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Compressive Imaging Systems For Video Surveillance Applications

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ABSTRACT
Video surveillance is one of the most important Internet of Things (IoT) applications, and it deals with a large volume of data. Compressive sensing is a new approach that may be used to develop IoT platforms since it lowers raw data transfer and achieves network traffic load balancing. The paper's main contribution is to design and construct a cost-effective IoT-enabled compressed sensing-based image system for video surveillance. The suggested work's efficiency will be measured in terms of sample reduction, reconstruction quality, and energy consumption.

Keywords: Compressive sensing (CS), Video frame, OMP, IoT, Thingspeak.

1. INTRODUCTION

The Internet of Things (IoT) is a concept that involves battery-powered devices that collect data from their surroundings via sensors and communicate it to the cloud for specific applications [1,2,3,4,5]. However, because of their high energy consumption, IoT devices have lower computing capability and network longevity. As a result, numerous technologies such as cooperative transmission, multi hop networks, and compression techniques are used to reduce energy usage and improve network lifetime.

Compressive sensing (CS) is a new approach that may be used in the design of IoT platforms to reduce raw data transfer and accomplish network traffic load balancing [6,7].
One of the most important IoT applications is video surveillance [8]. Video surveillance generates a large amount of data that must be transferred over the internet and stored in the cloud for analysis. The intruder's presence is detected by the video surveillance system, which also provides additional protection by documenting the intruder's activities. It is not essential to transmit the whole video from the imaging equipment when using compressed sensing because it is sufficient to communicate the compressed measures alone. Because the notion of CS imaging differs from that of traditional imaging sensors, it is necessary to develop special structures for CS imaging. The paper's main contribution is the design and implementation of a CS imaging system for video surveillance. The imaging system's extracted CS measurements are saved on the cloud platform [9] for subsequent analysis. The measurements are retrieved at the monitoring end, and the video is reconstructed using the CS recovery technique.
In [11,12,13] the authors have developed automatic transmission of information through the wireless sensor networks.

2. VIDEO CS SYSTEMS – PROCESS FLOW

The overview of the video surveillance framework is shown in Figure 1. The video is captured with a CS imaging system, and the compressed measurements are extracted and sent to the cloud. To get the measurements, the input video signal is multiplied by a measurement matrix, and the CS measurements are delivered separately. Using a suitable CS recovery method, the original video may be recreated from the measurements at the monitoring station or control room. Intrusion detection or machine vision applications such as object tracking and facial recognition can be done with the video that was retrieved. Below is a detailed description of the CS imaging system. As indicated in equation, the CS principle is used to the sparse input signal (1).

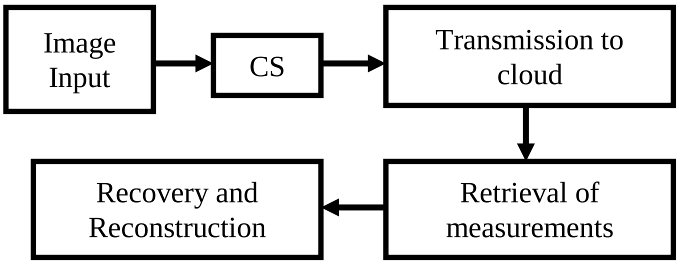

Fig.1 Overview of Processing of Video CS system

$$Y_1 = x_1 * A \quad (1)$$

Where the measurements are denoted by Y_1, the sparse input signal is denoted by x_1, and the measurement matrix is denoted by A.

The CS measurements are obtained by multiplying the measurement matrix with the input video. In this work Toeplitz matrix is used as the measurement matrix. The data was stored and analysed using the Thingspeak IoT platform in this project. Thingspeak is an open source IoT platform that uploads and saves data via fields [10]. For analysis, Thingspeak is connected to MATLAB. The system will be able to respond to the scenario by sending text based on the analysis. The original video is reconstructed at the receiver end using an existing basic orthogonal matching pursuit technique.

3. PERFORMANCE EVALUATION

The proposed device is a bidirectional, independent DC-DC converter. A dual full-bridge topology is used to achieve the power ranking. When using a bidirectional DC to DC converter in the electric traction drive between the Power Electronic Interface (PEI) and the Energy Storage System (ESS), it's critical to specify the electric tracking system's. These specifications include the degree of the vehicle's hybridization, as well as the drive rail configuration, electric AC drive system, and DC to DC PEI configuration. In this paper, the energy for electric vehicle charging comes from two sources: battery and solar, as well as a bidirectional DC to DC converter that converts mechanical energy to electrical energy, allowing the energy to be used more effectively. The bidirectional DC to DC converters convert power between charging and discharging operations.

The video was used as the input signal for the simulation, and the frames were retrieved from the video. Each video frame is subjected to CS with DCT as the transform basis and a toeplitz matrix as the measurement matrix. After the CS measurements were retrieved, they were sent to the Thingspeak IoT platform over a wireless link.

The measurements were retrieved at the receiver end, and the existing Orthogonal Matching Pursuit technique was utilised to recover them. MATLAB was used to design the suggested CS-based image sensor. The system's performance was assessed using equations (3) and (4) to assess the quality of the reconstruction (3) and to determine the percentage of samples that were reduced (4). The PSNR (dB) is calculated using Equation (3) (Jean-Bernard & Lydia 1998)

$$\text{PSNR}=\frac{\left(2^{b}-1\right)}{MSE} \qquad (3)$$

where b is the frame's bits per pixel and MSE is the mean squared error, as illustrated below

$$MSE=\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(I(m,n)-R(m.n)\right)^{2}$$

where I(m.n) signifies the original frame's pixel value and R(m,n) signifies the reconstructed frame's pixel value.

The percentage of sample reduction (PS) is computed as follows:

$$P_S=\left(1-\frac{L}{Q}\right)*100\ \% \qquad (4)$$

Where L represents the number of measurements per 8 × 8 block and Q represents the number of samples per 8 × 8 block.

For testing, samples of videos were taken from the database. The frames were first taken from the video. For further processing, the frames were scaled to 256 × 256 pixels and separated into 8x8 blocks. To collect the measurements, each block was sparsified and a Toeplitz measurement matrix of size Mx64 was used. M=20,30,40,5 each block was used in the analysis. The CS reconstructed frames of the hallway footage are shown in Figure 6.

 

Fig.5 Video frames after recovery

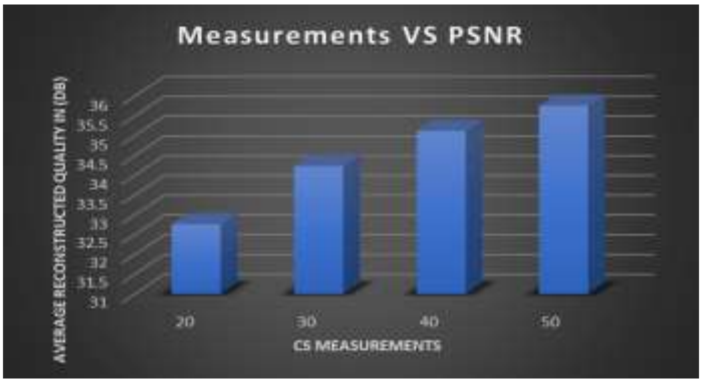

Fig. 6 Trade off between measurements and PSNR

Figure 5 demonstrates that the reconstructed frames exhibit acceptable clarity, with overall PSNRs of 32.65 dB, 34 dB, 35.34 dB, and 35.85 dB for 20, 30, 40, and 50, respectively. It has been noticed that as the number of measurements grows, so does the PSNR. It is also obvious from the data that the PSNR is within the permitted range, as shown in Fig 6. When evaluating 20, 30, 40, and 50 video samples per block, Table 1 illustrates the percentage reduction in overall video samples.

Table1. Comparison of the Number of CS measurements extracted with the reduction of samples per block in a video frame

No. of CS Measurements	Reduction of Video frame samples per block (%)
20	68.75
30	53.13
40	37.5
50	21.87

It is obvious from the table that as the number of measurements grows, the proportion of samples reduced drops. As a result, there is an obvious tradeoff between PSNR and sample reduction.

4. CONCLUSION AND FUTURE DIRECTION

For video surveillance application, a CS-based efficient IoT framework was created. DCT transform basis and Toeplitz matrix were used for performing CS on the video frames. MATLAB software was used to create and simulate the CS imaging system. The CS recovery was carried out in MATLAB, and the system's performance was assessed using metrics like PSNR and the reduction in the number of samples to be transferred for reconstruction. The system can be implemented in real time hardware and analyze the data using Thingspeak.

5. REFERENCES

[1]. Kannan, G., and N. Manoharan. "Concept on Internet of Things (IoT) sensors based Non-Destructive Evaluation Technique (NDE)." Indian Journal of Public Health Research & Development 9, no. 3 (2018).
[2]. Li, Ran, XiaomengDuan, Xu Li, Wei He, and Yanling Li. "An energy-efficient compressive image coding for green internet of things (IoT)." Sensors 18, no. 4 (2018): 1231.
[3]. Linda, G. Merlin, G. Themozhi, and Sudheer Reddy Bandi. "Color-mapped contour gait image for cross-view gait recognition using deep convolutional neural network." International Journal of Wavelets, Multiresolution and Information Processing 18, no. 01 (2020): 1941012.
[4]. Themozhi, G., and S. Rama Reddy. "Output Voltage Regulation in ZVS Bidirectional DC to DC Converter Using Neural Network." IUP Journal of Electrical & Electronics Engineering 5, no. 3 (2012).
[5]. LA Li, Ran et al. “Measurement Structures of Image Compressive Sensing for Green Internet of Things (IoT).” Sensors (Basel, Switzerland) vol. 19,1 102. 29 Dec. 2018.
[6]. A. Canovas, J. M. Jiménez and J. Lloret, "An Intelligent System for Video Surveillance in IoT Environments," in IEEE Access, vol. 6, pp. 31580-31598, 2018.
[7]. K. Muhammad, R. Hamza, J. Ahmad, J. Lloret, H. Wang and S. W. Baik, "Secure Surveillance Framework for IoT Systems Using Probabilistic Image Encryption," in IEEE Transactions on Industrial Informatics, vol. 14, no. 8, pp. 3679-3689, Aug. 2018.
[8]. Rajasekhar, D., and N. Manoharan. "Seawater Surveillance Robot." Medico-Legal Update 18, no. 1 (2018).
[9]. D Arivazhagan, S Sundaram, “Challenges of Cloud Computing, Security Issues and Potential Operational Areas in Data Transportability, Segregation, Backup, Portability and Recovery”,International Journal of Emerging Technologies and Innovative Research, Volume 5, Issue 7, Pages:681-683, 2018.
[10]. https://thingspeak.
[11]. R. Sundar, M. Dheepak, G. Jegadeeswari, Dr. S.V. Saravanan (2018) “Humanoid Robot for Remote Surveillance” International Journal of Mechanical Engineering and Technology (IJMET), 9 (8), 653-659
[12]. Veerakumar P., Dheepak M., Saravanan S.V. “PLC based automatic control for onboard ship gangway conveyor system” International Journal of Mechanical Engineering and Technology Volume 8, Issue 3.

[13]. Dr.T.Sasilatha, M Parameswari, P Kumar, “Efficient energy management approach for tracking location in wireless sensor networks”, EAI Endorsed Transactions on Energy Web, Volume 5, Issue 20, 2018.
[14]. Dr.T.Sasilatha, “Autonomous and manual voice operated fire fighting Robot”, International journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE), Volume 2, Issue 6, 2016.
[15]. T. Sasilatha and Sentil B Suresh N, (2016) "System on chip (SOC) based cardiac monitoring system using kalman filtering with fast fourier transform (FFT) signal analysis algorithm, Journal of medical imaging and health informatics 6, 1-9