An energy-efficient framework for multimedia data routing in Internet of Things (IoTs)

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Abstract

The Internet of Things (IoTs) is an integrated network including physical devices, mobile robots, cameras, sensors, vehicles, etc. There are many items embedded with electronics, software to support a lot of applications in different fields. These internet-based networks have many different types of data to be transmitted and processed. Either reducing data transmission or lowering energy consumption for such networks is critically considered. Compressed sensing (CS) technique is known as a novel idea to compress and to reconstruct correlated data well with a small certain number of CS measurements. This paper proposes an energy-efficient scheme for data routing for IoTs utilizing CS techniques. The ideas show how to apply CS into IoT applications with different kinds of data like images, video streaming and simply as sensor readings. After the CS sampling process, the IoT system only needs to transmit a certain number of CS measurements instead of sending all collected sensing data. At the receiver side, the system can reconstruct perfectly the original data based on the measurements. Different kinds of IoT data is analyzed to be used with CS. Data routing methods are suggested for suitable cases. Simulation results working on different types of multimedia data are provided to clarify the methods. This work also provides an additional way to protect the sensing data for security purposes in the networks.

1. Introduction

The Internet of Things (IoTs) is providing many applications in different fields. The main goal is to create an internet-based network to connect everything including electronic devices and human demands [1]. The networks can connect to control different devices and systems remotely. Systems are in smart houses or industrial/military fields which can contact to each other for different purposes. IoTs support other networks for further effectiveness.

Traditional wireless sensor networks (WSNs) collect data from a sensing area to be sent to a base-station (BS). The BS could be at fixed positions to gather sensing data. With the integration between IoTs and WSNs, the data can be sent through cloud or internet to be stored everywhere needed. The BS could be set up anywhere to be able to collect data [2–5].

IoTs facilitate smart home with many kinds of applications [6]. All electronic equipments are connected into the internet. Their owner can control each device like turning on/off or set up schedules for all the connected equipments. In addition, different kinds of sensors are installed inside the house for monitoring

purposes. Air condition, fire alarm systems work based on the information provided by the sensors.
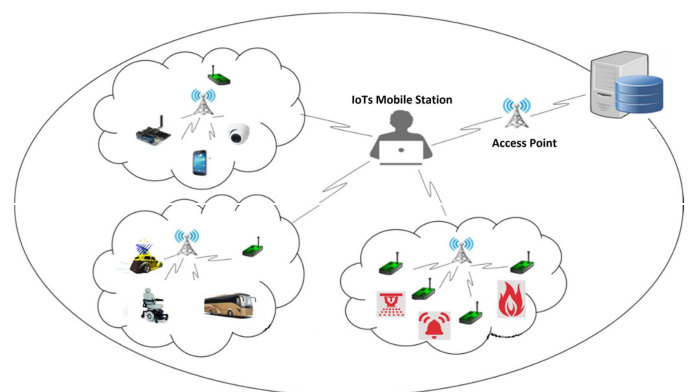
Figure 1. A general picture of IoT applications in the real world. Many application are integrated into IoTs with different kinds of data

IoTs also support monitoring systems for other systems, such as the systems to monitor oil leak underwater, the systems to observe earth quake, etc [7–9]. The systems can send and store their data in the

internet. The BS or data processing center can be anywhere to analyze the date. However, a huge of data transmitting via the internet requires high bandwidth or high speed transmission lines that cost a lot. We are looking for energy-efficient methods to reduce the load burden for such networks.

Compressed sensing (CS) [10, 11] techniques support compressible data to send only a certain number of CS measurements to be able to recover the whole data with an acceptable quality of service (QoS). The number of data packets could be reduced significantly if CS is applied into the systems. Generally, data transmitting via IoTs is often high correlated and compressible that basically satisfies the requirements to be able to employ CS in the systems. With CS, the IoT systems do not need to send all sensing values but only a much smaller number of CS measurements that saves power consumption.

There are many data collection methods utilizing CS to reduce sensing data in a lot of applications in different fields. In [12–14], random walk routing integrates CS to exploit the random distribution of sensors to sample and to collect CS measurements from WSNs. Other routing methods, such as tree-based [15, 16], cluster-based [17–19] and neighborhood based [20, 21] also employ CS to reduce sensing data in such networks significantly. Currently, CS is also applied to mobile sensor networks or robotic networks to exploit the mobility of robots [22–26]. The mobile sensors or robots share their readings to each other and form CS measurements to be able to reconstruct data at each distributed robot. The methods not only reduce data transmitting in such networks but also support the communications within the networks. In [27], the authors exploit Modulation and Coding Scheme (MCS) to possibly reduce the transmission power in IoTs networks. In overall, CS techniques are shown to be promising to support sensing data in different fields.

In this paper, an energy-efficient method is proposed to integrate CS into the systems to reduce significantly data transmission in the IoTs networks. Since there are different kinds of data that need to be considered in IoTs, our method is flexible to be able to sample and reconstruct those data. In addition, the method is deployed with different kind of data in different systems to show the effectiveness of the methods. Sensing data from WSNs, event detection data and video data would be considered to able to apply CS to reduce significantly data transmission. Energy consumption is also analyzed and simulated.

The remainder of this paper is organized as follows. Compressed sensing (CS) Background and Problem Formulation are addressed in Sections II and III, respectively. Simulation results are provided in Section IV. Finally, Conclusions and Future work are in Section V.

2. Compressed Sensing (CS) Background

2.1. Data Representation

Compressed sensing (CS) has been known as a signal processing method to reduce redundant data [10, 11]. Hight correlated data can be sampled as a certain number of CS measurements and then reconstructed perfectly. In general, the requirements to be able to utilize CS are the signals should be sparse or compressible in proper domains.

In order to clarify the signal representation, a data vector $\underline{X} \in R^N$ ($\underline{X} = [x_1\, x_2 \ldots x_N]^T$) is considered as k-sparse vector if $\underline{X}$ has k non-zero entries in the canonical basis and the rest of $\underline{X}$ can be considered as zeros. In other cases when $\underline{X}$ is dense in canonical basis, but the vector is sparse in other domains, for instant Wavelet or DCT, $\underline{X}$ is still considered sparse in the domains. It could be represented as $\underline{X} = \Psi\Theta$ in which Θ has only k non-zero transformed coefficients. $\Psi \in R^{N \times N}$ is called the sparsifying matrix.

2.2. Data Sampling

$\underline{X}$ with N elements could be sampled to be able to achieve M measurements while $M \ll N$. The ways of sampling also could be variable.

Vector $\underline{Y} \in R^M$ ($\underline{Y} = [y_1\, y_2 \ldots y_M]^T$) is called measurement vector that includes M CS measurements. Each measurement is a linear combination of vector $\underline{X}$ as $y_i = \sum_{j=1}^n \varphi_{i,j} x_j$. The vector is calculated as $\underline{Y} = \Phi\underline{X}$ where $\Phi \in R^{M \times N}$ is called the measurement or sampling matrix and is often a full-Gaussian matrix [11] or a binary matrix [28]. y_i represents the ith CS measurement and $\varphi_{i,j}$ represents the corresponding entries of Φ at the ith row. The CS techniques allow $M \ll N$. This could support any systems applying CS much easier to store, to transmit, and to retrieve $\underline{Y}$ compared to the uncompressed $\underline{X}$.
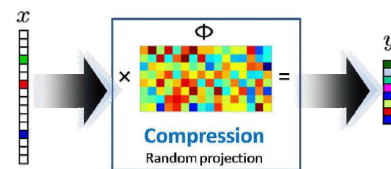

Figure 2. Sparse signal vector $\underline{X}$ can be sampled to be $\underline{Y}$ with much shorter for the compression purpose

2.3. Data Recovery

Based on the measurement vector $\underline{Y}$, the data vector $\underline{X}$ could be reconstructed perfectly. The length of $\underline{Y}$ presents the number of CS measurements which is required as $M = \mathcal{O}(k\, log\, N/k)$ following the l_1 optimization problem given by [11]. The original data

vector $\underline{\mathbf{X}}$ can be recovered with high probability as

$$\hat{\underline{\Theta}} = Arg\,Min \parallel \underline{\Theta} \parallel_1, Subject\,to \quad \underline{\mathbf{Y}} = \Phi\Psi\underline{\Theta}. \quad (1)$$

where $\underline{\mathbf{X}}$ is sparse in Ψ domain as $\underline{\mathbf{X}} = \Psi\underline{\Theta}$ with $\parallel \underline{\Theta} \parallel_1 = \sum_{i=1}^{N} |\theta_i|$. The l_1 optimization problem can be solved with Basis Pursuit (BP) [10].

In practical, noise should be considered. The CS measurements are collected as: $\underline{\mathbf{Y}} = \Phi\underline{\mathbf{X}} + \underline{\mathbf{e}}$, and $\|\underline{\mathbf{e}}\|_2 < \epsilon$ to be able to recover $\underline{\mathbf{X}}$ as follows

$$\hat{\underline{\Theta}} = Arg\,Min \parallel \underline{\Theta} \parallel_1, Subject\,to \parallel \underline{\mathbf{Y}} - \Phi\Psi\underline{\Theta} \parallel_2 < \epsilon. \quad (2)$$

3. Problem Formulation

3.1. Data Analysis

Since IoTs facilitate many applications in different fields, there are also different kinds of data transmitting in the networks. Fortunately, all kinds of data such as images, temperatures, humidity, vibration, light, etc. are highly correlated. In other words, they are compressible that satisfy the CS conditions to be able to sample and reconstruct data.

As mentioned in the Section 2, sensing data can be considered as N scalar values contained in the vector $\underline{\mathbf{X}}$ which is compressible or sparse in proper domains as

$$\underline{\mathbf{X}} = \Psi\underline{\Theta}, \quad (3)$$

where $\underline{\Theta} = [\theta_1\,\theta_2\ldots\theta_N]^T$. $\underline{\Theta}$ has k non-zero elements (in other words, large transformed coefficients). The rest of θ_i can be considered as zeros. $\underline{\Theta}$ normally has this property

$$|\theta_1| \geq |\theta_2| \geq \ldots \geq |\theta_N|. \quad (4)$$

Ψ referred to as the sparsifying matrix, is an orthogonal basis of $\mathbf{R}^N$. If $\underline{\mathbf{X}}$ is a k-sparse vector, Ψ is an identity matrix. Otherwise, Ψ can be chosen from another domain such as Wavelet, DCT (discrete cosine transform), etc. In the simulation result section, we would show DCT and Wavelet for sparsifying the data.

As mention in Equation 4 the coefficients obey a power law decay if there exist constants θ_1 and q such that $|\theta_i| \leq \theta_1 i^{-q}$. It is clear that the larger q, the faster the magnitudes decay the more compressible a signal could be. The presentations of this kind of signals are illustrated in Figures 5 and 8.

3.2. Proposed General Algorithms for Data Aggregation in IoTs

As mentioned the previous sections, CS techniques support many applications with data compressing for energy-efficient purposes. In the proposed Algorithm 1, there are three basic phases including Collecting data, Creating CS measurements and Reconstructing sensing data.

In the first phase, sensing data is collected and analyzed or sorted to be able to apply CS. Each procedure is addressed in details in simulation section according to different kinds of data.

Phase 1. Collecting Data:
- Sensing data is collected at each IoTs device, as sensor, camera
- The data is analyzed/sorted before the CS sampling process

Phase 2. Sampling into CS measurements:
- The collected data is multiplied to a chosen measurement matrix
- A random seed is stored to be sent along with CS measurements. This is the hidden key for security and privacy purposes.

Phase 3. Reconstructing Original Data
- Creating the measurement matrix based on the random received along with the CS measurements
- An appropriate Ψ is chosen to be able to recover $\hat{\underline{\Theta}}$ following equations in Section 2
- Recover the sensing data $\hat{\underline{\mathbf{X}}}$ as $\hat{\underline{\mathbf{X}}} = \Psi\hat{\underline{\Theta}}$
- Normalized reconstruction error is considered to evaluate the recovery progress as $\frac{\|\underline{\mathbf{X}} - \hat{\underline{\mathbf{X}}}\|_2}{\|\underline{\mathbf{X}}\|_2}$

Algorithm 1: Compressed Sensing Based Energy-Efficient Data Routing for Internet of Things (IoT-CS)

In the second phase, the collected data is sampled and CS measurements are created. The measurement matrix is chosen depending on the way the data is collected. As mentioned in [13, 19, 25], sparse binary measurement matrices [28] help to reduce significantly energy consumption for data routing methods, such as random walk, clustering and random mobile routing. In other cases, Gaussian matrix could be chosen as a measurement matrix to sample and create CS measurements. A random seed that corresponds to the measurement matrix created needs to be sent to the receiver side attached to the CS measurements for the recovery process. Without the seed, the receiver cannot reconstruct the whole data right. This is the key point to protect the sensing data via the networks.

In the last phase (Phase 3), after receiving a certain number of CS measurements, the data processing center creates the same measurement matrix based on the seed and reconstruct all sensing data. Note that, the greater the number of CS measurements collected, the higher quality the reconstructed data at the base-station or data processing center.

4. Energy Efficiency Analysis

In this section, the energy consumption for data processing and transmitting is analyzed and compared.

Generally, energy consumption for transmitting and receiving data in wireless sensor networks (WSNs) [29], denoted as P_{Tx} and E_{Rx}, are formulated, respectively as

$$E_{Tx} = E_{T_0} + E_A(d, N) \qquad (5)$$

and

$$E_{Rx} = E_{R_0}. \qquad (6)$$

E_{T_0} and E_{R_0} are two energy consumption levels of electrical elements for coding, modulating or signal processing. They do not depend on transmitting distances, denoted as d, in either WSNs or IoTs systems. In this paper, we only consider the consumed energy of the power amplifier $E_A(d, N)$ which is a function of d. N represents the number of sensor readings, specified as scalar values. The total energy consumption for transmitting data in such networks contain two parts, the energy consumed over a distance d and the amount of data to be transmitted as N following

$$E_A(d, N) = P_A(d)N. \qquad (7)$$

As mentioned in the Section 2 and Section 1, the number of CS measurements required to be able to reconstruct N scalar values could be M, while $M \ll N$. Conclusion can be made that the energy consumption could be much smaller to transmit M CS measurements compared to sensing N values. Note that, only raw data is considered for simplicity. In the real systems, all the raw data is modulated and encoded to be transmitted via channels.

5. Simulation Results

In this section, different kinds of the most common data in IoTs are processed utilizing CS to compress and to recover simply. Simulation results are provided as follows.

5.1. IoT–CS Work with Image
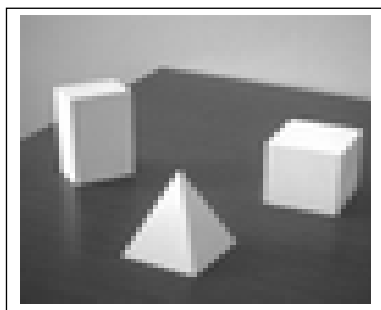
Figure 3. An example of an image to be compressed and reconstruct

Figure 3 shows the image that would be processed to be sent via a IoT system. The image is read into

scalar coefficients. These coefficients are often highly correlated or compressible. After reading, we achieve a scalar vector $\underline{\mathbf{X}}_{N \times 1}$. A measurement matrix $\Phi \in R^{M \times N}$ is chosen to create CS measurements. Only M measurements are created by multiplying $\Phi \underline{\mathbf{X}}$ as shown in Section 2 and are sent to the receiver side of the IoT system. Instead of sending N values, only M linear combination measurements are sent that significantly reduces data transmitting in the system.
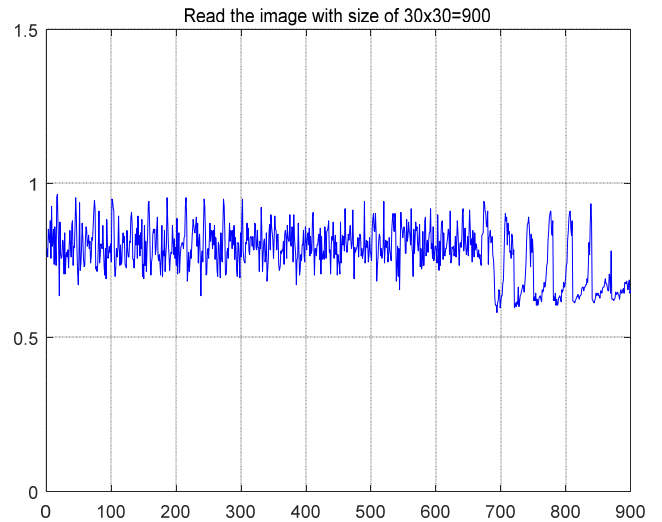
Figure 4. An image is read with a random selection of 30x30 to make 900 points
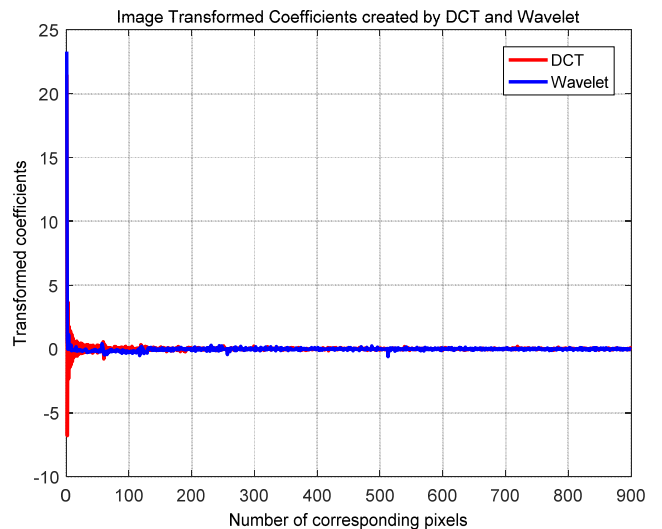
Figure 5. The image is partly transformed by both DCT and Wavelet basics

At the receiver side, N original values are reconstructed based on the CS measurements collected. Figure 6 shows the reconstruction error that evaluates the quality of the recovery process based on different number of CS measurements. Figure 6 also provides

the comparison between DCT and Wavelet working as the sparsifying basis since the original data is dense, as mentioned in Section 3.1. Wavelet basis seems to work as well as DCT in this kind of data. In other kinds of data, DCT could perform better than Wavelet in CS recovery processes.
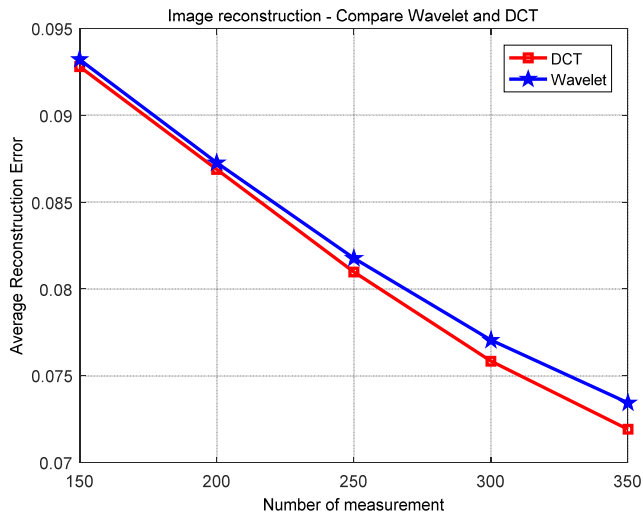

Figure 6. The image is reconstruct by the CS recovery algorithm L1 using both DCT and Wavelet basics

5.2. IoT–CS Work with temperature

In this section, assume that all sensor nodes need to send their readings to a Base-station (BS) or data processing center through a IoT system. The data need to be as precise as possible. Real temperatures are chosen for this experiment to clarify the method. These real temperatures are collected from the project Sensorscope: Sensor Networks for Environmental Monitoring [30]. As shown in Figure 7 the temperatures seem dense in canonical basis but they are actually sparse in other domains, such as DCT (discrete cosine transform) or Wavelet. Both DCT and Wavelet are chosen for sparsifying the temperature data to be able to apply CS to reconstruct at the receiver side.

Figure 8 shows the transformed coefficients achieved from both DCT and Wavelet sparsifying basics. The large coefficients focus on the very first values and remainder are very small. This means that the data is compressible as mentioned in Section 3.1.

Figure 9 shows the reconstruction errors after all the sensing data is recovered. With the CS performance to reconstruct data, only $M = 500$ CS measurements are required at the data processing center to be able to recover 2000 values of temperatures at the normalized reconstruction error as 0.1 . The reconstruction errors via different number of CS measurements are provided with both basics as DCT and Wavelet. It is shown in Figure 9 the basis DCT works better than the
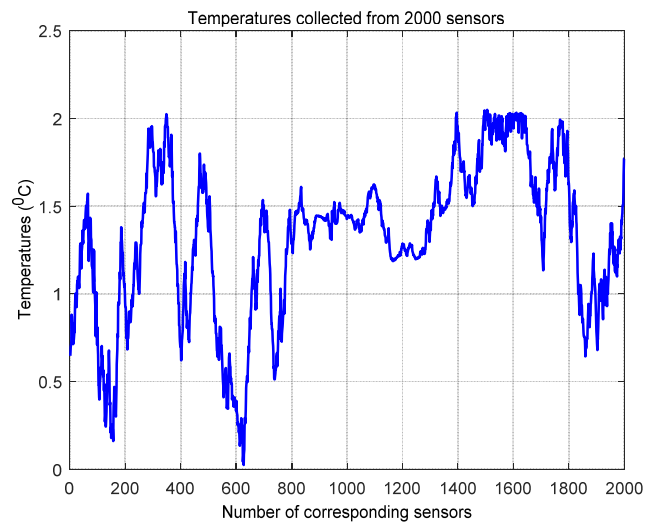

Figure 7. Temperatures collected from 2000 sensors randomly distributed in a sensing area
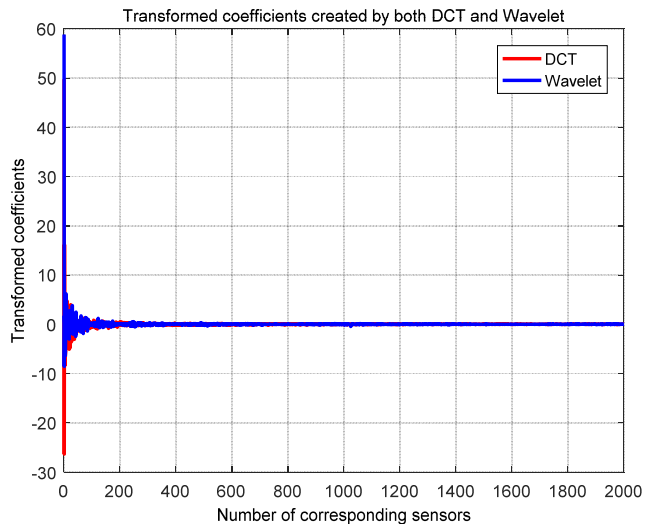

Figure 8. Transformed coefficients corresponding to 2000 sensor readings created by DCT and Wavelet for comparison purposes

Wavelet as the sparsifying matrix. Note that, the greater the number of CS measurements created, the lower the reconstruction error. As shown in Figure 9, in comparison, DCT basis works better than Wavelet basis with CS performance on high correlated data, especially temperature data. This finding could be used for other applications working with this kind of data.

5.3. IoT–CS Work Video Streaming Data

This would support many applications for camera surveillance installed to manage traffic or monitor public places. Objects change in the videos are important and needed to focus on. This type of data is different from the others. It is known that it includes many frames of pictures in each playing time unit.
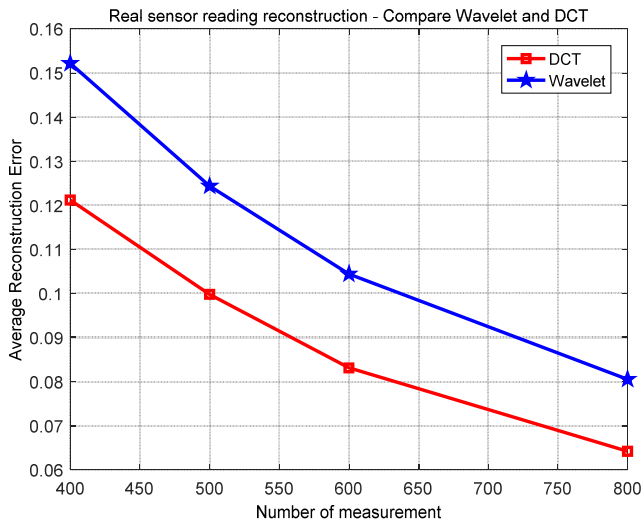
Figure 9. Reconstruction errors from the CS reconstruction processes with DCT and Wavelet as sparsifying basics

Each image or picture is not considered to be sampled. The main idea is, the difference between each frame of picture is considered to be sampled. Let's consider N pictures in a time unit. Only the first picture is sent via the IoT system. The difference between two picture is defined as follows.

$$\underline{\mathbf{X}} = \underline{\mathbf{P}}_i - \underline{\mathbf{P}}_{i+1}, \tag{8}$$

where $\underline{\mathbf{P}}_i$ represents one picture in an unit of time. If all the objects in the video streaming do not move, it means that there is no difference between N picture and the scalar vector $\underline{\mathbf{X}}$ has all zeros.
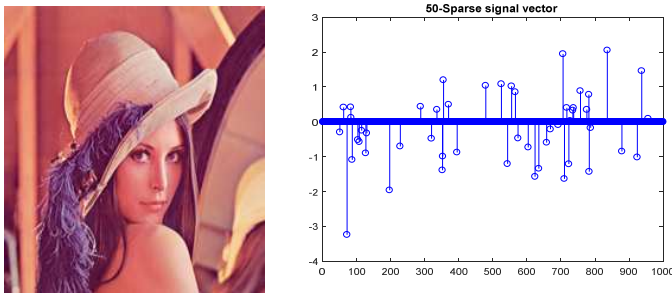

Figure 10. An illustration of a video streaming with the first picture and the rest are some changing if the video streaming may have. The first picture and 1000 random Gaussian scalar values representing the differences between 1000 pictures including the first one.

Normally, some objects move between frames of pictures and almost of the other do not. This creates a sparse vector with only some non-zero elements and the rest are zeros as shown in Figure 10. Sending the sparse vector is also an energy saving paradigm. However, with CS the sparse vector, noted as $\underline{\mathbf{X}}$, needs

to be sampled to reduce the data transmission in IoT networks. Figure 10 shows a k-sparse vector with only 50 non-zero elements and the rest contains zeros due to the unchanged points between pictures in the video streaming. It is obvious that $\underline{\mathbf{X}}$ is a sparse random vector and also highly correlated since the objects randomly move between consecutive picture frames smoothly.

As mentioned, if only N scalar values from $\underline{\mathbf{X}}$ are sent, this could also be an energy-efficient method. However, using CS in this case could be more energy-efficient. Only M measurements are sent after the CS sampling process. This method can reduce much smaller compared to the video streaming data.
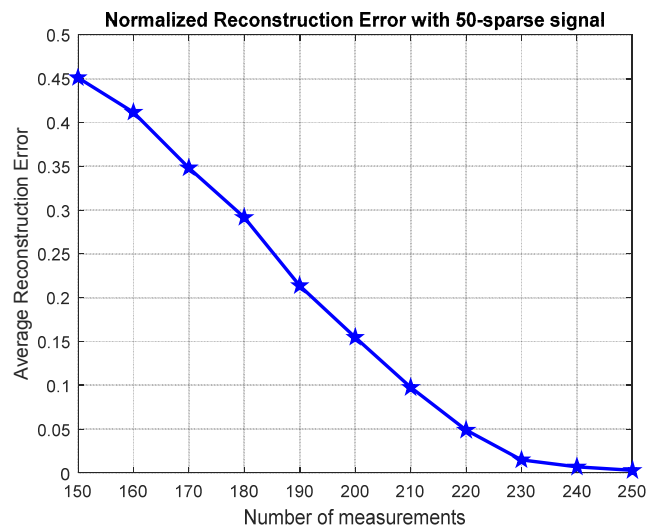

Figure 11. Reconstruction error in the recovery 50–sparse signal length 1000 based on small number of CS measurements

Figure 11 shows the reconstruction error with different number of CS measurements collected. It is clear that the difference between picture frames or the sparse vector is reconstructed perfectly with appropriate number of CS measurements. Based on the difference as know as $\underline{\mathbf{X}}$, the original pictures are recovered following the inversion of the Equation 8.

* **Discussion:** Table 1 provides a comparison of different methods to transmit a video streaming through IoT systems. With IoT-CS, the amount of data transmitting reduces significantly that up to 80% as shown in Figure 11.

6. Conclusions and Future Work

In this paper, a framework of energy-efficient methods utilizing compressed sensing (CS) to send data via IoT systems is proposed to reduce significantly power consumption for transmitting data. A certain amount of data reduced is mentioned clearly based on the analysis and the simulations. The method can be applied to many different kinds of data collecting from devices

Table 1. Comparison table to show the benefit of using IoT–CS

Transmission Paradigm	Data to be transmitted	Note
Transmit all frames of pictures	$P_1 + P_2 + ... + P_{N+1}$	
Transmit the first picture and all the differences between the picture frames	$P_1 + \underline{\mathbf{X}}_{N \times 1}$	$N \gg M$
IoT-CS: Transmit the first one and the CS measurements sampled from the differences	$P_1 + \underline{\mathbf{Y}}_{M \times 1}$	Reduce up to 80%

connecting to IoTs. Simulation results are provided to clarify the energy-efficient problems and show promise for many applications in the real world. This work also clarifies the proper domains to be able to apply with different kinds of data transmitting in the systems. DCT should be the right choice for sensing data. The hidden random seeds to generate CS measurements support security and privacy purposes in the IoT networks. In the future work, more details for each method would be calculated and formulated. More applications would be mentioned and guided to be used more efficiently. Propagation for transmitting data also should be considered.

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