# RESOLVING DATA-ASSOCIATION UNCERTAINTY
## *In Mutli-object Tracking through Qualitative Modules*

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Abstract: In real-time tracking, a crucial challenge is to efficiently build association among the objects. However, real-time interferences (e.g. occlusion) manifest errors in data association. In this paper, the uncertainties in data association are handled when discrete information is incomplete during occlusion through qualitative reasoning modules. The formulation of the qualitative modules are based on exploiting human-tracking abilities (i.e. common sense) which are integrated with data association technique. Each detected object is described as a node in space with a unique identity and status tag whereas association weights are computed using CWHI and Bhattacharyya coefficient. These weights are input to qualitative modules which interpret the appropriate status of the objects satisfying the fundamental constraints of object's continuity during tracking. The results are linked with Kalman Filter to estimate the trajectories of objects. The proposed approach has shown promising results illustrating its contribution when tested on a set of videos representing various challenges.

# 1 INTRODUCTION

Practically, tracking is a difficult problem due to direct and indirect influence of real-time factors which result in ambiguities because the objects lost their contextual information. In broader aspect, various kinds of occlusions can be observed in real scenarios such as: 1) object-to-object and 2) object-to-scene occlusion, we have addressed later type of occlusion.

In this paper, the uncertainties due to incomplete data which produce plausible association are handled using qualitative modules during entire tracking. Technically, the ambiguities in data association and object's identity management are addressed by providing the explicit support through qualitative reasoning and tracking with linear Kalman filter. The inference takes place by combining both sources of information during tracking as shown in Figure. 1. Our goal is to reliably track objects under severe occlusion without any scene restriction and prior training. The paper is organized as follows: section 2 entails the reviews of the relevant literature; the proposed approach is described in section 3. Experimental results are presented in section 4. Finally, the conclusion and future directions are sketched in section 5.

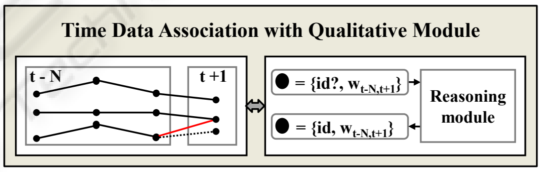


Figure 1: In this, nodes represent the detected objects and the connecting lines indicate the association among the objects at time $t$ whereas red line shows the wrong association. The data association module is linked to the qualitative module which generates the respective motion status-tags.

# 2 RELATED WORK

Tracking has been extensively studied; a detailed review on visual tracking is given in (Blake, 2006). Handling occlusion is challenging when tracking real scenarios. One of the approaches is global data association such as Probabilistic Data Association (Bar-Shalom and Fortmann, 1987) which finds the correspondence of target with all possible global explanations. Alternatively, a solution is suggested by (Khan, 2005), taking a time-window $N$ to find the correspondence of target object in $i+N$ space.

Most of the research in vision underpinned the statistical techniques to build an association among the moving objects. On the contrary, qualitative reason-



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ing allows an explicit control to determine the consistent generation of possibilities (Bennett, 2008). Sherrah and Gong (Sherrah and Gong, 2000) proposed a view-based approach with Bayesian framework and explicit probabilistic reasoning to handle the plausible interpretation of incomplete data due to occlusion. Another example of similar technique is suggested by (Bennett et al., 2008) in which logical reasoning engine interprets the spatio-temporal continuity of objects during tracking to overcome the error due to incomplete data during occlusion. However, in their work, the ambiguity is handled through long-term reasoning unlike our proposed work. But, we are more focused to exploit the logics with likelihood such as (Halpern, 1990). More recently, Frintrop et al. (Frintrop et al., 2009) exploited the cognitive approach to optimally detect object and an observation model is built on the suitable features which is then associated with Condensation algorithm. Thus, the qualitative reasoning provides a powerful mechanism to handle inconsistent situations and can complement the performance of statistical techniques.

# 3 PROPOSED APPROACH

## 3.1 The Motivation

We investigate the behaviors and properties of moving object in world domain and how a human's cognitive system processes that information as shown in Figure. 2. The qualitative modules interpret the real-world tracking scenarios and assign the status-tags to each detected object. It is assumed that the object's motion is continuous function of time until it leaves the scene. In the following, the formulation of each qualitative module is presented.

Let set of $n$ objects are detected at each time frame $t$, so:

$$O^t_{id} = [O_1, O_2, .O_{id} ..., O_n]$$

each individual object is indicated by unique identity $id$ and represented by $(id, f, tag, w)$ structure where
$id$ : is the unique identity which remains the same during the entire course of tracking.
$f$ : is the frame number.
$tag$ : represents the motion status-tags which are inferred by the qualitative modules.

$$tag = \{norm_{id}, new_{id}, exit_{id}, occ_{id}, over_{id}, reap_{id}\}$$

where $tag$ represents motion status-tag of *normal*, *new*, *exit*, *occludee*, *overlaper* and *reappear* respectively at time $t$ (explained in section 3.3).
$w$ : indicates the association-weight which is explained in section 3.2.

## 3.2 Association-weight Computation

The association-weights among objects are measured by integrating the Correlation Weighted Histogram Intersection (CWHI) (Pathan et al., 2009) and Bhattacharyya Coefficient (BC), a general description is in (Kailath, 1967). The association likelihood is computed iteratively in a time-window N. Search space criteria are adapted which enables the efficient enumeration of multiple possibilities, thus overcome the search space problem with reliable computation of likelihood. The formulation is given as:

$$w = C_{bc,cwhi} = BC + CWHI \tag{1}$$

## 3.3 Qualitative Modules

In this section, the abstract qualitative reasoning is presented to infer the status-tags of the moving object during tracking.

### 3.3.1 Normal Tag

The normal concept is based on the fact that the object is moving with ideal pace keeping its visual characteristics and motion consistency satisfying the continuity constraints during entire tracking. This module determines the normal tag of the moving object:

$$norm(O^t_{id}) = \big\{max(O^t_?, LIST\_Of\_OBJ(N)) \wedge SEARCH\_SPACE(O^t_?, LIST\_of\_OBJ(N))\big\}$$

where $max(..,..)$ computes the maximum likelihood of the detected object in time $t$ with the list of the objects. $N$ represents the time-window for data association, the $SEARCH\_SPACE(..,..)$ function checks the possibility of existence of an object in the predicted region.

### 3.3.2 New Tag

The new tag and new identity is assigned using the following inference. The association of new object is determined with the list of objects. Besides, the object does not fall into the search space of existing objects:

$$new(O^t_{id_{new}}) = \big\{min(O^t_?, LIST\_Of\_OBJ(N)) \wedge \neg SEARCH\_SPACE(O^t_?, LIST\_of\_OBJ(N))\big\}$$

where $min(..,..)$ shows that the new detected object ($O^t_?$) has the minimum likelihood with the list of objects. $SEARCH\_SPACE(..,..)$ checks the possibility of existence of objects in the predicted region.

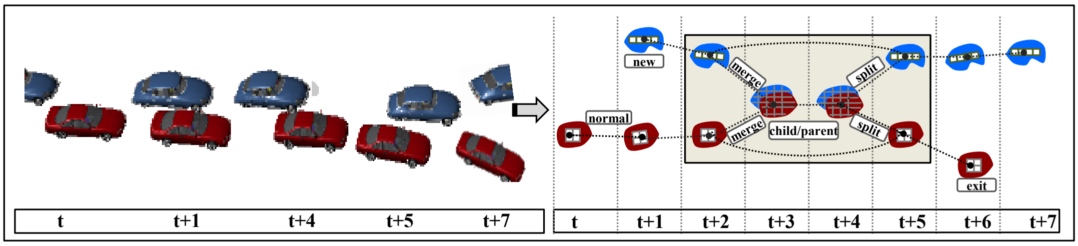


Figure 2: From the world domain (left) to the proposed domain of object space (right).

#### 3.3.3 Exit Tag

The exit status-tag of object is determined by two functions. First, the maximum association of the object with the list of objects are computed. Second, the object must fall in exit region. On the basis of the output of these two functions, the exit tag is assigned to the object:

$$exit(O^t_{id}) = \{max(O^t_?,\ LIST\_Of\_OBJ(N)) \\ \wedge\ EXIT\_ZONE(O^t_?)\}$$

where $max(..,..)$ shows that the maximum likelihood of the object (i.e. $O^t_?$) with the list of objects. $EXIT\_ZONE(..)$ checks the presence of object in exit zone of the scene.

#### 3.3.4 Overlaper Tag

The participation in the overlap is computed and is used to decide the status-tag of the moving object. Both the objects must fall into the conflicted region and the likelihood weights of both objects are computed with the conflicted object. The object which retains its visual characteristics during occlusion is set to overlaper and becomes the parent of the *Occludee*. The occluded object is updated frame-by-frame using depth first search strategy:

$$over(O^t_{id}) = \{max(O^{t-1}_{id}, O^{t*}_?) \\ \wedge(SEARCH\_SPACE(O^{t-1}_{id}, O^{t*}_?)\}$$

where $max(..,..)$ finds the maximum likelihood weight with the conflicted object (i.e. $O^{t*}_?$). This is a key parameter because on this basis the decision of overlaper and occludee status-tag is is made. $SEARCH\_SPACE(..,..)$ checks the presence of objects in conflicted region.

#### 3.3.5 Occludee Tag

This qualitative module determines the status-tag for occludee. The decision is taken on the basis of two assumptions. The first assumption is similar to above module (i.e. Overlaper Tag). However, in the second, the participation of occludee in the occlusion must be less then its overlaper. The object becomes the child of its overlaper and the visual characteristics are updated at each successive frame. The qualitative representation shows the occluded mode of the object which satisfies the continuity constraints criteria:

$$occ(O^t_{id}) = \{min(O^{t-1}_{id}, O^{t*}_?) \\ \wedge(SEARCH\_SPACE(O^{t-1}_{id}, O^{t*}_?)\}$$

where $min(..,..)$ finds minimum likelihood contribution with the conflicted object (i.e. $O^{t*}_?$). $SEARCH\_SPACE(..,..)$ checks the object presence in the search space of the conflicted region.

#### 3.3.6 Reappear Tag

The reappeared object's relation is computed through backward chaining into the entire history of moving objects and maximum correspondence is computed. The object is assigned the same identity when it went to occlusion and the child-parent relationship is ended. The following formulation determines the reappear tag:

$$reap(O^t_{id}) = \{max(O^t_?, O^*_{id})\}$$

where $max(..,..)$ returns the maximum association weight of reappeared object.

### 3.4 Tracking Module

Kalman filter used for tracking and is defined in terms of its states, motion model, and measurement equations (Welch and Bishop, 1995). In this paper, each Kalman-based tracker is associated with every moving object which enters in the video sequence. We consider the center of gravity of moving objects (i.e. $xc^x_t$ and $xc^y_t$) at time $t$ as the states for Kalman-based tracker, hence the state vector and measurement vector is:

$$x_t = \begin{bmatrix} xc^x_t & xc^y_t \end{bmatrix}^T, \quad z_t = \begin{bmatrix} yc^x_t & yc^y_t \end{bmatrix}^T$$

In the following, $A$ is the transition matrix and $H$ is the measurement matrix of our tracking system along with the Gaussian process $w_{t-1}$ and measurement $v_t$ noise. These noise values are entirely dependent on


Figure 3: a) Shows the results of tracking with plausible associations which are pointed by red arrows whereas the white circles indicate the occlusions. b) presents the results of tracking and association of our proposed approach. The status-tags with identity of the objects are shown in right-side of the images. c) the data association uncertainties during tracking are pointed by red arrow whereas the white circles point the occlusions. d) presents the results of traffic sequence using proposed approach. The yellow arrow indicates the resolved data association ambiguities (Please zoom-in both the results for better visibility).

the system that is being tracked and adjusted empirically. The equations of our tracking system are:

$$x_t = Ax_{t-1} + w_{t-1} \qquad (2)$$

$$z_t = Hx_t + v_t \qquad (3)$$

When a new moving object is detected, a new tracker is initiated with associated states ($x_t$ and $z_t$). In the next frames, normal tracking continues until any tracking event is observed which is then handled by the proposed approach.

# 4 EXPERIMENTAL RESULTS

In this section, the results of our approach are presented which are applied to two different datasets taken from our video database. The approach is first tested on a synthetic video, later applied on real scene.

## 4.1 Synthetic Sequence

Figure 3 shows the tracking results for the synthetic video. In this sequence, the segmentation is ideal and visual features of the detected object during normal motion remain the same. It can be seen from the video sequence that the occlusion event is observed four times in random intervals of time as indicated by white circles. The labellings and status-tags are presented along with the tracking paths of moving objects.

In Figure 3(a), the results of missed associations are identified in frame $t+25$, $t+35$, $t+37$ and $t+41$ which are indicated by red arrows. These ambiguities are observed when the objects split after occlusions. In Figure 3(b), the results of our proposed approach are presented in which the qualitative reasoning modules are used with data association. The resolved uncertainties are highlighted with yellow arrows whereas the identities with status-tags are shown on right side of images. It can be observed that the tracking is successfully done by keeping all the real-time tracking events under consideration.

## 4.2 Traffic Sequence

The robustness of the proposed approach is demonstrated on a real-time traffic sequence where the objects are moving in both the parallel and opposite tracks as shown in Figure 3. The multiple occlusions and separations are taken place in short interval of time which is the key challenge here. Moreover, the camera position is not parallel to road but instead, it is tilted which results in perspective view and therefore a significant variation in object's size is observed.

Figure 3(c) shows the outcome of tracking and identity management before applying our proposed approach. The errors due to wrong association weights are indicated by red arrows during split in $t+76$, $t+83$, $t+88$, $t+96$ and $t+103$ where the objects lost their identities when occlusion is over. In Figure 3(d), these uncertainties are handled by our six qualitative modules which are integrated for data association. For example, it can be seen that in $t+76$ and $t+83$ the correct identities are successfully identified after split using our qualitative modules. The respective identity and status-tag can be seen in right-side of the frame. Throughout the tracking, it can been seen that all the real-time events are occurred ( for example new entry, exit entry, occlusion and separation) in the sequence and plausible interpretations (i.e. highlighted by yellow arrows) are efficiently handled by our proposed technique.

# 5 CONCLUSIONS AND FUTURE WORK

In this paper, limitations of data-association during conflicted situations are resolved by assigning the logical tags to the moving object which explicitly control these ambiguities even if the discrete data is incomplete. The proposed approach is successfully tested on synthetic simulation and real-time traffic sequences. Future work will be focused to interpret the behaviors of moving objects.


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