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Role of Compressed Sensing Based Image Sensor for Smart Surveillance Applications

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Abstract
Internet of Things (IoT) is the interconnection of physical objects through internet for improving quality of life and involves potential applications such as healthcare, smart cities, manufacturing and automation etc. Compressive sensing is an emerging technique that can be adopted in the design of IoT platforms as it reduces the raw data transmission and achieve traffic load balancing throughout networks. Video surveillance is one such significant applications of IoT and it deals with huge amount of data. Compressed Sensing concept can be used to reduce the amount of data being transmitted in the wireless link. The main contribution of the paper is to design and implement an efficient IoT enabled compressed sensing-based imaging system video surveillance applications. The performance of the proposed work will be evaluated in terms of reduction in samples, reconstruction quality and energy.

Keywords: *Internet of Things (IoT), Compressive sensing (CS), Video surveillance applications, CS recovery algorithm.*

1. Introduction

Internet of Things (IoT) deals with battery powered devices that can collect data from the environment through sensors and transmit it to the cloud for providing specific services. However, the IoT devices have less computational capability and network lifetime due to the energy consumption. Thus, to reduce the energy consumption and to improve the lifetime of the network different approaches are adopted such as cooperative transmission, multi hop network and compression techniques. Compressive sensing (CS) is an emerging technique that can be adopted in the design of IoT platforms as it reduces the raw data transmission and achieve traffic load balancing throughout networks.

Video surveillance is one such significant applications of IoT. Video surveillance deals with huge amount of data which has to be transmitted through internet and stored in cloud for further analysis. The video surveillance system detects the intruder's presence and also provides more security by recording the activity of that person. With the help of compressed sensing technique, it is not necessary to transmit the entire video from the imaging system as it is sufficient to transmit the compressed measurements alone. Since the concept of CS imaging is different from conventional imaging sensors it is essential to design specific structures suitable for CS imaging. The main contribution of the paper is to design and implement a CS imaging system for video surveillance applications. The extracted CS measurements from the imaging system are stored in the cloud platform for further analysis. The measurements are retrieved at the monitoring end and CS recovery algorithm is used to reconstruct the video.

2. Methodology

Fig.1 shows the overview of IoT enabled video surveillance framework. CS imaging system is used to capture the video and extract the compressed measurements which are further transmitted to the cloud.

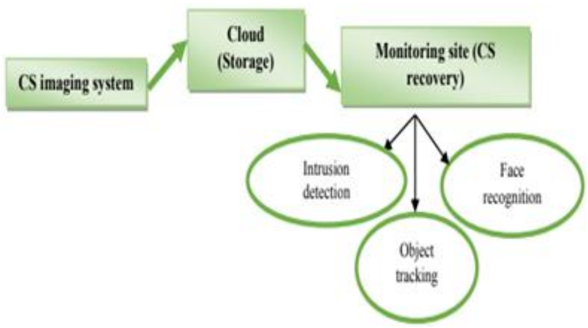


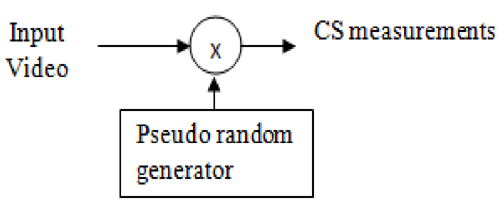
Figure: 1 IoT enabled video surveillance framework

The advances in CMOS technology have paved the way for the development of CS imaging systems. There are specific requirements for designing the imaging system such as low power consumption, low cost, high speed, and high resolution.

The input signal is multiplied with a measurement matrix to obtain the measurements and the CS measurements are alone transmitted. At the monitoring site or control room the original video can be reconstructed from the measurements using an appropriate CS recovery algorithm. The retrieved video can be used for intrusion detection or machine vision applications such as object tracking and face recognition. The CS imaging system is explained in detail below. The concept of CS is applied to the sparse input signal as shown in equation (1)

$$Y=x*A \qquad (1)$$

Where Y denotes the measurements, x denotes the sparse input signal and A denotes the measurement matrix.



The pseudo random generator is designed using the linear feedback shift register. The LFSR is a shift register which sequences through (2n-1) states, where n represents the number of shift registers used in designing the LFSR [1]. The contents of the register are shifted one position towards right for every rising edge of the clock pulse. The feedback from the left most registers of LFSR is given via XNOR or XOR gate [1], [2]. The initial value to the LFSR is called as input as all is 1s or 0s cannot be used as LFSR would get locked up. A LFSR with maximum feedback polynomial will generate a sequence of random numbers and takes a very long cycle [1], [6], [7]. Fig.2 shows the block diagram of LFSR.

The rules for selecting feedback polynomial are as follows [1], [2]: A. The input to the first shift register is represented as 1. B. The tap bits are represented by the power of the terms in the maximum feedback polynomial. The first and last bit is the input and output tap respectively. C. If the number of taps in the polynomial are even then the LFSR is said to be maximum length. D. The set of taps taken together, not pair wise must be relatively prime. With the help of pseudo random generator a random matrix of size M x N is generated where M denotes the number of CS measurements and N denotes the number of samples.

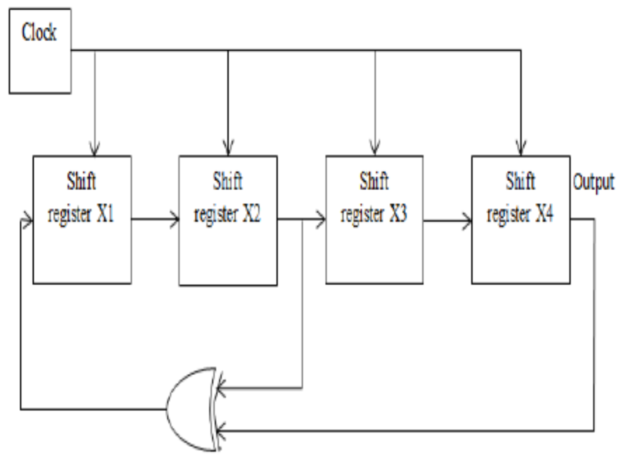


Figure 2: Block diagram of LFSR

The generated random matrix is multiplied with the input video to obtain the CS measurements are stored in cloud. In this work things peak IoT platform was used for storing and analyzing the data. Things peak is an open source IoT platform which uses fields to upload and save data. Things peak is interfaced with MATLAB for analysis. Based on the analysis the system will be able to react to the situation by sending text. At the receiver end existing simple orthogonal matching pursuit algorithm is used for reconstructing the original video.

3. Performance Evaluation

The simulation was done with the video as the input signal where the frames are extracted from the video. CS is applied to each video frame using DCT as the transform basis and random matrix as the measurement matrix. For generating the random matrix pseudo random generator using 8 bit LFSR was used. The maximum feedback polynomial for 8 bit LFSR X8+ X6 + X5 + X4 + 1 will produce 2 8 -1 = 255PN sequence [1], [2]. Fig 3 depicts the

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block diagram of 8 bit LFSR. Once the CS measurements are extracted, they were transmitted through wireless link to the Things peak IoT platform. At the receiver end the measurements were retrieved and existing Orthogonal Matching.

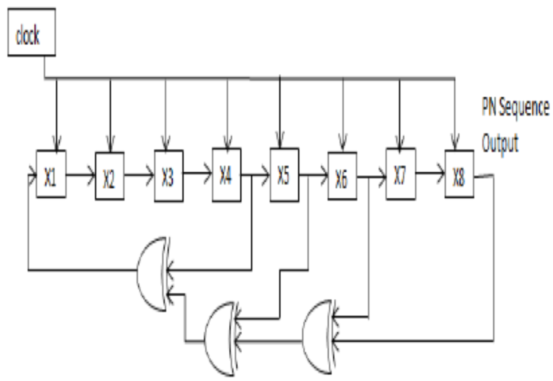

Figure 3: Block diagram of 8 bit LFSR

Pursuit algorithm was used for recovery. The proposed CS based imaging sensor was designed using Cadence and MATLAB. The design was done in Cadence and the recovery was implemented using MATLAB. The design of the LFSR in the CS imaging system is shown in fig 4.

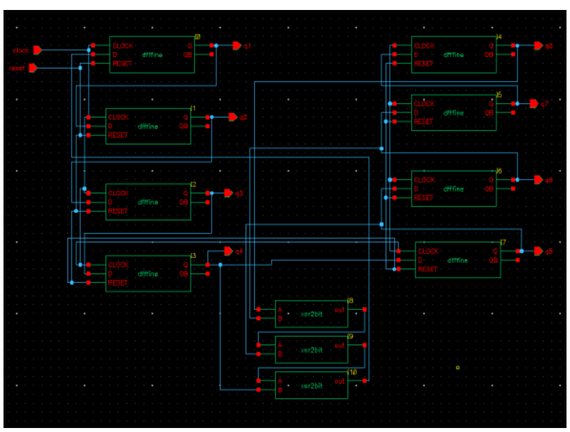

Figure 4. Design diagram of 8 bit LFSR

The system performance was evaluated using percentage of reduction in samples and reconstruction quality using equation (3) and (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 bits per pixel of the frame and MSE represents the mean squared error as shown 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) denotes the pixel value of the original frame and R (m,n) denotes the pixel value of the reconstructed frame.

The percentage of reduction in samples (P_S) is calculated as shown below

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

Where L denotes measurements per 8 x 8 block and Q denotes samples per 8 x 8 blocks. Sample videos were taken from the database for evaluation. Initially the frames were extracted from the video. The frames were resized to 256 x 256 and divided into 8x8 blocks for further processing. Each block was sparsified and the random measurement matrix of size Mx64 was applied to obtain the measurements. The analysis was made for M=20,30,40,5 per block. Figure 6 shows the CS reconstructed frames of the hallway video.

Figure 5: Reconstructed CS frames

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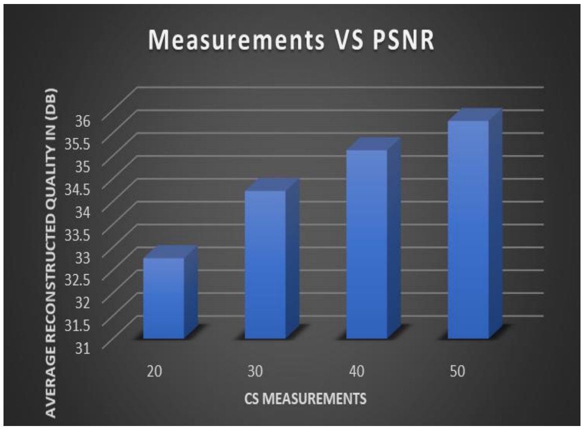

Figure 6: No. of CS Measurements VS PSNR

Fig.5 shows that the reconstructed frames have acceptable clarity and the overall PSNR achieved for 20, 30. 40, 50 are 32.76dB, 34.23dB, 35.12dB, 35.76dB respectively. It is observed that as the number of measurements increases the PSNR also increases. From the results it is also clear that the PSNR is in the acceptable range which is depicted in Fig 6. Table 1 shows the percentage of reduction in overall video samples when considering 20, 30, 40 and 50 per block.

Table 1: Comparison of Number of CS measurements percentage of reduction of samples

No. of CS Measurements	Percentage of reduction in video samples
20	68.74
30	53.13
40	37.5
50	21.87

From the table it is clear that as the number of measurements increases the percentage of reduction in samples decreases. So there is a clear tradeoff between PSNR and reduction in samples.

4. Conclusions

CS based efficient IoT framework was developed for video surveillance application. CS imaging system was designed using the tanner tool and the simulation was verified using MATLAB software. Pseudo random generator using LFSR was used for generating the random measurement matrix for the CS process. CS recovery was done in MATLAB and the system performance was evaluated using metrics such as PSNR and reduction in samples to be transmitted for reconstruction.

References

[1] 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.

[2] 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.

[3] 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.

[4] 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.

[5] 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.

[6] Shanthi H.J., Mary Anita E.A, “Secure and efficient distance effect routing algorithm for mobility (SE_DREAM) in MANETs” Smart Innovation, Systems and Technologies, 2016.

[7] Sujatha, V., Mary Anita, E.A., “Fuzzy based scheme for detection of Sybil node in wireless sensor networks” Journal of Advanced Research in Dynamical and Control Systems, 2017