Classification Data in Multi-Sensor Multi-Track Association

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Abstract

Association of multiple tracks from multiple sensors is generally based on the kinematic state information of the tracks. With increasing sensor and processing capabilities, the ability for sensors to provide classification data is increasing. A method is described for including this classification data in the calculation of association probabilities. It is shown that it is necessary to incorporate the classification data at the hypothesis level, and that the difficulty in ascertaining classification similarity implies that large classification sets are difficult to use, and may not provide any benefit.

1 Introduction

Demands on system reliability and accuracy mean that the use of more than one sensor is becoming increasingly common. The challenge that arises from this is the requirement to fuse the data from the individual sensors in an intelligent manner. In the presence of multiple targets, where a target is any object of interest, a pre-cursor to the data fusion stage is data association. This is the calculation of the correlation between the different sensor data sets. It has previously been shown that association is more reliably achieved through track forming prior to association, and track association probabilities may only be calculated by first calculating association hypothesis probabilities[1]. The particular case of interest here is the association of tracks from non-cooperative targets, being observed by infra-red and radar sensors.

Association hypothesis probabilities, and hence track association possibilities, have traditionally been based purely on the track kinematics from each sensor, i.e. target positions and velocities[2]. However, it is feasible that more information may be extracted from the sensors in the form of classification data. A method is then required for incorporating the classification data in to the association process.

2 Classifications

It is difficult to specify the form that target classification data will take, and with the increasingly sophisticated countermeasure systems being employed by the non-cooperative targets, the reliability of a typical classification system is also difficult to judge. For these reasons a very simple, but probably realistic, classification capability is defined. Each measurement is assigned a classification, which is inherited by the track to which the measurement is assigned.

The classification system is assumed to be low resolution, providing only three different classifications to be considered:

$$\begin{aligned} C_U &: \text{ Unknown classification} \\ C_T &: \text{ Target classification} \\ C_{\bar{T}} &: \text{ Non-target classification} \end{aligned}$$

If a sensor is unable to provide any classification data due to insufficient information content in the measurements, then each measurement is assigned a classification of C_U.

If a sensor is able to provide classification data, the classification may be correct or incorrect. A probability of being able to classify correctly is therefore required, and is likely to be based on empirical evidence gathered for each sensor.

In the model of the classification process, if a sensor measurement is of a target, *and* the sensor is considered able to classify, *and* is considered to classify the measurement correctly, then the measurement, and hence the track to which the measurement is allocated, is given the classification C_T.

As an example, consider the IR sensor. Its ability to classify will depend on the size of the object (in terms of pixels).[1] Assuming a pixel field of view of 1mR (1 milli-radian), an object 5m wide at 1km from the sensor will "populate" only 5 pixels (figure 1), assuming the IR signature of the object is sufficiently high over its entire width to measured by the sensor. The probability of being able to classify may then be modelled as (for example) (figure 2)

$$
\begin{aligned}
P_C &= \quad 0.05 \quad && \text{Size}<2 && (1)\\
P_C &= \tfrac{0.9}{18}\text{Size} - 0.05 \quad && 20\leq\text{Size}\geq 2 && (2)\\
P_C &= \quad 0.95 \quad && \text{Size}>20 && (3)
\end{aligned}
$$

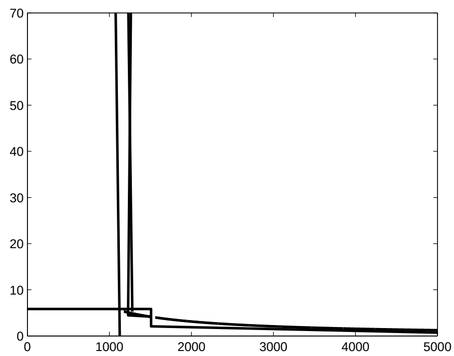

Figure 1: Pixel size of 5m object vs Range

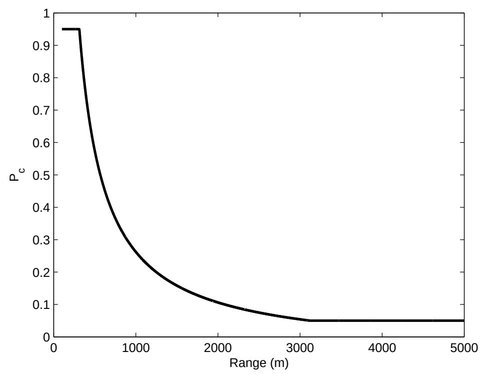

Figure 2: P_c of 5m object vs Range

These values can be combined with a probability of classifying correctly, P_V to give

$$
\begin{aligned}
P(C_U|T) = \quad & P(C_U|\bar{T}) = \quad 1 - P_C && (4)\\
P(C_T|T) = \quad & P(C_{\bar{T}}|\bar{T}) = \quad P_V P_C && (5)\\
P(C_{\bar{T}}|T) = \quad & P(C_T|\bar{T}) = \quad (1-P_V)P_C && (6)
\end{aligned}
$$

Equation 4 is the probability of being unable to classify.
Equation 5 is the probability of classifying correctly.
Equation 6 is the probability of classifying incorrectly.

3 Modification of Association Probabilities

Given a hypothesis containing a set of associations between tracks from two sensors, the probability of that hypothesis may be modified to take into account the track classifications. For each association pair in the hypothesis, the probability of the classifications of the two tracks agreeing can be calculated as

$$P(C_j|h) = P(C_j|T)P_{k(j)} + P(C_j|\bar{T})(1 - P_{k(j)}) \tag{7}$$

[1]Other factors will play a significant role in terms of classification ability, but they are being ignored here.

where:

C_j	is the given classification of track j from the second sensor
$P(C_j\|T)$	is the probability of classifying track j from sensor 2 as C_j (either C_U, C_T or $C_{\bar{T}}$) given it is a target
$P_{k(j)}$	is the probability that track k from the first sensor, which associates with track j from the second sensor according to the hypothesis, is a target
$P(C_j\|\bar{T})$	is the probability of classifying track j as C_j given it is not a target

The probability of classification agreement between association pairs can then be calculated for all association pairings in the hypothesis, thereby modifying the overall hypothesis probability

$$P'(h|\Gamma) = P(h|\Gamma) \prod_{j=1}^{J} P(C_j|h) \tag{8}$$

where:

$P'(h\|\Gamma)$	is the modified hypothesis probability given the track dynamics data and the classification data
$P(h\|\Gamma)$	is the hypothesis probability given only the track dynamics data

4 Effect of Classification Measurement Interdependency

Considering the potentially very larger numbers of hypotheses that must be considered, and the associated computational load, it is tempting to consider applying the classification data at the final stage of the association process, after individual track association probabilities have been calculated. In this way, the number of classification agreement probabilities that must be calculated is vastly reduced. At first glance there doesn't appear to be any problem with taking this route. However, consider the argument for the necessity of hypotheses when using only kinematic data. The measurements from one sensor are not independent of the measurements from another sensor, as they are potentially measurements of the same object.

The association probability between two measurements can be very significantly influenced by the consideration of other measurements (termed secondary measurements) from the same sensors, with the influence of secondary measurements increasing with decreasing statistical distance between the secondary measurements and those being considered for association.

Statistical distance has an obvious meaning when considering spatial positions and velocities, but the same thinking can also be applied to classification. Consider two sensors each providing a classification measurement. This is all the data available to decide whether the measurements associate or not. If one classification measurement is "target" and the other is "non-target", then the conclusion is that the measurements probably don't associate. Similarly, if both measurements are "target", or both measurements are "non-target", then the conclusion would be that they probably do associate.

However, if in the first case the first sensor provides another classification measurement of "target", then the available evidence more strongly supports the original conclusion of non-association, as not only is the classification different, but there are now two possible association pairings.

Taking it one step further, if the second classification measurement from the first sensor is "non-target", then the probability of non-association between the original measurements decreases further, as not only are there two possible association pairings, but the second association pairing between the two "non-target" classification measurements is, based on the evidence, much more probable than the original association pairing.

As in the kinematics case, the presence of other measurements other than those being considered for association affects the probability of association, and so association hypotheses must be considered to calculate association probabilities. Furthermore, the influence of the secondary measurements increases with decreasing statistical classification distance. In other words, a classification of "non-target" is "closer" to another classification of "non-target" than to a classification of "target".

The concept of statistical classification distance is fairly simple to evaluate when only two possible classifications are being considered, but as more classifications are allowed, it becomes more difficult to evaluate. Is the classification "cup" closer to "vase" or "teapot" (figure 3)?

Figure 3: Cup, teapot and vase, highlighting difficult classification task

This question can only really be answered by empirical tests, which are difficult and time consuming, thereby preventing the extensive use of large classification sets in many problems, including here in association probability evaluation.

5 Conclusion

With the increasing availability of processing power and high performance sensors, the provision of classification information from sensors is becoming more likely. In a situation where non-cooperative targets are present, potentially several kilometres away from the sensor, the reliability and resolution of the classification data is likely to be limited, to the point where maybe only three classifications, "Target", "Non-Target" and "Unknown" are feasible.

Given these possible classifications, and empirically gained knowledge of the *a-priori* classification probabilities, a method for updating association probabilities based on kinematic data with the classification data has been presented. It has been shown that it is necessary to apply the classification data at the hypothesis probability calculation stage due to the interdependence of the classification measurements. This is despite it being preferable in terms of computational load to apply the classification data at the track association stage.

Finally, the problems that arise when larger (high resolution) classification sets are considered are mentioned, with the necessity for time consuming empirical tests preventing the use of such sets.

References

[1] C. M. Rogers, "Methods of Multisensor Tracking", Proc. London Communications Symposium 2003

[2] Y. Bar-Shalom, X. Li, "Multitarget-Multisensor Tracking: Prinicples and Techniques", Yaakov Bar-Shalom, ISBN 0-9648312-0-1, 1995

[3] C. M. Rogers, "A Bayesian Alternative to the Statistical Distance Approach to Association", Proc. London Communications Symposium 2004