Adaptive State Multiple-Hypothesis Tracking

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Abstract: In tracking algorithms where measurements from various sensors are combined the track state representation is usually dependent on the type of sensor information that is received. When a multi-hypothesis tracking algorithm is used the probabilities of the different hypotheses containing tracks in different representations need to be re-evaluated when track state representations are changed. For the particular case of trilateration a method is presented to adapt the state representation as more information becomes available. A discussion is given on how to re-evaluate the probabilities of the hypotheses leading to a method for the trilateration case. This is illustrated by a simple example.

1 Introduction

In target tracking applications where different target information becomes available at different times, it is desirable to adapt the state description of estimated targets to the composition of this information. One of such applications is tracking with multiple (range, range rate) sensors. A potential track is started in range coordinates $(r, \dot{r})$. When a detection from another sensor (located elsewhere) is associated to the track, the state representation is changed to $(x, y, \dot{x}, \dot{y})$. This transformation is called trilateration.

In the presence of multiple targets, missdetections and false alarms, estimating the correct target states is a complex task, because incorrect intersensor association give rise to so called 'ghosts'.

To decrease the number of hypotheses that is consumed by ghost associations, valuable a priori information can be used. Since tracking occurs using different representations simultaneously, also a priori information should be given in different representations.

This paper presents adaptive state multiple hypothesis tracking (ASMHT) to resolve the association problem. A simple example shows hypotheses probabilities can be estimated more accurately when the representation of prior and estimated information is adaptable.

2 Trilateration

Suppose we have two sensors: one at $(x, y) = (s_1, 0)$ and one at $(x, y) = (s_2, 0)$. Figure 1 gives a schematic representation of this configuration. Both sensors measure the range and Doppler shift of reflected signals. A detection made by sensor i on time $t = t_n$ is denoted by

$\boldsymbol{z}^i(n)$. The distribution of the estimated target state $\boldsymbol{x}$ on time $t = t_n$ given measurements $\boldsymbol{z}^i(k \ldots n)$, with $t_k < t_n$ is denoted by $p_n(\boldsymbol{x}|\boldsymbol{z}^i(k \ldots n))$. Note that when detections of only one sensor are made, the state vector $\boldsymbol{x}$ is efficiently described by: $(r^i, \dot{r}^i)$, the range and radial velocity to sensor i.

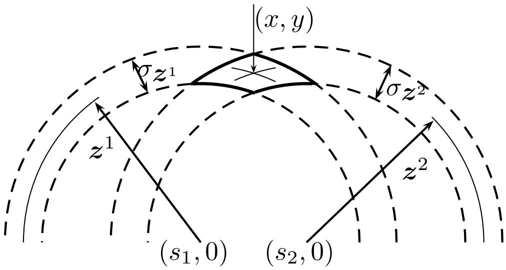

Figure 1: Trilateration

From the measurements of two sensors $\boldsymbol{z}^i$ and $\boldsymbol{z}^j$ we find the position and velocity of the detected object in cartesian coordinates, by means of trilateration. The covariance is found by using the Jacobian of this transformation [KBKG06]. In figure 1 this can be seen graphically. Shown are a detection $\boldsymbol{z}^1$ of sensor 1 and detection $\boldsymbol{z}^2$ of sensor 2, both originating from the same target. In the figure both sensors have a beam width of 180 degrees. It is assumed here that the targets and both radars are situated in a single plane, so their location can be described completely by their x and y coordinates.

The state distribution given detections of both sensors is denoted as $p_n(\boldsymbol{x}|\boldsymbol{z}^i(k \ldots n), \boldsymbol{z}^j(m \ldots n))$, where m denotes the time when the first detection of sensor j was associated to the track and thus indicates the moment at which trilateration could be applied. More generally, the track distribution is denoted as $p_n(\boldsymbol{x}|\boldsymbol{Z})$, where $\boldsymbol{Z}$ denotes the complete set of associated detections, regardless if they originate from one or more sensors. The sensors update the track independently once trilateration has been done, using extended Kalman filters.

2.1 Multiple Hypothesis Association

When multiple detections per sensor occur, it is not known beforehand which detections should be associated together. Incorrect inter-sensor associations result in so called 'ghosts'. To increase the probability that the correct association is found, a multiple-hypothesis tracking algorithm is used.

To facilitate for missed detections and asynchronous sensor updates a flexible state representation is used. A potential track is always initiated in (range, range rate) coordinates. When a contact of another sensor is associated the state representation is changed from $\boldsymbol{x} = (r^i, \dot{r}^i)$ to $\boldsymbol{x} = (x, y, \dot{x}, \dot{y})$. The track might otherwise be missed by the other sensor and only be updated with detections from the first sensor, preserving the state description $(r^i, \dot{r}^i)$ of the track.

Now, we have hypotheses describing tracks in range coordinates and hypotheses describing tracks in cartesian coordinates. We need a method to relate the hypotheses that have different state representations to each other.

3 New Source Model

When a new detection arrives, the hypotheses that describe a new target and a false alarm should be updated with the probability of such events, P_{nt} and P_{fa} respectively. It is shown in [Bla86] that instead of the explicit probabilities of these events, the false alarm and new target densities β_{fa} and β_{nt} can be used. This results from the fact that it is assumed that β_{nt} is constant over the uncertainty of the measurement.

Here we assume that the new target density is known as a function of the tracking (cartesian) coordinates $(x, y, \dot{x}, \dot{y})$. This density can be transformed to the coordinates of sensor i $(r_i, \dot{r}_i)$, [The92]. These densities are called $\beta_{nt}(\boldsymbol{x})$ and $\beta_{nt}^i(\boldsymbol{r}^i)$ respectively and defined as the expected number of new targets that arise per unit volume per unit scan time.

Typically, the probability density of false alarms is given in measurement coordinates, since false alarms are sensor related. This pdf we call $\beta_{fa}^i(\boldsymbol{z}^i)$. Since false alarms are described in sensor coordinates, this representation is sufficient to estimate the probability that a detection is a false alarm.

Unwanted detections that originate from the environment are usually called clutter and are omitted here.

In the case of trilateration, the volume of the new source depends on the hypotheses and it is no longer allowed to compare the false alarm and new target densities. Initially, we form a new track (in $r_i, \dot{r}_i$ coordinates) and thus use $\beta_{nt}(r_i, \dot{r}_i)$ and $\beta_{fa}(r_i, \dot{r}_i)$ to compare the new target hypothesis with the false alarm hypothesis. Then, when a detection of another sensor is associated, the trilateration operation is performed and the state representation is changed. Therefore, we will have to re-evaluate the probability P_{nt}.

$$P_{nt} = \int p_1(\boldsymbol{x}|\boldsymbol{z}^i(k \dots n), \boldsymbol{z}^j(n))\beta_{nt}(\boldsymbol{x})d\boldsymbol{x} \tag{1}$$

Here $p_1(\boldsymbol{x}|\boldsymbol{z}^i(k \dots n), \boldsymbol{z}^j(n))$ denotes the predicted target distribution of the trilaterated state $\boldsymbol{x}$ given detections $\boldsymbol{z}^i(k \dots n)$ of sensor i and detection $\boldsymbol{z}^j(n)$ of sensor j on the initiation time of the track. Thus, a backward prediction, or retrodiction will have to be made in the new state representation, given all the measurements.

4 State and State Representation Dependent Detection Probability

We introduce a state dependent detection probability of sensor i:

$$P_d^i(\boldsymbol{x}) = 1 - P_m^i(\boldsymbol{x}) \tag{2}$$

$P_m(\boldsymbol{x})$ denotes the probability that no detection is made by sensor i given a target with state $\boldsymbol{x}$. $P_d^i(\boldsymbol{x})$ denotes the total probability that sensor i detects a target with state $\boldsymbol{x}$. Note that here sensor information like beamwidth can be introduced. Also information about occlusions could be represented here.

To calculate the probability that a track with state distribution $p_n(\boldsymbol{x}|\boldsymbol{Z}(k \dots n))$ is detected by sensor i we weigh the detection probability with the target distribution and take the avarage:

$$P_d = \int p_n(\boldsymbol{x}|\boldsymbol{Z}(k \dots n) \cdot P_d^i(\boldsymbol{x}) d\boldsymbol{x} \tag{3}$$

The probability of the event that a track is missed by sensor i is given by:

$$P_m = \int p_n(\boldsymbol{x}|\boldsymbol{Z}(k \dots n-1)) \cdot P_m^i(\boldsymbol{x}) d\boldsymbol{x} \tag{4}$$

Note that we are free to choose the coordinate system in which we want to solve this integral. This could be cartesian, polar, or other coordinates.

When the state description changes to a representation where the detection probability is represented more complete, the detection probability of previously associated contacts could be reconsidered, since it may be that the state on which the detection probability was based can be estimated more accurately now.

5 Example

To show the possible advantage of applying a priori information in different state representations, knowledge of the antenna beams is assumed. An example of 2 stationary (range,doppler)radars with a very simple antenna model will be given.

The model in the example assumes that detection probability is unity inside and zero outside the bundle and depends only of the location of a target and not of its velocity, nor any other kinematic or non-kinematic properties of the target.

An angle of ϕ_b defines the beamwidth of the antennas. To find the detection probability of each sensor given a track consisting of only one sensor we need $P_d^i(\boldsymbol{x})$ as a function of range coordinates. This is best done using polar coordinates: $P_d^i(r^i, \phi^i) = P_d^i(\phi^i) = 1, |\phi^i| < \phi_b/2$ and 0 elsewhere.

Now we need to represent the distribution of the target state $p_n(\boldsymbol{x}|z^i(k \dots n))$ in the same coordinates. Since no angle information is known, we assume the target is distributed uniformly in ϕ^i: $p_n(\boldsymbol{x}|\boldsymbol{z}^i(k \dots n)) = \frac{1}{2\pi} p_n(r^i|\boldsymbol{z}^i(k \dots n))$

$$P_d^i = \int \frac{1}{2\pi} p_n(r^i|\boldsymbol{z}^i(k \dots n)) P_d^i(\phi^i) d\phi^i dr^i \tag{5}$$

$$= \frac{1}{2\pi} \int p_n(r^i|\boldsymbol{z}^i(k \dots n)) dr \int P_d^i(\phi^i) d\phi^i = \frac{\phi_b}{2\pi} \tag{6}$$

A schematic representation of the sensors and the beamwidth of their antennas can be seen in figure 2.

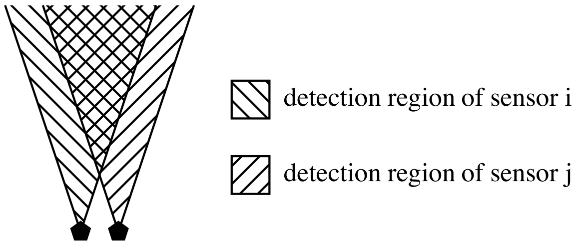

Figure 2: detection regions of both sensors

Thus, in the case the track consists of detections made by one sensor only, the estimated detection probability is equal to the beamwidth of the sensor.

If a contact of sensor j is associated to the track, the state representation is changed from $(r, \dot{r})$ to $(x, y, \dot{x}, \dot{y})$. The detection probability $P_d^j(p_n(\boldsymbol{x}|\boldsymbol{z}^i(k \dots n), \boldsymbol{z}^j(n)))$ is used to update the hypothesis probability. The detection probabilities $P_d^i(p_h(\boldsymbol{x}|\boldsymbol{Z}))$ for $h = k \dots n$ could now be re-estimated by using the new state representation and retrodiction.

6 Conclusion

This paper introduces the concept of ASMHT. The description of a priori knowledge as well as the description of estimated states changes adaptively as new information becomes available. Furthermore, hypothesis probabilities of past associations can be estimated more accurately. A simple example shows how ASMHT can be applied. The example here is trivial. However, a probabilistic framework is presented which can be applied in less trivial settings.

7 Acknowledgments

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References

[Bla86] S.S. Blackman. *Multiple-target tracking with radar applications*. Artech House, 1986.

[KBKG06] J van Kleef, J Bergmans, L.J.H.M Kester, and F.C.A. Groen. Trilateration and Tracking with Ristributed Radars. In *Proc. of Fusion 2006*, volume 174, Florence, Italy, 2006.

[The92] C.W. Therrien. *Discrete random signals and statistical signal processing*. Prentice Hall, 1992.