Compressive Sensing-based Target Tracking for Wireless Visual Sensor Networks

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***Abstract*—**Limited storage, channel bandwidth, and battery lifetime are the main concerns when dealing with Wireless Visual Sensor Networks (WVSNs). Surveillance application for WVSNs is one of the important applications that requires high detection reliability and robust tracking, while minimizing the usage of energy as visual sensor nodes can be left for months without any human interaction. In surveillance applications, within WVSN, only single view target tracking is achieved to keep minimum number of visual sensor nodes in a 'wake-up' state to optimize the use of nodes and save battery life time, which is limited in WVSNs. Least Mean square (LMS) adaptive filter is used for tracking to estimate target's next location. Moreover, WVSNs retrieve large data sets such as video, and still images from the environment requiring high storage and high bandwidth for transmission which are limited. Hence, suitable representation of data is needed to achieve energy efficient wireless transmission and minimum storage. In this paper, the impact of CS is investigated in designing target detection and tracking techniques for WVSNs-based surveillance applications, without compromising the energy constraint which is one of the main characteristics of WVSNs. Results have shown that with compressive sensing (CS) up to 31% measurements of data are required to be transmitted, while preserving the detection and tracking accuracy which is measured through comparing targets trajectory tracking.

***Keywords*—** Compressive sensing, LMS, Surveillance applications, Target tracking, WVSN

I. Introduction

Wireless Visual Sensor Networks (WVSNs) have gained significant importance in the last few years and have emerged in several distinctive applications [1], [2]. Due to the evolvement of new technologies and techniques, there are immediate needs for automated energy-efficient surveillance systems. WVSN has targeted various surveillance applications in commercial, law enforcement and military purpose as well as traffic control, security in shopping malls and amusement parks. Systems have been developed for video surveillance including highway, subway and tunnel monitoring, in addition to remote surveillance of human activities such as elderly or patients care.

Visual sensor nodes are resource constraint devices bringing the special characteristics of WVSNs such as energy, storage and bandwidth constraints which introduced new challenges [3]. In WVSN large data sets such as video, and still images are to be retrieved from the environment requiring high storage and high bandwidth for transmission. Higher complexity of data processing and analysis is also challenging which are all quite costly in terms of energy consumption. Furthermore, wireless channels in surveillance applications are subject to noisy conditions; therefore, detection and tracking reliability within such resource constrained condition is the main challenge when designing WVSN surveillance applications. Energy efficient processing and efficient compression techniques are the strongest candidates to overcome such constrains while transmitting data for WVSN applications and hence minimize energy expenditure [2], [4].

Much work is present in the literature for surveillance applications within WVSNs [5], [6], [7]. Moreover, there is significant literature for target tracking surveillance applications in WVSN. Kalman filtering [8], [9] is relatively the best linear estimator for target tracking. Kalman filters are robust under optimal conditions, otherwise adaptive approaches are needed to solve these problems which can be either computationally expensive or not always be applicable in real time tracking.
Classical active contour [10] for target tracking fails in tracking multiple targets at once so occlusion problems are difficult to solve. In [11], the active contour is modified to resolve occlusion problem by performing merging and splitting when two targets get close together or move apart. However, there is a probability that the target is lost if the displacement of the target between two consecutive frames is large. Least Mean Sqaure (LMS) algorithm is relatively simple, has much lower computational complexity than the original Kalman filters and other adaptive algorithms; it does not require correlation function calculation nor does it require matrix inversions. Moreover, it is suitable for real time image applications [12], [13].

Based on the above literature, to attain a trade off between computational complexity and detection and tracking accuracy in the context of energy constrained WVSN, an image processing scheme is required with optimal pre-processing and post-processing can provide intended target detection and tracking accuracy within energy constraint nature of WVSN. Moreover, high volume data sets acquired in WVSN surveillance applications, should be represented in such a way that it requires optimum storage, energy, and allow reliable transmission due to the constraint on the physical and radio resources. In a surveillance application within WVSN, an image is captured and required to be sampled for storage as well as to be transmitted through wireless channel. According to Shannon-Nyquist sampling theory the minimum number of samples required to accurately reconstruct the signal without losses is twice its maximum frequency [14]. It is always challenging to reduce this sampling rate as much as possible, hence reducing the computation energy and storage. Recently proposed Compressive Sensing (CS) [14] is expected to be a strong candidate to overcome the above mentioned limitations where CS has been considered for different aspects of surveillance applications due to its energy efficient and low power processing as reported in [15], [16]..

CS theory shows that a signal can be reconstructed from far fewer samples than required by Nyquist theory as it is always challenging to reduce the sampling rate as possible, provided that the signal is sparse (where most of the signal's energy is concentrated in few non-zero coefficients) or compressible in some basis domain [17].
In [15], compressive sensing for background subtraction and multi-view ground plane target tracking are proposed. A convex optimization known as basis pursuit or orthogonal matching pursuit is exploited to recover only the target in the difference image using the compressive measurements to eliminate the requirement of any

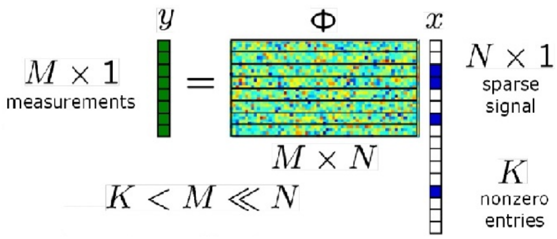

Fig. 1. Compressive sensing measurement process

auxiliary image reconstruction. Other work in compressive sensing for surveillance applications has been proposed in [18], where an image is projected on a set of random sensing basis yielding some measurements. In this paper, the impact of CS is investigated in designing target detection and tracking techniques for WVSNs-based surveillance applications, without compromising the energy constraint which is one of the main characteristics of WVSNs. CS is expected to reduce the size of sampled data with low complexity processing due to its low power simple process [17], hence saving space, energy of processing and transmission as well as channel bandwidth. Hence, a compressive sensing-based single/multi target tracking using LMS is proposed which is expected to reduce energy consumption, space requirement and communication overhead, with acceptable tracking reliability which will be represented as minimal mean square error (MSE).

The rest of the paper is organized as follows, Introduction to CS is presented in Section II. Section III presents the proposed system model. The proposed technique for CS-based target tracking is given in Section IV. Simulations and results are provided in Section V and finally the conclusion in Section VI.

II. Compressive Sensing theory

Suppose image X of size $(N \times N)$ is K-sparse that either sparse by nature or sparse in $\boldsymbol{\Psi}$ domain, CS exploits the sparsity nature of frames, so it compresses the image using far fewer measurements [19], [17], [20]. Although, it is not necessary for the signal itself to be sparse but compressible or sparse in some known transform domain $\boldsymbol{\Psi}$ according to the nature of the image, smooth signals are sparse in the Fourier basis, and piecewise smooth signals are sparse in a wavelet basis. $\boldsymbol{\Psi}$ is the basis invertible Orthonormal function of size $(N \times N)$ driven from a transform such as the DCT, fourier, or wavelet, where $K \ll N$, that is, only K coefficients of $\boldsymbol{x}$ are nonzero and the remaining are zero, thus the K-sparse image $\boldsymbol{X}$ is compressible. CS then guarantees acceptable reconstruction and recovery of the image from lower measurements compared to those required by shannon-Nyquist theory as long as the number of measurements satisfies a lower bound depending on how sparse the image is. Hence, $\boldsymbol{X}$ can be recovered from measurements of size M where $M \geq K \log N \ll N$. Eq.(1) shows the mathematical representation of X

$$\mathbf{X} = \mathbf{\Psi S} \tag{1}$$

$\boldsymbol{S}$ contains the sparse coefficients of $\boldsymbol{X}$ of size $(N \times N)$, $s_i =< \boldsymbol{X}, \psi_i^T >= \psi^{TX}$, $S = \boldsymbol{\Psi}^{TX}$. The image is represented with fewer samples from $\boldsymbol{X}$ instead of all pixels by computing the inner product between $\boldsymbol{X}$ and $\boldsymbol{\Phi}$, namely through incoherent measurements $\boldsymbol{Y}$ in Eq.(2), where $\boldsymbol{\Phi}$ is a random measurement matrix of size $(M \times N)$ where $K << M << N$. Fig.1 shows the CS measurement process [21].

$y_1 =< x, \phi_1 >$, $y_2 =< \mathbf{x}, \phi_2 >, \cdots, \mathbf{y_m} =< x, \phi_\mathbf{m} >$.

$$Y = \mathbf{\Phi} X = \mathbf{\Phi \Psi} S = \mathbf{\Theta} S \tag{2}$$

Since $M < N$, recovery of the image X from the measurements Y is undetermined, However, if S is K-sparse, and $M \geq K \log N$ it has been shown in [17] that X can be reconstructed by ℓ_1 norm minimization with high probability through the use of special convex optimization techniques without having any knowledge about the number of nonzero coefficients of X, their locations, neither their amplitudes which are assumed to be completely unknown a priori [20], [19], [22]

$$\mathbf{min} \|\hat{X}\|_{\ell_1} \ \mathbf{subject\ to}\ \mathbf{\Phi}\hat{X} = Y \tag{3}$$

Convex optimization problem can be reduced to linear programming known as Orthogonal Matching Pursuit (OMP) which was proposed in [23] to handle the signal recovery problem. It is an attractive alternative to Basis Persuit (BP) [24] for signal recovery problems.The major advantages of this algorithm are its speed and its ease of implementation. As seen, the CS is a very simple process as it enables simple computations at the encoder side (sensor nodes) and all the complex computations for recovery of frames are left at the decoder side or BS.

III. System model

This work proposes a compressive sensing model which is expected to reduce space requirements and communication overhead with low processing complexity while preserving detection and tracking accuracy.

Consider for a surveillance application a WVSN model composed of V visual sensor nodes and one or more BS. Each sensor node i is required to capture images from a video sequence and detect the presence of objects. At the time where a sensor node enters a 'wake-up' state, the time reference for the frame count is assumed to be $t = 0$. Hence, a single snapshot at $t = 0$ is expected to be stored within the memory allocated at the sensor node; that is assumed to be the background for the intended target tracking; denoted as $X_\mathbf{b}$. The following frames are the subsequent captured frames $X_\mathbf{t}$ with $t > 0$. Hence, $X_\mathbf{b}$ and $X_\mathbf{t}$ are the background and test images respectively of size $(N \times N)$ each. Let us assume most features of the targets are known to the monitoring center. However, the existence and the location of targets are required for monitoring. The receiver or BS also has prior explicit information of the background. To achieve higher compression rates, the foreground target is extracted first by background subtraction resulting in the difference frame. Hence, assuring sparsity as the difference frame is always sparse regardless the sparsity nature of real frames. Within the image frame, The extraction of foreground target $X_\mathbf{d}$ is achieved at each sensor node where CS is then applied for transmission through the wireless channel. At the BS side, the receiver decompresses the received compressed data obtaining $\hat{X}_\mathbf{t}$ to predicts the intended target's next location for tracking. The system model for the proposed WVSN is shown in Fig. 2

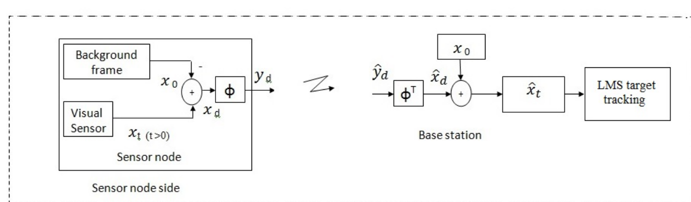

Fig. 2. The proposed model for WVSN-based surveillance application

IV. Proposed CS-based tracking algorithm

A. Compressive Sensing

At each sensor node, after each image frame is being captured, some preprocessing might be required. In our case, to assure sparsity

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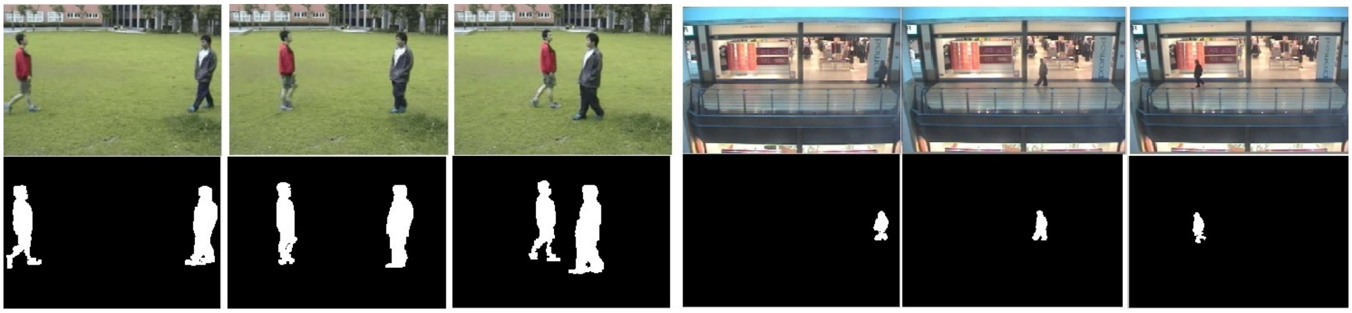


Fig. 3. First row shows test frames and background subtraction results in second row, the background subtracted frames are then compressed and used as a references to test detected location using CS. Left set of frames for scheme"1" (outdoor scheme) Right set of frames for scheme"2" (indoor scheme)

within the image frame, the foreground target is extracted first by background subtraction by subtracting $X_{\mathbf{t}}$ from $X_{\mathbf{b}}$ resulting in the difference frame $X_{\mathbf{d}}$. Hence, instead of producing the compressed measurements for $X_{\mathbf{b}}$ and $X_{\mathbf{t}}$ separately, the compressed measurements are produced directly for $X_{\mathbf{d}}$, as the difference frame is always sparse regardless of the sparsity nature of real frames. CS process is then applied to $X_{\mathbf{d}}$ by multiplying it by a random projection sensing matrix $\mathbf{\Phi}$ producing the compressed measurements $Y_{\mathbf{d}}$. At the BS side, the received compressed data is decompressed for the reconstruction of the estimated data $\hat{X}_{\mathbf{d}}$. As mentioned, $X_{\mathbf{b}}$ is known to the BS, making it possible to reconstruct the original test frame $\hat{X}_{\mathbf{t}}$ by adding $X_{\mathbf{b}}$ to $\hat{X}_{\mathbf{d}}$. Below are the steps undertaken during the entire process

- **Step 1:** $X_{\mathbf{d}} = |X_{\mathbf{t}} - X_{\mathbf{b}}| > Th$, where *th* is a given threshold to extract the foreground target
- **Step 2:** $\mathbf{\Phi}$ is a randomly chosen sensing matrix of size $M \times N$, where $M \ll N$
- **Step 3:** produce the compressed measurements $Y_{\mathbf{d}} = \mathbf{\Phi} X_{\mathbf{d}}$
- **Step 4:** sensor nodes transmits $Y_{\mathbf{d}}$ through the wireless channel
- **Step 5:** at the receiver side, $\mathbf{\Phi}$ must be known for the decompression of $Y_{\mathbf{d}}$. $\hat{X}_{\mathbf{d}}$ is reconstructed from the compressed measurements $Y_{\mathbf{d}}$, resulting in a frame with only the foreground target present.
- **Step 6:** the real frame $\hat{X}_{\mathbf{t}}$ is then obtained by adding $\hat{X}_{\mathbf{d}}$ to the background frame $X_{\mathbf{b}}$ which is also has to be known to the receiver side apriori.
- **Step 7:** the targets locations are obtained after reconstructing the real frame producing a trajectory for the complete path of each moving target

B. Least Mean Square (LMS) tracking

The LMS algorithm, is referred to as adaptive filtering algorithm since the statistics are estimated continuously, hence it can adapt to changes. LMS incorporates an iterative procedure during the training phase where it estimates the required coefficients to minimize the mean square error (MSE). This is accomplished through successive corrections to the expected set of coefficients which eventually leads to the minimum MSE. The LMS implementation process has been illustrated in Fig.(4).

As shown in Fig.4 the outputs are linearly combined after being scaled using corresponding weights. The weights are computed using LMS algorithm based on MSE criterion. Therefore the spatial filtering problem involves estimation of a signal from the received signal, by minimizing the error between the reference signal, which closely matches or has some extent of correlation with the desired signal estimate and the output. The LMS algorithm is initiated with an arbitrary value $\mathbf{w}(\mathbf{0})$ for the weight vector at $n = 0$. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error. The weight update can be given by

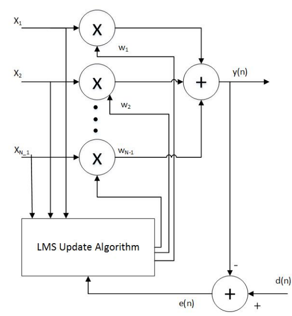


Fig. 4. An N-tap LMS adaptive filter

the following equation

$$w(n+\mathbf{1}) = w(n) + \mu \boldsymbol{x}(n) e(n) \tag{4}$$

where, $x(n)$ is the input signal, μ is the step size parameter, $e(n)$ is the MSE between the predicted output $y(n)$ and the reference signal $d(n)$ which is given by

$$e(n) = (d(n) - y(n))^{\mathbf{2}} \tag{5}$$

the output $\boldsymbol{y}(n)$ is calculated as follows

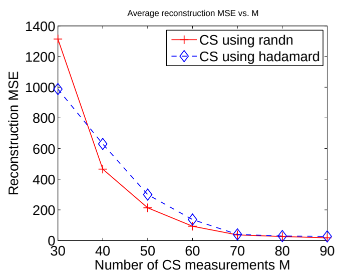
$$y(n) = x(n) w(n) \tag{6}$$

μ is selected by the autocorrelation matrix of the filter inputs.

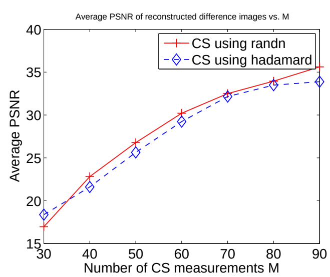
V. Simulations and results

Based on the system model proposed, simulations and experiments are conducted to evaluate the performance of the CS-based target detection and tracking algorithm. Simulations are performed for the WVSN-based surveillance application in both outdoor and indoor scenes for single and multi-target tracking. Background and target's appearance are assumed to be static to investigate the effect of CS on the detection and tracking algorithms, hence schemes are chosen to reflect this assumption. Moreover, to illustrate the relation between the number of measurements required for CS to guarantee reconstruction and how sparse the image is. Simulations are performed on 2 different schemes with different sparsity levels; "outdoor scheme" is chosen to resemble an outdoor scenes for multi target tracking captured by [25]. While "indoor scheme" filmed for the EC funded CAVIAR project found in [26] for indoor scenes tracking a single target.

Mean square error (MSE) and peak signal to noise ratio (PSNR) are used as performance indicators to test the reliability of CS. MSE and PSNR are compared for different number of CS measurements *M*, where the MSE is the reconstruction error measured between real and reconstructed frames and PSNR is measured after frames recovery to reflect the quality of image reconstruction which will later on reflects the ability of reliable tracking. The background frame and $\mathbf{\Phi}$ are known to the receiver node. Two candidate sensing matrices have been compared; normally distributed random numbers using Matlab function ”randn” and a walsh-hadamard. Although the measurements are defined by a matrix multiplication, the operation of matrix-by-vector multiplication is seldom used in practice, because it has a complexity of O(MN) which may be too expensive for real time applications. When a randomly permutated Walsh-Hadamard matrix is used as the sensing matrix, the measurements may be computed by using a fast transform which has complexity of O(K log(N)) [27]. The Hadamard matrix, is an $(N \times N)$ square matrix whose entries are either +1 or -1 and whose rows are mutually orthogonal, the matrix is first randomly reordered then, M samples are randomly chosen to construct the $(M \times N)$ random sensing matrix $\mathbf{\Phi}$.



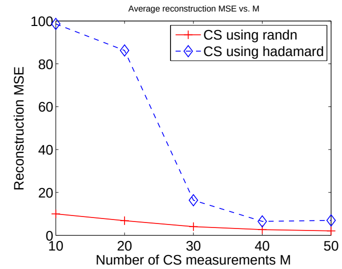
(a) Reconstruction MSE



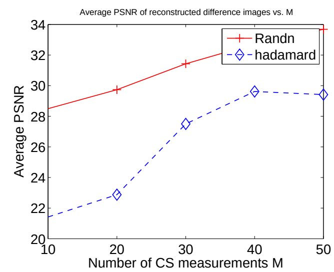
(b) PSNR

Fig. 5. Comparing reconstruction MSE and PSNR using randn and walsh sensing matrices for ”outdoor scheme”

As stated earlier, the ability of reliable tracking depends on acceptable recovery of images. In other words, if CS fails in image reconstruction the targets location can not be detected. Hence, choosing the right value of M is critical in image reconstruction and afterwards tracking. It is clear from the results in Fig.5 and 6 for outdoor and indoor schemes respectively that for different sparsity levels different values of M and compression rates are required. When reaching optimum value of M least MSE while preserving a $33dB$ PSNR. For illustration, MSE decreases as M increases till reaching the optimum value, it has been shown that the lower bound on M is depending on how sparse the difference frame $X_{\mathbf{d}}$ is or in other words proportional to the ratio between the number of non-zero coefficients and the total number of pixels in a frame. For ”outdoor scheme”, CS sets M to 90 in Fig.5(a) to achieve satisfactory results. While for ”indoor scheme”, it is obvious from Fig.6(a) that for single-target tracking (where there is lower number of non-zero coefficients), better MSE is achieved with lower M, reduced to 50 for ”indoor scheme”



(a) Reconstruction MSE



(b) PSNR

Fig. 6. Comparing reconstruction MSE and PSNR using randn and walsh sensing matrices for ”indoor scheme”

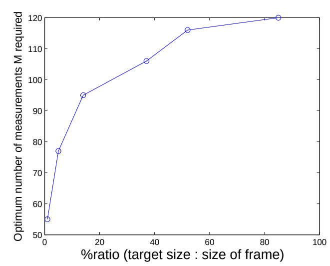


Fig. 7. Relation between the percentage ratio of target size:frame size vs. M

compared to multi-target tracking while maintaining least MSE and $33dB$ PSNR as in Fig.6.

As for MSE, Fig.5(b), 6(b) show the effect of M on PSNR for the different schemes. For each scheme, according to the sparsity nature of each scheme, the number of measurements M required will differ to obtain guaranteed reconstruction which is defined here in terms of PSNR. For low values of M it is hard to achieve a good PSNR, to reach the acceptable value, M should increase till reaching its optimum value as discussed earlier. To illustrate this for the ”indoor scheme”, to achieve a PSNR of $\approx 33dB$ M reached 50, while for the ”outdoor scheme” if the same M is used, we could not attain a PSNR higher than $25dB$.

The above simulation were carried out using two different sensing matrices, Randn and walsh-Hadamard. They are compared with respect to MSE and PSNR as in Fig.5 and 6. It is clear from the results that when reaching the optimum value of M both sensing matrices perform nearly the same except in some cases in Fig.6 shows that Randn gives slightly a better performance than Hadamard. But this can be negligible when compared to the reduction in complexity gained by using Hadamard matrix which helps in accomplishing the

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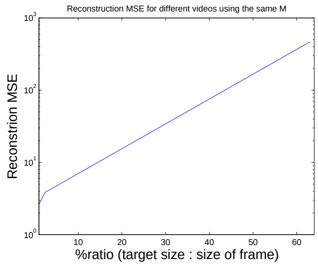
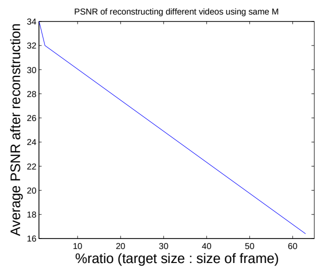


(a)



(b)

Fig. 8. Relation between the percentage ratio of target size:frame size and (a) reconstruction MSE, (b) average PSNR

main objective to save sensor nodes power and as a result maximizes their lifetime.

Fig.7 and 8 summarize and demonstrate the effect of the target size ratio on the number of measurements M needed in terms of reconstruction MSE and PSNR (the target size ratio is expressed as a ratio between non-zero pixels representing the target and the total size of the image frame, which reveals how much space the target acquires and how sparse the image is). It is clear from Fig.7 that for smaller target sizes, lower values of M are used while at the same time achieving the least MSE and PSNR of $\approx 33dB$ as in Fig.8(a) and 8(b), respectively. While for larger target sizes, a higher M is required to achieve the same performance achieved for frames with smaller targets. Experiments were carried out using the same M set to 50 for the 2 schemes (different sparsity levels). For example, frames with small size targets gave better reconstruction results in terms of least MSE and a $33dB$ PSNR as in Fig.8(a) and 8(b). Whereas, if the targets size grew bigger such as acquiring 60% space of the total frame size, with M set constant reconstruction results in high MSE and only $18dB$ PSNR. In that case M should be set to 90 or higher based on the sparsity nature to reach a low MSE and a PSNR of $\approx 30dB$ that was attained by lower M ($M = 50$) when compressing frames with targets of size $< 10\%$ of the frame size. These results reflect the constraint of the lower bound of M discussed in sec.II and give a key to the problem when M is required to be kept as small as possible. Where in that case the size of targets is controlled by zooming or changing the location of sensor nodes while bearing in mind to keep the scene of interest in the camera's field of view. By taking snapshots from a further location the total space acquired by the target is hence reduced and as a result M can be reduced, and the goal of reducing the size of transmitted data is met .

Another performance indicator is the correlation coefficient. After reconstructing the compressed measurements, the correlation coefficient indicates how likely the reconstructed frame correlates with the original one. Fig.9 shows by increasing M till reaching its optimum

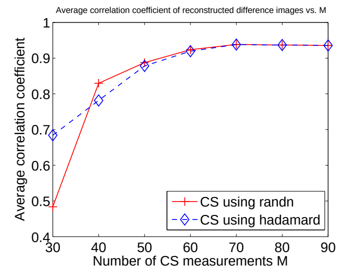


Fig. 9. Correlation coefficient for different M

values the correlation coefficients is nearly 100%, this implies that CS has not affected the image quality after recovery, whereas less number of measurements were required reducing the size of transmitted data.

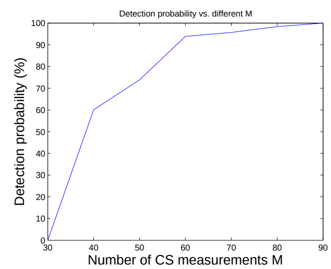


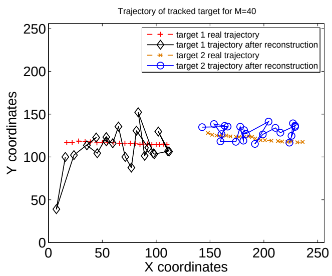
Fig. 10. Probability of detection vs different values of M

Fig.10 shows the probability of detection for different values of measurements M, it is clear from the graph that for lower values of M the target is misdetected. This reflects the fact that the reconstruction can not be guaranteed with lower values of M. The probability of detection increases till reaching 100% as M increases to its optimum value selected during the CS process.

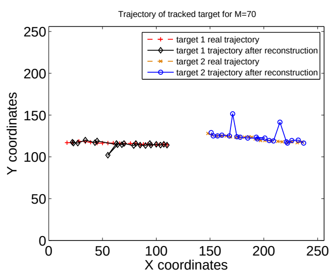
CS states that when enough measurements are used for compression, the reconstruction is done with high accuracy depending on a lower bound of M. Trajectory tracking of moving targets is considered to reflects the degree of reconstruction accuracy. Tracking reliability is tested by comparing the moving target's real and predicted trajectories using LMS. Fig.11 and 12 show the (x,y) position plots of the path tracked for the targets in the camera's scene. Fig.11(a) and 11(b) show that (for "outdoor scheme") for lower values of $M <$ optimum value (40 and 70 respectively), frames can not be reconstructed properly and as a result the targets tracks are not matching their real trajectories, whereas for optimum values of M reaching 90, LMS accurately predicted the target's locations and the results are closely matching the real target trajectory before compression. Fig.12 illustrates the same for "indoor scheme".

VI. Conclusion

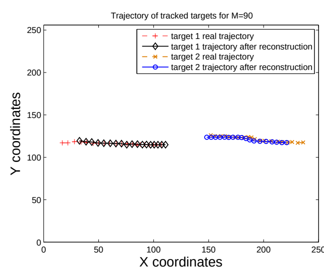
Experiments were carried out to evaluate the performance of CS and its effect on target detection and tracking. Simulations have shown that CS is a strong candidate to reduce the size of images as WVSNs are resource constrained (Limited storage, channel bandwidth). Results have shown that using CS up to 31% measurements of data are required to be transmitted, while preserving the reconstruction quality which is measured in terms of MSE and PSNR. The reconstruction MSE decreases till reaching the lower bound on the number of compressed measurements while preserving the acceptable PSNR. In addition, for different schemes where the sparsity nature of each image differs, CS chooses the compression rates accordingly. Moreover, surveillance application within WVSNs is one of the important applications that requires high detection reliability and



(a) M=40



(b) M=70



(c) M=90

Fig. 11. Comparing predicted trajectory of multi-targets using LMS for "outdoor scheme" (using different M for CS)

robust tracking. Hence, CS should not affect the performance of target tracking. After image reconstruction, the impact of CS on target tracking is investigated using LMS to predict target's next location. Target's trajectory tracking has been used as a performance indicator for the LMS algorithm. Results have demonstrated that the predicted path closely matches the target's real path which illustrates the accuracy of LMS and that CS has not affected the performance of target detection and tracking.

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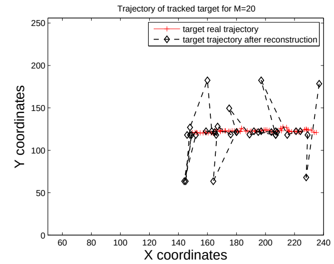
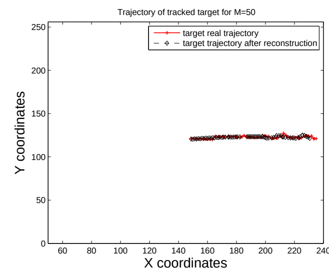


(a) M=20



(b) M=50

Fig. 12. Comparing predicted trajectory of single target using LMS for "indoor scheme" (using different M for CS)

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