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# Video Surveillance Using Adaptive-Rate Compressive Sensing

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**Abstract:** ***We provide a novel adaptive rate compressive sensing technique for video surveillance with the use of side information .This method exploits the advantages of low resolution information of an image. Unlike the current compressive sensing techniques we consider the upper bound on the number of significant coefficients which contains the image in the video sequence to be unknown. We develop our method based on background subtraction using single pixel camera. For each image in the video sequence the proposed technique assign a set of compressive sensing measurements to adjust from image to image***

**Keywords:** Compressive sensing, background subtraction**.**

## 1. Introduction

Visual surveillance needs collection of large amount of data in search of information contained in small sequence of the video. This often requires wastage of large amount of resources. Without such foreground information the surveillance of video is useless .Since it is unknown when these unwanted sequences will appear many systems are forced to gather the same amount of data without considering the scene content. The resources are wasted in collecting the unwanted data in the case of this static method. But it is not evident how to collect the useful date without wastage of resources since the instants of scene activity is unknown. If the information is available beforehand the data can be collected only for that times when foreground objects are present. If we have some side information regarding the video real time decision can be made about the scene activity.

The side information can be obtained through two sources. In this paper the scene activity is being determined by availing the observations from a secondary visual sensor. Compressive sensing methods are also used for imaging [2]-[7].

Here the main task of CS is to observe a region with the purpose of obtaining foreground video. By using CS the foreground can confined to small number of pixels. In our approach we use the extra information in order to predict the number of pixels needed in the next frame [1].

## 2. Compressive Sensing

Compressive sensing is a novel theory in sensing of certain class of discrete signals. By CS the signal of interest can be accurately inferred using the measurements acquired by the sensor and it captures fewer measurements than the ambient space in which the signal reside.

A traditional camera uses NxN array of photo detectors in order to produce $N^2$ measurements of gray scale image F. F is vectorised column major as **f** . CS theory suggests that **f** can be determined using far fewer measurements than $N^2$ of them. The compressive measurements records linear combinations of pixel values $\boldsymbol{\xi}=\boldsymbol{\Phi}\mathbf{f}$ where $\boldsymbol{\Phi}$ is the measurement matrix.

Three conditions has to be satisfied for performing CS. First **f** should be sparse or compressible .A vector is said to be sparse if few of its elements are only non-zero, if a vector is said to be s-sparse then there are s non zero elements in that vector. A vector is said to be compressible if its larger magnitudes can be represented by using far fewer measurements and vice versa. Second the measurement matrix should exhibit *restricted isometry property (RIP).* Finally there should be appropriate decoding procedure.

## 3. Background subtraction using compressive sensing

Background subtraction is basically decomposition of an image into foreground and background components. Foreground usually represents the object of interest in the environment of observation. The images that we observe are of NxN size and $X_t$ will denote the image at time instant t. Vectorizing $X_t$ as column major will give $\mathbf{x_t}$ and the compressive measurement process can be represented as $\mathbf{y_t}=\boldsymbol{\Phi}_t\mathbf{x_t}$ at time instant t.

Here we represent $\mathbf{x}_t$ as

$$x_t=f_t+b \qquad (1)$$

where **b** is deterministic static component of each image in the video sequence and $\mathbf{f_t}$ is a random variable.

Considering the work of Cevher *et al.*[9] , the background subtraction in compressive domain can be done. If **b** is known using the model described in (1) and using compressive image measurements the estimate of $\mathbf{f_t}$ can be generated as follows:

$$f_t=\Delta(\xi_t,\Phi_t) \qquad (2)$$

where $\boldsymbol{\xi}_t = \mathbf{y}_t - \boldsymbol{\beta}_t$ and $\boldsymbol{\beta}_t=\boldsymbol{\Phi}_t\mathbf{b}$

For the task of background subtraction using compressive sensing there are several other existing techniques than the one prescribed above as mentioned in the [12],[13].But in this paper the method which is more feasible to adaptive strategy is used.

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## 4. Sensing matrix design

Adaptive rate measurement matrix for the purpose of recovering sparse signals from lower measurements is constructed. The sensing matrix is constructed based on the technique used on the hadamard transform [14].The measurement matrix $\mathbf{\Phi}$ is formed by randomly row-permuting a Hadamard matrix. For a given $M_t$ ,$\mathbf{\Phi}_t$ is formed as a $M_t x N^2$ matrix using the following equation

$$\Phi_t=\sqrt{N^2/M_t}*\Phi_{1:Mt} \qquad (3)$$

Where $M_t$ values will be determined by the adaptive sensing strategy prior to time and $\Phi_{1:Mt}$ corresponds to the submatrix for the first $M_t$ rows. Phase diagrams are used for finding the minimal values of $M_t$.. Given phase diagram is a numerical representation of how useful the generated matrices are for CS. A phase diagram is a function defined over *phase space*. The approximations are made based on the percentage of trials that result in successful signal recovery.

## 5. Low-resolution tracking

This method utilizes much richer form of side information than the random projections. The image is divided into low resolution and high resolution components. The low resolution image is represented as $Z_t$. The low and high resolution images are related by down sampling operation. Consider $t_z$ as the coordinates of a pixel in the image plane of the low-resolution camera. The effect of down sampling operation on coordinates can be defined by using $\mathbf{t_x}$ which denotes the corresponding coordinate in the image plane of the compressive camera. The down sampling factor D=N/L. Each pixel in $Z_t$ maps to the center of a unique DxD block of pixels in $X_t$. The effect of the downsampling operation on image intensity is given by averaging the intensities within the block.

Given $Z_t$ , the tracking of foreground objects is assumed to be possible. At each time index, a zero-skew affine warp parameter $\mathbf{p_t}$ can be estimated that maps coordinates in an object template image, T, to their corresponding in $Z_t$. Markov dynamical system is governing the time evolution of $\mathbf{p_t}$. By using $\mathbf{p_t}$ we can calculate the position of the tracked object's bounding box using the markov's equations. The area of the bounding box specifies the number of foreground components. The formula for the area of a polygon from its corner coordinates is used for tracking the foreground object of interest from the video.

**Figure 1:**Extracted frame from the video sequence.


**Figure 2:**Low resolution tracking of the frame

## 6. Comparison of different data bases

Different video sequences from two data bases are used for the comparison of different image parameters. Equations are derived for the image parameters. There are mainly reference image and the test image used for comparison. Totally there will be four images in the graph. The reference image represents the ideal values of the parameters using equations.

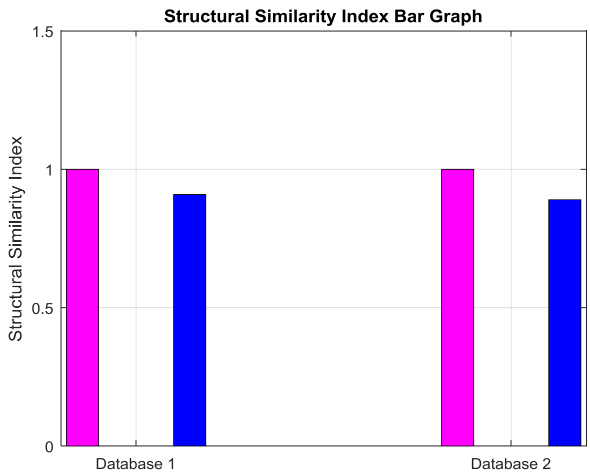

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**Figure 3:**Structural similarity index graph for two databases

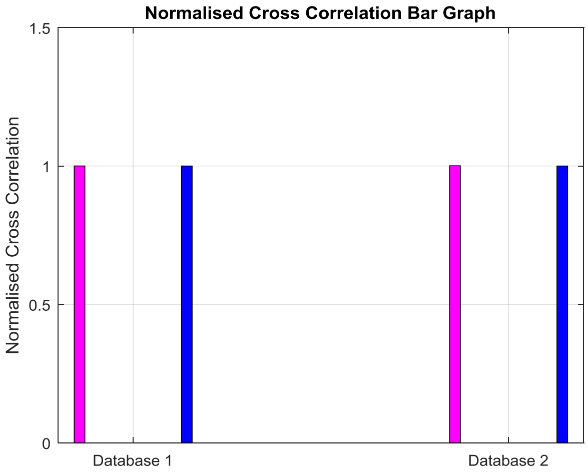


**Figure 4:** Normalized cross correlation graph for two data

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