

## Real Time Compressive Image Sequence Tracking

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### Abstract:

It is a challenging task to develop effective and efficient appearance models for robust object tracking due to factors such as pose variation, illumination change, occlusion, and motion blur. Existing online tracking algorithms often update models with samples from observations in recent frames. Despite much success has been demonstrated, numerous issues remain to be addressed. First, while these adaptive appearance models are data-dependent, there does not exist sufficient amount of data for online algorithms to learn at the outset. Second, online tracking algorithms often encounter the drift problems. As a result of self-taught learning, misaligned samples are likely to be added and degrade the appearance models. In this paper, we propose a simple yet effective and efficient tracking algorithm with an appearance model based on features extracted from a multiscale image feature space with data-independent basis.

The proposed appearance model employs non-adaptive random projections that preserve the structure of the image feature space of objects. A very sparse measurement matrix is constructed to efficiently extract the features for the appearance model. We compress 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. A coarse-to-fine search strategy is adopted to further reduce the computational complexity in the detection procedure. The proposed compressive tracking algorithm runs in real-time and performs favorably against state-of-the-art methods on challenging sequences in terms of efficiency, accuracy and robustness.

### INTRODUCTION:

Numerous effective representation schemes have been proposed for robust object tracking in recent years.

One commonly adopted approach is to learn a low-dimensional subspace (e.g., eigenspace [7], [16]), which can adapt online to object appearance change. Since this approach is data-dependent, the computational complexity is likely to increase significantly because it needs eigen-decompositions. Moreover, the noisy or misaligned samples are likely to degrade the subspace basis, thereby causing these algorithms to drift away from the target objects gradually. The compressive sensing (CS) theory [17], [18] shows that if the dimension of the feature space is sufficiently high, these features can be projected to a randomly chosen low-dimensional space which contains enough information to reconstruct the original high-dimensional features.

The dimensionality reduction method via random projection is data-independent, non-adaptive and information-preserving. In this paper, we propose an effective and efficient tracking algorithm with an appearance model based on features extracted in the compressed domain. Numerous effective representation schemes have been proposed for robust object tracking in recent years. Existing online tracking algorithms often update models with samples from observations in recent frames. First, while these adaptive appearance models are data-dependent, there does not exist sufficient amount of data for online algorithms to learn at the outset. Second, online tracking algorithms often encounter the drift problems. TRACKING algorithms find how an image region moves from one frame to the next.

In this case, we can train a classifier in advance to distinguish between an object and the background. This implies the existence of an error function to be minimized, such as the sum of squared differences (SSD) between the two image regions. The SSD error function makes the "constant brightness assumption," i.e., the brightness of the object does not change from frame to frame. This paradigm makes no assumptions about the class of the tracked object. Yet, quite often, we are interested in tracking a particular class of objects such as people or vehicles.

The question then is how to integrate the tracker and the classifier. One approach is to use the tracker and the classifier sequentially. The tracker will find where the object moved to and the classifier will give it a score. This scheme will repeat until the classification score will fall below some predefined threshold. The disadvantage of such an approach is that the tracker is not guaranteed to move to the best location (the location with the highest classification score) but rather find the best matching image region. Furthermore, such an approach relies heavily on the first frame.

### BLOCK DIAGRAM:

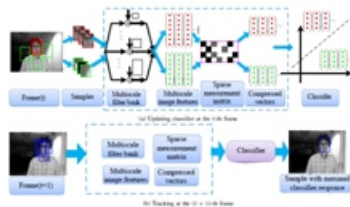


Fig. 1. Main components of the proposed compressive tracking algorithm.

### Existing Tracking Algorithms :

D. Ross, J. Lim, R. Lin proposed a method based on approach is to learn a low dimensional subspace, which can adapt online to object appearance change. H. Grabner, M. Grabner have been proposed to extract discriminative features for object tracking. Alternatively, high-dimensional features can be projected to a low dimensional space from which a classifier can be constructed. D. Ross, J. Lim, R. Lin proposed a method based on approach is to learn a low dimensional subspace, which can adapt online to object appearance change. H. Grabner, M. Grabner have been proposed to extract discriminative features for object tracking. Alternatively, high-dimensional features can be projected to a low dimensional space from which a classifier can be constructed.

### Motion Model:

In the tracking framework, we apply an affine image warping to model the object motion of two consecutive frames. The tracking process is governed by the two important components: state transition model which models the temporal correlation of state transition between two consecutive frames, and observation model which measures the similarity between the appearance observation and the approximation using the target model.

### RELATED WORK:

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 [45]. Given the wide range and long study of visual tracking, our proposed tracking method borrows many ideas from previous work. First, we use the popular particle filter framework that considers tracking as an estimation of the states for a time-series state space model. The particle filter, also known as the sequential Monte Carlo method [14], recursively constructs the posterior probability density function of the state space using Monte Carlo integration. It has been developed in the computer vision community and applied to tracking problems under the name Condensation [21]. It is later extended in many variations such as the Rao-Blackwellized particle filter [25].

There are also recent studies using particle filters similar to our method. For example, [19] proposes an object-tracking method based on combination of local classifiers in the presence of partial occlusion. The weight for combining local classifiers is selected adaptively using particle filters. The proposed method relates to previous work on appearance-based trackers. Early examples include using the sum of squared difference (SSD) as a cost function in the tracking problem [4] and using mixture model to model the appearance variation [22]. The work in [47] incorporates an appearance-adaptive model in a particle filter to realize robust visual tracking and classification algorithms. Our modeling using linear template combination is related to both subspace- and template-based tracking approaches. The appearance of the object is represented using an eigenspace [6], affine warps of learned linear subspaces [18], or an adaptive low-dimensional subspace [38].

### Proposed method:

We propose an effective and efficient tracking algorithm with an appearance model based on features extracted in the compressed domain. The main components of the proposed compressive tracking algorithm. Traditional tracking approaches often use techniques such as normalized correlation or template matching. Such approaches are typically limited to situations in which the image motion of the object is simple (e.g., translation) and the viewpoint of the object is either fixed or changing slowly.

Darrell and Pentland (1993) extended these tracking approaches to allow a set of learned views for an object. Unlike eigenspace approaches, they represented these views individually and used correlation hardware to perform a brute-force match between all the stored views and the input images.

## **SIMULTANEOUS TRACKING AND RECOGNITION:**

In this section, we extend our  $\chi^2$  tracker and propose a simultaneous tracking and recognition method using  $\chi^2$  minimization in a probabilistic framework. When we locate the moving target in the image, we want to identify it based on the template images in the gallery. Typically, tracking is solved before recognition. When the object is located in the frame, it is cropped from the frame and transformed using an appropriate transformation. This tracking and recognition are performed sequentially and separately to resolve the uncertainty in the video sequences. The recognition after tracking strategy poses some difficulties such as selecting good frames and estimation of parameters for registration.

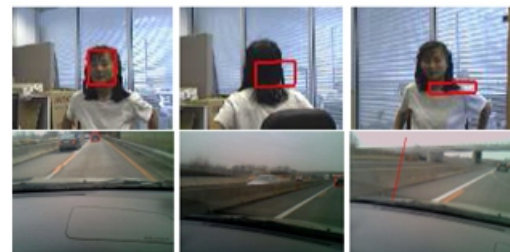
## **Nonnegativity Constraints:**

In principle, the coefficients in a can be any real numbers if the target templates are taken without restrictions. However, we argue that in tracking, a tracking target can almost always be represented by the target templates dominated by nonnegative coefficients. Here by “dominated” we mean that the templates that are most similar to the tracking target are positively related to the target. This is true when we start tracking from the second frame. The target is selected in the first frame manually or by a detection method. The target in the second frame will look more like the target in the first frame such that the coefficient is positive when the target in the first frame is used to approximate the target in the second frame. In new frames, the appearance of targets may change, but new templates will be brought in (may replace old templates) and the coefficients will still be positive for the most similar target templates in the following frames.

## **Discussion:**

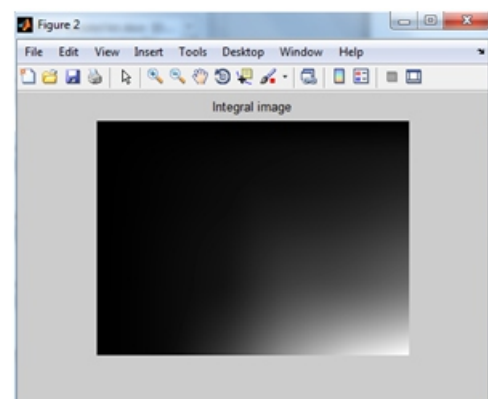
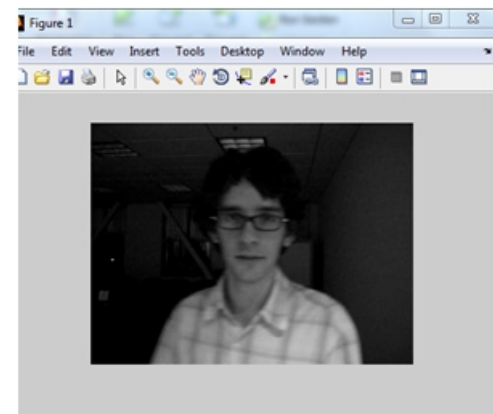
The experiments demonstrate the robust tracking performance of our algorithm.

However, our tracker can fail when there is a very large pose change or the target moves completely out of the frame and reappears. Fig. 18 shows two failure cases of our tracker. In the top row, the woman’s head is rotating out of-plane for 180 degrees and the target varies from frontal face in left image to back of her head in middle image. Tracker drifts away from the target after the rotation is complete and the woman’s frontal face reappears in the right image. In the bottom row of Figure the target moves completely out of the frame in the middle image. The tracker is tracking the background without knowing it. When the target reappears in the right image, the tracker cannot recover after losing track of the target.

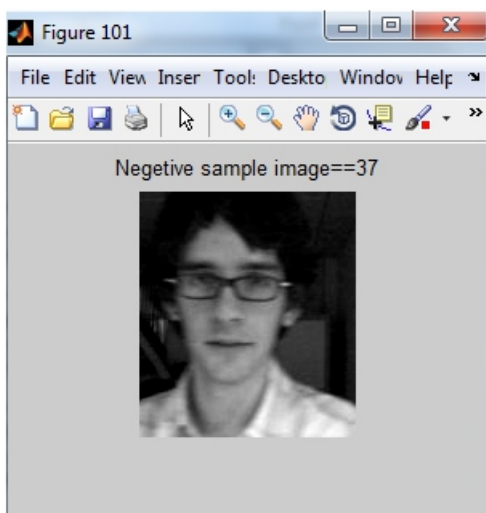
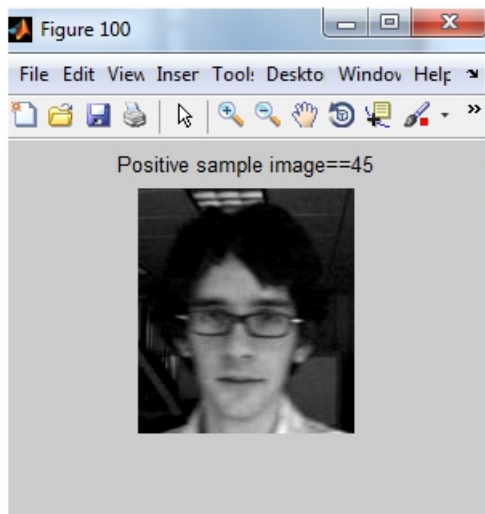


**Fig. Two failed tracking cases.**

## **EXPERIMENTAL RESULTS:**







## CONCLUSION:

In this paper, we propose using sparse representation for robust visual tracking. We model tracking as a sparse approximation problem and solve it through an  $\ell_1$ -regularized least squares approach. For further robustness, we introduce nonnegativity constraints and dynamic template update in our approach. In thorough experiments involving numerous challenging sequences and four other state-of-the-art trackers, our approach demonstrates very promising performance. We also extend our work to simultaneous tracking and recognition and apply it to IR-based vehicle classification. The experimental results demonstrate clearly the effectiveness of our proposed method.

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