## Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>Dempster-Shafer</td>
</tr>
<tr>
<td>ECM</td>
<td>Electronic Counter Measures</td>
</tr>
<tr>
<td>ESM</td>
<td>Electronic Support Measures</td>
</tr>
<tr>
<td>GCS</td>
<td>Ground Control System</td>
</tr>
<tr>
<td>IFF</td>
<td>Identification Friend or Foe</td>
</tr>
<tr>
<td>IRST</td>
<td>Infra Red Search and Track</td>
</tr>
<tr>
<td>JEM</td>
<td>Jet Engine Modulation</td>
</tr>
<tr>
<td>JPDA</td>
<td>Joint Probabilistic Data Association</td>
</tr>
<tr>
<td>JPIF</td>
<td>Joint Probabilistic Identity Fusion</td>
</tr>
<tr>
<td>MHT</td>
<td>Multi Hypothesis Tracking</td>
</tr>
<tr>
<td>MSC</td>
<td>Modified Spherical Coordinates</td>
</tr>
<tr>
<td>NN</td>
<td>Nearest Neighbour</td>
</tr>
<tr>
<td>PLS</td>
<td>Dempster Shafer plausibility</td>
</tr>
<tr>
<td>PRF</td>
<td>Pulse Repetition Frequency</td>
</tr>
<tr>
<td>PW</td>
<td>Pulse Width</td>
</tr>
<tr>
<td>RADAR</td>
<td>RAdio Detection And Ranging</td>
</tr>
<tr>
<td>RCS</td>
<td>Radar Cross Section</td>
</tr>
<tr>
<td>RMS</td>
<td>Root Mean Square</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>RWR</td>
<td>Radar Warning Receiver</td>
</tr>
<tr>
<td>SPT</td>
<td>Dempster Shafer support</td>
</tr>
</tbody>
</table>


References


A.4.2 IFF confusion matrix

The confusion matrix describes the mapping from a received parameter to a proper probability assignment or likelihood value.

<table>
<thead>
<tr>
<th>Response</th>
<th>Friend</th>
<th>Enemy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>0.85</td>
<td>0.15</td>
</tr>
<tr>
<td>No</td>
<td>0.3</td>
<td>0.7</td>
</tr>
</tbody>
</table>

Table A.3  Confusion matrix for IFF response.

The matrix used in this work is shown in Table A.3. After a measurement, the likelihood function is set up according to this matrix. For example, if a response is received, all friendly types will have the likelihood value 0.85, while other types will be assigned the value 0.15.
### Table A.1 Kinematic/RCS properties

<table>
<thead>
<tr>
<th>ID</th>
<th>Type/Class</th>
<th>Front area (m²)</th>
<th>Side area (m²)</th>
<th>Wing area (m²)</th>
<th>v&lt;sub&gt;max&lt;/sub&gt; (m/s)</th>
<th>alt&lt;sub&gt;max&lt;/sub&gt; (m)</th>
<th>a&lt;sub&gt;max&lt;/sub&gt; (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Friendly</td>
<td>Fighter</td>
<td>4</td>
<td>15</td>
<td>30</td>
<td>800</td>
<td>15000</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Attack</td>
<td>5</td>
<td>20</td>
<td>40</td>
<td>800</td>
<td>12000</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Bomb</td>
<td>12</td>
<td>60</td>
<td>90</td>
<td>400</td>
<td>10000</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Cargo</td>
<td>20</td>
<td>100</td>
<td>120</td>
<td>200</td>
<td>10000</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Missile</td>
<td>0.1</td>
<td>1</td>
<td>1</td>
<td>2000</td>
<td>20000</td>
<td>-</td>
</tr>
<tr>
<td>Enemy</td>
<td>Fighter</td>
<td>5</td>
<td>20</td>
<td>40</td>
<td>800</td>
<td>15000</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Attack</td>
<td>8</td>
<td>30</td>
<td>40</td>
<td>800</td>
<td>12000</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Bomb</td>
<td>12</td>
<td>60</td>
<td>90</td>
<td>400</td>
<td>10000</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Cargo</td>
<td>20</td>
<td>100</td>
<td>120</td>
<td>200</td>
<td>10000</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Missile</td>
<td>0.1</td>
<td>1</td>
<td>1</td>
<td>2000</td>
<td>20000</td>
<td>-</td>
</tr>
<tr>
<td>Neutral</td>
<td>Airliner</td>
<td>20</td>
<td>100</td>
<td>120</td>
<td>200</td>
<td>10000</td>
<td>3</td>
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</tbody>
</table>

*With afterburner active*

### Table A.2 Doppler/engine distributions

<table>
<thead>
<tr>
<th>ID</th>
<th>Type</th>
<th>min rotation</th>
<th>max rotation</th>
<th>min (*)</th>
<th>max (*)</th>
<th>Engines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Friendly</td>
<td>Fighter</td>
<td>6000</td>
<td>10000</td>
<td>11000</td>
<td>12000</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Attack</td>
<td>6000</td>
<td>10000</td>
<td>11000</td>
<td>12000</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Bomb</td>
<td>4000</td>
<td>7000</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Cargo</td>
<td>3000</td>
<td>6000</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Missile</td>
<td>10000</td>
<td>15000</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Enemy</td>
<td>Fighter</td>
<td>6000</td>
<td>12000</td>
<td>11000</td>
<td>12000</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Attack</td>
<td>5000</td>
<td>8000</td>
<td>11000</td>
<td>12000</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Bomb</td>
<td>3500</td>
<td>6000</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Cargo</td>
<td>3000</td>
<td>5000</td>
<td>-</td>
<td>-</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Missile</td>
<td>10000</td>
<td>15000</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Neutral</td>
<td>Airliner</td>
<td>3000</td>
<td>6000</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
</tbody>
</table>

* With afterburner active
The error covariance matrix for $x$, obtained from the Kalman filter is denoted $P_x$. The covariance matrix for the absolute velocity can be approximated using Gauss approximation formula:

$$
P_p = g_x'(x)P_x g_x'(x)^T
$$

**Eq A.18**

### A.4 Probability distributions

In order to calculate the probabilities or probability masses for a target, the classifier must have access to a library of distribution functions (for continuous parameters) and likelihood functions (or mappings) for discrete parameters. The distributions and mappings in this thesis are approximations and would have to be refined if the system should be implemented in an aircraft.

#### A.4.1 Area, kinematic and doppler distributions

The distributions for altitude, velocity and acceleration are based on the performance of the different types and thus allows the classifier to rule out certain types. The area distribution is given as the expected values for front, side and wing area respectively. The values used in this work is summarized in Table A.1.

In the same manner, the values for the doppler distributions as well as number of engines are given in Table A.2.
The receiving antenna has an effective aperture area $A_r$, which will absorb the power

$$I_r = \frac{P}{4\pi R^2} = \frac{P_i G_i \sigma}{(4\pi R^2)^2}. \quad \text{Eq A.11}$$

If the same antenna is used both for transmitting and receiving pulses, we can express the antenna only by its gain and use:

$$S = I_r A_r = \frac{P_i G_i A_r \sigma}{(4\pi)^2 R^4}. \quad \text{Eq A.12}$$

which leads to

$$S = \frac{P_i G^2 \lambda^2 \sigma}{(4\pi)^3 R^4}, \quad \text{Eq A.14}$$

where $\lambda$ represents the wavelength.

### A.3 Calculation of velocity and variance

The state vector given from the Kalman filter specifies velocity in the cartesian directions. However, what is interesting from a classifying point of view is the absolute velocity and its variance. The state vector for velocity, $x$, can be defined as:

$$x = [v_x \quad v_y \quad v_z] \quad \text{Eq A.15}$$

The relation between directional and absolute velocity:

$$g(x) = \sqrt{\frac{v_x^2}{\lambda^2} + \frac{v_y^2}{\lambda^2} + \frac{v_z^2}{\lambda^2}} \quad \text{Eq A.16}$$

thus,
Transformation from Cartesian coordinates to MSC can be done with the following equations:

\[
\frac{1}{r} = \frac{1}{\sqrt{x^2 + y^2 + z^2}} \quad \text{Eq A.3}
\]

\[
\theta = \tan\left(\frac{-z}{\sqrt{x^2 + y^2}}\right) \quad \text{Eq A.4}
\]

\[
\psi = \tan\left(\frac{y}{x}\right) \quad \text{Eq A.5}
\]

\[
\dot{r} = (\dot{x}\cos\psi + \dot{y}\sin\psi) \cdot \cos\theta - \dot{z}\sin\theta \quad \text{Eq A.6}
\]

\[
\dot{\theta} = \frac{(\dot{z}\cos\theta + (\dot{x}\cos\psi + \dot{y}\sin\psi)\sin\theta)}{r} \quad \text{Eq A.7}
\]

\[
\dot{\psi} = (\dot{y}\cos\psi + \dot{x}\sin\psi) \cdot \frac{1}{r} \quad \text{Eq A.8}
\]

### A.2 The radar equation

Assume that the radar transmits the power \( P_t \) isotropically in all directions. At a distance \( R \) this will induce the power density \( I_s \)

\[
I_s = \frac{P_t}{4\pi R^2}. \quad \text{Eq A.9}
\]

The antenna gain, \( G \), in the lobe direction amplifies the intensity by a factor \( G \). Assume the target has the projected area \( \sigma \). The power striking the target will then be

\[
P = I_s G \sigma = \frac{P_t G \sigma}{4\pi R^2}. \quad \text{Eq A.10}
\]

If the projected area can be assumed to be a sphere, the signal is reflected isotropically from the target. The power density at the distance \( R \) from the target is
In order to fuse information from different sensors the sensor must be able to express target position in the same coordinate system. In Modified Spherical Coordinates (MSC), the position of the sensing platform is chosen as origo. The distance, bearing and elevation to the target is denoted $r$, $\psi$, $\theta$, respectively. The state vector is selected as

$$X = \begin{bmatrix} \theta, \dot{\theta}, \psi, \omega, \frac{\dot{r}}{r}, \frac{1}{r} \end{bmatrix}^T,$$

*Eq A.1*

where $\omega$ is related to $\dot{\psi}$ and $\theta$ through

$$\omega = \dot{\psi} \cdot \cos \theta.$$

*Eq A.2*

The advantage with MSC is that the state vector is related to the states actually measured by the sensor; distance, bearing and elevation. Also, when using angle only sensors such as IRST or RWR, the distance to the target is non-observable. When using MSC, the non-observable state $(1/r)$ is explicit in the state vector [Sta87]. This will lead to improved numerical performance.

![Modified Spherical Coordinates (MSC)](image-url)

*Figure A.1* Modified Spherical Coordinates (MSC).
• Presentation of the results to a user (the pilot) has not been treated. If for instance a target is classified as a fighter and there is no new information available for a long time, even though the probabilities will decrease due to decay of information, the information to the pilot must remain as fighter until another class becomes more probable. Likewise if many classes or types are almost equal probable, perhaps fluctuating between fighter and attack, the information to the pilot must be that we are undecided or perhaps the class that has been most probable earlier. This is a filtering problem that can be solved at a higher level in the system.

• Another issue when integrated in a more advanced system is that there might be different reliability in the sensors. For once, if a target is performing large manoeuvres, the RCS measurements is not very reliable. The unreliable sensor reports can then be fully rejected or their importance can be reduced. This can be achieved by assigning more or less belief as uncommitted for that sensor.
There are a number of issues that are not addressed enough in this thesis and need to be investigated further.

- It should be interesting to see how the system performs when tested in a complex scenario with real data. Especially important is to evaluate the performance of the RCS classifier with real data.

- The problem mentioned in chapter 4.2.4 with amplifying antennas during radar cross section measurements has not been implemented. Since the effect of the antenna gain is so large that the measurements will distinguish themselves distinctively from earlier measurement the feeling is that some kind of thresholding could be used.

- The possibility to use missile launches as a classification parameter has not been used. This could prove very effective in detection and classification of missiles.

- Jet Engine Modulation should be investigated further. How time consuming is the analysis, are there range limitations and is it at all possible to make such measurements in flight?

- The identity fusion takes a relatively small amount of computational power. Instead the time consumption in the system derives to the largest extent from the calculation of probabilities, that is the classification from attributes to target type/class/identity where there is a discrete measurement and a continuous probability distribution describing the relationship between attribute and the target’s nature. There might be ways of improving this classification in a way that makes it more computational effective, perhaps by neural networks.
• The method for association of RWR information to targets, named Joint Probabilistic Identity Fusion (JPIF) is presented in chapter 6.3. There are substantial gains with this method since the RWR has poor angle resolution and the RWR information provides important clues to the nature of the target.

• It is not obvious that the Radar Cross Section can be used with the model in this thesis. But as sensor resolution gets better and better the possibilities increase. However, tests on real data have to be used in order to answer this question.

• The system simulation in chapter 6.6 shows that the fusion system works as expected with the tested target parameters. But the performance depends on the target probabilities and their quality.
7 Conclusions

This chapter summarizes the results in the previous chapter as well as conclusions drawn in other chapters.

• Bayes law and Dempster-Shafer reasoning are the two most used methods for identity fusion. While the Bayesian approach has the advantage that the structure is easy to implement and there are no difficulties in determining which hypothesis that is most likely, the Dempster-Shafer approach has convenient representation of uncertainty as well as a powerful combination methodology. By using the Bayesian approach to classify measured attributes and utilising Dempster-Shafer for fusion, the best is brought from the two methods.

• Implementation in a real aircraft must be preceded by an extensive study of how the likelihoods should be set in order to reflect reality in a correct way. During the simulations, this has been the most time consuming part since it contains integral evaluation.

• Misassociation on a track to track basis will affect the classification in a negative way. It is therefore necessary to have sharp accuracy in the sensors along with tracking filters with small prediction errors and good association algorithms. The track association simulations in chapter 6.2 shows that the track association process benefits from the introduction of attributes and target identifications. This can be accomplished without any substantial increase in time complexity provided that attribute likelihoods and target identification is computed anyway.

• Old information from sensors like the Radar Warning Receiver, Data Link and IFF is to be saved on a central track file. Mix-up in association of targets to the central tracks can have the effect that a target ‘inherits’ the history of another. Hence, the information must decay with time.
Turning to the attack target (target 2), in Figure 6.14c we see that at the start of the simulation, fighter is the most probable class, due to “leakage” of RWR information from the fighter. The association of RWR reports to the attack target would have been more rare if there had been more evidence speaking against the proposition that the aircraft is a fighter.

When the aircraft fails to respond to the IFF after 60 seconds, the utility for enemy types grows, but after 170 seconds, when an IFF response is received, the friendly attack becomes the most probable type. However, as we can see in Figure 6.14d, the difference to friendly fighter is only marginal.

The phenomenon we can see in Figure 6.14c, when the utility for fighter decreases when no more evidence is added, is in some cases an undesired behaviour. If, for example, a target is classified on the basis of RWR reports and it suddenly turns off its radar the “forgetting” will, as time goes by, decrease the probability of that classification. This is undesired since our objective is to classify the target and thus we don’t want the target class to change just because its radar has ceased to operate.

A solution could be to filter the output such that when a certainty about a target is achieved, a threshold of probability or utility of another class has to be passed in order for the target to change estimated class.
If we analyse the results starting with the enemy fighter (target 1) in Figure 6.14a and Figure 6.14b, we see that the utility for fighter is always largest, due to the RWR measurements. The dip in fighter utility between 80 and 100 seconds in Figure 6.14a derives from the fighter’s passage in front of the attack, with the effect that a great part of the RWR reports are assigned to the attack target.

In Figure 6.14a we can also see the effect of the doppler measurement after 90 seconds as a dramatic decrease in bomber probability. In Figure 6.14b the effect of the IFF interrogation ignorance is seen as an increase in enemy fighter utility after 60 seconds and the change in RWR data is seen an increase in utility for the enemy fighter between 120 and 140 seconds.

![Figure 6.14 Results from the system simulation. Top-left (a): Utilities for classes on the enemy fighter. Top-right (b): Utilities for types on the enemy fighter. Lower-left (c): Utilities for classes on the friendly attack. Lower-right (d): Utilities for types on the friendly attack.](image-url)


## 6.6 System simulation

During the previous simulations, RCS, kinematics and RWR reports have been used to classify targets. This system simulation uses all local sensors to create an opinion of the targets.

![Scenario](image.png)

*Figure 6.13 Scenario. Two targets approach the own platform. One enemy fighter (left) and one friendly attack (right).*

The scenario in Figure 6.13 was created. It consists of two targets, one enemy fighter and one friendly attack aircraft.

The fighter flies at an altitude of 10000m with a velocity of 300m/s and the attack aircraft at 9000m and 240m/s. After 60 seconds the fighter makes a 45 degree, 2g turn, changing its course to pass in front of the attack aircraft.

The fighter uses its radar every five seconds, but at first the RWR is unable to detect if it is a friendly or a hostile type, thus the RWR states “fighter radar” with a probability of 0.6, the rest is uncommitted. After 120 seconds, the RWR states friendly fighter with the probability 0.15 and enemy fighter with the probability of 0.45.

After 60 and 170 seconds the own platform decides to run an IFF test. At the first IFF interrogation none of the aircraft responds. At the second attempt, the attack aircraft responds as a friend, while still no response is received from the fighter.

After 35 seconds a doppler measurement on the attack is performed and after 90 seconds it is performed on the fighter, revealing the rotation rate of the engines. Thus, since the performance of the attack and fighter aircraft are very similar, in this case only radar cross section and the RWR are able to separate them.
6.5.2 Classification using Bayes law

As mentioned earlier the major difference between Bayesian reasoning and Dempster-Shafer is its representation of belief. Figure 6.12 shows the Bayesian probabilities corresponding to the utilities in Figure 6.11.

Comparing the Bayesian classification in Figure 6.12 and the utilities in Figure 6.11 we see that they are essentially the same. Since the Bayesian probabilities adds to the unity sum, the probability for the fighter, attack and missile rises when the other classes are ruled out.

Figure 6.12 Bayesian probabilities from the kinematic classification. Left (a): Probabilities for target 1. Right (b): Probabilities for target 2.
The targets are tracked for 150 seconds and averaged over 100 Monte Carlo simulations. Classification was performed using the implemented system structure in section 5.2, but also with a Bayesian classifier in order to demonstrate differences in their representation of probabilities.

### 6.5.1 Classification using the implemented structure

The implemented system uses Dempster’s rule to combine the measured parameters, altitude, velocity and acceleration. The utilities for each class is calculated and a decision maker would then use the utilities to decide which target class that is the most probable. Figure 6.11 shows the utilities for the targets.

![Classification graphs](image-url)

*Figure 6.11 Utilities calculated from the fused data. Left (a): Utilities for target 1. Right (b): Utilities for target 2.*

When only kinematics is concerned the only available evidence are “negative” evidence, or in other words evidence that rule certain classes out. If we bring this back on the support/plausibility level, it means that the support will be zero for all classes and the evidence effects the plausibility of the classes “ruled out”. No evidence speaks against the fighter, attack and missile classes and therefore they will remain fully plausible and consequently the utility for those classes will remain at 0.5.
Hence, the simulation shows that the improved accuracy is of little use when the target is manoeuvring since the problem with the linear filter remains. However, the RCS classification is intended for beyond visual range classification where the target might be tracked for some time. A solution should then be to find segments where the course can be estimated and use these segments for classification.

### 6.5 Classification from kinematic data

A classification from kinematics only in terms of altitude, velocity and acceleration is interesting since these parameters can be measured by the passive IRST in combination with another platform.

In this simulation the kinematics were taken from the radar with a scenario as shown in Figure 6.10.

![Figure 6.10 Scenario. Two targets approaching the own platform. The left is denoted target 1 and the right is target 2. Target 1 accelerates from 110m/s to 300m/s, while target 2 climbs from 8500 to 10000 meters.](image)

The left target in Figure 6.10 is denoted target 1 and the right is denoted target 2. Both targets start at an altitude of 9000 meters. After 50 seconds target 1 makes a 0.4g turn which is too small to influence the probabilities, but after 100 seconds it starts to accelerate from 110m/s up to 300m/s. Here the measured velocity exceeds the performance of the cargo planes and the probabilities for those are decreased.

Target 2 continues to fly straight at the own platform but after 70 seconds it starts climbing up to 10000 meters. This means that both cargo and bomb aircraft will be assigned lower probabilities since their maximum altitude is specified below 10000 meters.
The simulations show that a better course estimate is needed if the classification should be 100% correct. But as shown in Figure 6.8b, even though the false class (fighter) has a higher probability during a great part of the simulation, the difference is only marginal and the differences to the more unlikely classes of bomb and cargo aircraft are much larger.

When measuring on a manoeuvring target using a kalman filter that estimates a linear flight path, the measurements will have poorer quality than if the target was flying straight. This means that when the target is in a manoeuvre, the measured course will get even worse, making classification of a manoeuvring target very hard.

There are ways of increasing the quality for instance by more frequent measurements or by parallel filters [Nor96]. This is not investigated further here, but the fused sensor reports described in 6.4.1 was tested on an attack aircraft in a 2g turn. The resulting probabilities are shown in Figure 6.9.

There are only minor differences between Figure 6.9a and Figure 6.9b and the improvements with the fused sensors mainly occur after the turn is completed. The large bulge in both figures between approximately 70 and 90 seconds that derive from the turning are roughly the same size in both cases.
we can see this for example when the target is an attack aircraft. The problem is caused by the estimation of course and acceleration. When the targets are roughly the same size, an accurate estimation of the aspect angles is needed.

When considering the attack target, Table 6.4 also shows the fused course and acceleration has improved the classification in terms of the most probable target. We see that even though difference in average probability for the attack and fighter hypothesis are basically the same as when using radar only, the most probable class is better, especially in cases 2 and 3.

If, as in case 1, the target is heading almost straight at the own platform, a deviation in course estimation will have the effect that the side of the aircraft should be partly visible to the radar. If there are small differences in front area and great differences in side areas, as between bomb/cargo and fighter/attack, the classifier will decide in favour of the smaller object.

This phenomenon is dependent upon the geometry between the target and the own platform and will work in the other direction if the target is observed from an aspect angle where it is facing a side or the wing towards the own platform. But since the side and wing areas defined in appendix A.4 differs more between the involved classes, it cannot be observed in this simulation.

Figure 6.8 shows the probabilities for different classes when studying case 1, head on encounter.

![Figure 6.8](image)

*Figure 6.8  Probabilities for different classes when the target is a friendly attack aircraft. Left (a): True course and acceleration. Right (b): Course and acceleration measured from radar.*
A set of simulations with fusion of radar and IRST kinematics in order to gain better course and acceleration estimates was also carried out. These are also accounted for in Table 6.4.

It should also be mentioned that when feeding the algorithm with true course and acceleration, a 100% correct classification was achieved.

<table>
<thead>
<tr>
<th>True Target class</th>
<th>Course vector</th>
<th>Case</th>
<th>F %</th>
<th>A %</th>
<th>B %</th>
<th>C %</th>
<th>M %</th>
<th>Right</th>
<th>Wrong</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fighter</strong></td>
<td>RR</td>
<td>1</td>
<td>34.2</td>
<td>32.4</td>
<td>19.9</td>
<td>13.5</td>
<td>0</td>
<td>100</td>
<td>0</td>
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<tr>
<td></td>
<td>RR</td>
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<td>35.6</td>
<td>33.8</td>
<td>18.4</td>
<td>12.2</td>
<td>0</td>
<td>100</td>
<td>0</td>
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<tr>
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</tr>
<tr>
<td></td>
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<td>34.3</td>
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<tr>
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</tr>
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<td>0</td>
</tr>
<tr>
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<td>2.6</td>
<td>6.9</td>
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<td>100</td>
<td>0</td>
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<tr>
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<td>41.8</td>
<td>50.4</td>
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</tr>
</tbody>
</table>

Table 6.4 Classification of a target using RCS with estimated course vector from both radar and from fused sensors (Radar and IRST). Columns 4 to 8 shows the averaged probability over all simulations. Column 9 and 10 shows how often the classifier has had the highest probability on the correct class.

The defined RCS for the classes in appendix A.4 implies that it should be hard to separate the classes fighter and attack and relatively easy to separate large objects as bomb/cargo planes from the rest. In Table 6.4
6.4.2 RCS evaluation

As suggested in section 4.2.4, the stochastic behaviour of the RCS makes it necessary to use a running average. This implies that the course vector has to be averaged in the same manner. To evaluate the model the scenario in Figure 6.7 was used.

![Figure 6.7](image)

*Figure 6.7 Scenario for the RCS measurements. Three cases, the solid line represents case 1 (head on encounter), the dotted is case 2 (45 degree deviation from head on) and the dashed represents case 3 (perpendicular trajectories).*

An aircraft is approaching the own platform at the same altitude and at a speed of 100m/s. Three cases are evaluated as shown in Figure 6.7, denoted case 1, 2 and 3. The evaluation used only RCS for classification and the possible targets were limited to the set of friendly aircraft in appendix A.4 in order to simplify presentation. Conclusions from these classification can be applied to any set of aircraft.

During each simulation the target is tracked for 150 seconds and a running average over 10 samples for classification is used. This is repeated in 100 Monte Carlo iterations and the targets were classified with a Bayesian classifier using the specified RCS in appendix A.4 with no general measurement uncertainty.

Table 6.4 shows the results as an average of the probability for each class during the simulation (columns 4 to 8) as well as an indicator of how often the classifier had the highest probability on the correct class (columns 9 and 10). Hence a 90% entry in the column for right classification means that the correct class had the highest probability during 90% of the time.
The simulation results in Table 6.3 show that the RMS of the errors are improved in all of the measured states course, elevation and position. This is of course an effect of the better angular accuracy of the IRST. A more thorough investigation, also including association errors in the radar to IRST association is covered by Malmberg [Mal96].

This fusion process is used in the following section covering RCS evaluation and then referred to as “course from fused sensors” or “RR+IR”.

<table>
<thead>
<tr>
<th></th>
<th>Straight</th>
<th>2g turn</th>
<th>4g turn</th>
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<tr>
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<td>RR</td>
</tr>
<tr>
<td>RMSE</td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>elevation</td>
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</tr>
<tr>
<td>RMSE</td>
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<td>32.78</td>
<td>197.6</td>
</tr>
<tr>
<td>position</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6.3  Comparison of fused accuracies in course and position estimation.
The jagged peaks in Figure 6.6 comes from a combination of the
forgetting described in section 5.2.2 and the fact that measurements are
discrete.

There is no clear answer to the question of which association algorithm
that is best. Since a RWR report can only originate from one target, it
seems appropriate to assign the measurement to one specific target. But
since that can prove difficult due to the track association problem, the
risk of false classifications is overwhelming. As discussed in section
5.2.3, the JPIF method should reflect the true probabilities better.

6.4 Radar Cross Section.

The model for RCS classification described in section 4.2.4 requires a
good estimation of the target course in order to get a correct class
estimation. A velocity vector is available from the kalman filter in the
radar which can be used as a course vector. However, this radar course
vector will prove very noisy, especially when elevation is concerned due
to the poorer resolution in that direction (See Table 6.1). If multiple
sensors are tracking the target, the fused sensor data can be used to
establish a better estimation of the target kinematic states.

First a simulation was performed to illustrate the improvement in
course as a result of sensor fusion between radar and IRST, then an
evaluation of the RCS classification is given.

6.4.1 Course estimation

A target was placed 35 km away from the own platform and three
cases were simulated, straight trajectory, a 2g turn and a 4g turn. The
target is at the same altitude as the own platform and the manoeuvre is
performed in the x-y plane.

Both the IRST and the radar track the target during the whole
simulation. The sensor reports are fused and both course and position are
derived from the fused data.

The RMSE of the deviation between true and estimated course as well
as position is given in Table 6.3.
“friendly fighter” with the confidence of 0.5. Other than the RWR reports nothing is known about the targets, which means that all types except the friendly fighter will be equally likely.

The targets are tracked for 200 seconds and the results are averaged over 100 monte carlo iterations. Results are shown in the form of utilities for the two targets (Utilities are described in section 2.2.6).

Comparing the plots in Figure 6.6c and Figure 6.6d, we see that the unknown target has in average received more probability of being a friendly fighter when using JPIF than when using the “best choice” approach. This depends of course on the fact that the association does not have to be the most probable and thus the target will receive a small probability of being a friendly fighter with every RWR report. If there had been information indicating that target 2 is not a fighter, the probabilities would of course be lower.

Figure 6.6 Classifications from RWR reports. Top-left (a) and lower-left (c): Target utilities using “Best choice”. Top-right (b) and lower-right (d): Target utilities using JPIF.
In Figure 6.4a only the cases correct association and false association are considered, the probabilities for undetected and new track is zero.

If a central track file is used to store old sensor information, there is a probability that the fused sensor tracks are wrongly associated to the track file. In Figure 6.4a the association to the track file is 100% correct, but in Figure 6.4b a mix-up occurs after 40 seconds. After this the cargo plane continues to be associated to the track file that the fighter has created (i.e. they change history). In the right graph of Figure 6.4 we can see that the classifier recovers from the misassociation. The problem discussed earlier about tracks changing history only apply when a sensor reports at infrequent intervals. If, as in the previous example, reports are frequent and at equal instances in time, the classifier will recover from the misassociation.

An investigation of the relative rise times between Bayesian and Dempster-Shafer approaches can be found in [Bue97].

### 6.3 Associating a RWR with other sensors

The scenario in Figure 6.5 was used to evaluate the JPIF approach described in section 5.2.3 for association of RWR to other sensors, in this case a radar. To be able to evaluate JPIF, it has been compared to the other method described in section 5.2.3, the “Best choice” approach.

![Figure 6.5](image.png)

*Figure 6.5 Scenario for RWR associations. Two targets approaching the own platform. The left target (target 1) emits radar signals every five seconds, while nothing is known about the right target (target2).*

The two targets are separated by 4km, enough to create ambiguity in RWR association due to the poor resolution. The left target (denoted target 1) emits radar signals every five seconds indicating the type
As predicted, the attributes have improved the track association process. There are still association errors deriving from large deviations in position estimation but as Figure 6.2 and Figure 6.3 show, good and reliable attributes provide a great improvement.

A recursive classifier operating on the fused tracks will be slowed down by misassociations. Figure 6.4a shows the recursive probabilities for target 1 being a fighter with different probabilities for misassociations.

Figure 6.3  Bar chart showing average of wrongly associated weights using JPDA. Left bar corresponds to JPDA with kinematic association only and the right corresponds to association with both kinematic and attribute data.

Figure 6.4  Recursive classification from misassociated tracks. Left (a): Rise time as a function of misassociation probability. Right (b): Recovery from track file misassociation.
Figure 6.2 shows the association errors when Nearest Neighbour is used and Figure 6.3 shows the mean weight of the wrongly associated tracks using JPDA.

<table>
<thead>
<tr>
<th>Set</th>
<th>Target 1</th>
<th>Target 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fighter</td>
<td>Cargo</td>
</tr>
<tr>
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<tr>
<td>2</td>
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<td>0.6</td>
</tr>
<tr>
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<tr>
<td>4</td>
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<td>0.3</td>
</tr>
</tbody>
</table>

Table 6.2 Attributes assigned to the targets.

**Figure 6.2** Bar chart showing the errors in track association using the scenario in Figure 6.1 and Nearest Neighbour for track association. The left bar in every couple is association errors without attributes, the right is association errors with attributes.
6.2 Track association using both kinematic and attribute data

The track to track association methods Nearest Neighbour and Joint Probabilistic Data Association were tested using kinematic association as described in section 3.6 and also with the modified distance function described in Eq 3.11 that utilises both kinematic and attribute data.

![Figure 6.1](image)

*Figure 6.1 Scenario. The own aircraft starts from the bottom with a speed of 200 m/s, with two aircraft approaching at 100m/s from the top. The approaching aircraft have differing attributes in the sense that one is a fighter and the other is a cargo plane.*

The scenario is described in Figure 6.1. It contains two aircraft, one is a fighter and the other is a cargo plane. They are separated by 100 meters and the distance to the own platform is between 30 and 60 kilometres. The targets are flying at the same altitude as the own platform and travelling with a speed of 100 m/s.

Two radar sensors mounted on the own platform are used to illustrate the association problem. First Nearest Neighbour and JPDA are applied using only the kinematic data to perform the track association. Then, attributes in terms of target class probabilities are assigned to the targets to test the impact of attributes of different quality. The attribute sets have been labelled 1 through 4 with corresponding class probabilities described in Table 6.2

The targets are tracked for 100 seconds and a Monte Carlo simulation consisting of 100 iterations has been performed for each of the attribute sets.
6 Simulations & results

This chapter describes the simulations performed to evaluate the different parts of the system. First, track association with both kinematic and attribute information is performed and evaluated. Then RWR association with JPIF is compared to association through the most probable pairing (best choice). This is followed by simulations on classification from radar cross section, RCS. Finally tests are carried out on the whole implemented classification and fusion system, first with kinematic data only and then with informations from all local sensors.

6.1 Simulation conditions

All sensors measure the targets position through all or some of range (r), bearing (ψ) and elevation (θ) to the target. The IRST tracking filter uses Modified Spherical Coordinates (MSC) for tracking, while the tracking filter in the radar transforms measurements into cartesian coordinates and performs tracking in a cartesian system. MSC as well as conversions between the coordinate systems are described in appendix A.1.

The measurement noise is implemented with the ambition to reflect the true accuracies in the sensors. The standard deviations are set as in Table 6.1.

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<td>10mrad</td>
<td>20mrad</td>
</tr>
<tr>
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<td>-</td>
<td>1mrad</td>
<td>1mrad</td>
</tr>
<tr>
<td>RWR</td>
<td>-</td>
<td>50mrad</td>
<td>50mrad</td>
</tr>
</tbody>
</table>

Table 6.1 Standard deviations for sensor noise.

The noise is added to the measurements as additive white noise.

A sample frequency of 1 Hz has been used for the data collection, but because of initial effects in the Kalman filters, no data collected during the first 20 seconds are used for classification.
with large variance there will be a small probability for targets capable of larger accelerations, which will lead to classifications in favour of those targets. This forces a solution where acceleration is used only as a rough estimate of the nature of the target, where a confidence level is used to ignore measurements that doesn’t contribute with useful information.

The classification strategy is to compare the maximum measured attributes, velocity, altitude and acceleration, with the performance of the set of aircraft types.

5.2.5 Identity Fusion

The fusion of identity statements is made with a Dempster-Shafer algorithm. The reason for this choice was merely because of the convenient representation of uncertainty. The algorithm uses the tree structure in Figure 1.1 to direct subsets to their parents.

Since the identity fusion is done with the Dempster-Shafer method, probabilities are given as upper and lower bound and consequently classification is performed by the method described in section 2.2.6 in order to get unambiguous results.

5.2.6 Restrictions

Time has prevented me from implementing external sensors. However, they act merely as an additional sensor and it should be easy to extend the system to include them. Also, for the same reason no advanced system for multi-sensor tracks has been implemented, instead the central track file is correlated to the radar.
Figure 5.5 shows the RWR association and identity fusion process. A recursive updating strategy is used to obtain more secure classifications as more reports are made available. Old RWR information is fused with other track information before calculating the association probabilities, since a better track identification will improve the association process. The contribution to each track from the new RWR reports are then calculated and the JP1F identification is performed on each track before the final identity fusion with all local information is performed.

5.2.4 Kinematics

Kalman filters implemented by Norberg were used for tracking in the radar and IRST [Nor96]. These filters use only position and velocity as states, and thus another filter was introduced, calculating acceleration and its approximate variance. The problem here is that since acceleration is the derivate of velocity it will be very noisy. A low pass filter can be introduced to get rid of high frequency noise with the drawback of losing detection ability of large manoeuvres with a short time span. Also, the variance of the acceleration will be quite large making it difficult to make decisions. As for small accelerations (a target in a straight trajectory)
fusion as well as combined with the forgetting matrix, $M$ and stored as the new states. When there is no new information, the stored probabilities are sent alone to the fusion process.

The values in the matrix $M$, has to be chosen with respect to the misassociation probabilities, since the necessity to forget old information is related to the risk of measurement errors and misassociations.

5.2.3 **Associating RWR with other sensors**

The kinematic properties of the RWR are more diffuse than those from the other sensors. This combined with the fact that a threat warning can be very valuable for the situation awareness, makes it important to associate the RWR report to the right target reported by other sensors.

The straight forward way to fuse RWR tracks with tracks from other sensors is to calculate the most probable combination of association and then combine the RWR reports with those sensor tracks on a one to one basis. This is easiest achieved by using a Nearest Neighbour algorithm and then associating the RWR report with the “closest neighbour”. This will from here on will be denoted “Best Choice” to emphasise that attributes are concerned.

The technique proposed by Noonan and Pywell abandons the one to one principle [Noo97]. Instead they propose an approach called Joint Probabilistic Identity Fusion (JPIF), which uses JPDA track fusion and association. Attributes are associated to all association hypotheses weighted by the association probability.

This association method should lead to a smoother assignment of evidence as well as it should reflect the true association better, since it considers the uncertainty in the track association.

Additionally, the RWR may declare its emitter statement on different levels of abstraction. In some cases it may only have enough information to make a statement that the emitter is a fighter radar or only give a carrier frequency. Yet, in some cases, it can deliver information about the exact emitter type, which can lead to an aircraft type identification.
5.2.2 Decay of information

For some parameters, like the maximums of altitude, velocity and acceleration, the “forgetting” can be achieved by a factor that reduces the maximum value with time.

For recursive loops, which keeps probabilities for different hypotheses on the target, forgetting is achieved by Markov chain modelling. Hence, the current state is mapped to the previous as:

$$P_t = M \cdot P_{t-1},$$  \hspace{2cm} Eq 5.1

where the states $P_t$ and $P_{t-1}$ consist of the probabilities for each possibility the sensor is able to distinguish. That is, the RWR has states related to target types.

This is illustrated in Figure 5.4. When new information is available it is classified/identified and combined with the previous states or probabilities. The combined probabilities are then sent on to identity.
Since not all sensors track the targets at all instances in time, there is a need for a central track file that keeps old information from the different sensors.

### 5.2.1 Parameter filtering and identification

In Figure 5.2 the box Filtering and Identification takes care of the local parameters.

The RCS is filtered in the sense of a running average over the last 10 samples and the identification is made based on the filtered average. The kinematic filter keeps track of the highest measured altitude and velocity for the track.

The IFF and doppler parameters are classified with a recursive classifier. Figure 5.3 shows schematically how the filtering and classification algorithms are related.
5.2 System structure

The information exchange through Data Link and Ground Control is a two way communication, as described in section 3.3. This means that external information has to be fused after the information gathered locally in the aircraft is sent out on the link as illustrated in Figure 5.1. Otherwise there is a danger that the same information starts rotating in the system.

![Flowchart for fusing of external information.](image)

A problem with the structure in Figure 5.1 occurs when there is identity information about a target in the external sources and not in the local. An example could be the fusion of local passive sensors like IRST and RWR. As mentioned earlier, the poor resolution in the RWR makes it difficult to associate on a kinematic basis when the scenario is ambiguous. We normally don’t want to include external information prior to the local fusion, but here an exception could be made including external information for cases which are difficult to solve otherwise. The resulting fused information should not be sent out on the Data Link and thus a parallel algorithm must be used for the link data.

Figure 5.2 shows an overview of the part of the system that fuses locally gathered information. First, reports from radar, IRST and IFF are fused using a track to track fusion algorithm and associated to old information on the track file. Second, attributes from the combination of new and old information on the tracks are filtered and classification on the attributes is performed as shown in section 5.2.1. Third, radar warning information is added through the scheme specified further in section 5.2.3. Finally, when all locally gathered information is associated to the tracks, the identity information is fused.
Table 5.1 describes only the parameters available from local sensors. The external, (Ground Control and Data Link), can contribute with similar reports and also with complete classifications. The performance of the implemented RWR lies somewhere in between a RWR and an ESM device. Hence it is capable of extracting emitter type but the position estimation is poor.

5.1.2 Setting the likelihood functions

Perhaps the most important part in a classification system like this is the mapping between the measured data and the probabilities of the causes (class/type/id). Normally these values will be derived from intelligence sources and knowledge about sensors and aircraft. However, in order to evaluate system performance the likelihood functions for the aircraft in the test had to be defined. The values that are used to set the likelihood functions in this work are accounted for in appendix A.4.
This chapter presents the implemented system design and also points out advantages and drawbacks with the chosen solution.

5.1 General

The classifier must be constructed in a way that allows access to old information. This comes from the fact that some features of a target is measured at discrete instances in time. This can, for example, be the case for the analysis of Jet Engine Modulation, which include a Fourier transform and thus takes a lot of time to perform. Other reasons why some sensors are not updated at every time instant is that the target may be out of the sensor visibility field or the fact that information is not available periodically, as in the RWR.

This need for feedback of old results can be divided into two subgroups, local feedback (in the sensor) and external feedback (from other sensors). An example of local feedback is the need to keep old velocity measurements to be able to calculate the maximum measured velocity over a number of time intervals.

For some parameters this feedback can be obtained by including old information on the track file, while it is more difficult for instance with the RWR reports, especially if there are many emitter sources. Here a feedback of the probabilities for the different types or classes is to be used (i.e. recursive updating).

5.1.1 Classification Parameters

Most of the parameters described in Chapter 4 were chosen as information providers for the classification system. The information from the Infra Red sensor is considered too weak to contribute with any substantial classification information, except in some special cases. For other parts of the system the IRST is still important such as correlation between engine rotation speed and afterburner. Should it later on be considered necessary or to be a great improvement, it is easy to modify the system to include these parameters.
4.7 Summary

A major problem is of course to gather information regarding the attributes for the different aircraft operating in the neighbourhood. For own forces this might be relatively easy, but when the enemy is concerned there might be gaps in the database. JAS 39, MIG 29 and Tu22 are three aircraft that are operating in Northern Europe, where JAS 39 and MIG 29 are fighter/attack aircraft while Tu-22 is a medium range tactical bomber. For these types useful attributes could look like:¹

<table>
<thead>
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<th>MIG 29</th>
<th>Tu-22</th>
</tr>
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<td>40</td>
<td>100</td>
</tr>
<tr>
<td>Engines</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>IFF</td>
<td>Friend</td>
<td>Enemy</td>
<td>Enemy</td>
</tr>
<tr>
<td>Emitter</td>
<td>Type 1</td>
<td>Type 2</td>
<td>Type 3</td>
</tr>
<tr>
<td>Band [GHz]</td>
<td>10-12</td>
<td>9-11</td>
<td>6-8</td>
</tr>
</tbody>
</table>

* With afterburner active.

These aircraft types are not used further in this work. Instead new types are defined with attributes according to appendix A.4.

¹ These attributes are used only to illustrate how attributes may differ between different types of aircraft and has little to do with the real performance and attributes.
4.4 Infra Red Search and Track

The Infra Red Search and Track (IRST) device is a passive sensor designed to detect radiation in the infrared frequency band.

4.4.1 Missile Launch

The detection of a missile launch can be used for three purposes. First, it can be used to rule out all types of aircraft that are unable to carry missiles. Second, it can be used for identification of the new object as a missile. Third, it can be valuable information in a threat warning system.

4.4.2 Afterburner detection

Not all jet engines have afterburners installed. In fact afterburners are limited to fighters and attack aircraft, and to some special types of bombers. The obvious possibility here is to rule out types not equipped with afterburner. The knowledge of whether the afterburner is active or not can be used in combination with the Jet Engine Modulation since the afterburner extends the interval for possible number of revolutions.

4.5 Identification Friend or Foe

The IFF sensor only states if an aircraft is friendly. If it is hostile or has a malfunctioning IFF device, no response is received. On the other hand, a positive response stating a friendly aircraft is considered very reliable since it is assumed that the correct response only can be generated by own forces.

4.6 Cross Relations

Several of the features of an aircraft are dependent on other parameters. For instance if the afterburner is active, the engine rpm is higher than the maximum value without afterburner and Radar Cross Section is related to manoeuvre detection since some heavy manoeuvres include an increase in roll angle.

Also, given radar range measurement and the received power of an intercepted radar signal, the emitter estimation can be made more accurate.
4.3.2 Radar emitter estimation

Sometimes “electronic fingerprints” enables the ESM to distinguish between emitters and emitter types. This “fingerprinting” can be achieved by the existence of unique sets of parameters like frequency, pulse width (PW), pulse repetition frequency (PRF) and scan rate/time. Emitter type can sometimes be directly associated to a platform or at least narrow the possible types down to just a few.

4.3.3 Received Power

The radar's transmitted power is a basic quantity that defines its range performance. The power quantity that can be most readily measured is the peak effective radiated power (ERP), which is the product of the peak transmit power, the antenna gain and losses between transmitter and receiving antenna. If the main radar beam points towards the ESM equipment the antenna gain in the transmitting radar can be measured and the peak transmit power estimated [Wil93]. Different radars transmit on different power levels, making it possible to rule certain radar types out. In order to unambiguously estimate emitter type, radar range measurements, which are more accurate than those of the ESM, are combined with the power measurement.

4.3.4 Frequency

The carrier frequency of a pulsed signal can be measured with high accuracy. According to Wiley, systems currently in use are accurate to less than less than 1% of the measured frequency [Wil93]. At frequencies spanning from 1 GHz to 20 GHz such a frequency measurement would be accurate to between 1 and 20 kHz. Since radar frequencies can be acquired by either measurements or available information, frequency measurements can provide a useful piece of information. The exact frequencies of operational radar emitters are classified information and are not printed in open literature. However, Herskowitz presents the frequency bands for some common emitters [Her96].

Frequency measurements are often used within the ESM to estimate the emitter type. It should therefore only be used for classification when an emitter estimation is unavailable.
connection to the problems it may cause. Lately though, several articles have been published regarding the use of the radar signature generated by JEM for target identification [Pel92], [Cuo95] and [Bel93].

Typically, JEM identifiers are adaptive neural networks fed with the periodogram of the target return. For military applications, the need of training a neural network can present a problem due to unavailability of certain aircraft types.

Studying the autocorrelation sequence of the retrieved scattering it is possible to determine the engine rotational speed and also number of engines [Bel93]. A measurement of number of engines can in some cases be an invaluable piece of information for the determination if a target is a threat. For instance, a measurement indicating one engine only, rules out all operational Russian and most European fighters, thus limiting the number of possible types.

### 4.3 Electronic Support Measures

Most threat weapons have a Radio Frequency (RF) targeting or guidance component. For systems where RF is employed, the primary measurement or warning system on the aircraft is the Electronic Support Measures (ESM). ESM is an extension from the Radar Warning Receiver (RWR), of which the latter is used primarily for threat warning. ESM on the other hand is used not only for threat warning, but also for detection and identification of non-threat emitters as well as for determination of emitter location [Noo97].

The ESM may provide measured emitter parameters like frequency, Pulse Width (PW), Pulse Repetition Frequency (PRF), received power and scan time or rate. A Probability Of signal Interception (POI) is specified for an ESM, with POI approaching 100% for modern equipment [Noo97]. For samples of emitter parameters for some airborne radar systems see [Her96].

#### 4.3.1 Emitter location

Concerning positioning, ESM can contribute with azimuth Direction Of Arrival (DOA) and elevation DOA, equivalent to bearing and elevation respectively. If the broadcasting emitter is mounted on the ground, the range can be estimated. However, if the emitter is airborne, range estimation depends on triangulation or power measurements. Lack of accurate emitter location makes track association difficult in dense environments.
If the target consists of many scattering points with random phases, the received signal amplitude will have a Rayleigh distributed probability density function (pdf). This results in an exponential pdf for the RCS [Bar88]. The front, side and wing RCS-areas are then the expectance value of these distributions.

![Radar Cross Section density function](image)

**Figure 4.3** Example of density function. The expectance value of the dotted line is set to 20m$^2$ corresponding to the front area of a transport aircraft. The solid line corresponds to the front area of an interceptor which has a expectance value of 5m$^2$.

Given a probability density function like the one in Figure 4.3 and a measured RCS with some kind of uncertainty, probabilities can be derived for the types. Since the RCS is exponentially distributed, very large fluctuations will appear between each received echo. It is therefore suggested to use a running average over a number of past measurements.

Another problem with RCS measurements is that if the targets radar is pointing in the direction of the measuring platform, it will act as a lens and amplify the received echo to very large values. This effect has to be taken into consideration in order to receive correct classifications.

### 4.2.5 Jet Engine Modulation

In radar science it is well known that the rotating parts of an aircraft may cause modulation phenomena in the spectral response from the target. The phenomena occurs when a radar observes a jet aircraft at an aspect angle that allow electromagnetic radiation to be backscattered from moving parts in the compressor and blade assembly of the jet engine and has been observed at angles up to 60 degrees from a nose-on aspect. In the existing radar literature this modulation is often mentioned in
4.2.3 Acceleration

From the tracking filter, an acceleration can be derived that could be used to estimate target manoeuvring. Since manoeuvring capabilities differ greatly between different types of aircraft, a measure of manoeuvre magnitude is useful. However, acceleration in itself is a very noisy estimate, making it hard to get unambiguous measurements. The strategy for classification should be the same as for altitude and velocity, meaning that the highest measured acceleration is used.

4.2.4 Radar Cross Section

Through the radar equation the radar echo gives a measurement of the target size (See appendix A.2). A radar pulse striking a target reflects in different directions and add up to the received amplitude echo. Radar cross section is defined as the cross section of a metallic sphere which gives the same echo as the object.

However, an aircraft can hardly be approximated to have the physical dimensions of a sphere as there are great differences in reflecting areas depending on aspect angle. We can instead approximate an aircraft by using three areas: front, side and wing area. But the echo does not depend as much on physical aspects of the target as it does on separate reflection elements as edges, antennas or engine inlets. This implies that radar cross sections have to be measured or calculated from models.

If we know the course vector of the target, we can split the target into front, flank and side area, thus approximating it with a box according to Figure 4.2.

![Figure 4.2](image)

*Figure 4.2 Approximation of the aircraft with a box. Each type is then assigned side, wing and front areas.*

In order to estimate which sides of the target that are visible to the radar, a manoeuvre detection of some kind is needed. One solution, though simple, is to use the measured target acceleration to create a mapping between acceleration and roll angle.
It should not be hard to prove a correlation between altitude and a specific type of aircraft, but a classifier could easily be deceived by a change in enemy tactics. A better way is to use the maximum altitude of a specific type to rule it out.

A fuzzy membership for the different aircraft types has been chosen since it will give a smoother identification when a target is near a breakpoint in the membership function (Figure 4.1). The breakpoint \( \text{alt}_{\text{max}} \) in Figure 4.1 corresponds to where it starts to be unlikely that the target is of “Type B”.

A drawback with the “rule out” strategy is that only targets with worse performance than the measured can be ruled out. For lower altitudes or velocities we are unable to make any conclusions. Also, a “forgetting” factor has to be introduced to compensate for measurement and miscorrelation errors.

### 4.2.2 Velocity

The radar measures the radial velocity of the target by Doppler shifts. If there exists an estimate of the target course, it is possible to estimate its velocity.

There is no clear correlation between aircraft velocity and tactical mission. It would probably be possible to estimate a probability density function for velocities for the different types of aircraft. However, this would lead to a weaker identification if the aircraft behaves in a way it is not supposed to.

The maximum speed is on the other hand well known for most types of aircraft. If a velocity measurement is received, indicating a speed outside the possible region for a certain type, this can be used to rule out that type with a similar membership function as in Figure 4.1.
This chapter analyses the possibilities, for each sensor, in terms of classification using measured attributes and kinematic data.

4.1 General

Target classification has been discussed in a number of articles and reports. Örnkloo discusses classification using the radar parameters: velocity, acceleration and radar cross section [Örn95]. Carlsson treats classification using the same radar parameters in combination with a Radar Warning System (frequency only) [Car97].

However, since a modern aircraft possesses additional sensors and each sensor is capable of measuring other parameters than those mentioned above, a more unambiguous classification might involve other attributes. Below is a listing of potential attributes that are possible to extract from the different sensors and how they can be used.

4.2 Radar

By using measurements from a pulsed doppler radar, it is possible to extract a number of target features. These include kinematic attributes as position, velocity and acceleration, but also Radar Cross Section (RCS) and Jet Engine Modulation (JEM) phenomenon.

4.2.1 Position

Considering position, the radar measures distance, bearing and elevation to the target. This combined with knowledge of the own position makes it possible to calculate the absolute position of the target. Since behaviour of an aircraft has a correlation to the tactical mission this can be used for classification. For example, a fighter normally uses a high altitude in order to get an advantage in aerial combat.

However, a fighter aircraft may for a number of reasons assume a low or a medium altitude, it could for instance act as an escort for a bomber or a transport.
By taking the logarithm of Eq 3.7 and reducing the constants we see that the modified distance function is achieved by adding \(-2\log \left[ P(Z_i|W_j) \right] \) to the distance defined in Eq 3.1, arriving at the expression:

\[
\begin{align*}
    d_{\text{mod}}^2 &= d_{ij}^2 - 2\log \left[ P(Z_i|W_j) \right] \\
    &\quad \text{Eq 3.11}
\end{align*}
\]

Similarly, when applied to JPDA we have

\[
    P(H)_{\text{attrib}} = P(H) \cdot P(Z_i|W_j) \\
    \quad \text{Eq 3.12}
\]

If Dempster-Shafer has been used to calculate an identity or attribute mass vector, this information can be used in an analogous manner. Suppose that Dempster’s rule of combination yields the factor \( k \) as a measure of the disagreement between the mass vectors of the associated tracks. Then the factor \( 1-k \) is equivalent to the term \( P(Z_i|W_j) \) used in Eq 3.7 [Bla86].

Thus the modified hypothesis probability used in JPDA should be:

\[
    P(H)_{\text{attrib}} = P(H)(1-k) \\
    \quad \text{Eq 3.13}
\]

When using JPDA, each track is updated with all neighbour tracks according to the probabilities of the association (section 3.6.3). In the same way, attributes from one sensor can be associated to multiple targets from another sensor, weighted by the association probability.

If \( P(H) \) denotes the probability of the association, \( A \) denotes an attribute and \( P(Y|A) \) denotes the probability for event \( Y \) given the attribute \( A \) from a sensor, we have

\[
    P(Y|A) = \sum_i P(H_i)P_i(Y|A). \\
    \quad \text{Eq 3.14}
\]

This is introduced by Noonan and Pywell and referred to as Joint Probabilistic Identity Fusion (JPIF) [Noo97].
3.6.4 Track association including attributes

When the kinematic information is insufficient to perform a correct association, attribute information can be included to improve it. This is easily done by modifying the distance function [Bla86].

Eq 3.3 describes the posteriori probability of the measured data. If attributes are included, the posteriori probability becomes:

\[ f_{ij}(\tilde{y}_{ij}, Z_i, W_j) = f(\tilde{y}_{ij})P(Z_i|W_j), \quad \text{Eq 3.7} \]

where \( P(Z_i|W_j) \) is the probability for the track \( i \) to produce a measurement \( Z_i \) given the measurement \( W_j \) of a track from another sensor. This can be rewritten as

\[ P(Z_i|W_j) = \sum_Z P(Z_i|Z)P(Z|W_j), \quad \text{Eq 3.8} \]

where \( Z \) represents the set of attributes that can be measured. The general equation for calculating \( P(Z_i|W_j) \) with any relationship between the apriori probabilities is:

\[ P(Z_i|W_j) = \sum_n \frac{P(Z_i|H_n)P(H_n)}{P(H_n)}P(H_n|W_j) \quad \text{Eq 3.9} \]

In a case where target type vectors are computed (a vector containing probabilities for the different hypothesis), if all types are equally probable in the scenario and if the likelihood function \( P(Z_i|H) \) sums to unity, then the probability \( P(Z_i|W_j) \) is calculated as a scalar vector multiplication between the type vectors of track \( Z_i \) and \( W_j \).

\[ P(Z_i|W_j) = P_{Z_i} \cdot P_{W_j}, \quad \text{Eq 3.10} \]

where \( P_{Z_i} \) represent the estimated type vector for track \( Z_i \) and \( P_{W_j} \) represents the type vector from track \( W_j \). Otherwise, as in most cases, the attributes must be sent to the fusion system and used in the association process according to Eq 3.9.
The density of new targets, or rather targets detected by sensor B, but not by sensor A is

\[ \beta_N = (1 - P_{TA})P_{TB}\beta_T \]  

\textit{Eq 3.4}

With the designations above, a possible hypothesis is that track B3 belongs to track A1 and that B1 and B3 belong to neither A1 nor A2 is written:

\[ P(H) = C_{g_{31}}P_{TB}(1 - P_{TB})^2 \beta_E^2 \]  

\textit{Eq 3.5}

The component \( g_{31} \) in Eq 3.5 is the probability for the track residual (see Eq 3.3), \( P_{TB}(1-P_{TB}) \) is the probability that A1 is tracked by both sensors while A2 are not, and \( \beta_E^2 \) is the probability of two targets detected by sensor B and not by sensor A.

Since the combination of all hypotheses covers all possible events, the probabilities should be normalized before they are used.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>A1</th>
<th>A2</th>
<th>( P(H) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-</td>
<td>-</td>
<td>( C(1 - P_{TB})^2\beta_N^3 )</td>
</tr>
<tr>
<td>2</td>
<td>B1</td>
<td>-</td>
<td>( C_{g_{11}}P_{TB}(1 - P_{TB})\beta_N^2 )</td>
</tr>
<tr>
<td>3</td>
<td>B1</td>
<td>B2</td>
<td>( C_{g_{11}g_{22}}P_{TB}^2\beta_N )</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>B2</td>
<td>( C_{g_{22}}(1 - P_{TB})P_{TB}\beta_N^2 )</td>
</tr>
</tbody>
</table>

\textit{Table 3.2}   \textit{Example of some of the ten possible hypotheses in Figure 3.6, just to give an idea of how the hypothesis probabilities are calculated.}

The probability for the association A1-B1 is then calculated as

\[ P(A1 \leftrightarrow B1) = P(Hypothesis 2) + P(Hypothesis 3). \]  

\textit{Eq 3.6}

For situations like the one described in Figure 3.4, where kinematic data are unreliable and many targets are inside the correlation gate, JPDA should be preferred.
3.6.3 Joint Probabilistic Data Association

Joint Probabilistic Data Association, or JPDA, tries to associate tracks on a “all neighbours” basis. That is, instead of updating each track with a single target track from another sensor, all available targets inside the track correlation gate is used to update the track, weighted with the probability of that association. This makes JPDA useful for dense or ambiguous scenarios such as association of threats to targets or where there are many false tracks.

Consider the conflict situation shown in Figure 3.6. Through the correlation gate, track B3 is ruled out as a possible association for track A2. The weights for B2 and B1 are reduced by the fact that they are present in both correlation gates. From the sensor tracks, a number of possible hypothesis is formed, each depending on a number of factors:

- Probability for the residuals, $\tilde{y}_{ij}$, between the tracks associated in the hypothesis.

- The updating probability, $P_T$. For a sensor A, $P_{TA}$ is the probability that sensor A have a track on a given target.

- The probability density of new targets, $\beta_T$ (and a constant C which doesn’t have to be calculated, as it disappears in the normalization).
3.6.2 Nearest Neighbour

In order to further explain the Nearest Neighbour algorithm, we look at the following example. We have three tracks from two different sensors, denoted $A$ and $B$, with gates as illustrated in Figure 3.5.

![Figure 3.5 Example of three targets (B1,B2,B3) and three tracks from another sensor (A1,A2,A3). Gates are marked with circles.](image)

To solve the association problem described in Figure 3.5 the relative distances between the tracks are entered in an association matrix. Using Nearest Neighbour, the solution that has the smallest total distance is chosen. Suppose these distances are as in Table 3.1.

<table>
<thead>
<tr>
<th>Track</th>
<th>B1</th>
<th>B2</th>
<th>B3</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>x</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>A2</td>
<td>10</td>
<td>8</td>
<td>x</td>
</tr>
<tr>
<td>A3</td>
<td>8</td>
<td>8</td>
<td>x</td>
</tr>
</tbody>
</table>

*Table 3.1 Association matrix for the example in figure 3. Rows and columns represent tracks and measurements respectively. An x marks that the measurement is outside the gate.*

Munkres algorithm is an algorithm described by Blackman and Malmberg delivering an optimal solution using $O(n^2m)$ operations, where $n$ is the smallest and $m$ is the largest of the number of columns and rows [Bla86], [Mal96]. Using this algorithm on the association matrix in Table 3.1 yields the solution A1-B3, A2-B2 and A3-B1.
3.6.1 Measures of distance

In order to perform these techniques a measure for distance is needed and a common approach is to use the normalised distance function. Considering two tracks with corresponding states $\hat{x}_1$ and $\hat{x}_2$ with covariances $P_1$ and $P_2$ respectively, the normalized distance is defined as:

$$d_{1,2}^2 = (\hat{x}_1 - \hat{x}_2)^T S_{1,2}^{-1} (\hat{x}_1 - \hat{x}_2)$$  \hspace{1cm} Eq 3.1

$$S_{1,2} = P_1 + P_2$$  \hspace{1cm} Eq 3.2

Given independent normal distributed state estimates, this distance function is $\chi^2$-distributed with M degrees of freedom, where M is the size of the state vector [Bla86].

This yields the density function

$$f(\tilde{y}_{ij}) = \frac{e^{-\frac{d_{ij}^2}{2M}}}{(2\pi)^{\frac{M}{2}} \sqrt{|S_{ij}|}}$$  \hspace{1cm} Eq 3.3

where $\tilde{y}_{ij}$ is the residual between the track state vectors, thus $\tilde{y}_{ij} = (\hat{x}_i - \hat{x}_j)$. 

---

Methods for track association

![Image](image-url)
A better accuracy will of course narrow the limits of the cone, limiting the number of probable associations. Another solution to this problem is the introduction of identity estimation to improve the reliability in the association. Suppose, for instance, that of the three targets inside the cone, one is known to be a friend and one is known to be a cargo plane. If the received radar signal indicated a hostile radar, we can assume that it is most likely that the emitter is located on the third target. This way of using attributes for track association is called attribute association, which is further explained in section 3.6.4.

3.6 Methods for track association

There are three main methods suitable for track association. These are Nearest Neighbour (NN), Joint Probabilistic Data Association (JPDA) and Multi Hypothesis Tracking (MHT). Nearest Neighbour associates tracks such that the shortest possible total distance is achieved. Joint Probabilistic Reasoning calculates a probability for all sensor tracks inside a certain region that they belong to a specific track from another sensor. It then updates the sensor tracks with all tracks from the second sensor, weighted with the probability that it is the correct association. MHT calculates probabilities for the different association hypotheses and updates the track with all these hypotheses. During the following measurements all but one hypothesis will be ruled out. Time complexity for the different methods is such that MHT is most time consuming, followed by JPDA and NN. The computational load increases faster for JPDA and MHT with the number of targets [Mal96].
a track association problem. Sensor measurements from one sensor must be associated to the right set of measurements on the same target from other sensors. The problem of associating tracks from different sensors differs slightly from associating sensor reports for a certain sensor to existing sensor tracks. Malmberg and Blackman both discuss track association and are recommended to the interested reader [Mal96], [Bla86].

Gating is a technique used to eliminate measurements that are too improbable. A gate is applied to the predicted state in the track and targets outside the gate are ruled out (Figure 3.3). If there are multiple targets present within the gate, other association methods have to be used.

![Figure 3.3 Example of one existing track file(cenred) and four sensor tracks. A gate (dotted) is applied resulting in the exclusion of the two tracks outside the gate. The remaining tracks can be handled by one of the methods in section 3.6.](image)

In order to make the right association, sensor accuracy in position is crucial. Assume that a Radar Warning system indicates a threatening radar in a certain direction. If the angle measurement has an uncertainty of, say 3 degrees in both azimuth and elevation and a gate is applied to angles wider than say 10 degrees, the Radar Warner describes a cone inside which the target exists (Figure 3.4). Targets near the centre of the cone are more probable causes of the threat than those farther out. Unless a gate is applied there are no sharp edges of the cone and thus targets outside also represent a small probability of causing the threat.

If the radar indicates multiple targets inside the cone, we might have difficulties associating the Radar Warner report to the right Radar target.
3.4 Target tracking

To track a target it is necessary to filter measurements to estimate current, and predict future, states. These predictions are then compared with the actual measurements for associating the measurements to a given track. In target tracking the most widely used filter is the Kalman filter, which for linear systems is an optimal estimator in the sense that the variance for the prediction error $E\left\{ \tilde{x} \cdot \tilde{x}^T \right\}$ is minimized. If the system is nonlinear (as target tracking), a linearisation leads to the extended Kalman filter.

Multi Sensor Integration (MSI) is the process by which identification, classification, kinematic state estimates and other target information is derived from sensors and other contributors such as Ground Control Systems or Data Link. Since the merging of sensor data is computationally costly, the computational load should be distributed. A common approach is to decentralise the formation of tracks, which means that each sensor tracks the targets individually. The sensor tracks are then merged into multisensor tracks in a central processor. This means that tracks only are sent to the central processor when they contain new information and subsequently a lesser amount of information has to be sent through the local data communication system.

![Flowchart of information flow in a local-central tracking system.](image)

In the central track file, data from all sensors are assigned to a target so that old information from a sensor can be used even if there is no current track from that sensor.

3.5 Data and Track Association

When tracking multiple targets, the data association problem arises. In each sensor, data measurements must be associated to the right target. In the same way, for a system fusing reports from multiple sources, there is
The receiver is discussed further in section 4.3 and by Noonan and Pywell, but for further information of estimation techniques see Wiley [Noo97], [Wil93].

3.2.4 Identification Friend or Foe

Identification Friend or Foe (IFF) identifies friendly aircraft within a certain range. Usually a coded transmission is used to “interrogate” the target and a friendly aircraft receives and decodes the transmission and returns the proper response.

3.3 External Sources

The evolution of data communication has made it possible to exchange computer based information between platforms. Local computer networks can be established between aircraft in order to increase the sensor knowledge base. This can be useful for instant triangulation with passive sensors, e.g. to determine range to the target.

![Diagram](image)

*Figure 3.1 Illustration of platform communication. Three aircraft form a local network using a data link to communicate. Information can also be exchanged with a ground or airbased supreme command.*

In this thesis Ground Control and Data Link are considered able to contribute with information (Figure 3.1). This information may include position, attributes and even estimations of identity or class.
Besides search and track tasks, the radar supplies launched missiles with target data. There are also radars that are developed especially for navigation and weather detection applications.

A radar is an active sensor, which means that it emits radiation. These emissions can be detected and sometimes classified by radar receivers. From a tactical aspect it is therefore necessary to use radar as seldom as possible.

### 3.2.2 Infra Red Search and Track

An IRST sensor device detects electromagnetic radiation in the infrared frequency band, caused by e.g. the heat from the aircraft propulsion system. Since the IRST is passive, i.e. emits no radiation, it can not provide target distance information from one single measurement. On the other hand, angle measurements are more accurate than for the radar. The IRST should also be able to detect missile launches and whether the afterburner is in use or not.

### 3.2.3 Electronic Support Measures

Generally there are three levels of receivers for electronic warfare. These include Radar Warning Receivers (RWR), Electronic Support Measures (ESM) and equipment for Electronic Intelligence (ELINT). Their main differences are [Noo97]:

- RWR are used primarily for threat detection.
- ESM is used for threat warning, detection and classification of all kinds of emitters and for determining emitter location.
- ELINT is used for detection, recording and analysis of radar and radio signals as well as locating emitters.

In this thesis it is considered that the electronic receivers on the aircraft have the signal processing capabilities of an ESM unit which measures parameters like frequency, Pulse Repetition Frequency and received power.

Much like the IRST, the ESM is able to make angle only measurements on target position. However, measured power can be used for range calculation, provided knowledge of the emitting radar.
This chapter gives an overview of the concept Multi Sensor Fusion. It gives a brief description of the sensors and introduces a couple of track association algorithms.

3.1 General

Fusion of sensors and information is by no means a new invention. People do it every day by combining visual and auditory information to get an accurate description of what is going on around them. Similarly, fighter pilots have been manually combining data from different sensors. But since the number of sensors as well as their capacity increases, the need for automatic fusion of the sensor information becomes apparent.

The fusion of sensors can be very profitable. For example can the combination of the radar range measurement and the angular accuracy in an IRST result in an improved position estimation [Mal96].

If there are several targets, the algorithm must figure out which sensor tracks from the different sensors that originate from the same target. These track association algorithms are described in section 3.6 as well as methods of improving the association, given knowledge about the targets.

3.2 Sensors

Mounted on the aircraft are a number of sensors. Common for most military airborne platforms are radar, IFF, some kind of radar warning system and the ability to communicate with a Battle Control System (possibly on ground). Additionally, some modern aircraft are fitted with IR-sensors and the ability to receive information from other platforms via data link.

3.2.1 Radar

The radar is the primary tactical sensor of the aircraft. It provides long range all-weather detection of targets. The radar can provide estimations of range, bearing and elevation from one single measurement. It can also provide measurements of target attributes like velocity (from measuring doppler shift), and radar cross section.
support and plausibility limits.

Since the Dempster-Shafer method can fuse data at any level of abstraction (type, class, identity or other measures) it is useful for fusion of different sensor reports. Sensor conflicts are handled as in Table 2.2 while sensor errors (if the sensor is considered malfunctioning) are ignored or assigned to uncertainty.

In contrast to what some of the literature claims, Bayesian reasoning can also handle different abstraction levels, but this calls for additional structure, since the sensor reports have to be expanded to the lowest level of abstraction (in this case target type) [Bue88],[Wal90].

To illustrate how the two methods present data, a sensor report supporting type 1 and 2 with a probability of 0.4 respectively and an uncertainty of 0.2 was used to classify in terms of targets one through five. The result is shown in Figure 2.2.

![Figure 2.2](image)

**Figure 2.2** a.) Bayesian probabilities for the classes 1 to 5. b.) Dempster-Shafer Support and Plausibility for the same types. The left bar in each couple corresponds to support and the right to plausibility.

Note that the Bayesian probabilities are in the interval specified by the support and plausibility limits and that the Bayesian method has assigned probabilities to classes 3, 4 and 5, even though there are no evidence supporting that assignment.

The Bayesian approach is much easier to implement since its structure is much less complex than the Dempster-Shafer method. Dempster-Shafer could also in some situations require more memory space since it can work with combinations of the elements.
2.2.7 Time complexity

In a general problem the computational load for calculation of support, plausibility and common probability assignments (probability masses) grows exponentially with the number of possible hypotheses. The reason for that is the need to calculate the parameters for all subsets and supersets of a proposition [Bar81]. However, if the propositions are structured in a hierarchy, the computational load can be reduced significantly. For example, Shafer and Logan has developed a method for combination of hierarchic belief functions that reduces the time complexity to linear [Sha87].

2.2.8 Other methods

Other methods that could be considered for identity fusion are neural nets and fuzzy logic. Neural nets are often very good in classifying from raw data, see for example the Jet Engine Modulation article by Coumo, Pellegrini and Piazza [Cuo95]. But a drawback when applied to a problem like this is the need to train the network since the available parameters and their validity differ depending on the scenario. For a fuzzy approach on the other hand, the number of membership functions needed to implement a fusion system and a classifier would be very high. I have been unable to find indications of similar systems using any of these two methods other than Jensen and Carlsson’s fuzzy Sensor Management System [Jen97]. As pointed out by Linn and Hall most systems use a knowledge based approach and the big issue seems to be an argument between a Bayesian or a Dempster-Shafer classifier and thus my efforts have been concentrated on this issue [Lin91].

2.3 A comparison between Bayes and Dempster-Shafer

When classifying on the sensor level where all available information is given in a certain level of abstraction (identity, class, or type), there is no real difference between the methods and as mentioned the two methods give the same result if the hypothesis are mutually exclusive and also if there is no general level of uncertainty.

The major difference between Bayesian and Dempster-Shafer reasoning is that Dempster-Shafer uses only known information to set up the interval in which the probability lies, where the Bayesian method assigns an exact probability to all classes. Generally speaking we can say that the Bayesian approach tries to estimate the probability limited by the
2.2.6 Decisionmaking from intervals

In a Dempster-Shafer system it can be complicated to make rational decisions due to the interval representation. The ambiguity occurs when there are two or more intervals overlapping or encapsulating each other. Schubert mentions three different models of which he discusses one, developed by Strat [Sch94],[Str90]. In this model, expected utility intervals are constructed as

\[ [E(x), \bar{E}(x)], \]

where \( E \) and \( \bar{E} \) is called the lower and upper expected utility respectively. There is a general way to compute \( E \) and \( \bar{E} \) which is described by Strat. However, in this case the lower and upper bounds of the expected utility will be equal to support and plausibility. The expected utility, \( E \), is then calculated as:

\[ E(x) = \underline{E}(x) + \rho \cdot [\bar{E}(x) - \underline{E}(x)]. \]

Eq 2.21

There are different ways of choosing \( \rho \) and Schubert discusses the issue. The simplest alternative is to chose \( \rho=0.5 \), which maximizes the expected utility [Sch94]. The choice with highest expected utility is then preferred as the most likely.

As an orientation Schubert also mentions a model originally developed by Smets and Kennes called the Transferable belief model which transforms belief functions combined by Dempster’s rule to probabilities [Sme94].

This transformation is achieved by

\[ BetP(x) = \sum_{x \subseteq A \in \mathcal{R}} \frac{m(A)}{|A|} = \sum_{A \subseteq \mathcal{R}} m(A) \frac{|x \cap A|}{|A|}, \]

Eq 2.22

where \(|A|\) is the number of elements in set \( A \) and \( BetP(x) \) is the probability that should be used to decide which proposition that is most probable. In practise Eq 2.22 splits probability masses for sets into equal probabilities for all set members.
In this case we have:

\[ 0.23 \leq P(F) \leq 0.38 \quad \text{Eq 2.15} \]

\[ 0.62 \leq P(A) \leq 0.77 \quad \text{Eq 2.16} \]

In Eq 2.15 and Eq 2.16 the intervals have been calculated by:

\[ Spt(F) = m(F \cap \Theta) = m(F) \quad \text{Eq 2.17} \]

\[ Pls(F) = Spt(F) + m(\Theta \cap \Theta) \quad \text{Eq 2.18} \]

Thus, if the sensors provide information on type level of detail (yielding probabilities for different types rather than for different classes), the support for a class consisting of types \( a \) and \( b \) can be derived as

\[ Spt(a \cup b) = m(a) + m(b) + m(a \cup b), \quad \text{Eq 2.19} \]

where \( m(a) \) is the probability mass assigned to type \( a \), \( m(b) \) is the mass assigned to type \( b \) and \( m(a \cup b) \) is the mass assigned to the union of type \( a \) and \( b \). Hence, if we try to identify on a type to type basis, we can derive class and identity probabilities from the type probability masses.
2.2.5 Dempster-Shafer, an example

Consider two different sensors, S1 and S2. S1 indicates a target being a fighter with the probability \( m_1(F)=0.6 \) and uncertainty \( m_1(\Theta)=0.4 \). When saying a sensor is uncertain it means that the target can be of any class, including F. In the same manner S2 indicates that the target is an attack aircraft with the probability \( m_2(A)=0.8 \) and uncertainty \( m_2(\Theta)=0.2 \). If \( m_1 \) and \( m_2 \) represents the probabilities from sensor S1 and S2 respectively, we have through Dempster’s rule of combination [Wal90]:

\[
\begin{array}{|c|c|c|}
\hline
& m_2(A)=0.8 & m_2(\Theta)=0.2 \\
\hline
m_1(F)=0.6 & m(F \cap A)=0.48 & m(F \cap \Theta)=0.12 \\
m_1(\Theta)=0.4 & m(A \cap \Theta)=0.32 & m(\Theta \cap \Theta)=0.08 \\
\hline
\end{array}
\]

Table 2.1 Example of Dempster-Shafer combination rule. \( m_1(F) \) denotes the confidence Sensor 1 has in the hypothesis that the target is a Fighter. Similarly \( m_2(A) \) denotes Sensor 2 confidence in target being an Attack craft. \( m(\Theta) \) denotes uncertainty, or to what extent the Sensor is unable to distinguish between the classes.

Since it is considered impossible for an aircraft to be of more than one class the intersection of fighter and attack is impossible. Thus, the factor of conflict, \( k \) is assigned to 0.48. For the attack aircraft the new mass assignment will be

\[
m(A) = \frac{m(A \cap \Theta)}{1 - k} = \frac{0.32}{0.52} = 0.62 \quad Eq \ 2.13
\]

The other results in Table 2.1 are normalized in a similar manner as:

| m(A)=0.62 | m(F)=0.23 | m(\Theta)=0.15 |

Table 2.2 The disallowed intersection Fighter\( \cap \)Attack is removed and the remaining probabilities are normalized.

As described in section 2.2.3 Dempster-Shafer reasoning report results as support (Spt) and plausibility (Pls) intervals, where support are evidence directly supporting the proposal or its subsets. Plausibility represent to what extent there are no evidence that contradicts the proposal. The probability for an event to occur is in the interval
2.2.4 Dempster’s rule of combination

If there is more than one probability mass function based on different and independent sources, the combined mass function called the orthogonal sum can be calculated using Dempster’s rule. Suppose that there are different subsets of $\Theta$, called $a_n$ and $b_m$ with mass assignments $m(a_n)$ and $m(b_m)$. Then, Dempster’s rule of combination states the combined mass assignment

$$m(a_n \cap b_m) = \frac{m(a_n)m(b_m)}{1 - k},$$

where $k$ represents the conflict between the sources and can be calculated as

$$k = \sum_{a_i \cap b_j = \phi} m(a_i)m(b_j).$$

Thus, impossible combinations of $a_n$ and $b_m$ are assigned to the empty frame $\phi$. The introduction of the factor $k$ in Eq 2.11 assures a normalization of the combined mass to the unit interval $[0, 1]$.

If we have a mass assignment $m(a_i \cap b_j)$ where $a_i$ is a subset of $b_j$, the mass assignment is simplified as $m(a_i)$. Take for example a mass supporting a JAS39 fighter and a mass supporting the fighter class. Thus the combined mass assignment $m(JAS39 \cap Fighter) = m(JAS39)$. Since the belief in a set can be derived from the belief in its subsets, no information is lost by the combination.

The Dempster-Shafer method can be used for combining beliefs over a number of measurements in a similar way as the recursive updating of Bayesian reasoning. This is simply achieved by fusing new probability mass functions with those from past measurements.

Note also that evidence that are to be combined using Dempster’s rule must be independent [Wal90].
convenient representation for uncertainty, which the standard Bayesian method lacks. In the Bayesian formulation uncertainty about a measurement (or ambiguity) is solved by spreading the probability of that measurement over all types or classes depending on which level the classifier is working.

The Dempster-Shafer method introduces a probability mass measure, which is the basic metric within evidence theory. It makes it possible to assign belief to a hypothesis without assigning any to its negation. Thus, if $H$ denotes a hypothesis,

$$m(H) + m(\overline{H}) \leq 1.$$  \hspace{1cm} \text{Eq 2.8}

The remaining probability is assigned to the frame of discernment, $\Theta$. The frame of discernment is the set of all possible hypothesis that the sensor is able to distinguish. For example, if we are rolling a dice, $\Theta$ would contain the propositions of the result from one to six. Ambiguities in measurements are often assigned as a probability mass to the frame of discernment (See the example in section 2.2.5).

Instead of assigning values to the negation of a proposition, Dempster-Shafer’s method uses support and plausibility intervals to describe the probability of different hypotheses. Support, is the amount of confidence directly supporting a certain proposition, while plausibility is to what extent it is possible but not yet proven. Mathematically, for a proposition $A_i$, we have:

$$Spt(A_i) = \sum_r m(A_r),$$  \hspace{1cm} \text{Eq 2.9}

where $A_r \subseteq A_i$, and

$$Pls(A_i) = \sum_{A_r \cap A_i \neq \phi} m(A_r) = 1 - Spt(\overline{A_i}).$$  \hspace{1cm} \text{Eq 2.10}

Instead of working with individual types only, Dempster-Shafer can also work with sets of types or sets of classes, depending on the available information. If all hypotheses are mutually exclusive and there is no general level of uncertainty, the algorithm gives the same result as Bayes [Wal90].
Since it is desirable to use all information about a target, recursive updating seems to be a useful method. However, measurements must be independent of earlier measurements if the likelihood function $P(e|e_n,H)$ should be easy to calculate. Since all sensors have random errors, opinions from the same sensor that are sufficiently separated in time can be approximated as being independent, thus motivating the use of time separated opinions from the same sensor [Bog87]. If the condition of independence between $e$ and $e_n$ is fulfilled, the likelihood is calculated as

$$P(e|e_n,H) = P(e|H). \quad \text{Eq 2.7}$$

When the classifier has reached a high probability for a certain identity on a target, it takes some time to reset it. This can be a problem if the track is wrongly associated with another, thus keeping old measurements that could be from another target. The solution to this problem is to introduce a “forgetting” that allows the probabilities to drift towards an equilibrium. This will be further discussed in section 5.2.2.

### 2.2.3 Dempster-Shafer Reasoning

Dempster and Shafer have derived a generalisation of the classic Bayesian theory in order to overcome several weaknesses [Bar81], [Bog87], [Sha87], [Wal90] and [Sha76]. One of the improvements in this method, denoted Dempster-Shafer or evidential reasoning, is a
reasoning and since we normally don’t have a clue of their value they are chosen to be the same for all possible targets.

\( P(H_i | \tilde{e}) \) is called the a posteriori probability and is the probability that the target is of type \( H_i \) after the measurement.

Note that since the expression in the denominator is the same for all \( P(H_i | \tilde{e}) \) it can be seen as a normalizing constant and is therefore unnecessary to calculate.

If we have data from multiple sources the likelihood \( P(\tilde{e} | H_i) \) is computed as a conjoint multiplication of the sources likelihood vectors. Thus, if the sources are conditionally independent

\[
P(\tilde{e} | H_i) = \prod_{k=1}^{N} P(e_k | H_i), \quad \text{Eq 2.5}
\]

where \( N \) is the number of sources [Pea88].

### 2.2.2 Recursive Updating

One of the features of Bayes rule is that it is possible to use recursive updating. Let \( e_n = e_1, e_2, \ldots, e_N \) denote a sequence of measured data observed in the past, let \( e \) denote a new measurement and let \( H \) denote a hypothesis. From Bayes rule, we arrive at the formula

\[
P(H | (e_n, e)) = P(H | e_n) \cdot \frac{P(e | (e_n, H))}{P(e | e_n)}.
\quad \text{Eq 2.6}
\]

Comparing Eq 2.6 with Eq 2.4 we see that \( P(H | e_n) \) has assumed the role of the a priori probability, thus the a priori probability is updated as soon as new information is available [Pea88]. By this modification of the a priori probabilities the classifier will have more information to base its decision on. This is illustrated in Figure 2.1.
2.2 Classification methods

2.2.1 Bayes decision theory

The classic statistical method to handle decision problems is by a theorem first discussed in the eighteenth century by Thomas Bayes. Consider two events, \( H \) and \( e \). The probability for the event \( H \) to happen (or hypothesis \( H \) to be true), given that event \( e \) has occurred, is

\[
P(H|e) = \frac{P(H \cap e)}{P(e)}, \quad \text{Eq 2.1}
\]

which is called the conditional probability for event \( H \), given that event \( e \) has already happened. Since

\[
P(H \cap e) = P(H)P(e|H) = P(e)P(H|e), \quad \text{Eq 2.2}
\]

Eq 2.1 can be written as the inversion formula or Bayes law

\[
P(H|e) = \frac{P(e|H)P(H)}{P(e)} \quad \text{Eq 2.3}
\]

In Eq 2.3, \( H \) denotes a hypothesis and \( e \) denotes an event. Hence \( P(H|e) \) is the probability for hypothesis \( H \) to be true given that event \( e \) has happened.

If we have multiple sources of information, e.g. if different features of a target is measured, the inversion formula in Eq 2.3 can be extended to multiple dimension. Let event \( \bar{e} \) be the state vector of the measured features and \( H_i \) is a subset of all target types. Bayes rule then yields

\[
P(H_i|\bar{e}) = \frac{P(\bar{e}|H_i) \cdot P(H_i)}{\sum_{i=1}^{N_T} P(\bar{e}|H_i)P(H_i)}, \quad \text{Eq 2.4}
\]

where \( N_T \) is the number of states in \( H_i \). \( P(H) \) in equation Eq 2.1 and \( P(H_i) \) in Eq 2.4 are the so called a priori probabilities. These are the probability that the target is of type \( H_i \) before the measurement is obtained. To choose these probabilities can be difficult in Bayesian
2 Identity Fusion

This chapter is an overview of the methods suitable for identity fusion. The most widely used, the Bayesian and Dempster-Shafer methods, are further explained.

2.1 General

There are a number of algorithms suitable for the recognition and fusion of identity. In the literature describing identity fusion, statistical methods are the most commonly used, but other approaches can include adaptive neural nets or fuzzy set theory. The statistical methods are so-called parametric methods that try to establish a mapping between parameters (or features) and identity.

According to Harris, Bailey and Dadd there are three levels where identity fusion can be performed [Har98]. These are:

- **Data level fusion.** Data is fused directly from sensor output and identification is performed based on the fused data.

- **Feature level fusion.** Features like spectral signatures, pulse characteristics, or edge orientation are extracted from each sensor. These features are then combined and identity statements are based on the fused features.

- **Decision level fusion.** Instead of working on the sensor level, decision level fusion works on propositions of the environment, thus combining information like target class or type.
The next two chapters treat the implemented system. In chapter 5, the implementation is accounted for and chapter 6 contains simulations and discusses the results on the different parts of the system.

Finally, the work is concluded with chapter 7 that summarizes the results obtained in the previous chapters, chapter 8 that points out issues that need further treatment and three chapters containing appendix, references and abbreviations.
The sensor information are to be fused in a system like the one shown in Figure 1.2.

![Sensor Fusion Diagram](image)

*Figure 1.2  Sensor Fusion*

The objective of this master thesis is to answer the following questions:

1. Which algorithm/algorithms are suitable for fusion of identity and class information?
2. Which parameters from the different sensors should be used by the algorithm?
3. How can identity/class information improve association of sensor tracks?
4. How can target speed and acceleration etc. be used for extraction of class information.

Subjects closely connected with the above specified goals will also be investigated as well as other aspects on data fusion.

### 1.4 Readers guide

This is a description of the layout of this thesis and a short introduction to what the different chapters discuss. The intention has been to first introduce background and basic theory needed for identity fusion, then discuss how the available information should be used and present the implemented system. Finally results of simulations on various parts of the system and future work are discussed.

The introductory part consist of the first three chapters. In chapter 2, the different classification and fusion techniques suitable for a target identification problem are introduced and discussed. This is followed by an introduction to sensor fusion and track association. Finally, the value of different attributes for target identification are discussed.
communication with friendly forces. These external sources can provide information which the own sensors have not yet discovered.

1.2 Purpose of the master thesis

The purpose of this thesis is to investigate the possibility to make unambiguous identification and classification of aerial targets. Issues important for identification such as which sensor attributes to use for identity fusion will be investigated. Also, the performance of identity information improvements in track association will be evaluated.

1.3 Problem Description

The aircraft can be divided into a hierarchy consisting of identity, class and type, where identity means friend or foe, class means fighter, attack aircraft etc. while type means JAS39, Su27 or others as illustrated in Figure 1.1. The term identity fusion is used both in this thesis and in the literature to cover fusion at any of these abstraction levels.

![Aircraft hierarchy diagram](image)

*Figure 1.1 Aircraft hierarchy.*

The work to be carried out is to investigate how class and identity information derived from the aircraft sensors should be used in order to generate an accurate description of the environment. The sensor suite can consist of Radar, Infra Red Search and Track (IRST), Identification Friend or Foe (IFF) and a Radar Warning Receiver but also include external information sources such as Ground Control System or Data Link from other aircraft.
1 Introduction

This chapter gives a brief introduction to the problem area, and defines the objectives of this thesis.

1.1 Background

Due to the quick course of events in modern air combat, where own and enemy forces might be mixed on the battlefield, a quick and unambiguous identification of targets is crucial for the pilot to make the right decisions. It is also desirable to classify targets in terms of interceptor, attack, bomber and so on. Knowledge of the target class can aid the pilot in deciding which targets to attack and which targets that poses a threat to the own forces or the own aircraft.

Today, identification is often achieved by some kind of Identification Friend of Foe sensor (IFF) and to some extent by a radar warning receiver (RWR). However the IFF sensor is only able to identify an object if it is willing to cooperate. Failure to do so does not necessarily mean that the object is hostile. Absence of response can be due to fault in the receiving aircraft’s identification equipment. In the same way, the RWR will only supply information if the object is using its radar. Hence, a non co-operative identification device is needed to avoid confusion regarding the identity of targets.

Several sensors which have the possibility to give identity information are already mounted in the aircraft. These sensors, which can include Radar, Radar Warning Receiver, Infra Red Search and Track, and Identification Friend or Foe, are designed to give the pilot information about the tactical environment. This information can include the number of objects in the environment, their present course and their identity. The sensor data can also contain clues to the class of the target. Perhaps one sensor alone does not contribute with enough information to state the target class. But if the data from all sensors are combined, it might be enough to figure out not only target identity (whether target is friend or foe), but also target class or even the exact type

Modern aircraft have contact with a ground or airborne supreme command and some aircraft also have access to a data link for

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