International Journal on Recent and Innovation Trends in Computing and Communication ISSN: 2321-8169
Volume: 3 Issue: 2 159– 164

Compressive Tracking With Heavy Occlusion Avoidance - A Review

Jayashree Baskaran
Department Of Computer Science
School Of Engg., And Tech., Pondicherry University
Puducherry, India
jbaskaran2@gmail.com

Pradheeba Ulaganathan
Department Of Computer Science
School Of Engg., And Tech., Pondicherry University
Puducherry, India
prathiba.ulaganathan@gmail.com

Abstract—The objective of this article is to audit the tracking strategies, characterize them into distinctive classifications, further more distinguish new patterns. Tracking the targets undergoes various classic problem because of variety of reasons, including camera movement, illumination variability, occlusions and drift problem. To give an improvement to the solution of drift problem in online tracking a separate section called compression tracking has been chosen. In this review, we have taken various compression tracking techniques along with their working, merits and demerits. This paper we have given some tenets to avoid the heavy occlusion by using L1 regularization.

Keywords- *tracking; occlusion;compression tracking;*

*****

I. INTRODUCTION

Generally a tracking system is used for the observing of persons or objects on the move and supplying a timely ordered sequence of respective location data to a model e.g. capable to serve for depicting the motion on a display capability. Tracking, generally finds its use in videos. It is the process of locating a moving object (or multiple objects) over time using a camera. It has a variety of uses, some of which are:

- human-computer interaction
- security and surveillance
- video communication and compression
- augmented reality
- Traffic control
- medical imaging and
- Video editing.

It additionally estimates the movement of an object in a picture plane because it moves around a scene. Machine controlled systems that facilitate security personals to sight and track folks are gaining importance. Video police investigation permits North American country to remotely monitor a live or recorded video feed which regularly includes folks. There has been an incredible propagation of video surveillance cameras in public locations like stores, ATMs, highways, traffic signals, schools, buses, subway stations, and airports so as to sight and track the moving objects. Detection and tracking of moving objects is extremely necessary to watch public transportation, and important assets.

In video object following, totally different quite options, like color, texture, and gradient, may be used to live the importance of particles, wherever the gap functions, that square measure outlined for those options, between the tracked object of the previous frame and every assumption (particle) within the current frame square measure calculated. For following non-rigid objects, a color histogram is sometimes used since the steadiness of a color histogram is healthier than that of different options underneath the non-rigid motion. However, a color histogram suffers from look variations due to changes in illumination. Therefore, varied techniques are mentioned within the coming sections.

In the environments under surveillance monitoring, background gets changing frequently for this reason, we need to update the value in the background images. First of all in the real time video tracking the object have to get separated from the background and then the tracking have to be made. For this kind of segmentation various approaches available and the discussions with the various approaches are explained in this paper. Tracking is an important topic in computer vision and it has been studied for several decades. In this section, we summarize studies that are related to our work a thorough survey can be found in . Tracking the non-stationary appearance of objects undergoing significant pose, illumination variations and occlusions still remains a challenge for the community.

The general object tracking methods are classified into three categories, namely, point tracking, kernel tracking and Silhouette tracking. In point tracking, the objects detected in consecutive frames are described by points, and therefore the association of the points relies on the previous object state which might embrace object position and motion. This approach needs an external mechanism to observe the objects in each frame. In Kernel tracking, kernel refers to the object form and look, for instance, the kernel may be an oblong guide ortemplate elliptical form with an associated hist ogram. Objects are half-tracked by computing the motion of the kernel in consecutive frames. This motion is sometimes within the sort of a constant quantity transformation like quantity transformation like translation, rotation, and affine. In Silhouette tracking, tracking is performed by estimating the object region in every frame. Silhouette following ways use them knowledge encoded within the object region. This information is often within the kind of look density and form models that are sometimes within the kind of edge maps.

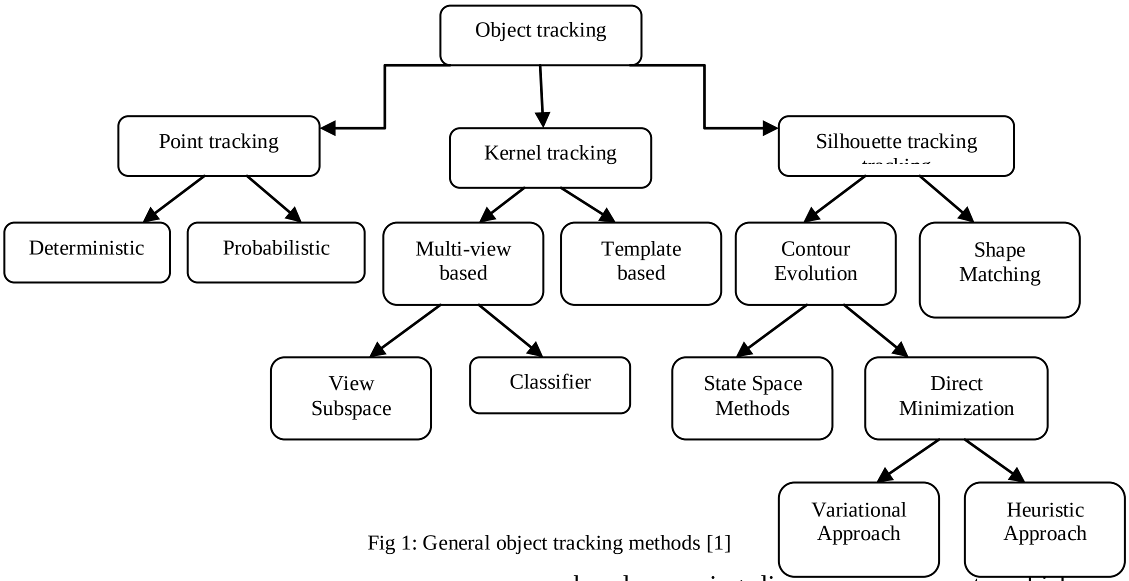

Fig 1: General object tracking methods [1]

II. COMPRESSIVE OBJECT TRACKING TECHNIQUES – A LITRATURE SURVEY

1. Compressive Target Tracking using Particle Filtering Method:

Tracking multiple targets in video is a classic problem in many areas. It is challenging for a variety of reasons, including camera movement, illumination variability, occlusions and not the least, the large dimensionality of the observed signal. It then becomes feasible to apply a number of estimation methods in order to find the target locations. They address sequential estimation, i.e. the filtering problem.

If the dynamics and/or the observations are nonlinear but the noise remains Gaussian, then the unscented Kalman filter (UKF) proposed by E.Wan et al [2] is used currently as one of the best solutions. But still it leads to large errors in the true posterior mean and covariance of the transformed Gaussian random variable (GRV), which may lead to sub-optimal performance and sometimes divergence of the filter.

one for each target, still to improve the performance without undue complexity, they look at compressive sensing [3], which allows to the exact reconstruction of sparse signals from a small number of incoherent measurements, typically by solving an L1 minimization problem. It is assumed that compressive sensing is only a low-dimensional subspace of the state changes so that re-estimation is carried out whenever the prediction residual increases beyond a threshold. If they consider using a standard Kalman filter in the reduced state subspace [4], the compressive measurements are used for multi-view tracking. But still it has problem, where compressive sensing inversion needs to be performed at every time step. Recently E.Wang et al [5] proposed a system which is made effective by applying compressive sensing ideas in a multi-particle-filter frame-work; it is possible to preserve tracking performance while achieving considerable dimensionality reduction, avoiding costly feature extraction procedures. Additionally, the target locations are estimated directly, without the need to reconstruct each image. This can be done using linear measurements which, under certain conditions, preserve crucial observability properties.

2. Compressive Sensing Used for Object Tracking in Video Sequences

Now a day's video surveillance systems are widely used in many places like airports, banks, shops, traffic monitoring and within the premises of private houses so as to track an object or entities. However, this form of tracking is useful for the security purposes, but still it affects the privacy of an individual. Dufaux et al. [6] proposed an efficient privacy enabling technology for Motion JPEG 2000 videos which consists of scrambling the transform-domain coefficients of the regions of interest in a video sequence. Moreover, since there are some problems in recovering the full scene once the encryption key is made available at the decoder. In the same way, Chan et al. [7] observed that it is not necessary to capture individuals' identity to perform this task.

In fact, it could be sufficient to segment the crowd in order to find the average person dimension, and to track the motion of people as a whole regardless of individuals. Moreover, Rachlin and Baron [8] proposed the secrecy of compressive sensing measurements. They asserted that acquiring, transmitting and storing the video sequence in the projection domain is computationally secure, it means that the random projections enable decoding and any kind of further processing. In fact, even though CS cannot achieve a perfect security level. But Cevher et al. [9] had shown that CS can be effectively used to perform background subtraction in the projection domain, provided that the background estimator is linear.Cossalter et al [10] proposed a new coding scheme suitable for video surveillance applications that allows tracking of video objects without the need to reconstruct the sequence, thus enabling privacy protection. At the decoder, they exploit the sparsity that characterizes background subtracted images in order to recover the location of the foreground object. In addition, by leveraging compressive sensing, they achieve compression, encoding a limited number of random projections, as well as secrecy.

3. *Improved Adaptive Compressive Sensing and Processing (ACSP) Method*

This implementation of ACSP identifies a set of delay-Doppler shifts that are likely to appear in the radar return waveform with nonzero probability. Although this ACSP method was shown to reduce tracking error versus non-adaptive CSP, it roughly approximated the distribution of the target state to be uniformly distributed with fixed parameters throughout the duration of the tracking scenario. This resulted in a fixed sized dictionary of delay-Doppler shifts.

To improve estimation performance an adaptive compressive sensing and processing (ACSP) method is proposed by Kyriakides [11] that creates a dictionary containing delay-Doppler shifts likely to be found in the radar return waveform according to tracking information. This improved ACSP method improves tracking performance by adapting the size and content of the dictionary compared to non-adaptive CSP and a fixed sized dictionary ACSP method. The method demonstrates the improvement in tracking performance when adjusting the size of the delay-Doppler dictionary based on tracking information when using a fixed dictionary size. Recently T.Bai et al [12] proposed a structured compressive sensing based tracking algorithm for intelligent optical sensing, which exploits the random feature reduction and the structured sparse representation of the target visual appearances. The efficiency of the tracker is improved by a random feature reduction together with the Block Orthogonal Matching Pursuit (BOMP) algorithm. This method can achieve a more efficient tracking without losing the robustness compared to the reference trackers.

4. *Visual tracking via Sparse Representation*

Compressive sensing or sparse representation has played a fundamental role in many research areas. The problem is to exploit the compressibility and sparsity of the true signal and use a lower sampling frequency than the Shannon-Nyquist rate. Sparsity then leads to efficient estimation, compression, dimensionality reduction, and modelling. Roughly speaking, compressive sensing is a technique for reconstructing a signal (e.g., an image) using the prior knowledge that the reconstruction is sparse or compressible le. With this technique, the signal is represented by a sparse set of basic functions. That is, all of the coefficients corresponding to the basic functions vanish except for a few. The challenges in designing a robust visual tracking algorithm are caused by the presence of noise, occlusion, varying viewpoints, background clutter, and illumination changes. Williams et al [13] extended the use of statistical learning algorithms for object localization. This approach is demonstrated in real-time tracking systems where the sparsity of the RVM means that only a fraction of CPU time is required to track at frame rate.

However problem of automatically recognizing human faces from frontal views with varying expression and illumination, as well as occlusion and disguise. These problems are solved by Wright et al [14]. This new framework provides two crucial issues in face recognition: feature extraction and robustness to occlusion. The theory of sparse representation helps predict how much occlusion the recognition algorithm can handle and how to choose the training images to maximize robustness to occlusion. The problem is that the full potential of sparsity in robust object detection and recognition together is yet to be uncovered.

In the same way, Xue Mei et al [15] proposed a robust visual tracking method by casting tracking as a sparse approximation problem in a particle filter framework. Specifically, to find the tracking target in a new frame, each target candidate is sparsely represented in the space spanned by target templates and trivial templates. The sparsity is achieved by solving an l_1-regularized least-squares problem. The proposed approach demonstrates excellent performance in comparison with previously proposed trackers. Still there are some problem in simultaneous tracking and recognition.

Recently, T. Zhang et al [16] formulate object tracking in a particle filter framework as a multi-task sparse learning problem, which is denoted as Multi-Task Tracking (MTT). Since the model particles as linear combinations of dictionary templates that are updated dynamically, learning the representation of each particle is considered a single task in MTT. Compared with regular exhaustive search-based methods, the main advantage of Monte Carlo sampling methods is the reduction of sampling patches. Lan Wang et al [17] proposed an effective method for Markov Chain Monte Carlo (MCMC) sampling on compressive sensing on visual tracking discriminative Haar-like features are extracted from the high dimension feature space by using compressive sensing. The extraction of features reduces the computation complexity and guarantees the real time of tracking. These algorithms will provide the accuracy, robustness, and speed.

5. *Compressive Tracking in Real Time Scenario*

The objective of real time tracking is to associate target objects in consecutive video frames. The complexity of the problem is when the tracked object changes orientation over time. Real time tracking is the process of locating a moving object (or multiple objects) over time using a camera. Adding further to the complexity is the possible need to use object recognition techniques for tracking. For these situations video tracking systems usually employ a motion model which describes how the image of the target might change for different possible motions of the object.

Various researches have done effective real time video compression. Dorin et al [18] proposed a new method for real-time tracking based on the mean shift iterations and found the most probable target position in the current frame. The dissimilarity between the target model and the target candidates is expressed by a metric derived from the Bhattacharyya coefficient. But still there was some drifting problem with these approaches. Later to reduce visual drift problem which was encountered in object tracking, a two-stage sparse representation method was proposed by Yan et al[19] to improve the performance of the classifier and robustness of the algorithm, the kernel function was applied on the sparse representation. Moreover, the dimension of the target was reduced via compressive sensing.

Babenko et al [20] addressed the problem of tracking an object in a video given its location in the first frame and no other information. They used a “tracking by detection” technique where these methods train a discriminative classifier in an online manner to separate the object from the background. And also proposed a novel online MIL algorithm for object tracking that achieved superior results with real-time performance. However Li at el [21] addressed the problems in l_1 tracker to provide the solution to those problems by proposing real-time compressive sensing tracking (RTCST) by exploiting the signal recovery power of compressive sensing

(CS). Dimensionality reduction and a customized orthogonal matching pursuit (OMP) algorithm were adopted to accelerate the CS tracking. RTCST still produces competitive tracking accuracy compared to the l_1 tracker.

Wu et al [22] proposed an effective and efficient tracking algorithm integrating motion estimation appearance model based tracking in the compressed domain. The idea is that the features are extracted from the multi-scale image feature space based on compressive sensing theories. The motion information has been integrated into appearance model based tracking by introducing motion estimator, i.e., particle filter. In the year 2014, Zhang et al [23] and made more effective and efficient compressive tracking. A very sparse measurement matrix is constructed to efficiently extract the features for the appearance model, where they compressed the sample images of the foreground target and the background using the same sparse measurement matrix. The tracking task is formulated as a binary classification via a Naive Bayes classifier with online update in the compressed domain. The proposed compressive tracking algorithm runs in real-time and performed challenging sequences in terms of efficiency, accuracy and robustness.

III. PROPOSED WORK

As per the survey, we have discussed about the various merits and demerits in the proposed methods. According to the demerits that we discussed we found that there is a need to improve the tracking algorithm for object detection and recognition under high occlusion. So as to overcome these demerits we splitting the proposed system into two sections, in first section we focus on the appearance model by means of the Principle Component Analysis (PCA) and the avoidance of occlusion while tracking by means of L1 regularization and in the second section we use the output of the first section and then perform compression operation and classification of the target image from the background.

The Principal component analysis is a statistical procedure that uses an orthogonal transformation to convert a set of observation of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. Principal Component Analysis are linear transformation methods and closely related to each other. We are using this PCA for the tracking purposes so as to track the object accurately. L1 regularization is employed for trailing an object regardless of the obstacles.Regularization is that the method of introducing some extra info so as to stop over-fitting at the start the regularization is about to a continuing worth. An image observation can be assumed to be generated from a mathematical space of the target object once there's no occlusion. During this case, the most likely image patches are often effectively pictured by the PCA basis vector. After that the occlusion is avoided by means of L1 regularization and it is done by comparing the previous frame of the object with the current frame.
Then the occlusion avoided frame is taken to the multi scale image stage, here the multi scale image is formed by convolving the input image and the single image is spitted into multiple images where $z = (z_1, z_2, \ldots\ldots z_n)$ by means of filters. After that the features are extracted from the multi scaled images and represented in the matrix format. Now it is the turn for sparse matrix measurement, which is considered as X. The sparse matrix X consists of positive, negative and zero entries these entries are compressed by considering only the non zero entries from the matrix X [23]. In the last phase, the compressed image is classified into foreground and background using the same sparse measurement matrix. The tracking task is formulated as a binary classification via a Naive Bayes classifier with online update in the compressed domain. By this way the object is getting tracked in the compressed manner. So, we suggest that this proposed system may overcome the heavy occlusion in the compressive tracking.

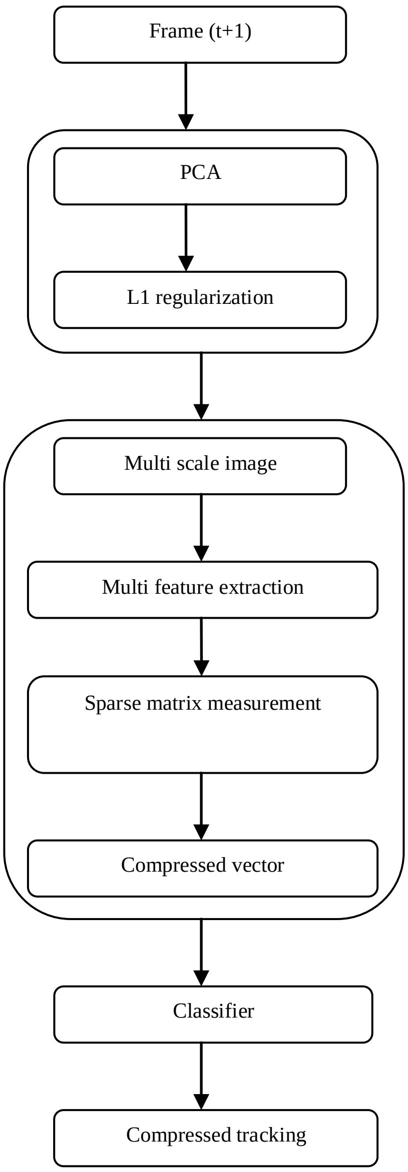

Fig 2: Proposed System Architecture

ISSN: 2321-8169
155– 158

TABLE I. COMPARISON OF COMPRESSIVE OBJECT BASED TRACKING BASED ON ACCURACY AND ERROR RATE

Paper	**Methods used**	**Merit**	**Demerit**	**Success Rate (SR) /Accuracy Rate (AR)**	**Location Error Rate (LER)/Average tracking Error (ATE)**
Eric Wang et al [5]	Compressive Particle Filtering (CPF)	Reduce the number of pixels and accurate in a multiple-target setting	-	-	-
T.Bai et al [12]	Structured Compressive Sensing based Tracking	More efficient implementation with the random projection and richer descriptive capabilities	-	AR >68%	LER <20%
Xue Mei et al [15]	Simultaneous tracking and recognition, l_1 minimization	Target templates are dynamically updated and non negative constrains are filtered	tracker will lock on the occluding object	-	-
Lan Wang et al [17]	Two-stage compressive tracking MCMC	This method is crucial for object tracking compared with other tracking	used to alleviate drift problem	-	-
Yan et al[19]	Dimensionality reduction and kernel sparse representation	Effective Compression and robust object tracking and solve drift problems	-	SR is between 82% - 99%	ATE < 12 %
Li at el [21]	Real-Time Compressive Sensing Tracking And Orthogonal MatchingPursuit (OMP) Algorithm	Consistently highest accuracy and robustness among all the compared tracking algorithms.	more accurate and robust results have to achieved.	-	ATE < 30%
Zhang et al [23]	Fast Compressive Tracking	Track the right objects accurately	-	SR = 99%	Centre LER < 10%

IV. CONCLUSION

We show a broad overview of item following systems furthermore give a concise audit of related points. We isolate the compressive tracking method into various categories based on the use of this method in various applications. We also discussed detailed about the background subtraction which is very much need in tracking scenarios for subtracting the target objects from the background. We have pointed out various Troubles in tracking objects that are emerging because of camera movement, illumination variability, occlusions ,non rigid object structures, pose variation and shape deformation .In this survey, we provided a detailed summary on different methods (like particle filtering , Kalman filter etc.) in various scenarios to overcome the troubles that we mentioned above . We suggested methods to overcome heavy occlusion in compressive tracking by using the L1 regularization method. We hope this suggestion will provide good and accurate results.

At the end of this paper, a discussion is made to point the future work needed to improve the tracking algorithm persistent tracking (where items vanish and return after a drawn out stretch of time).We expect that this survey on compressive tracking in video with rich theoretical details of the tracking methods along with bibliography contents will give valuable contribution to research works on object tracking and encourage new research.

V. REFERENCES

[1] Yilmaz, O. Javed, and M. Shah, “Object tracking: A survey,” ACM Computing Surveys, vol. 38, no. 4, 2006.
[2] E. Wan and R. van der Merwe, “The unscented Kalman filter for nonlinear estimation,” in Proceedings of the IEEE Adaptive Systems for Signal Processing, Communications and Control Symposium (AS-SPCC), 2000.
[3] D. Donoho, “Compressed sensing,” IEEE Transactions on Information Theory, vol. 52, no. 4, pp. 1289–1306, 2006.

[4] D. Reddy, A.C. Sankaranarayanan, V. Cevher, and R. Chellappa, “Compressed sensing for multi-view tracking and 3-D voxel reconstruction,” in Proceedings of the IEEE International Conference on Image Processing (ICIP), 2008.

[5] Eric Wang, Jorge Silva and Lawrence Carin, “Compressive Particle Filtering For Target Tracking” IEEE/SP 15th Workshop on Statistical Signal Processing, 2009.

[6] F. Dufaux, M. Ouaret, Y. Abdeljaoued, A. Navarro, F. Vergnenegre, and T. Ebrahimi. Privacy enabling technology for video surveillance. In Proceedings of SPIE, volume 6250, pages 205–216, 2006.

[7] A. Chan, Z. Liang, and N. Vasconcelos. Privacy preserving crowd monitoring: Counting people without people models or tracking. In IEEE Conference on Computer Vision and Pattern Recognition, Anchorage, Alaska, 2008.

[8] Y. Rachlin and D. Baron. The secrecy of compressed sensing measurements. In Proc. Allerton Conference on Communication, Control, and Computing, Monticello, IL, USA, September 2008.

[9] V. Cevher, A. Sankaranarayanan, M. Duarte, D. Reddy, R. Baraniuk, and R. Chellappa. Compressive sensing for background subtraction. In Proc. European Conf. On Computer Vision, Marseille, France, October 2008.

[10]Cossalter, M., Marco Tagliasacchi, and Giuseppe Valenzise. "Privacy-enabled object tracking in video sequences using compressive sensing." Advanced Video and Signal Based Surveillance, 2009. AVSS'09. Sixth IEEE International Conference on. IEEE, 2009.

[11] I. Kyriakides,” Configurable compressive sensing and processing using tracking information for delay-Doppler radar applications”, Radar Conference (RADAR), 2012 IEEE.

[12] Tianxiang Bai, Youfu Li, and Jianyang Liu, “Structured Compressive Sensing for Robust and Fast Visual Tracking” , Sensors, 2012 IEEE.

[13] O. Williams, A. Blake, and R. Cipolla, “Sparse Bayesian Learning for Efficient Visual Tracking,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 27, no. 8, pp. 1292-1304, Aug. 2005.

[14] J. Wright, A.Y. Yang, A. Ganesh, S.S. Sastry, and Y. Ma, “Robust Face Recognition via Sparse Representation,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 31, no. 2, pp. 210-227, Feb. 2009.

[15] X. Mei and H. Ling, “Robust visual tracking and vehicle classification via sparse representation,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 11, pp. 2259–2272, 2011.

[16] T. Zhang, B. Ghanem, S. Liu, and N. Ahuja, “Robust visual tracking via multi-task sparse learning,” in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp. 2042–2049, 2012.

[17] Lan Wang, Pingyang ,”Visual Tracking Based On Compressive Sensing MCMC Sampling”, Systems, Man, and Cybernetics (SMC), 2013 IEEE International Conference on 13-16 Oct. 2013.

[18] Dorin Comaniciu ,Visvanathan Ramesh ,Peter Meer,” Real-Time Tracking of Non-Rigid Objects using Mean Shift “,IEEE CVPR 2000.

[19] Qingsen Yan, Linsheng Li , “Kernel sparse tracking with compressive sensing”, Computer Vision, IET (Volume:8 , Issue: 4), 2013.

[20] B. Babenko, M.-H. Yang, and S. Belongie, “Robust object tracking with online multiple instance learning,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 8, pp. 1619–1632, 2011.

[21] H. Li, C. Shen, and Q. Shi, “Real-time visual tracking using compressive sensing,” in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp. 1305–1312, 2011.

[22] J.Wu, Daquan Chen and Rui Yi,”Real time compressive tracking with motion estimation “,the IEEE International Conference on Robotics and Biomimetics (ROBIO) Shenzhen, China, December 2013.

[23] Kaihua Zhang, Lei Zhang, and Ming-Hsuan Yang, “Fast Compressive Tracking”, IEEE Transaction On Pattern Analysis And Machine Intelligence, 2014.