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Implemetation of Fast Compressive 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 aspose variation, illumination change, occlusion, and motion blur. Existing online tracking algorithms often update models with samplesfrom 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 tolearn at the outset. Second, online tracking algorithms often encounter the drift problems. As a result of self-taught learning, misalignedsamples are likely to be added and degrade the appearance models. In this paper, we propose a simple yet effective and efficienttracking algorithm with an appearance model based on features extracted from a multiscale image feature space with data-independentbasis. The proposed appearance model employs non-adaptive random projections that preserve the structure of the image featurespace of objects. A very sparse measurement matrix is constructed to efficiently extract the features for the appearance model. Wecompress sample images of the foreground target and the background using the same sparse measurement matrix. The tracking task isformulated as a binary classification via a naive Bayes classifier with online update in the compressed domain. A coarse-to-fine searchstrategy is adopted to further reduce thecomputational complexity in the detection procedure. The proposed compressive trackingalgorithm runs in real-time and performs favorably against state-of-the-art methods on challenging sequences in terms of efficiency,accuracy and robustness.

Introduction:

The compressive sensing (CS) theory showsthat if the dimension of the feature space is sufficientlyhigh, these features can be projected to a randomly chosenlow-dimensional space which contains enough informationto reconstruct the original high-dimensional features. The dimensionality reduction method via random projection(RP) is data-independent, non-adaptive andinformation-preserving. In this paper, we propose an effectiveand efficient tracking algorithm with an appearance modelbased on features extracted in the compressed domain.The main components of the proposed compressive trackingalgorithm are shown by Figure 1. We use a very sparsemeasurement matrix that asymptotically satisfies the restricted isometry property (RIP) in compressive sensing theory thereby facilitating efficient projection from the image feature-space to a low-dimensional compressed subspace. Fortracking, the positive and negative samples are projected(i.e., compressed) with the same sparse measurement matrixand discriminated by a simple naive Bayes classifier learnedonline. The proposed compressive tracking algorithm runs atreal-time and performs favorably against state-of-the-art trackerson challenging sequences in terms of efficiency, accuracyand robustness.

BLOCK DIAGRAM:

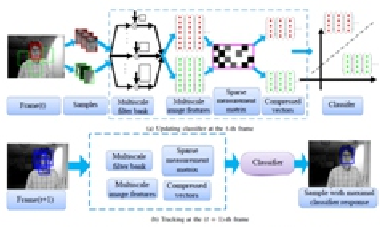

Fig. 1: Main components of the proposed compressive tracking algorithm.

RELATED WORK:

Discriminative algorithms pose the tracking problem as abinary classification task with local search and determine thedecision boundary for separating the target object from thebackground. Avidan [4] extends the optical flow approachwith a support vector machine classifier for object tracking,and Collins et al. [5] demonstrate that the most discriminativefeatures can be learned online to separate the target objectfrom the background. In [6] Grabner et al. propose an online-boosting algorithm to select features for tracking.

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However,these trackers use one positive sample (i.e., the currenttracker location) and a few negative samples when updatingthe classifier. As the appearance model is updated with noisyand potentially misaligned examples, this often leads to thetracking drift problem. An online semi-supervised boostingmethod is proposed by Grabner at al. to alleviate thedrift problem in which only the samples in the first frameare labeled and all the other samples are unlabeled. Babenkoet al. [10] formulate online tracking within the multiplein-stance learning framework where samples are consid-eredwithin positive and negative bags or sets.

A semi-supervisedlearning approach [33] is developed in which positive andnegative samples are selected via an online classifier withstructural constraints. Wang et al. present a discriminativeappearance model based on superpixels which is able to handleheavy occlusions and recovery from drift. In [13], Hare et al.use an online structured output support vector machine (SVM) for robust tracking which can mitigate the effect of wronglabeling samples. Recently, Henriques et al. [15] introduce afast tracking algorithm which exploits the circulant structureof the kernel matrix in SVM classifier that can be efficientlycomputed by the fast Fourier transform algorithm.

Random projection and compressive sensing:

The compressive sensing theory states that if a signal is K-sparse (i.e., the signal is a linear combination of only K basis it is possible to near perfectly reconstruct the signal from a small number of random measurements. The encoder in compressive sensing (using (1)) correlates signal with noise (using random matrix R) , thereby it is a universal encoding which requires no prior knowledge of the signal structure. In this paper, we adopt this encoder to construct the appearance model for visual tracking. Ideally, we expect R provides a stable embedding that approximately preserves the salient information in any K- sparse signal.

This strong theoretical support motivates us to analyze thehigh-dimensional signals via their low-dimensional randomprojections. In the proposed algorithm, a very sparse matrix isadopted that not only asymptotically satisfies the JL lemma,but also can be efficiently computed for real-time tracking.

Very sparse random measurement matrix:

This matrix is easy to compute which requires only auniform random generator. More importantly, when P = 3,it is sparse where two thirds of the computation can beavoided.We observe that good results can beobtained by fixing a = 0.4 in our experiments. Therefore, thecomputational complexity is only o(cn) (n = 100 in this work)which is very low. Furthermore, only the nonzero entries of Rneed to be stored which makes the memory requirement alsovery light.

Eigenspaces and Parametric Transformations:

The previous section showed howrobust estimation canimprove the reconstruction of an image that is alreadyaligned with the eigenspace. In this section we considerhow to achieve this alignment in the first place. It is impractical to represent all possible views of anobject at all possible scales and all orientations. Onemust be able to recognize a familiar object in a previouslyunseen pose and hence we would like to representa small set of views and recover a transformationthat maps an image into the eigenspace. In the previoussection we formulated the matching problem asan explicit nonlinear parameter estimation problem. Inthis section we will simply extend this problem formulationwith the addition of a few more parametersrepresenting the transformation between the image andthe eigenspace.

Haar-like features :

Haar-like features are digital image features used in object recognition. They owe their name to their intuitive similarity with Haar wavelets and were used in the first real-time face detector.The key advantage of a Haar-like feature over most other features is its calculation speed. Due to the use of integral images, a Haar-like feature of any size can be calculated in constant time.A simple rectangular Haar-like feature can be defined as the difference of the sum of pixels of areas inside the rectangle, which can be at any position and scale within the original image. This modified feature set is called 2-rectangle feature. Viola and Jones also defined 3-rectangle features and 4-rectangle features. The values indicate certain characteristics of a particular area of the image.

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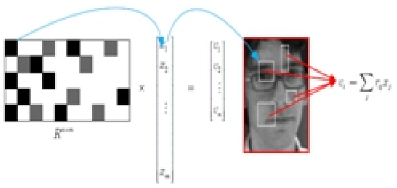
Each feature type can indicate the existence (or absence) of certain characteristics in the image, such as edges or changes in texture. For example, a 2-rectangle feature can indicate where the border lies between a dark region and a light region.

Fast compressive tracking:

The commonly used techniques used for real time compressive tracking involves: Naives Bayes Classifier, Appearance based models, Particle filtering, Adaptive block matching, Kernel based object tracking, Wavelet transform, Optical flow, Static Computational Optical Under sampled Tracker (SCOUT), Mean shift, K-means clustering, Dynamic Time Warping Technique, Adaptive Motion Estimation (FAME), Adaptive Filtering Method, Sparse Representation, Compressed Tracking.In this section, we present our tracking algorithm in details. The tracking problem is formulated as a detection task and our algorithm. We assume that the tracking window in the first frame has been determined. At each frame, we sample some positive samples near the current target location and negative samples far away from the object center to update the classifier. To predict the object location in the next frame, we draw some samples around the current target location and determine the one with the maximal classification score.



Graphical representation of compressing a high-dimensional vector x to a low dimensional vector v. In the matrix R, dark, gray and white rectangles represent negative, positive, and zero entries, respectively. The blue arrows illustrate that one of nonzero entries of one row of R sensing an element in x is equivalent to a rectangle filter convolving the intensity at a fixed position of an input image.

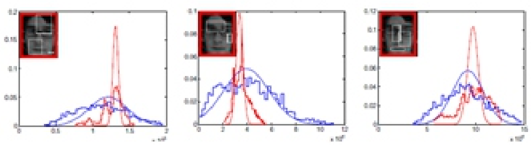
1.EFFICIENT DIMENSIONALITY REDUCTION:

For each sample z Rw×h, to deal with the scale problem, we represent it by convolving z with a set of rectangle filters at multiple scales {h1,1, . . . , hw,h} defined as hi,j(x, y) =1, 1≤ x ≤ i, 1≤ y ≤ j
0, otherwise

where i and j are the width and height of a rectangle filter, respectively. Then, we represent each filtered image as a column vector in Rwh and then concatenate these vectors as a very high-dimensional multi-scale image feature vector x =(x1, ..., xm)_ Rm where m = (wh)2. The dimensionality m is typically in the order of 106 to 1010. We adopt a sparse random matrix R in (2) with s = m/4 to project x onto a vector v Rn in a low-dimensional space. The random matrix R needs to be computed only once off-line and remains fixed throughout the tracking process. For the sparse matrix R in (2), the computational load is very light. we only need to store the nonzero entries in R and the positions of rectangle filters in an input image corresponding to the nonzero entries in each row of R. Then, v can be efficiently computed by using R to sparsely measure the rectangular features which can be efficiently computed using the integral image method.

ANALYSIS OF LOW-DIMENSIONAL COMPRESSIVE FEATURES

Each element vi in the low-dimensional feature v Rn is a linear combination of spatially distributed rectangle features at differentscales. As the coefficients in the measurement matrix can be positive or negative, the compressive features compute the relative intensity difference ina way similar to the generalized Haar-like features. TheHaar-like features have been widely used for object detection with demonstratedsuccess. The basic types of these Haar-like features are typically designedfor different tasks. There often exist a very large number of Haar-like features which make the computational load very heavy.



This problem is alleviated by boosting algorithms for selecting important features. Recently, Babenko adopted the generalized Haar-like features where each one is a linear combination of randomly generated rectangle features, and use online boosting to select a small set of them for object tracking. In our work, the large set of Haar-like features are compressively sensed with a very sparse measurement matrix. The compressive sensing theories ensure that the extracted features of our algorithm preserve almost all the information of the original image. Therefore, we can classify the projected features in the compressed domain efficiently without curse of dimensionality.

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Classifier Construction and Update

For each sample z Rm, its low-dimensional representation is v = (v1, . . . , vn)_Rn with m _ n. We assume all elements in v are independently distributedand model them with a naive Bayes classifier.

$$\frac{\prod_{i=1}^{n} p(v_i|y=1)p(y=1)}{\prod_{i=1}^{n} p(v_i|y=0)p(y=0)} = \sum_{i=1}^{n} \log\left(\frac{p(v_i|y=1)}{p(v_i|y=0)}\right),$$

where we assume uniform prior, p(y = 1) = p(y = 0), and y {0, 1} is a binary variable which represents the sample label. Diaconis and Freedman showed that the random projections of high dimensional random vectors are almost always Gaussian. Thus, the conditional distributions p(vi|y = 1) and p(vi|y = 0) in the classifier H(v) are assumed to be Gaussian distributed with four parameters (μ1i, σ1i , μ0i, σ0i) where

$$p(v_i|y=1) \sim N(\mu_i^1, \sigma_i^1), \qquad p(v_i|y=0) \sim N(\mu_i^0, \sigma_i^0).$$

The scalar parameters in are incrementally updated

$$\mu_i^1 \leftarrow \lambda\mu_i^1 + (1-\lambda)\mu^1$$
$$\sigma_i^1 \leftarrow \sqrt{\lambda(\sigma_i^1)^2 + (1-\lambda)(\sigma^1)^2 + \lambda(1-\lambda)(\mu_i^1 - \mu^1)^2},$$

Algorithm1. Compressive Tracking
Input: t-th video frame
1. Sample a set of image patches, Dγ = {z|||l(z) − lt−1|| < γ} where lt−1 is the tracking location at the (t-1)-th frame, and extract the features with low dimensionality.
2. Use classifier H to each feature vector v(z) and find the tracking location lt with the maximal classifier response.
3. Sample two sets of image patches Dα = {z|||l(z) − lt|| < α} and Dζ,β = {z|ζ < ||l(z) − lt|| < β} with α < ζ < β.
4. Extract the features with these two sets of samples and update the classifier parameters.

Output: Tracking location lt and classifier parameters.

We note that simplicity is the prime characteristic of our algorithm in which the proposed sparse measurement matrix R is independent of any training samples, thereby resulting in a very efficient method. In addition, our algorithm achieves robust performance as discussed below.

Difference with Related Work:

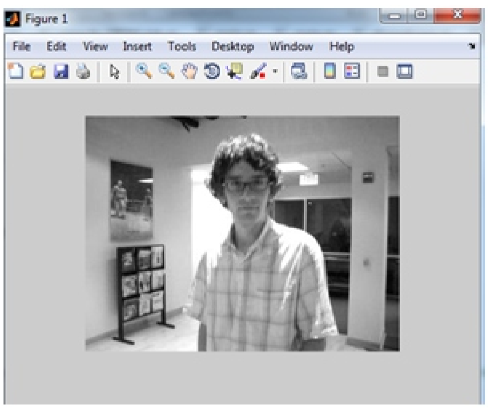
It should be noted that our algorithm is different from the recently proposed and compressive sensing tracker.

First, both algorithms are generative models that encode an object sample by sparse representation of templates using _1-minimization. Thus the training samples cropped from the previous frames are stored and updated, but this is not required in our algorithm due to the use of a data-independent measurement matrix. Second, our algorithm extracts a linear combination of generalized Haar-like features but these trackers use the holistic templates for sparse representation which are less robust as demonstrated in our experiments. Third, both of these tracking algorithms need to solve numerous time-consuming_1 minimization problems but our algorithm is efficient as only matrix multiplications are required.

DISCUSSION:

The proposed method is different from the MIL tracker [10]as it first constructs a feature pool in which each feature israndomly generated as a weighted sum of pixels in 2 to 4rectangles. A subset of most discriminative features are thenselected via an MIL boosting method to construct the finalstrong classifier. However, as the adopted measurement matrixof the proposed algorithm satisfies the JL lemma, the compressivefeatures can preserve the `2 distance of the originalhigh-dimensional features. Since each feature that representsa target or background sample is assumed to be independentlydistributed with a Gaussian distribution, the feature vector foreach sample is modeled as a mixture of Gaussian (MoG)distribution. The MoG distribution is essentially a mixture ofweighted `2 distances of Gaussian distributions. Thus, the `2distance between the target and background distributions isreserved in the compressive feature space, and the proposedalgorithm can obtain favorable results without further learning the discriminative features from the compressive feature space.

EXPERIMENTAL RESULTS:



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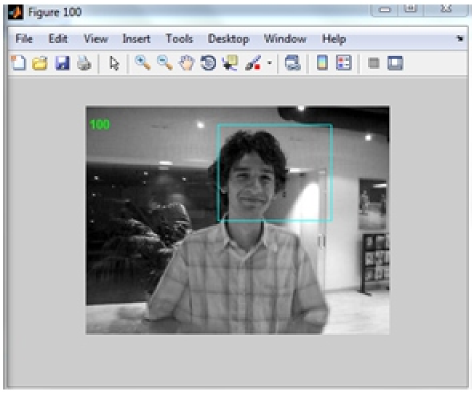

CONCLUSION:

Tracking the objects plays a vital role in security applications like criminal and terrorist detection and recognitionin real time applications which can be tracked with the help of cameras fixed in different purposes. Real timetracking requires capturing the information in the form of video signals and this requires storing the capturedinformation using lesser memory space due to unavailability of sufficient memory space. This paper provides aliterature survey on the state of art techniques used fir real time compressive tracking. The methods described aresimple yet robust tracking algorithms. The tracking task was formulated as a binary classification problem withonline update in the compressed domain by combining the merits of generative and discriminative appearancemodels to account for scene changes. The advantages of the algorithms are accuracy, robustness, and speed.

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