Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Dynamic object construction using belief function theory

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ARTICLE INFO

Article history: Received 26 December 2014 Revised 6 December 2015 Accepted 22 January 2016 Available online 30 January 2016

Keywords: Fragmentary detections Data association Object construction Belief function theory

ABSTRACT

Several video surveillance applications aim at detecting the object(s) appeared in the scene of interest. Assuming these objects may be of any kind, change detection algorithms are often used to detect objects or object subparts, that have then to be gathered to form the objects. We call 'object construction' this step of object fragments (elementary change detections) collecting, associating to the right object and fusing with other fragments. In this work, we model the uncertainty and the imprecision of the location of the detected fragments using Belief Function Theory (BFT). During object construction, two mechanisms compete, namely the data accumulation and their temporal removal or weighting. We show that BFT framework is suitable for implementing these mechanisms as well as the data association between the new detections that are unlabeled and the objects under construction. Tests on actual data were performed. They allow for the quantitative evaluation of the proposed method in term of robustness versus the object partial occultation and crossing. Proposed approach is also compared with several alternative approaches.

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1. Introduction

Tracking is an important field in computer vision used in several applications such as automated surveillance, human behavioral analysis and traffic monitoring [43,61]. Fundamentally, it aims at estimating automatically the trajectory of each moving object (either in the image or in the 3D scene). Since there may be several objects of interest, appearing and disappearing from the scene during the time period, main challenges are robustness to object merging, splitting and crossing. Considerable work has been done to discuss the object features (e.g. color, texture, optical flow, edge) used for their tracking and therefore the underlying object representation [61]: e.g., centroids [60] or set of points [52] in the case of objects that occupy small regions in an image, primitive geometric shapes like box or ellipse [10] in the case of simple rigid objects, silhouette or contour [62] in the case of non-rigid objects. However, the performance of a tracker not only depends on the object representation, from which some discriminative features are extracted, but also on the object detection that determines the precision and reliability of the extracted features. Thus, very different are the case of the already tracked objects, whose detection can be highly helped by the knowledge of their features (including a prediction model), and the case of the objects appearing in the scene which, by definition, are unknown. In this study we focus on this latter case.

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http://dx.doi.org/10.1016/j.ins.2016.01.047 0020-0255/© 2016 Elsevier Inc. All rights reserved.







In the absence of a priori or model on the objects (we do not discuss of application-specific object classes, such as parts of human bodies for people counting), detection is done by contradiction of a background model. Then, for objects having a non elementary size (conversely to radar application where a target, e.g. plane, ship or intruder, is generally represented by a point), the detections often correspond to fragments of the physical objects [64]. This fragmentary aspect is mainly due to occultation phenomena. For instance, using background subtraction techniques or Gaussian mixture models, occlusion may be caused by the object itself (self occlusion) or by other object(s) (inter-object occlusion) or by the background when this latter is highly similar to parts of the object. Now, any object having some undetected subparts appears divided into several fragments.

The step that then gathers the fragments into objects (object construction) is often presented as an initialization problem for tracking of non elementary objects or targets. Most works have been carried out in a supervised context, either based on a learning step [33] or based on object models, either rigid templates [12], or bag-of-features [63] or deformable part models [2,20] (models that also require intensive training). In this study, we focus on unsupervised approaches dealing with a priori unknown objects. The most popular solutions use a distance-based criterion to determine the fragments belonging to a same object and gather them [42,51,58,59]. However, using threshold and leading to a binary decision (belongs or not to the object), such approaches lead to coarse object estimation and are not effective in presence of close objects. In a finer way, studies [6,28] deal with the problem of object fragmentation (i.e. several measurements associated with a single object) and/or its dual problem, namely multiple objects corresponding to a single measurement. [6] introduces the concept of target-sets and uses constraints of spatial connectedness and coherent motion to define the objects themselves. However, they do not deal with the problem of false alarms nor the object localization imprecision due to object motion. In this work, the fragmentary detections are accumulated through several images (of a video sequence) like in [6]. However, rather than gathering them to get a crisp representation of the object, the fragments are used to provide a credal representation of the objects under construction, so that the problem boils down to a problem of data (the fragments) fusion.

By definition, objects under construction have none specific features (not yet) but the location of their detections. To exploit this feature in a more nuanced way than binary tests on pixel sets, we take into account the incomplete and imprecise nature of detections to propose an object representation using belief function (BF) framework [53,54]. Let us first specify in which way, subsets of associated fragments are imprecise and uncertain pieces of information for object construction. They are imprecise because detections are partial and incomplete and because objects are spatially moving. Accepting a certain level of imprecision in the object representation, some authors use bounding boxes of each subset of associated fragments. Specifically, rough sets [17,41] have been proposed to represent an object as a set of pixels bounded by a lower approximation set and an upper approximation set (lower and upper bounding boxes). However, such representations include also large parts of background so that they appear too coarse for several applications (e.g. multi-object tracking). Secondly, the fragments are uncertain information pieces due to the presence of false alarms and some possible errors in the labelling process of the fragments (data association step). To handle uncertainty on 2D elements (called cells), occupancy grids [8,19] have been proposed associating a probability value of its occupancy to each cell. The main drawback of this representation is then the ambiguity between uncertain occupancy and certain but partial occupancy of a cell. Finally, belief function theory appears as a natural choice since, besides allowing for the management of both uncertainty and imprecision, it provides a well-established framework with numerous operators. It has been applied with success for several image processing problems varying from medical imaging [4], remote sensing [32], video surveillance [31], tracking [24] to data association [18].

This work extends our preliminary studies presented in conference papers [45,46] by providing more details about the method (algorithm and toy example to illustrate it step by step) and validating it in terms of performance relative to alternative approaches. The remainder of this paper is as follows. Section 2 recalls some tools of belief function theory. Our approach for data association is described in Section 3 and a toy example is provided. Some illustrative results and a quantitative comparison with alternative approaches are provided in Section 4 while Section 5 gathers our perspectives and conclusions.

2. Background

In this section, we present the tools used in the following parts of this study as well as the state of the art of data association which is the object construction main problem. The definitions as well as the interpretations of belief functions are those developed by Smets in his transferable belief model [54].

2.1. Belief function definitions and tools

We denote by Ω the discernment frame and by 2^{Ω} the set of its subsets. Three belief functions are defined from 2^{Ω} to [0,1]: the mass (also called basic belief assignment or bba) *m*, the credibility *bel* and the plausibility *pl* [54]. An element $A \in 2^{\Omega}$ such that m(A) > 0 is a focal element of *m*. A categorical bba is a bba with only one focal element. A simple bba has two focal elements among them Ω . A bba with $m(\emptyset) = 0$ is a normal bba. Assuming a closed world, all bbas are normal whereas, for an open world, $m(\emptyset) \ge 0$ and $m(\emptyset)$ is often presented as the degree of conflict. Several operators have been proposed to modify a bba according to new information pieces or bbas. Let us present the ones used in this work.

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