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A Survey On Tracking Moving Objects Using Various Algorithms

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ABSTRACT

Sparse representation has been applied to the object tracking problem. Mining the self- similarities between particles via multitask learning can improve tracking performance. How-ever, some particles may be different from others when they are sampled from a large region. Imposing all particles share the same structure may degrade the results. To overcome this problem, we propose a tracking algorithm based on robust multitask sparse representation (RMTT) in this letter. When we learn the particle representations, we decompose the sparse coefficient matrix into two parts in our algorithm. Joint sparse regularization is imposed on one coefficient matrix while element-wise sparse regularization is imposed on another matrix. The former regularization exploits self-similarities of particles while the later one considers the differences between them.

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I. Introduction

Visual object tracking is an important topic in computer vision and has many applications including intelligent surveillance, human computer interface (HCI), augmented reality (AR), etc. Although great processes have been made and many tracking algorithms have been proposed but it remains an open problem to design a robust tracker in the real-world scenarios due to severe occlusions, large appearance changes, illumination changes, background clutter and abrupt motion. Recently, sparse representation and compress sensing have been applied to the object tracking problem. In the L1 tracker proposed by Mei and Ling, each candidate is sparsely represented by the target templates and trial templates. This representation is robust to illumination changes and partial occlusion, the stable signal recovery capability via the L1 norm minimization. To solve the L1 norm minimization efficiently, we adopt the accelerated proximal gradient (APG) approach and they claim the L1APG tracker run in the real-time. When particles are sampled from a large region and the brutal enforcement of the same structure on all particles, e.g. joint-sparsity, low-rank, may degrade the results. To overcome this problem, we propose our tracking algorithm based on robust multitask learning (RMTT). In our algorithm, we decompose the sparse coefficient matrix into two parts. A joint sparse regularization is imposed on, corresponding to the shared structure while an element-wise sparse regularization is imposed on which corresponds to the non-shared features. The joint sparsity exploits the similarities of particles while the element-wise sparsity considers the differences between candidates. Many experiments on the benchmark datasets show the superior performance over the state-of-art algorithms.

Tracking is an optical method that employs tracking and image registration techniques for accurate 2D and 3D measurements of changes in images. This is often used to measure deformation (engineering), displacement, strain, and optical flow, but it is widely applied in many areas of science and engineering. In its simplest form, tracking can be defined as the problem of estimating the trajectory of an object in the image plane as it moves around a scene. In other words, a tracker assigns consistent labels to the tracked objects in different frames of a video. Additionally, depending on the tracking domain, a tracker can also provide object-centric information, such as orientation, area, or shape of an object. One very common application is for measuring the motion of an optical mouse.

II. Literature Survey

Most tracking-by-detection algorithms train discriminative classifiers to separate target objects from their surrounding background. In this setting [15], noisy samples are likely to be included when they are not properly sampled, thereby causing visual drift. The multiple instance learning (MIL) paradigm has been recently applied to alleviate this problem. However, important prior information of instance labels and the most correct positive instance (i.e., the tracking result in the current frame) can be exploited using a novel formulation much simpler than an MIL approach. In this paper, we show that integrating such prior information into a supervised learning algorithm can handle visual drift more effectively and efficiently than the existing MIL tracker.

Sparse representation scheme is very influential in visual tracking field [8]. These L1 trackers obtain robustness by finding the target with the minimum reconstruction error via L1 norm minimization problem. However, the high computational burden of L1 minimization and absence of effective model for appearance changes may hamper its application in real world sceneries. In this research, we present a fast and robust tracking method that exploits a fast memory gradient pursuit algorithm (FMGP) with sparse representation scheme in a Bayesian framework to accelerate the L1 minimization process.

Combining multiple observation views has proven beneficial for tracking. In paper [17], we cast tracking as a novel multi-task multi-view sparse learning problem and exploit the cues from multiple views including various types of visual features, such as intensity, color, and edge, where each feature observation can be sparsely represented by a linear combination of atoms from an adaptive feature dictionary. The proposed method is integrated in a particle filter framework where every view in each particle is regarded as an individual task. We jointly consider the underlying relationship between tasks across different views and different particles, and tackle it in a unified robust multi-task formulation.

The use of multiple features for tracking has been proved as an effective approach because limitation of each feature could be compensated [10]. Since different types of variations such as illumination, occlusion and pose may happen in a video sequence, especially long sequence videos, how to dynamically select the appropriate features is one of the key problems in this approach. To address this issue in multicue visual tracking, this paper proposes a new joint sparse representation model for robust feature-level fusion. The proposed method dynamically removes unreliable features to be fused for tracking by using the advantages of sparse representation. As a result, robust tracking performance is obtained. Experimental results on publicly available videos show that the proposed method outperforms both existing sparse representation based and fusion-based trackers.

In paper [12], we formulate object tracking in a particle filter framework as a multi-task sparse learning problem, which we denote as Multitask Tracking (MTT). Since we 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.By employing popular sparsity-inducing `p;q mixed norms, we regularize the representation problem to enforce joint sparsity and learn the particle representations together. As compared to previous methods that handle particles independently, our results demonstrate that mining the interdependencies between particles improves tracking performance and overall computational complexity.

We address the problem of visual classification with multiple features and/or multiple instances. Motivated by the recent success of multitask joint covariate selection [3], we formulate this problem as a multitask joint sparse representation model to combine the strength of multiple features and/or instances for recognition. A joint sparsity-inducing norm is utilized to enforce class-level joint sparsity patterns among the multiple representation vectors. The proposed model can be efficiently optimized by a proximal gradient method. Furthermore, we extend our method to the setup where features are described in kernel matrices. We then investigate into two applications of our method to visual classification: 1) fusing multiple kernel features for object categorization and 2) robust face recognition in video with an ensemble of query images.

We propose a new particle-filter based tracking algorithm [14] that exploits the relationship between particles (candidate targets). By representing particles as sparse linear combinations of dictionary templates, this algorithm capitalizes on the inherent low-rank structure of particle representations that are learned jointly. This low-rank sparse tracker (LRST) has a number of attractive properties. **(1)** Since LRST adaptively updates dictionary templates, it can handle significant changes in appearance due to variations in illumination, pose, scale, etc. **(2)** The linear representation in LRST explicitly incorporates background templates in the dictionary and a sparse error term, which enables LRST to address the tracking drift problem and to be robust against occlusion respectively. **(3)** LRST is computationally attractive, since the low-rank learning problem can be efficiently solved as a sequence of closed form update operations.

Object tracking in a particle filter framework as a structured multi-task sparse learning problem [13], which we denote as Structured Multi-Task Tracking (S-MTT). Since we model particles as linear combinations of dictionary templates that are updated dynamically, learning the representation of each particle is considered a single task in Multi-Task Tracking (MTT). By employing popular sparsity-inducing *_p,q* mixed norms *(*specifically $p \in \{2,\infty\}$ and $q = 1$*)*, we regularize the representation problem to enforce joint sparsity and learn the particle representations together. As compared to previous methods that handle particles independently, our results demonstrate that mining the interdependencies between particles improves tracking performance and overall computational complexity.

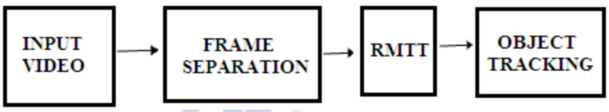
A. Disadvantages

Joint-Sparsity, Low-Rank, may degrade the results. Both MTT and LRST show the superior performance over both L1 and L1APG trackers. The background is cluttered and complex and the target were occluded. When a similar region appeared, L1apg was confused and hijacked by this region. When the occlusion was happened, MTT introduced large error and almost lost the target location.

III. Proposed System

Sparse representation has been applied to the object tracking problem. Mining the self-similarities between particles via multitask learning can improve tracking performance. However, some particles may be different from others when they are sampled from a large region. Imposing all particles share the same structure may degrade the results. To overcome this problem, we propose a tracking algorithm based on robust multitask sparse representation (RMTT). This is the main problem that they do not consider difference between particles when exploiting the dependencies. When we learn the particle representations, we decompose the sparse coefficient matrix into two parts in our algorithm. Joint sparse regularization is imposed on one coefficient matrix while element-wise sparse regularization is imposed on another matrix. The former regularization exploits self-similarities of particles while the later one considers the differences between them. The challenges of these videos include illumination variation , partial occlusion , pose change, background clutter and scale variation . Experiments on the benchmark data show the superior performance over other state-of-art algorithms.

Figure 1: *Object tracking in video*



A. Advantages

This representation is robust to illumination changes and partial occlusion. This algorithm captures a common feature among relevant tasks and identifies outlier tasks. In real world scenarios it has many applications in intelligent surveillance, human computer interface.

Figure 2: *Tracking object*

IV. Conclusion

In this paper, we have proposed an object tracking algorithm via robust multitask sparse representation. When we learn the sparse coefficient matrix, we decompose it into two halves. Joint sparsity regularization is imposed on one coefficient matrix and element-wise sparsity regularization is imposed on the other. This can exploits the dependencies between patches while considering the differences between them. Experiments on challenging video sequences show that our tracking algorithm performs better than several state-of-the-art algorithms.

V. Future Enhancement

We will investigate that the tracking of the object by an adaptation of the Hough Transform, which is used in the feature extraction procedure to interpret scanned segments as primitive features, defined by geometric evidence (points, lines, circles and blobs), and high-level features, generally referred to as landmarks (corners, columns, doors, etc.). The classification system uses features data, some heuristic rules, and data from a filter based tracking system to classify multiple objects.

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