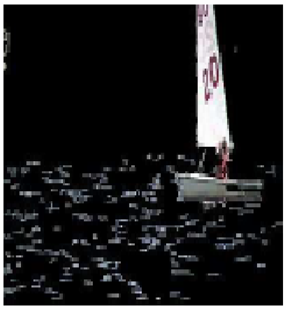
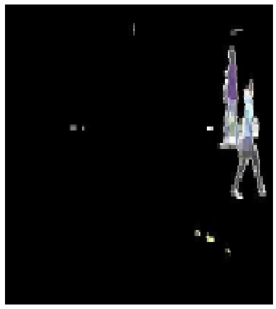


(e)



(f)

Figure 6. (a) to (f) Results attained by proposed approach w.r.t the input frames in Figure 2

Table 1. Forepart Detection Accuracy Analysis

Techniques	Precision (%)	Recall (%)	F-measure (%)	Time(s)
Compressive Sensing-Background Subtraction [20]	37.8	38.2	37.99	167
CS-BS [21]	77.2	75.8	76.49	74
Hybrid matrix based BS [22]	87.9	84.4	86.11	58
Proposed Forepart detection	89.6	86.7	88.12	53

The total number of frames being considered for carrying out the analysis is 35. The formulae for computing the performance measures are presented below.

$$P = \frac{Total\ correctly\ classified\ pixels}{Number\ of\ classified\ pixels} \quad \textbf{(11)}$$

$$\mathbb{R} = \frac{Total\ correctly\ classified\ pixels}{Total\ actual\ forepart\ pixels} \quad \textbf{(12)}$$

$$F = \frac{2PR}{P+R} \quad \textbf{(13)}$$

Based on the aforementioned formulae, the effectiveness of the proposed approach is tested with the analogous approaches. The performance of the proposed approach is satisfactory in terms of precision and recall, which improve the F-measure rate.

The least F-measure is shown by the compressive-sensing-background subtraction [20] with 37.99 percent. The hybrid matrix based BS closely follows the F-measure rate of the proposed work with 86.11 percent. The proposed work shows 88.12 percent as the F-measure rate, which is better than the compared works.

The main reason for the betterment of the proposed approach is that the dynamic choice of measurements. All the compared techniques choose the measurements in a non-adaptive way and the proposed approach selects the measurements with dynamic sparsity, which results in better compression rates. The following section analyses the proposed work with respect to the measurements.

4.2 Measurement Collection Analysis

The total measurements of the video frames and the forepart measurements being extracted are shown in Table 2. Measurements play an important role in determining the forepart of the frame and the energy consumption of the system is decided by the choice of measurements. Hence, this section analyses the measurements collection, as presented below.

Table 2. Measurement collection analysis

Techniques/ No. of frames	20	30	40
Compressive Sensing-Background Subtraction [20]	28962	38062	51807
CS-BS [21]	23749	34658	49872
Hybrid matrix based BS [22]	3897	4769	5397
Proposed Forepart detection	3449	4572	5138

The above presented table shows the number of measurements being selected for transmission to the destination. The lesser the number of measurements, the greater is the energy conservation. Better energy conservation leads to better lifetime of the network. As shown in the table, the measurements being extracted by the proposed approach is minimal, when compared to the existing approaches. Additionally, minimal measurement extraction leads to reduced computational overhead. The following section presents the energy consumption of the proposed approach.

4.3 Energy Consumption Analysis

Energy consumption is the most important factor for any energy stringent application. The main advantage of sensor networks is that the sensor nodes can be deployed even in human unfriendly environments, without any hassles.

Though it brings in numerous advantages, the sensor nodes cannot be maintained properly. This makes sense that it is highly complex to recharge or replace the battery backup. Hence, it is an absolute necessary to arrive at better energy conservation, which can be achieved by proper planning of energy consumption. The better way of energy consumption results in energy conservation, which leads to enhanced lifetime of the network. The energy consumption analysis of the proposed approach is shown in Figure 7.

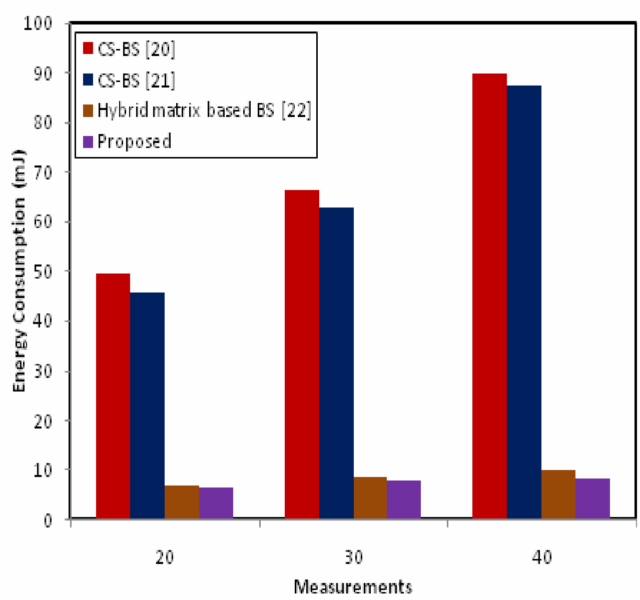


Figure 7. Energy consumption analysis

On observation, it is clear that the energy consumption of the proposed approach is very minimal. The main reason for minimal energy consumption is the extraction of feasible measurements. This leads to the improved lifetime of the WVSN. The energy consumption is measured in mJ. The following section presents the sparsity estimation of the adaptive and non-adaptive approaches.

4.4 Sparsity Estimation Analysis

The sparsity estimation is considered to perform this analysis and the approaches being taken into account are adaptive and non-adaptive. The non-adaptive approaches fix everything in advance. However, the adaptive approach chooses the parameters on the go. Though this idea is beneficial, it may introduce several issues such as infeasibility, error rates and so on. Figure 8 presents the sparsity approximation analysis.

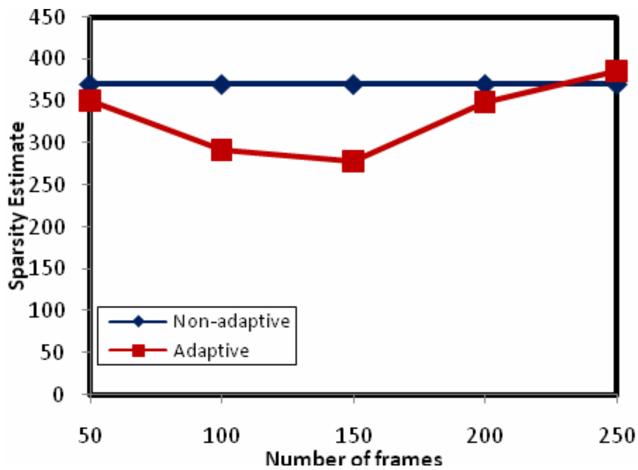


Figure 8. Sparsity estimation analysis

The above presented graph presents the sparsity estimation analysis, of both the adaptive and non-adaptive approaches. As shown above, the sparsity range is dynamic in the adaptive approach and is tuned with respect to the frame rate. The sparsity estimation of the adaptive approach goes up and down, whereas the sparsity estimate of the non-adaptive approach is static for all the frames. Hence, the objective of the proposed approach is attained with minimal energy consumption. The following section presents the conclusive remarks of the proposed work.

5 Conclusions

This article presents dynamic forepart detection with varying compressive measurements. It is well-known that WVSN is severely energy constrained, due to the transmission of live video streams that consumes more energy. Increased energy consumption leads to poor network lifetime and the major energy consuming activity is the data transmission.

This issue is addressed by detecting the forepart of the video frames, as the background of all the video frames is the same. The forepart is detected and the dynamic compressive measurements are computed. The selected compressive measurements alone are transmitted to the destination. This work computes the compressive measurements in a dynamic fashion.

The performance of the proposed work is evaluated in terms of detection accuracy rates, energy consumption, sparsity estimation and measurement analysis. The proposed approach proves better results, when compared to the existing approaches. In future, this work is planned to consider dynamic background scenes and to present different local processing schemes for WVSN.

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