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Industrial Sensor Networks - Signal Processing with Compressive Sensing

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Abstract

Automation and control systems in the industries are relying on different sensors to perform the process precisely. The traditional signal processing methods which has laid their foundation with the sampling theorem, produce gigantic volume of useless data during the series of processes associated with signal processing. Processing, communicating and storing the hilarious amount of data, which is generated by these sensors in a proper way became more challenging. Compressive Sensing (CS) is a ground-breaking platform for processing the signals, which can offer more concrete methods to resolve the problems of capacious data generated by the conventional paradigm. It can overcome the limits of Sampling Theorem and can offer much more to cater the associated issues. The CS concept proposes that signals that are sparse, can be successfully reconstructed from lesser number of samples which are acquired at a much lower rate than that specified with the Nyquist Sampling Theorem (NST). The theory is simplifying the whole process of sampling, encoding and compressing into a single step process simultaneously. Through this paper the compressive sensing scenario is examined through the Sensor Networks perspective in the industrial systems. Along with this, the paper puts an effort to explore the logistical, processing and storage challenges in consort with other major concerns in the realm using the CS approach as an operative tool. From the research it is clear that major challenges can be defied comfortably with the help of CS.

Keywords: Compressive Sensing, Industrial Sensors, Automation, Sparsity, Sampling, Nyquist Rate.

INTRODUCTION

The current epoch of IT explosion is characterized with various high resolution sensing systems. The conventional field of industrial production systems is revolutionized with the sophisticated and automated systems due to this progress. Industrial sensors with related signal processing elements has become an inevitable constituent of the control and automation arenas. Thousands of sensors are deployed on the floor for monitoring and controlling the complicated processes and this reduced the complexity of these processes. The effectual communication and storage of signals from these systems has been evolving as the fundamental challenge in communication Engineering. Even though transmission technologies have faced drastic advancement for managing the emerging challenges of IT explosion, sampling theorem remains as one of the very basic theorems in the field of DSP and communication for decades. Though, NST [1],[2] is the basic governing rule for digital communication world, it is placing so many constraints and challenges in communication.

While giving an overview of sensor systems in the automation and control, here NST is analysed and how the limitations of the theorem will become severe with the data deluge problem of the explosion created by these industrial sensor networks. The paper studies the CS perspective of sensor networks to identify the potential of CS to create revolutionary changes in the industrial sensor networks. It analyses the data deluge problem raised by the sensor networks and try to relate CS as one of the promising solution.

BACKGROUND

Industrial Sensor Networks

Industrial sensors are essential in automation and industrail process control. Measurement accuracy , along with high precision are very critical to these tightly controlled process loops in a typical factory floor and a field level. This is the most important level as the equipment of the level comprises of various sensors, transmitters and actuators which are performing the actual manufacturing tasks and transmit critical data for control and monitoring.

The sensors will convert the variables related with a physical process into electrical form. These sensor signals will be used for processing, analyzing, and taking decisions in order to make the controlling output. The different control methods are implemented to generate the designated output by comparing the present process variable with the set standard values. The controllers will produce the processed final outputs. These outputs will be applied as pneumatic or electrical signal to actuating element inputs by converting these electrical signals in to the process variables.

For ensuring the characteristics and the quality of the industrial process as anticipated, it requires the constant measurement of all the concerned variables, the real time transmission of data, and the rapid response of the equipment to the control signals from controller. Depending on the size the process area and the complexity of the process, the factory floor will have thousands of sensors. These various sensors, with necessary supporting elements, make any industrial process to a controlled process.

Sensors mostly produce change in capacitance, resistance, voltage or current with respect to a change of the measured physical variable. Also regardless of the type of the physical variable, sensor front ends can be generally categorized in to a few major categories: resistive, capacitive, magnetic/inductive, and current sense front ends. Major sensors include inductive proximity sensors, Photoelectric sensors, pressure sensors, rotary encoders, tachometers etc

Signal Processing in Sensor Networks

If we closely analyze various sensors systems, we see that only input signal chain is unique to the type of sensor element. In major cases, the remaining components of the back end processing system are very similar.The first part of the signal processing after the sensor element is an amplifier. Besides amplification,the amplifier may perform attenuation, filtering, buffering, offset adjustment, or level shifting. The conditioned output signal from this stage will be fed to an Analog-to-Digital Converter (ADC). The ADC converts the analog signal in to digital form that can be given directly into the processor. The processor process the collected information by performing various system routines, compensation algorithms and other processing tools. Finally, processed data are transmitted through a proper channel. The channel can be digital bus or traditional analog lines or wireless interface. This data can be utilized for further processing or to take decisions for continuous monitoring, or can be stored for reference.

THE CONVENTIONAL PARADIGM

Major Concerns in the Signal Processing

Most of the signal processing systems are working as per Nyquist/Shannon’s sampling theorem. Even though sensors are measuring the whole of the sensed data, a part only will be taken for final decision making. In the continuous and lengthy process of signal processing, if we adapt to the normal transform coding method with the conventional sampling theorem, There will be data loss with each stage of signal processing - sampling, filtering, analog to digital conversion, quantization and transform coding. Finally at decision making end, we are considering only a small part of the huge data which is acquired by the sensors. So the majority will be excluded during the signal processing.

While designing the industrial sensor modules, we need to think over the following questions

- What is the impact of the measurements in the decision making?
- What type of data has to be measured to reach at proper decisions?
- What parameter and what attributes are should be measured?
- How many channels are needed for the communication especially while taking multiple measurements?
- What will be the channel bandwidth to communicate the data?
- Weather the measurements must be sequential or simultaneous?
- What will be the sampling strategy?
- What will be the resolution and sampling rate needed for proper reconstruction of data?
- How can we avoid oversampling and how can we reduce sample size by applying proper compression and coding?
- Which type of power option need to be selected for effective use of power especially for battery powered sensor modules?
- How can we increase the hardware life by selecting minimum operation of the modules without having compromise on the precision and accuracy of measurements?

During the designing of the sensor systems, the above questions will lead to so many constraints which arise as a result of the outsized number of measurements (N). As N increases, volume of data dealt by the sensor device, Filters, ADC, Controller and Communication channel will increase. So the Storage and Power requirement for sensor modules and other hardware, signal processing complexity etc. will also be raised to a considerable extent. In order to be real time, we need high resolution and high speed devices which will add to the cost of production and the maintenance cost. Eventually this will lead to the increase in product price, which will not be an advantage in the competitive market. So to unravel these limitations, we need to reduce N needed without compromising on the precision of the process. Also as explained earlier, the processing of these the huge unwanted data becomes a wastege in terms of power, processing power, storage requirement, communication and transmission requirement, speed, hardware complexity and hardware lifetime. Now we will examine the global perspective of this data deluge problem arising as a consequences of the conventional method of signal processing.

Conventional Processing and Consequences – A Global Outlook

Sampling [1], [2] is the process of converting a signal which is a function of continuous time into a numeric sequence, which is a function of discrete time. This is the first step in the process of conversion of analog signal into a digital signal. This helps to shrink the volume of data to be processed and transmitted by only taking samples instead of the signal completely. The conventional technique of regenerating the sensed signals from measured data obeys the NST. The principal impact of the NST is that the theorem replaces a continuous signal which is band-limited by a discrete sequence without the loss of information. As per the sampling theorem, if a function x (t) contains no frequencies higher than f_{max} , the sufficient sample rate is $2f_{max}$ samples/second, or anything larger that for perfect reconstruction of the signal. The theorem specifies the lowest sampling rate to reproduce the original signal.

In many applications, the resulting Nyquist rate is very high that result in too many samples. It may be very costly, or sometimes physically impossible, to make a capable system to acquire the samples at the necessary rate. Thus, regardless of the surprising advances in the processing power of the high level chips, the acquisition and processing of signals in most of the application areas remains to pose massive challenges.

When we take the global perspective of this, the situation is becoming worse. Enormous amount of information has been generated in the digital world from various sensors on a day-to-day basis. This huge data has to be communicated, stored, managed, visualized, summarized, and finally analyzed to make sense, which is becoming a herculean task in the present scenario. As the capabilities of digital devices rise and prices fall, sensors and processing systems are creating and digitizing gigantic amount of new information. The technological advancement and the increase in the number of persons using the technology are contributing the main part in the data generation, making the data deluge problem worst.

The overflow of data from various sensors and other processing systems surpassed the capacity of all the storage technologies in 2007. The trend of data growth [3],[4], [5], which is very difficult to control, is ongoing. For example, the global mobile cellular subscriptions have grown to 7740 million in 2017 from 2205 million in 2005. Also the global internet users have increased to 3578 million in 2017 from 1024 million in 2005. The Global Information and Communications Technology (ICT) development from 2001 to 2017 per 100 inhabitants is shown in figure 1.

At present the entire scenario is governed by traditional sampling, which creates huge data in the sensor networks environment which is difficult to process, communicate and store. As indicated earlier, this approach becomes not practical if the signal of interest contains only small number of significant frequencies and the band limit is too large. It is challenging to build sampling hardware that operates at sufficient rates, which is very high normally. As the sampling rate is higher, more samples will be produced in unit time. So the speed of the hardware and the data rates should be increased to meet this high speed requirement. So the complexity and the cost of the equipment will increase along with the faster devices. Instead of the faster devices, if slower devices are used, the compromise will be in the processing time.

So many related consequences are also accompanying with this. With the increased sampling rate, more noise will be added to the system. The power consumption and cost of the system will be increased. Especially for the battery operated instruments, the battery life will be critical. The data deluge will be eventually resulting in congestion and collisions in data traffic, which will lead to data loss. The speed, storage space requirement and safety of the database also need to be improved drastically to cater these huge data. This also needs specialized and sophisticated software packages to control and monitor the entire system.

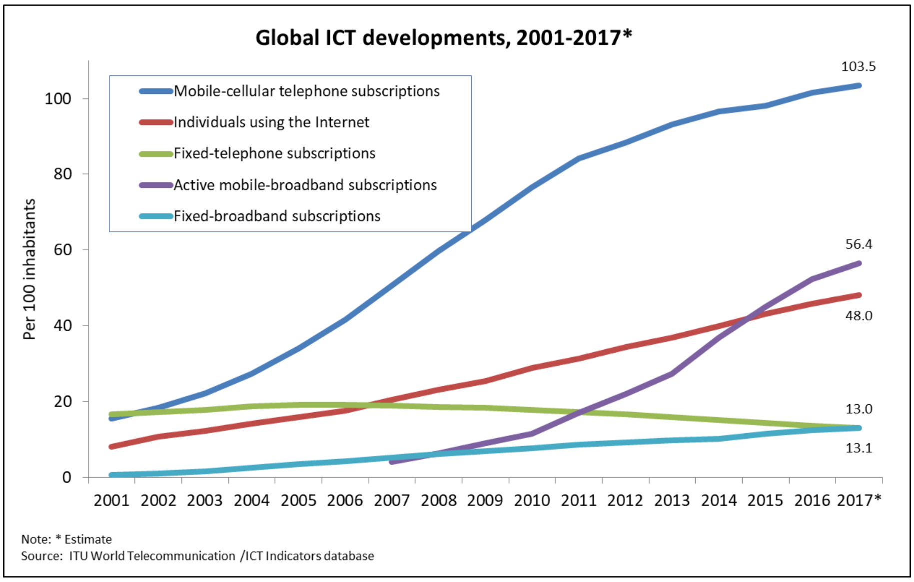

Figure 1: Global ICT Developments, 2001-2017

But there are many situations where we can do well with fewer samples. If the signal is strictly cyclic and repetitive in nature, most of its energy will be concentrated in few significant frequency components. Here we can go for low rate sub-Nyquist sampling, without compromising on quality. Most of the industrial sensor systems are of this kind. So there, the Nyquist rate will become very high which will create a data deluge situation. . So from the above discussion it is evident that there are numerous situations in the industrial Sensor systems, where Nyquist theorem is inappropriate and needs modifications, even though it is being considered as a standard. Reducing the data volume will be one of the basic solutions to control most of the issues mentioned above and to reduce the overheads in the communication and storage. We need to search for alternate sampling methods to reduce the sampling rate. In this context, CS is offering a viable solution for the sensor networks. Here lies the importance of CS concept as a better customizable option.

COMPRESSIVE SENSING – THEORETICAL OVERVIEW

In the traditional transform coding, first we will collect, say N number of samples as per NST to measure the specified process. Generally N will be very large and we need to find the transform coefficients of these N samples. Out of these N transform coefficients, only K largest elements are taken and the remaining samples are discarded. Then these K largest elements are encoded. The rest of the transform coefficients other than the significant coefficients are rejected making the data collection and sampling process rather wasteful. Instead of storing and discarding many measurements, it will be more efficient if we acquire only the needed signals to start with. In this attempt, measurement and compression is performed simultaneously [6]. So in CS, we are directly acquiring the compressed samples with linear projections, without passing through the intermediate stages.

CS can be applied to the situations where Nyquist rate sampling is neither feasible nor efficient. Compressive Sensing or Sub-Nyquist Sampling or Compressive Sampling or Compressed sensing [6], [7], [8] is a very efficient signal acquisition method which do sampling at a very low rate than Nyquist rate. For the reconstruction from these sample, it use the computational poweron this incomplete set of compressive measurements. CS can give sparse solutions for underdetermined linear systems and will be able to reconstruct the original signals from very few samples. CS depends on two principles for this: sparsity and incoherence. Sparsity is connected with the signals of interest and incoherence is related to the sensing modality.

Sparsity[7] expresses the idea that the information rate of a continuous time signal can be much smaller than suggested by its bandwidth. Most of the Natural signals can be expressed in compressed form, in terms of their projections on a suitable basis. If we are selecting a proper basis, a large number of projection coefficients will be zero. So these coefficients can be snubbed. If a signal has only K non-zero coefficients in a domain, it is said to be K-Sparse. A signal is said to be compressible if most of these projection coefficients are small enough and can be ignored. So the number of samples required for reconstruction can be reduced considerably.

In CS [6], [7], [8], we are concerned with two matrices - the incoherence matrix which is used to sample the signal of interest (measurement matrix) and the matrix to represent a suitable basis, in which the signal of interest will be sparse (representation matrix). Within the CS framework, low coherence between these two matrices translates to fewer samples required for reconstruction of signal. The measurement process is non-adaptive in that, it does not depend in any way on the signal x(t). From the random measurements, the signal can be recovered using Convex Optimization Methods or Greedy Algorithms.

CS combines both the sampling and compression into single step by measuring minimum samples that contain maximum information about the signal. It eliminates the need to obtain and store large number of samples only to drop most of them because of their negligible values as in traditional sampling. So this approach is far more efficient in data acquisition. This can offer more benefits in the fields of data communication; data storage, data management and data analysis as the number of signals will be lesser and less data will be generated from each measurement set up. This will result in the reduction of data collection time and energy consumption. This will also extend the battery life of the sensor networks.

METHODOLOGY

This work has been done as a preliminary study to identify the potentiality of CS in the sensor networks environment. Here we are trying to reconstruct an image with lesser number of samples using the CS methods. As the number of samples required for the reconstruction is reduced, the image can be represented with fewer coefficients and the storage and communication needs will be reduced considerably. As images are considered to be one of the most complicated sensor output data, this result can be used to generalize the fact that for any type of sensor networks, which produces sparse signals, we can reduce the communication overheads by applying the CS methods.

Software – MATLAB 7.0.1

Reconstruction Algorithm – Orthogonal Matching Pursuit (OMP)

We have used Orthogonal Matching Pursuit algorithm [9], [10] for the reconstruction of the signals, which belong to the class of Greedy Algorithms. Greedy algorithms are a group of powerful algorithms for reconstructing sparse representations, which rely on iterative approximation of the signal coefficients. This algorithm decomposes a signal into a linear expansion of functions that constitute a redundant dictionary. This algorithm was introduced by Mallat and Zhang [10]. OMP selects dictionary elements in a greedy fashion that best approximate the signal, at each iteration of the algorithm. This algorithm addresses sparsity preservation of the signal in the dictionary directly and completely recovers the elements of the signal that are described by the dictionary elements.

RESULTS AND DISCUSSIONS

Here we have taken the two famous standard test images – Circbw and Cameraman, in which the signal processing is performed using the OMP algorithm and reconstructed the images with different compression percentages of 100%,90%,80%, 70%, 60%, 50%, 40%, 30%, 20% and 10% when comparing with Shannon's rate. Even though the image quality is deteriorating with lower compression percentages, we were getting satisfactory reconstruction of the image till 30% with all important details and below that the images lacks some important details. This is giving an inference that we can reconstruct sparse signals satisfactorily with sub-Nyquist sampling rate. If it is possible for a sparse image, we can definitely apply this to any other sensor network signals, which are sparse.

As per the analysis, the CS algorithms are able to give satisfactory output of the input sparse signal with around 30-40% of samples out of the Nyquist sample spectrum for the Sensor signal. So it can provide better results for still lower rates, when considering the data traffic. If CS will come in to the lead role, we can reduce the data processing and communication volume to still better lower levels. So we can limit the flooding of data and can increase the processing speed with less processing, storing, communication and hardware requirements. So we can generalize the fact that for the sensor networks we can apply the various CS algorithms to resolve the issues concerned with the data deluge problems if the concerned signal is sparse or can be made sparse by converting in to a suitable domain.

Besides enabling sub-Nyquist measurement, CS possesses a lot of unique advantages. CS measurements are universal and the same random matrix works simultaneously with many sparsifying bases with high probability. Here we don't require any knowledge of the tinges of the data being picked up. CS is robust in that the measurements have equal priority due to the incoherent nature of the measurements, contrasting to the Fourier or wavelet coefficients in a transform encoder. So if we lost one or more measurements, the whole reconstruction process will not be corrupted. This enables a gradually better reconstruction of the data as more measurements are acquired. CS places most of its computational complexity in the recovery system only, which normally will have more extensive computational resources when compared with the input measurement system.

So despite the conventional approach, the novel approach of the CS will support to deal with the challenges involved in Industrial sensor Networks with such high-dimensional and voluminous data.

CONCLUSION

We are in the midst of an era of a digital revolution that is driving the development of modern types of high resolution industrial sensing systems along with the information explosion. The amount of data generated by these systems has been rising rapidly. The traditional methods of reconstructing the signals from the measured data are based on Nyquist/Shannon sampling theorem. But, in most of the applications, the resulting Nyquist rate is enormous, which ends up with too many samples. Also it imposes so many constraints to the communication system as discussed above.

CS is a new signal processing paradigm, which can be used to solve these limitations of traditional sampling for compressible signals. Thus CS can be applied for the reconstruction of sparse or compressible signals and can reduce the sampling rates considerably providing power, hardware complexity, storage, communication and cost advantages for the system. Also most of the signals in nature are sparse in some domain. Hence by converting the signal into a suitable domain will increase the range of signals for which we can apply the technique of CS. So CS sensing can play an effective role in managing the huge data associated with the industrial sensor networks.

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