Compressive Sensing based image processing in TrapView pest monitoring system

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Abstract – Missing information in image can be recovered by using the principles of lower sample rate methods, such as Compressive Sensing. This method can, at the same time, recover the missing information in the signal and do the compression of the original data. Lowering the sample rate is especially suitable for natural images in applications where minor visually loss of fidelity is acceptable. The goal is to achieve a substantial reduction in bit rate and image size. In this paper we analyze the performance and quality of Compressive Sensing approach applied on images captured by the TrapView automated camera station for pest detection. The reconstruction at the decoder side, if only small number of image samples is available, is tested in the paper. This is done with the goal to test different approach in image capturing – acquisition of only part of digital data, and then the reconstruction of the uncaptured/missing part, in order to obtain the original signal. This leads to decreasing the bit rate and transferred data volume through the mobile network, from the station to the TrapView cloud centre. It is shown that CS can provide a good quality image reconstruction with significantly reduced number of samples. The theory is tested using real images, obtained by the TrapView camera.

I. INTRODUCTION

The alternative ways for signal sampling are intensively studied in the recent years. Traditional sampling based on the Shannon-Nyquist theorem is time consuming and requires large number of signal samples to be stored and transmitted. This can be a limiting factor in applications that deal with high resolution images. Compressive Sensing (CS) [1]-[4] approach can, under certain conditions, ensure successful reconstruction of such images using significantly smaller number of samples, compared to the conventional approach. CS uses random sampling strategy and powerful mathematical algorithms to reconstruct an under-sampled signal [5]-[10].

Special CS conditions that need to be satisfied in order to provide high accuracy signal reconstruction are signal sparsity and incoherent acquisition procedure [1]-[3]. Namely, the signal has to be sparse in a certain transform domain, meaning that the information about the signal needs to be concentrated within a small number of coefficients. Incoherence property should provide linearly independent measurements and assures signal reconstruction from a small number of acquired samples.

From the acquired measurements, signal is reconstructed by using different optimization techniques, which can be based on various norms minimization. The optimal solution in a large number of applications is provided by using ℓ_1-norm minimization, for 1D signals, while in image processing applications, the commonly used optimization technique is the Total Variation (TV) minimization [3], [6]-[11]. Here, we will apply the CS approach with TV minimization in pest monitoring system, in order to speed up processing and decrease memory requirements for storing pest images.

TrapView automated pest monitoring system [12] utilizes automated traps that regularly send captured images of caught insects to the TrapView cloud. Therefore, TrapView is a platform for an early warning of the occupancy of traps. System also provides automated pest recognition, pest occurrence statistics and manual review of the taken pictures.

In the fields/orchards, where matrix monitoring concept is being implemented, the effort to increase the number of monitoring points leads to the Trapview automated traps being combined with conventional traps. This results in a need for a tool that allows the end users to optimize captured image prior sending over mobile network, thus reducing cost for communication and storing captured images.

Standard TrapView captured image is around 2MB large, and one system in field with 1000 automated camera stations normally generates 1TB volume of captured data per year. All the captured data should be sent over mobile network to the TrapView cloud in real time, which needs performances and proper bandwidth of mobile network, which is not always achievable out of the urban centers.

In this paper, we have explored the possibility to use CS to decrease the amount of relevant image data, but still to keep the quality of the final reconstructed image, in order to be successfully post-processed. Post-processing of the images is, in fact, counting the number of insect specimens and it is based on algorithms specialized for counting. Therefore, it is of great interest to save the quality of the reconstructed image as better as is possible, in order to minimize the possibility of error occurrence during counting. CS, as an emerging approach for reconstruction of the under-sampled signal, has been used as a tool for achieving both, compression and reconstruction of the images captured by the system.

The paper is organized as follows: Second part is theoretical background on the CS approach. Third part describes CS approach in image reconstruction, and its application in the TrapView pest monitoring system. Concrete results, using images captured by the TrapView system, are shown in the fourth part. Concluding remarks are given next, as well as literature overview.

II. Theoretical Background

Signal acquisition process in real applications is mainly done according to the sampling theorem. In order to be transmitted and stored, the data are compressed by using algorithms for data compression that can be computationally very complex. CS approach brings an idea to achieve compression in sense of the acquisition, and to deal with far less data than we usually do. Consequently, it is important to develop algorithms for the reconstruction of compressive sensed data, and certain solutions have already been proposed in the literature.

In CS scenarios, the acquisition procedure is performed by using small set of randomly chosen signal samples. This means that the signal acquisition rate is much smaller than that required by the Shannon-Nyquist theorem. However, certain conditions have to be satisfied in order to apply CS approach, such as incoherence of measurement process and signal sparsity. The sparse representation means that the information about the signal is condensed into few non-zero coefficients in the transform domain. An *N*-dimensional signal could be written in terms of its transform domain representation, as [3], [13], [14]:

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

where $\mathbf{X}_i$ is a transform domain coefficient, ψ_i is a basis vector, $\mathbf{\Psi}$ denotes $N\times N$ transform matrix and $\mathbf{X}$ is the signal in $\mathbf{\Psi}$ domain. The acquired measurements are stored in vector $\mathbf{y}$. Hence, we can write:

$$\mathbf{y} = \mathbf{\Phi}\mathbf{x} = \mathbf{\Phi}\mathbf{\Psi}\mathbf{X} = \mathbf{A}\mathbf{X}, \tag{2}$$

where $\mathbf{\Phi}$ is a measurement matrix and $\mathbf{A}$ is called a CS matrix.

The signal is reconstructed by solving the set of linear equations defined by (2). As there are *M* linear equations with *N* unknowns, this system is undetermined and can have infinitely many solutions. Therefore, the optimization algorithms should be used to find the solution of the problem, which is in fact, finding the sparsest solution of the system (2).

Commonly used algorithms for reconstruction of the under-sampled signals are based on minimization of different norms (commonly used is ℓ_1 - norm minimization) [2], [3], [13]-[16]. From the class of greedy algorithms, the Orthogonal Matching Pursuit (OMP) is the most commonly used. OMP is an iterative procedure that, in each iteration, searches for the maximum correlation between the measurements and the matrix [17]. There are also gradient based algorithms, such as [8], [18], [19] and threshold based algorithms [20], [21]. Regarding the reconstruction of natural images, different approaches are used. One of the commonly used approaches is known as the TV minimization, and it is based on the optimization problem defined using image gradient [11], [22]-[24]. Therefore, in this paper we will use TV minimization approach for pest images reconstruction.

III. Reconstruction of the TrapView images using the CS approach

Having in mind that natural images do not show sparsity property neither in the frequency nor in the spatial domain, for its reconstruction from a relatively small number of available samples, ℓ_1 - norm minimization is not very suitable. There are an alternative methods for image reconstruction and they are based on the fact that the image gradient is sparse. Therefore, minimization is reduced to the ℓ_1 - norm of the gradient minimization (TV minimization). For most real signals, TV minimization shows better results compared to the minimization based on the ℓ_2 - norm. TV method proved to be very efficient in the regularization of the image, without damaging the edges of objects in the image (i.e., keeping the edges of objects).

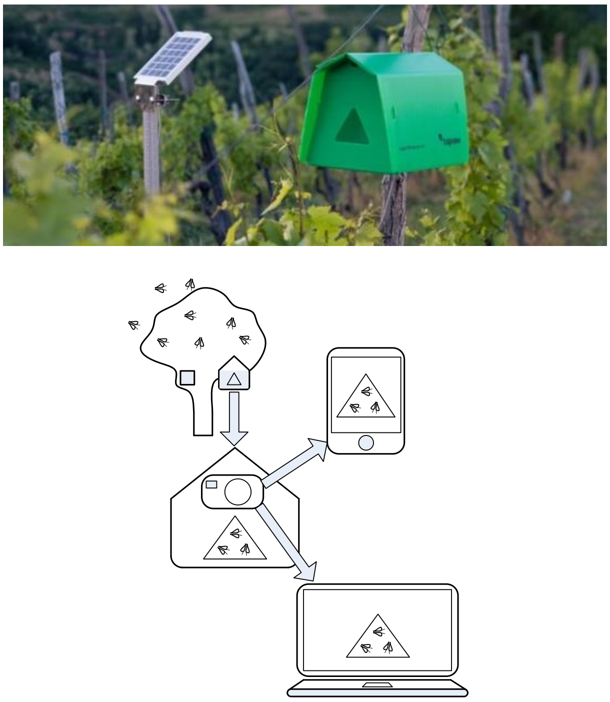


Figure 1: TrapView system

Starting from (2), and having available only the vector of measurements **y**, the goal is to estimate/reconstruct the entire image from the available samples in **y**. The measurements in real applications may also contain certain amount of noise, i.e.:

$$\mathbf{y} = \mathbf{AX} + \mathbf{n}, \tag{3}$$

where **n** is an additive noise. In order to solve (3), the regularization function can be defined as:

$$\Psi_{\lambda}(\varepsilon) = \arg\min_{\mathbf{X}} \frac{1}{\mu}\Phi_{reg}(\mathbf{X}) + \frac{1}{2}\|\mathbf{y} - \mathbf{AX}\|^2, \tag{4}$$

with $\Phi_{reg}(\mathbf{X}) = \sum_i \|\nabla_i \mathbf{X}\|$ for TVL1 problems. The TV of the signal **X**: $\sum_i \|\nabla_i \mathbf{X}\|$ represents a sum of the magnitudes of discrete gradient at each point, and can be defined as:

$$\nabla_{i,j}\mathbf{X} = \begin{bmatrix} \mathbf{X}(i+1, j) - \mathbf{X}(i, j) \\ \mathbf{X}(i, j+1) - \mathbf{X}(i, j) \end{bmatrix}. \tag{5}$$

Let us now define an acquisition procedure for the pest monitoring system TrapView. System is illustrated in Figure 1. A trap is placed in the field (orchard, vineyard) in order to catch targeted insects. At the same time, the system takes pictures of what was caught in the trap and send them to the cloud. The pictures are fed to the end user either via mobile or via web. Therefore, we have original image which can be under-sampled and such under-sampled image is sent to the web/mobile application.

The samples from the collected images are taken from the DCT domain, and are consisted of the two parts: low frequency coefficients of length K_1 and coefficients from the rest of the DCT plane K_2:

$$\mathbf{y} = \mathbf{y}_1 + \mathbf{y}_2, \tag{6}$$

where $\mathbf{y}_1$ are low frequency DCT coefficients, and $\mathbf{y}_2$ are the rest of the coefficients. During the acquisition procedure, low frequency coefficients are collected first, as they contain most of the image energy which is of great importance for preserving image quality. The TV minimization problem to be solved, is then defined as:

$$\min_{\mathbf{X}} \mathrm{TV}(\mathbf{X}) \;\; \textit{subject to} \;\; \mathbf{y}_1 + \mathbf{y}_2 = \mathbf{AX}, \tag{7}$$

Or, in discrete form:

$$\mathrm{TV}(\mathbf{X}) = \sum_{i,j} \sqrt{(\mathbf{X}_{i+1,j} - \mathbf{X}_{i,j})^2 + (\mathbf{X}_{i,j+1} - \mathbf{X}_{i,j})^2}\,. \tag{8}$$

Such automated insect monitoring approach reduces travel and time costs, especially in cases when there is need for monitoring large areas, consisting of several hundreds of square kilometers. Images are sent on daily basis to the end user. However, as images are of high resolution, it would be of great importance to reduce image size in order to speed up upload and download procedure by the end user.

IV. Experimental results

In the sequel, under-sampling and reconstruction of the images recorded by the TrapView camera, at the end user point, is done by using the CS approach.

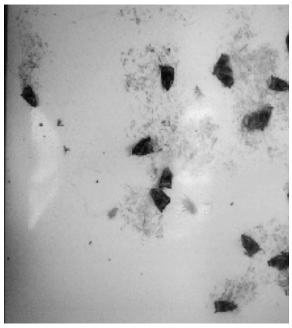
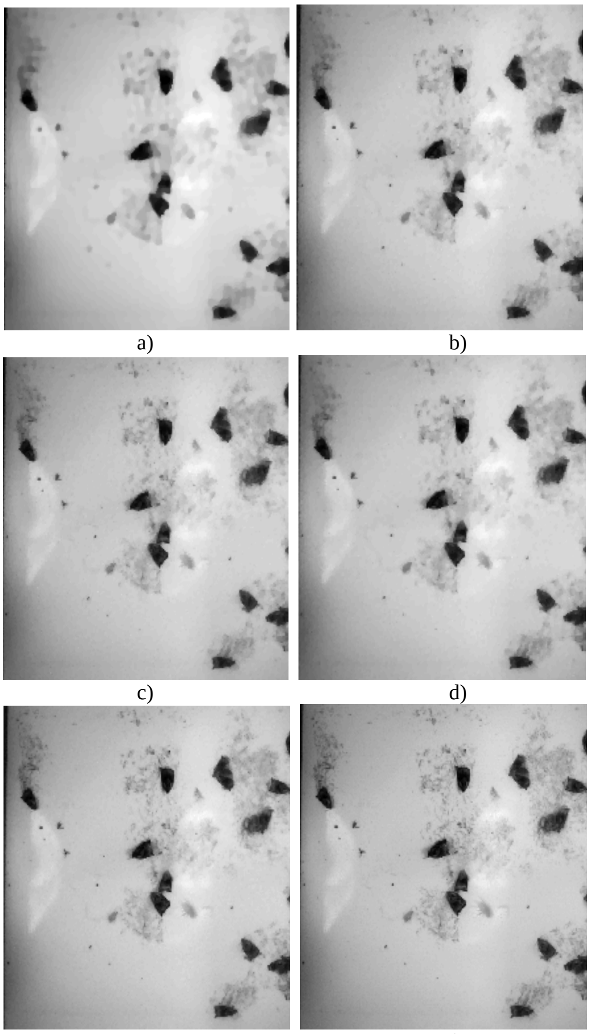


Figure 2: Original image



a) b) c) d) e) f)

Figure 3: Reconstructed images from the beginning phase, using different number of measurements: a) 2.7%, b) 10.68%, c) 15%, d) 21%, e) 30.14%, f) 39.67% of the total number of samples

We have observed the images collected at different phases. Firstly, the beginning phase is tested. Figure 2 shows original image recorded in this phase.

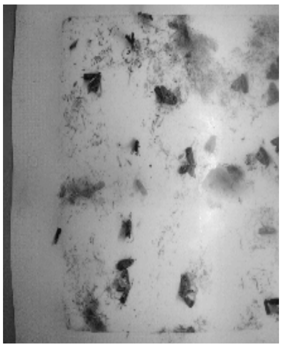
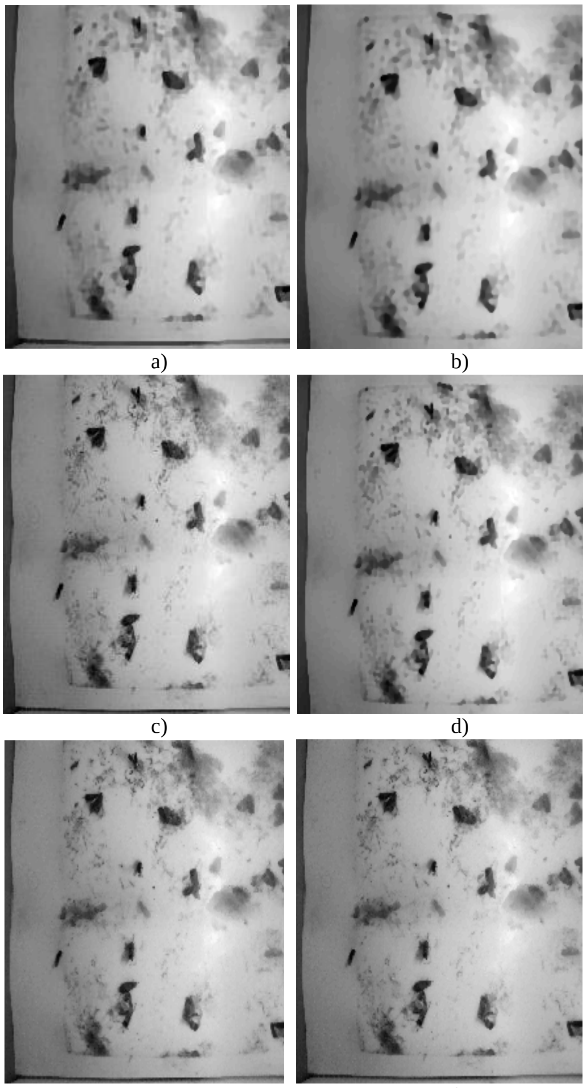


Figure 4: Original image



a) b) c) d) e) f)

Figure 5: Reconstructed images using different number of measurements: a) 2.7%, b) 10.68%, c)15%, d) 21%, e) 30.14%, f) 39.67% of the total number of samples

It can be seen that the adhesive tape is relatively clear and there is small number of collected insect specimens. The reconstruction is done by using different number of available samples: from around 3% to around 40% of the total number of samples. Certain number of the low-frequency coefficients is taken in every considered case, having in mind that important information about the image is concentrated mostly in these coefficients. The rest of the coefficients are randomly selected from the rest of the image samples. The reconstructed images are shown in Figure 3. It can be seen that, even with around 3% of the available samples, the image can be reconstructed with high quality.

The same procedure is repeated with an image from the mature phase, i.e. from the phase when the adhesive tape is densely filled with insect specimens. Original image is shown in Figure 4, while Figure 5 shows the reconstructed images. Number of measurements is from around 3% to around 40% of the total number of samples.

Quality of the images is tested by visually observing original and reconstructed image, and by measuring peak signal to noise ratio (PSNR). Values of the PSNR, for different number of measurements used and for images from the both phases, are shown in the Table 1. It can be seen that PSNR for the first image (beginning phase), is slightly higher compared to the second image (mature phase). The reason for this is smaller number of insect specimens present in the first image, which leads to its higher sparsity.

It can be seen that the image can be reconstructed with almost the same quality as the original image, by using relatively small set of available information. The PSNR around 33 dB is obtained by using 3% of the total number of samples for the images from the beginning phase, and around 11% for the images from the mature phase. Having in mind high PSNR, and by visually comparing the original and reconstructed image, it can be concluded that CS approach will not affect post-processing of the images, i.e., the process of specimens counting. In this paper, we have used frequency domain measurements. It is important to note that measurements can be also used from the spatial domain, depending on the optimization algorithm that is applied.

Table 1: Number of measurements used for image reconstruction and measures of image quality (PSNR) for the images from the both phases

Number of measurements (%)	K1	K2	PSNR (dB) – image 1	PSNR (dB) – image 2
2.7	4000	3000	33.08	31.14
10.68	4000	24000	36.02	33.91
15	4000	35000	36.94	34.88
21	4000	52000	38.08	35.98
30.14	4000	75000	39.30	37.19
39.67	4000	100000	40.56	38.47

V. CONLUSION

The possibility to apply CS reconstruction approach on the images used in pest monitoring system TrapView, is tested in the paper. The reduction of number of acquired samples, and transmission of only small set of collected measurements to the end user, is of great importance in reducing the memory requirements for storing these images. The main idea is to capture not the whole image (i.e. full set of samples), but only a small percent of image samples at the random positions. The image reconstruction by using only this small number of captured information and based on the CS algoritms, is tested. Therefore, the proposed method is not an compression method, but is related to the recovering of the missing information. The images captured at different phases are tested, and they are reconstructed by using different number of available samples (frequency domain measurements are used): from 3% to 40% of the total number of samples. It is shown that the quality of the reconstructed images, i.e. PSNR, is high. In all considered cases, the obtained PSNR is above 30 dB. The CS approach can also be applied in situations when image is spatially under-sampled, which is the topic of our future research.

ACKNOWLEDGMENT

This work is supported by the Montenegrin Ministry of Science, project grant funded by the World Bank loan: CS-ICT "New ICT Compressive sensing based trends applied to: multimedia, biomedicine and communications". The authors are thankful to Mr. Matej Štefančič, the director of EFOS, for providing us test images and support for writing the paper.

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