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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 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 the computational 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:

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 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 movesfrom one frame to the next.

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

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Thequestion then ishowto integrate the tracker and the classifier.One approach is to use the tracker and the classifiersequentially. The tracker will find where the object movedto and the classifier will give it a score. This scheme will repeatuntil the classification score will fall below some predefinedthreshold. The disadvantage of such an approach is that thetracker is not guaranteed to move to the best location (thelocation with the highest classification score) but rather findthe best matching image region. Furthermore, such anapproach relies heavily on the first frame.

BLOCK DIAGRAM:

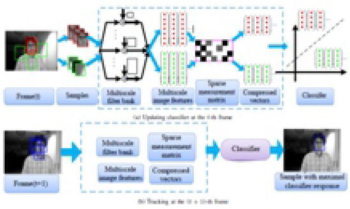

Fig. 1: Main components of the proposed compressive tracking algorithm.

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. Grabnerhave 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. Grabnerhave 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 warpingto model the object motion of two consecutive frames. Thetracking process is governed by the two important components:state transition model which models the temporalcorrelation of state transition between two consecutive frames,and observation model which measures the similaritybetween the appearance observation and the approximationusing the target model.

RELATED WORK:

Tracking is an important topic in computer vision and it hasbeen studied for several decades. In this section we summarizestudies that are related to our work; a thorough survey can befound in [45].Given the wide range and long study of visual tracking, ourproposed tracking method borrows many ideas from previouswork. First, we use the popular particle filter framework thatconsiders tracking as an estimation of the states for a time-series state space model. The particle filter, also known as thesequential Monte Carlo method [14], recursively constructsthe posterior probability density function of the state spaceusing Monte Carlo integration. It has been developed in thecomputer vision community and applied to tracking problemsunder the name Condensation [21]. It is later extended in manyvariations 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 inthe presence of partial occlusion. The weight for combininglocal classifiers is selected adaptively using particle filters.The proposed method relates to previous work onappearance-based trackers.Early examplesinclude using the sum of squared difference (SSD) as a costfunction in the tracking problem [4] and using mixture modelto model the appearance variation [22]. The work in [47]incorporates an appearance-adaptive model in a particle filterto realize robust visual tracking and classification algorithms.Our modeling using linear template combination is related toboth subspace- and template-based tracking approaches .The appearance of the object is represented usingan 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 techniquessuch as normalized correlation or template matching.Such approaches are typically limited to situations inwhich the image motion of the object is simple (e.g.,translation) and the viewpoint of the object is eitherfixed or changing slowly.

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

SIMULTANEOUS TRACKING AND RECOGNITION:

In this section, we extend our `1 tracker and propose a simultaneoustracking and recognition method using `1 minimizationin a probabilistic framework. When we locate the movingtarget in the image, we want to identify it based on the templateimages in the gallery. Typically, tracking is solved beforerecognition. When the object is located in the frame, it iscropped from the frame and transformed using an appropriatetransformation. This tracking and recognition are performedsequentially and separately to resolve the uncertainty in thevideo sequences. The recognition after tracking strategy posessome difficulties such as selecting good frames and estimationof parameters for registration.

Nonnegativity Constraints:

In principle, the coefficients in a can be any real numbers if thetarget templates are taken without restrictions. However, weargue that in tracking, a tracking target can almost always berepresented by the target templates dominated by nonnegativecoefficients. Here by "dominated" we mean that the templatesthat are most similar to the tracking target are positively relatedto the target. This is true when we start tracking from thesecond frame. The target is selected in the first frame manuallyor by a detection method. The target in the second framewill look more like the target in the first frame such that thecoefficient is positive when the target in the first frame is usedto approximate the target in the second frame. In new frames,the appearance of targets may change, but new templates willbe brought in (may replace old templates) and the coefficientswill still be positive for the most similar target templates inthe following frames.

Discussion:

The experiments demonstrate the robust tracking performanceof our algorithm.

However, our tracker can fail when there isvery large pose change or the target moves completely out ofthe frame and reappears. Fig. 18 shows two failure cases ofour tracker. In the top row, the woman's head is rotating outof-plane for 180 degrees and the target varies from frontal facein left image to back of her head in middle image. Trackerdrifts away from the target after the rotation is complete andthe woman's frontal face reappears in the right image. In the bottom row of Figure the target moves completely out ofthe frame in the middle image. The tracker is tracking theback-ground without knowing it. When the target reappears inthe right image, the tracker cannot recover after losing trackof the target.

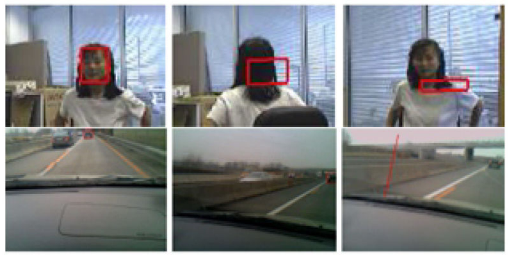
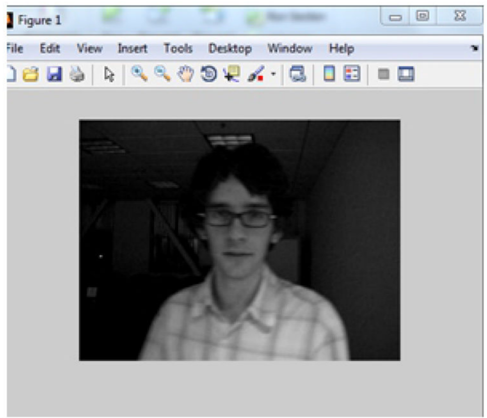
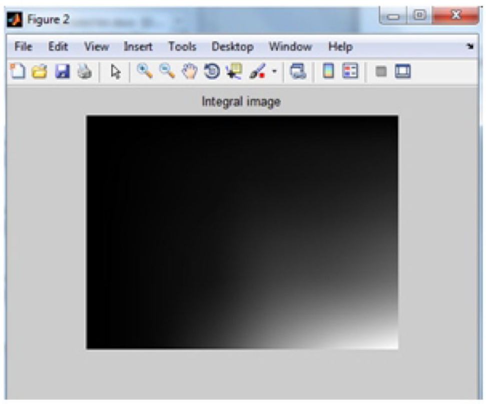


Fig. Two failed tracking cases.

EXPERIMENTAL RESULTS:





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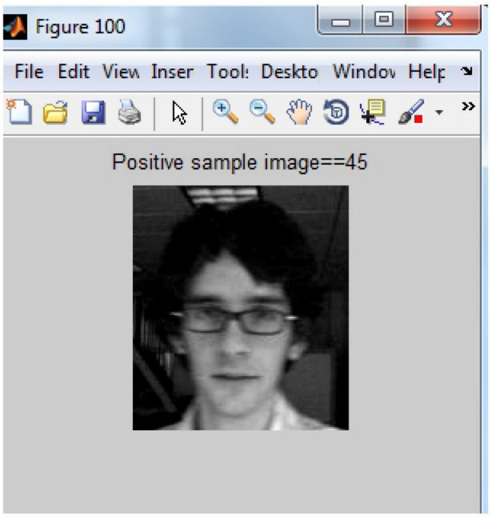

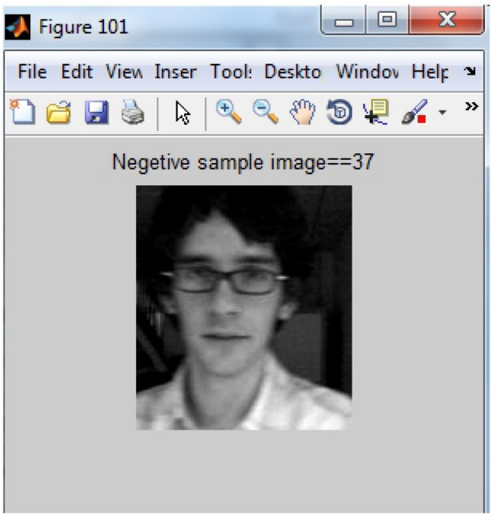

CONCLUSION:

In this paper, we propose using sparse representation for robustvisual tracking. We model tracking as a sparse approximationproblem and solve it through an `1-regularized least squaresapproach. For further robustness, we introduce nonnegativityconstraints and dynamic template update in our approach.In thorough experiments involving numerous challenging sequencesand four other state-of-the-art trackers, our approachdemonstrates very promising performance. We also extend ourwork to simultaneous tracking and recognition and apply itto IR-based vehicle classification. The experimental resultsdemonstrate clearly the effectiveness of our proposed method.

REFERENCES:

[1] M. Andriluka, S. Roth, and B. Schiele.“People-tracking-by-detection andpeople-detection-by-tracking”, in Proc. IEEE Conf. on Computer Visionand Pattern Recognition, 1–8, 2008.

[2] S. Avidan. “Ensemble Tracking”, in Proc. IEEE Conf. on Computer Visionand Pattern Recognition, 494–501, 2005.

[3] B. Babenko, M. Yang, and S. Belongie.“Visual Tracking with OnlineMultiple Instance Learning”, in Proc. IEEE Conf. on Computer Visionand Pattern Recognition, 2009.

[4] S. Baker and I. Matthews.“Lucas-kanade 20 years on: A unifyingframework”, Int’l Journal of Computer Vision, 56:221–255, 2004.

[5] M. D. Breitenstein, F. Reichlin, B. Leibe, E. Koller-Meier, L. V. Gool.“Robust tracking-by-detection using a detector confidence particle filter”,in Proc. Int’l Conf. on Computer Vision, 2009.

[6] M. J. Black and A. D. Jepson.“Eigentracking: Robust matching andtracking of articulated objects using a view-based representation”, Int’lJournal of Computer Vision, 26:63-84, 1998.

[7] Y. Cai, N. Freitas and J. Little. “Robust Visual Tracking for MultipleTargets”, in Proc. European Conf. on Computer Vision, 107–118, 2006.

[8] E. Cand`es, J. Romberg, and T. Tao. “Stable signal recovery fromincomplete and inaccurate measurements”, Comm. on Pure and AppliedMath, 59(8):1207-1223, 2006.

[9] V. Cevher, A. Sankaranarayanan, M. F. Duarte, D. Reddy, R. G. Baraniuk,and R. Chellappa.“Compressive Sensing for Background Subtraction”,in Proc. European Conf. on Computer Vision, 2008.

[10] R. T. Collins and Y. Liu.“On-Line Selection of Discriminative TrackingFeatures”, in Proc. Int’l Conf. on Computer Vision, 346–352, 2003.

[11] D. Comaniciu, V. Ramesh, and P. Meer. “Kernel-based object tracking”,IEEE Trans. on Pattern Anal.and Mach. Intell., 25:564–577, 2003.

[12] l1ls: Simple Matlab Solver for l1-regularized Least Squares Problems,[online] http://www.stanford.edu/~boyd/l1 ls/.

[13] D. Donoho. “Compressed Sensing”, IEEE Trans. Information Theory,52(4):1289-1306, 2006.

[14] A. Doucet, N. de Freitas, and N. Gordon.“Sequential Monte CarloMethods in Practice”.Springer-Verlag, 2001, New York.