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Tracking Technique Using Extracted Feature Compression

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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. While 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, these mis-aligned 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 the multi-scale image feature space with data-independent basis.

Our appearance model employs non adaptive random projections that preserve the structure of the image feature space of objects. A very sparse measurement matrix is adopted to efficiently extract the features for the appearance model. We compress samples of foreground targets 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 performs favorably against state-of-the-art algorithms on challenging sequences in terms of efficiency, accuracy and robustness.

INTRODUCTION:

Object tracking is a huge undertaking in the territory ofmachine vision. The improvement of super-capable machines,the accessibility of high definition cams at low expenses, andthe perpetually expanding interest for programmed featureinvestigation in applications like feature surveillance, activitychecking, and HMIs has created a lot of enthusiasm towardarticle following calculations.

In its least difficult structure,following can be expressed as the issue of assessing thetrajectory of an article in the picture plane as it moves arounda scene. In this we are going to study what is Articlefollowing? What is Compressive sensing? Furthermore what is quick compressive tracking?

COMPRESSIVE TRACKING:

We utilize an exceptionally meager estimation lattice that asymptotically fulfills the limited isometric property (Tear) in compressive sensing hypothesis , subsequently encouraging productive projection from the picture peculiarity space to a lowdimensional layered subspace. For tracking, the positive and negative specimens are anticipated (i.e., packed) with the same inadequate estimation grid and segregated by a basic credulous Bayes classifier learned on the web.

The proposed compressive tracking calculation runs at continuous and performs positively against state-of-the-art trackers on difficult arrangements regarding effectiveness, precision and vigor. The fundamental parts of the proposed compressive tracking calculation are indicated in above figure.

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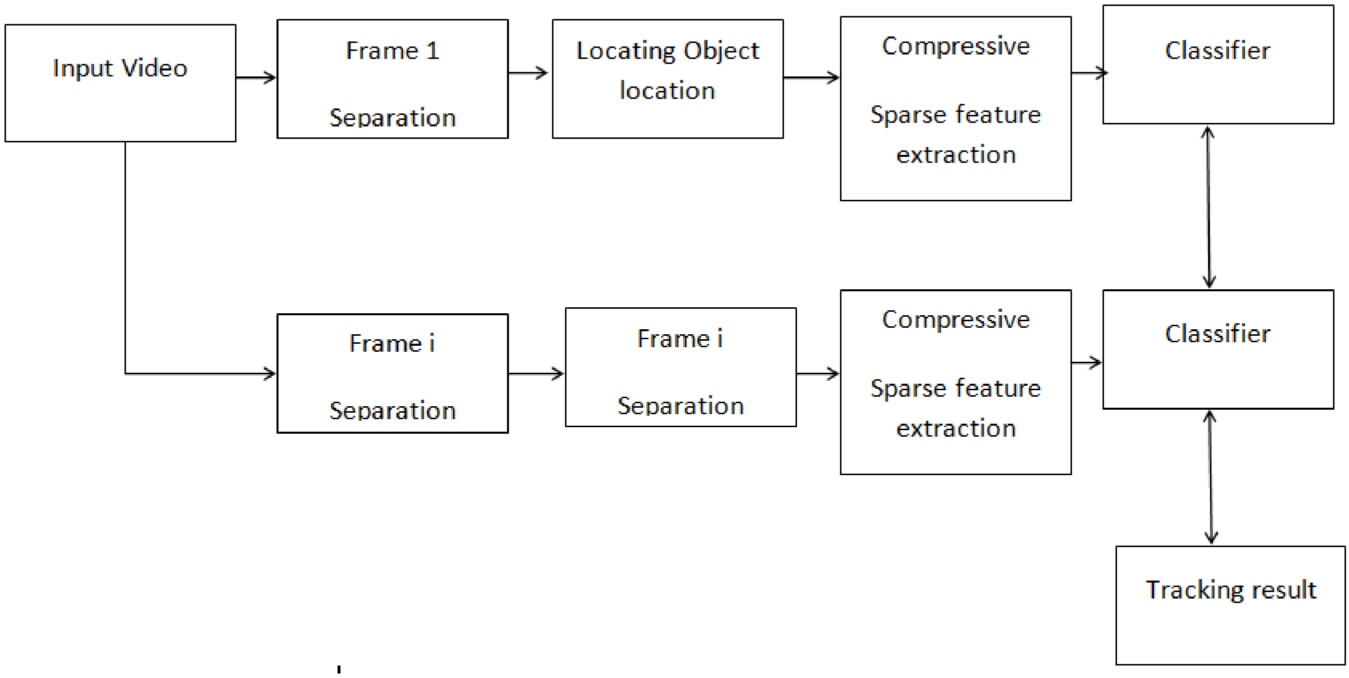
Block diagram:



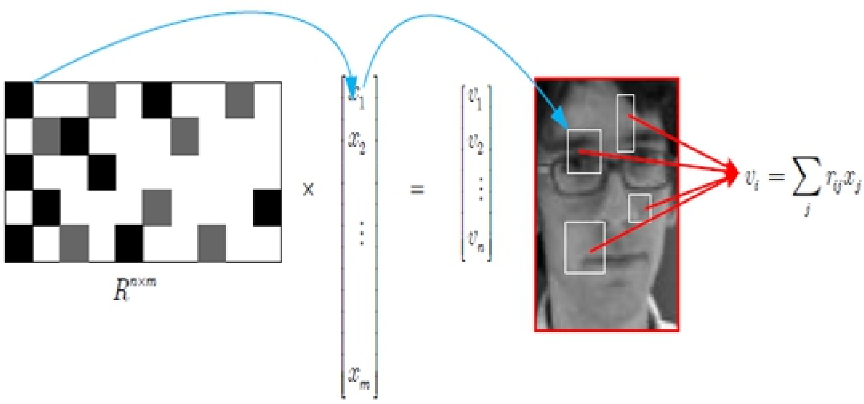
Existing Tracking Algorithm:

Despite that numerous algorithms have been proposed in theliterature, object tracking remains a challenging problem due to appearance change caused by pose, illumination, occlusion, and motion, among others. An effective appearance model is of prime importance for the success of a tracking algorithm that has attracted much attention in recent years. 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 ,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.

Another successful approach is to extract discriminative features from a high-dimensional space.

PROPOSED ALGORITHM:

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.



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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.

MULTI SCALE FILTER BANK:

Multi-scale filter banks, mainly based on oriented Gaussian derivatives and Gabor functions, to be used in the generation of robust features for visual object categorization. In order to combine the responses obtained from several spatial scales, we use the biologically inspired HMAX model (Riesenhuber and Poggio, 1999). We have tested the different sets of features on the challenging Caltech-101 database, and we have performed the categorizarion procedure with AdaBoost, support vector machines and JointBoosting classifiers, achieving remarkable results.

RANDOM MEASUREMENT MATRIX:

A random matrix R Rn×mwhose rows have unit length projects data from the high dimensional image space x Rmto a lower-dimensional space v Rn v = Rx
wheren _ m. Ideally, we expect R provides a stable embedding that approximately preserves the distance between all pairs of original signals. The Johnson- Lindenstrauss lemma states that with high probability the distances between the points in a vector space are preserved if they are projected onto a randomly selected subspace with suitably high dimensions. Baraniuk proved that the random matrix satisfying the Johnson-Lindenstrauss lemma also holds true for the restricted isometry property in compressive sensing. Therefore, if the random matrix R satisfies the Johnson-Lindenstrauss lemma, we can reconstruct x with minimum error from v with high probability if x is compressive such as audio or image. We can ensure that v preserves almost all the information in x. This very strong theoretical support motivates us to analyze the high-dimensional signals via its low-dimensional random projections. In the proposed algorithm, we use a very sparse matrix that not only satisfies the Johnson-Lindenstrauss lemma, but also can be efficiently computed for real-time tracking.

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 ashi,j(x, y) =1, 1≤ x ≤ i, 1≤ y ≤ j 0, otherwisewhere i and j are the width and height of a rectangle filter, respectively. Then, we represent each filtered image as a column vector in Rwhand then concatenate these vectors as a very high-dimensional multi-scale image feature vector x =(x1, ...,xm)_ Rmwhere 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 Rnin 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.

DIMENSIONALITY REDUCTION METHOD:

In machine learning and statistics, dimensionality reduction or dimension reduction is the process of reducing the number of random variables under consideration, and can be divided into feature selection and feature extraction.Feature selection approaches try to find a subset of the original variables (also called features or attributes). Two strategies are filter (e.g. information gain) and wrapper (e.g. search guided by the accuracy) approaches. See also combinatorial optimization problems.

In some cases, data analysis such as regression or classification can be done in the reduced space more accurately than in the original space.Feature extraction transforms the data in the high-dimensional space to a space of fewer dimensions. The data transformation may be linear, as in principal component analysis (PCA), but many nonlinear dimensionality reduction techniques also exist. For multidimensional data, tensor representation can be used in dimensionality reduction through multilinear subspace learning.

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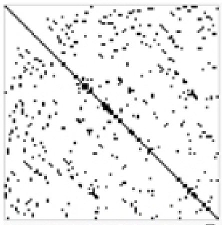
The main linear technique for dimensionality reduction, principal component analysis, performs a linear mapping of the data to a lower-dimensional space in such a way that the variance of the data in the low-dimensional representation is maximized. In practice, the correlation matrix of the data is constructed and the eigenvectors on this matrix are computed. The eigenvectors that correspond to the largest eigenvalues (the principal components) can now be used to reconstruct a large fraction of the variance of the original data. Moreover, the first few eigenvectors can often be interpreted in terms of the large-scale physical behavior of the system. The original space (with dimension of the number of points) has been reduced (with data loss, but hopefully retaining the most important variance) to the space spanned by a few eigenvectors.

SPARSE MEASUREMENT MATRIX:

In numerical analysis, a sparse matrix is a matrix in which most of the elements are zero. By contrast, if most of the elements are nonzero, then the matrix is considered dense. The fraction of zero elements over the total number of elements in a matrix is called the sparsity (density).Conceptually, sparsity corresponds to systems which are loosely coupled. Consider a line of balls connected by springs from one to the next: this is a sparse system as only adjacent balls are coupled. By contrast, if the same line of balls had springs connecting each ball to all other balls, the system would correspond to a dense matrix. The concept of sparsity is useful in combinatorics and application areas such as network theory, which have a low density of significant data or connections.

Large sparse matrices often appear in scientific or engineering applications when solving partial differential equations.When storing and manipulating sparse matrices on a computer, it is beneficial and often necessary to use specialized algorithms and data structures that take advantage of the sparse structure of the matrix. Operations using standard dense-matrix structures and algorithms are slow and inefficient when applied to large sparse matrices as processing and memory are wasted on the zeroes. Sparse data is by nature more easily compressed and thus require significantly less storage. Some very large sparse matrices are infeasible to manipulate using standard dense-matrix algorithms.



A sparse matrix obtained when solving a finite element problem in two dimensions. The non-zero elements are shown in black.

NAIVE BAYES CLASSIFIERS:

In machine learning, naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features.

Machine learning anddata mining:

Naive Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression,:718 which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers.

In the statistics and computer science literature, Naive Bayes models are known under a variety of names, including simple Bayes and independence Bayes. All these names reference the use of Bayes' theorem in the classifier's decision rule, but naive Bayes is not (necessarily) a Bayesian method; Russell and Norvig note that "[naive Bayes] is sometimes called a Bayesian classifier, a somewhat careless usage that has prompted true Bayesians to call it the idiot Bayes model."

COMPRESSIVE SENSING THEORY:

The compressive sensing (CS) hypothesis demonstratethat if the measurement of the gimmick space issufficiently high, these gimmicks can be anticipated to ahaphazardly picked low-dimensional space which containsenough data to remake the first high-dimensionalpeculiarities. The dimensionality lessening system througharbitrary projection (RP) is information autonomous, nonversatileand data protecting.

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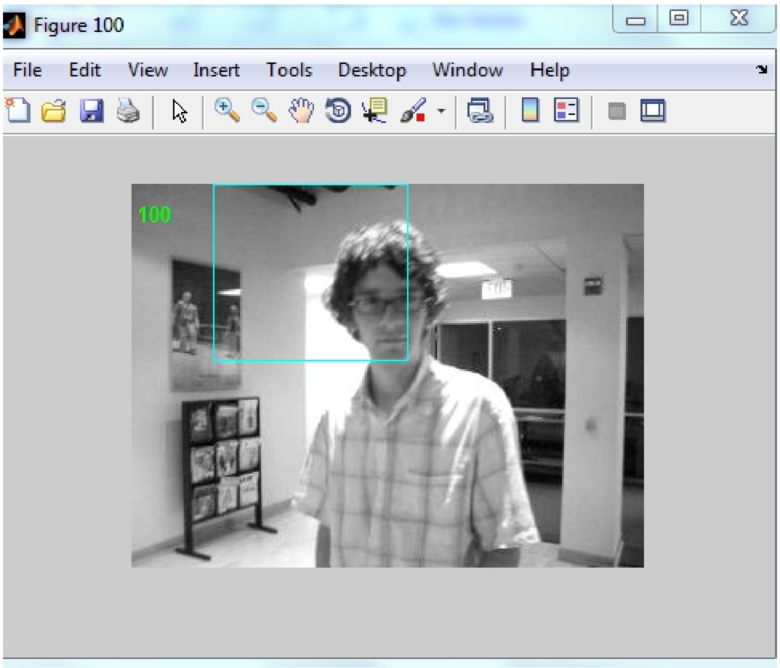
EXPERIMENTAL RESULTS:



CONCLUSION:

In this paper, we propose a simple yet robust tracking algorithmwith an appearance model based on non-adaptiverandom projections that preserve the structure of originalimage space. A very sparse measurement matrix is adoptedto efficiently compress features from the foreground targetsand background ones.A very sparse measurement matrix is adopted to productivelyclamp features from the frontal area targets and backgroundones. The tracking task is formulated as a binary classificationissue with online update in the packed domainThe tracking task is formulated asa binary classification problem with online update in thecompressed domain. Numerous experiments with state-ofthe-art algorithms on challenging sequences demonstrate thatthe proposed algorithm performs well in terms of accuracy,robustness, and speed.Our future work will focus on applications of the developedalgorithm for object detection and recognition under heavyocclusion. In addition, we will explore efficient detectionmodules for persistent tracking (where objects disappear andreappear after a long period of time).

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