Compressive Sensing Approach in the Table Grape Cold Chain Logistics

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Abstract—**A precise and accurate monitoring of different parameters such as temperature, relative humidity or gas level, in cold chain logistic, is important for preserving the quality of the transported goods. Constant parameters monitoring requires a large number of sensors and a large storage capacities, and can cause overloading during the communication. Therefore, in this paper we have observed an under-sampled signal describing the level of CO_2 in the cold chain, with an aim to recover the missing information by applying the Compressive Sensing approach. The reduced number of measurements will lead to decreased number of required sensors, reduced storage demands and will speed up the communication.**

Keywords-component; cold chain logistics, compressive sensing, reconstruction algorithms, table grape

I. Introduction

In the era of the globalization, the distances between regions become much smaller in the sense of communication and data exchange. However, the physical distance can still be very challenging, especially when we consider transportation of goods between distant world regions. The goods can be exposed to complex transportation process and thus, the cargo can be more or less damaged. The damages may appear by sudden change of certain parameter during the transportation, such as temperature, humidity, gas atmosphere, etc. In order to provide undamaged transportation in medical, pharmaceutical and food industry, the cold chain logistics are used [1]-[5].

The cold chain denotes a supply chain that is temperature-controlled. It includes the transportation of the goods, whose quality is usually temperature dependent, by applying physical and logistical methods for their protection during the transport. Changes in the temperature or other factors can cause damage of the cold chain goods (goods such as frozen food, agricultural products, various chemicals, medical drugs, etc.) and therefore, goods need to be held in cold stores as longer as possible [1]-[5]. Transportation is usually done in the cooled trucks, specialized cooled cargo ships, or by airplanes.

The temperature, humidity and gas atmosphere are important parameters in a cold chain logistics. The gas atmosphere is monitored mainly in terms of the levels of oxygen and carbon dioxide. A cold chain is the best way to preserve the quality of products, and in order to achieve this, the CCL parameters should be constantly monitored. The tolerances related to the parameters to be monitored exist, and they are dependent on the actual product being transported.

In this paper, our focus is on the signal describing the changes in the CO_2 level, in the table grape chain logistics. Specifically, the CO_2 level signal during the grape transportation from Zhuolu to Tianjin, China, has been observed. Variations in temperature, humidity, CO_2 level and other parameters, can affect the goods quality, since these variations can lead to changes in chemical processes into the food. CO_2 level varies in different stages of the transportation: when goods are put in the cold storage, during the transportation, unloading, etc. Transportation can lasts for several days, and the parameters needs to be monitored almost in the real time during the whole process. It requires large number of wireless sensors to be attached and active, which leads to traffic and communication systems overloading. Therefore, in this paper we exploit the possibility to use the Compressive Sensing (CS) approach to collect data and to transmit smaller number of signal coefficients to the end user. It is done with a goal to decrease the storage requirements and to speed up the communication, but to be able to recover the missing data and to perform the monitoring without losing the quality of the final information. Traditional methods used for monitoring require a large number of sensors that collect data in real-time. This may lead to communication systems overloading and reduce transmission efficiency [1].

CS is widely studied approach for signal sampling, providing an alternative way of signal acquisition and allowing successful signal analysis from the small set of the available signal samples [6]-[12]. CS is based on the various mathematical approaches for the reconstruction of the missing information [12]-[18]. The approaches depend on the signal nature, but also differ for 1D and 2D signals. Here, we will apply the 2D reconstruction approach [18]-[23], that will be explained through the text.

The paper is structured as follows: Section II presents cold chain logistics and parameter monitoring. Section III contains details related to the CS reconstruction procedure that is applied, while the experimental validation is given in the Section IV. Conclusion is in the Section V.

II. Cold Chain Logistics

Cold Chain Logistics (CCL) [1]-[5] involves the transportation of various products in the temperature controlled conditions. A large amount of products (food, medical drugs, etc.) are being damaged during the transport and have poor quality at the final destination, caused by changes in temperature, gas atmosphere, humidity, etc. during the transport. Various environmental factors affect quality and safety of perishable foods throughout the supply chain [2]. When considering the food CCL, levels of CO_2 and O_2 concentrations affect fruit metabolism and fruit shelf life [5]. That is the reason why constant and efficient gas atmosphere monitoring is important in food CCL.

Visibility and controllability in CCL is achieved by designing a system that will be able to monitor the whole process and to provide information between customers and suppliers. In that sense, technologies such as sensors, Radio Frequency Identification (RFID) and wireless networks are used.

In this paper our focus is on the CO_2 level monitoring in CCL of the grape. Having in mid their moisture content, table grapes can be easily damaged by pathogen infection, caused by changes in air quality, temperature and humidity during the transport. As transportation may last for several days, the real time monitoring can be time and power consuming. Therefore, the possibility to apply the CS approach to lower the amount of information required for efficient monitoring of the parameters of interest. Here, we assume two scenarios: 1) we have small signals recorded on daily of half-daily basis or in some other time interval, and 2) we deal with the whole signal (recorded during the whole CCL process). We try to recover the signals from the small set of randomly chosen samples that are sent to the end user. The original signal of interest is reconstructed from the received signal parts at the end user side. Note that the end-user will not have information in the real-time, but with the acceptable delay. The delay is caused by waiting sufficient number of samples to be received based on which the signal can be reconstructed.

III. CS-BASED UNDER-SAMPLING/RECONSTRUCTION PROCEDURE OF THE COLD CHAIN CO_2 SIGNAL

Until recently, signal acquisition is made according to the Sampling theorem – with a sampling frequency at least two times maximal signal frequency. After the acquisition, compression is common step in majority of the applications. CS aims at performing the compression during the acquisition. It is achieved by acquiring sparse signals according to the CS rules – random sampling showed to be the common CS sampling approach. The CS signal acquisition rate is much smaller than that required by the Shannon-Nyquist sampling theorem. However, much smaller number of samples is available in compare with the number of samples produced by sampling according to the sampling theorem. Various algorithms that recover signal information are developed. Some of them are more complex but also more precise, such as convex optimization [7], [13], [21], but there are also greedy approaches [15], [15], threshold based solutions [16], [21], etc.

An N-dimensional signal could be written in terms of its transform domain representation, as:

$$\mathbf{f} = \sum_{i=1}^{N} \mathbf{F}_i \psi_i = \mathbf{\Psi F}, \tag{1}$$

where $\mathbf{F}_i$ is weighting coefficient, ψ_i is basis vector, $\mathbf{\Psi}$ denotes $N\times N$ transform matrix. Domain $\mathbf{\Psi}$ is domain of sparsity – here, the signal is represented with small number of non-zero coefficients. If we model random acquisition of the M signal measurements (where $M<<N$ holds) with the measurement matrix $\mathbf{\Upsilon}$ (of size $M\times N$), then the vector of the available signal samples $\mathbf{f}_a$, of $M\times 1$ size, is modeled as:

$$\mathbf{f}_a = \mathbf{\Upsilon f} = \mathbf{\Upsilon\Psi F} = \mathbf{\Omega F}, \tag{2}$$

where $\mathbf{\Omega}$ is a CS matrix. CS deals with the undetermined systems of equations, such as (2), since there is smaller number of equations then unknowns. Optimal solution, i.e. the most sparse one among the infinite number of possible solutions, is obtained through an optimization algorithms usually based on norm-minimizations. Commonly used is the ℓ_1 norm minimization [11], [21]:

$$\min \|\mathbf{F}\|_1 \text{ subject to } \mathbf{f}_a = \mathbf{\Omega F}. \tag{3}$$

The observed CO_2 level signals do not exhibit sparsity property neither in time, nor in the frequency domain. Commonly applied 1D reconstruction algorithms fail to provide an accurate signal recovery, even if set of the available samples is large. Therefore, the reconstruction in 2D domain is proposed, by using the Total Variation (TV) minimization which are usual method for the reconstruction of the under-sampled 2D data [21]-[23]. It is based on the image gradient minimization.

Firstly, 1D CO_2 level signal $\mathbf{f}$ is reshaped into the matrix $\mathbf{I}$ that will act as an image to be under-sampled and recovered. The reshaping is done column-wise and quadratic matrix is obtained:

$$\mathbf{I} = \rho\left(\mathbf{f}, \sqrt{N}, \sqrt{N}\right), \tag{4}$$

where ρ denotes the vector-matrix conversion operator. The image is of $\sqrt{N}\times\sqrt{N}$ size. In the case when $\sqrt{N}$ is not an integer, the signal is zero-padded in order to obtain an integer value for $\sqrt{N}$. As a domain of sparsity, a two dimensional discrete cosine transform (2D DCT) domain is considered.

Let us now denote a set of image measurements as $\mathbf{D}_a$, taken from the 2D DCT domain, in a random manner from the zig-zag reordered 2D DCT coefficients (the matrix $\mathbf{\Psi}$ corresponds to the 2D DCT matrix). The image is reconstructed from the acquired measurements by solving an optimization problem. The optimization problem is defined as:

$$\min_{\mathbf{F}} \Im(\mathbf{F}) \text{ subject to } \mathbf{f}_a = \mathbf{\Omega F}, \tag{5}$$

where $\Im$ denotes TV operator, defined as a sum of the magnitudes of discrete gradient at each point:

$$\Im(\mathbf{F}) = \sum_{i,j} \|d_{i,j}\mathbf{F}\|_2 , \tag{6}$$

where the gradient approximation for the pixel ij, $d_{i,j}$, is described as:

$$d_{i,j}\mathbf{F} = \begin{bmatrix} F(i+1,j) - F(i,j) \\ F(i,j+1) - F(i,j) \end{bmatrix}. \tag{7}$$

IV. Experimental Results

In the sequel, the reconstruction of the under-sampled CO2 level signals is considered. Two cases are observed and described in the sequel. The temperature, humidity and CO_2 level in the table grape cold chain were acquired and monitored by using the sensor AM2322 (AOSONG, Guangzhou, China) for digital temperature and relative humidity measurements and CO_2 sensor ATI (analytical technology incorporated, New York, NY, USA). The range of temperature, humidity and CO_2 were from -40 ℃ to 80 ℃, 0% to 99.9%, and 0%-5% respectively, and the accuracy was ±0.3℃, ±2% and ±0.1%.

Example 1: CO_2 signal during the transportation process

In the first example, part of the CO_2 signal, related to the changes during the transportation process only, is used. The 1D signal is converted into the image, according to equation (4). Then, the 45 % of the image samples is chosen randomly and served as available samples used in the reconstruction process. After image reconstruction, the 1D signal is extracted using procedure that is reverse to image forming. The original and reconstructed images, as well as original and reconstructed signals are shown in Figure 1.

The zoomed regions of the original and reconstructed signals are also shown. Mean square (MSE) and relative mean square (RMSE) errors of the reconstruction, for different number of available samples, are shown in Table 1.

Example 2: CO_2 signal recorded during the whole process

In the second example, the whole CO2 level signal is observed. It includes parts when grape is put in the cold storage, cargo, transport and unloading. As in the previous example, the 1D signal is converted to the image firstly, and then the 45 % of the image samples is chosen randomly. The reconstruction is done using the acquired samples and the 1D signal is extracted. The original and reconstructed images, as well as original and reconstructed signals and their zoomed regions are shown in Figure 2, while MSEs and RMSEs for different number of available samples, are shown in Table 1.

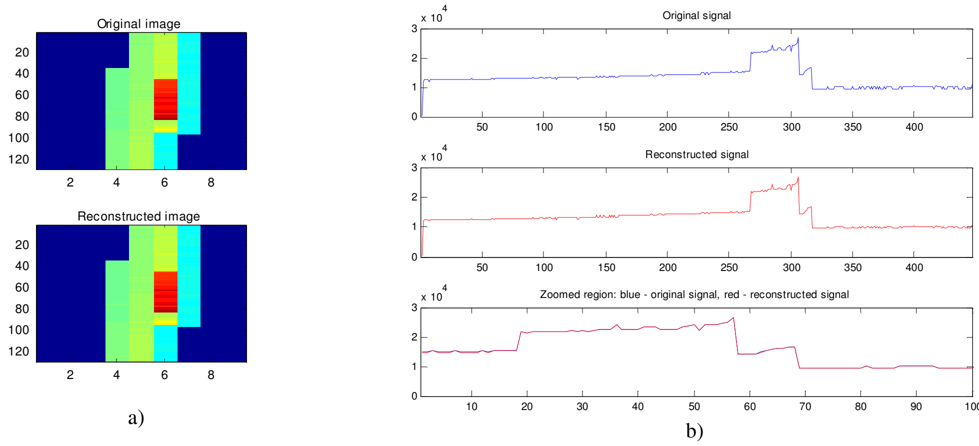

Figure 1. a) First row: original image; Second row: image reconstructed using 45 % of the available samples; b) First row: original signal; Second row: signal reconstructed using 45% of the available samples; Third row: Zoomed regions of the original signal –blue and reconstructed signal – red

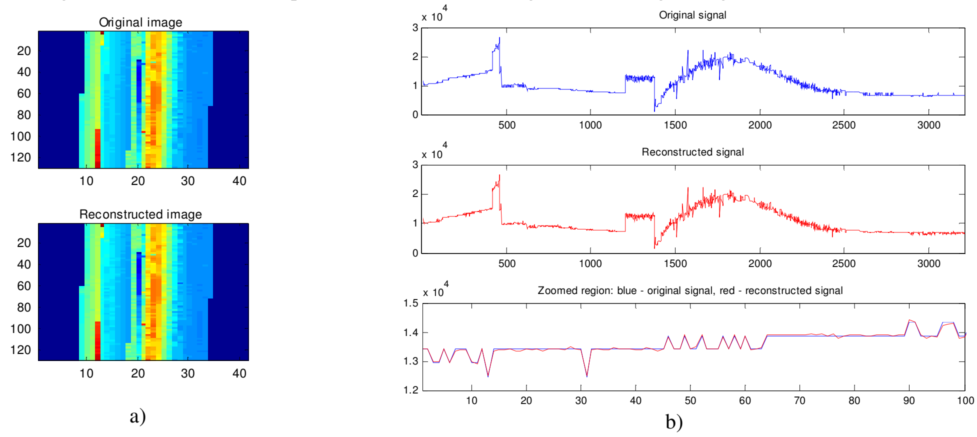

Figure 2. a) First row: original image; Second row: image reconstructed using 45 % of the available samples; b) First row: original signal; Second row: signal reconstructed using 45% of the available samples; Third row: Zoomed regions of the original signal –blue and reconstructed signal – red

TABLE I. MSEs and RMSEs between original and reconstructed signals for different percentage of available samples

Percentage of the available samples	*Signal from example 1: MSE (RMSE %)*	*Signal from example 2: MSE (RMSE %)*
30%	18.38 ($3.56*10^{-4}$)	$9.51*10^{3}$ (0.037)
35%	16.29 ($3.16*10^{-4}$)	$2.89*10^{3}$ (0.0112)
40%	14.71 ($2.85*10^{-4}$)	$1.07*10^{3}$ (0.0041)
45%	12.75 ($2.47*10^{-4}$)	532.04 (0.0021)
50%	12.03 ($2.33*10^{-4}$)	239.25 ($9.26*10^{-4}$)
55%	10.7 ($2.07*10^{-4}$)	149.95 ($5.8*10^{-4}$)
60%	10.24 ($1.98*10^{-4}$)	133.57 ($5.17*10^{-4}$)
65%	9.67 ($1.88*10^{-4}$)	130.39 ($5.05*10^{-4}$)
70%	9.16 ($1.77*10^{-4}$)	107.6 ($4.16*10^{-4}$)

V. CONCLUSION

The possibility to apply CS approach in the table grape cold chain logistic is considered in the paper. The parameter that is observed is the CO_2 level signal, within two cases: first - during the grape transportation and second - during the whole CCL process. It is shown that the signals can be reconstructed if only 45 % of the total number of samples is available. The reconstruction quality is measured by MSE and RMSE. Here, the 2D reconstruction is applied. It is done by firstly converting the signal into an image and then under-sampling. The same approach can be applied in the real-time monitoring. The proposed method may have benefits in reducing the number of sensors and avoiding communication systems overloading, that is common in traditional monitoring approach.

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