Radar and Thermopile Sensor Fusion
for Pedestrian Detection

Master’s Thesis performed in Automatic Control
at Linköping University
by
Shahin Rouhani
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**Titel**
Fusion av Radar och Infraröd Sensor för Detektion av Fotgängare
Radar and Thermopile Sensor Fusion for Pedestrian Detection

**Författare**
Shahin Rouhani

**Sammanfattning**
Abstract

During the last decades, great steps have been taken to decrease passenger fatality in cars. Systems such as ABS and airbags have been developed for this purpose alone. But not much effort has been put into pedestrian safety. In traffic today, pedestrians are one of the most endangered participants and in recent years, there has been an increased demand for pedestrian safety from the European Enhanced Vehicle Safety Committee and the European New Car Assessment Programme has thereby developed tests where pedestrian safety is rated. With this, detection of pedestrians has arisen as a part in the automotive safety research.

This thesis provides some of this research available in the area and a brief introduction to some of the sensors readily available. The objective of this work is to detect pedestrians in front of a vehicle by using thermoelectric infrared sensors fused with short range radar sensors and also to minimize any missed detections or false alarms. There has already been extensive work performed with the thermoelectric infrared sensors for this sole purpose and this thesis is based on that work.

Information is provided about the sensors used and an explanation of how they are set up during this work. Methods used for classifying objects are given and the assumptions made about pedestrians in this system. A basic tracking algorithm is used to track radar detected objects in order to provide the fusion system with better data. The approach chosen for the sensor fusion is a central-level fusion where the probabilities for a pedestrian from the radars and the thermoelectric infrared sensors are combined using Dempster-Shafer Theory and accumulated over time in the Occupancy Grid framework. Theories that are extensively used in this thesis are explained in detail and discussed accordingly in different chapters.

Finally the experiments undertaken and the results attained from the presented system are shown. A comparison is made with the previous detection system, which only uses thermoelectric infrared sensors and of which this work continues on. Conclusions regarding what this system is capable of are drawn with its inherent strengths and weaknesses.

**Nyckelord**
Pedestrian detection, radar, Thermopile, thermoelectric infrared sensor, sensor fusion, Dempster-Shafer, Occupancy Grid
for my parents,

Ali and Jila who have loved, supported and
guided me through everything I have undertaken in my life

for my brothers,

Shervin and Sharogh who I hold dearest in my heart
Abstract

During the last decades, great steps have been taken to decrease passenger fatality in cars. Systems such as ABS and airbags have been developed for this purpose alone. But not much effort has been put into pedestrian safety. In traffic today, pedestrians are one of the most endangered participants and in recent years, there has been an increased demand for pedestrian safety from the European Enhanced Vehicle safety Committee and the European New Car Assessment Programme has thereby developed tests where pedestrian safety is rated. With this, detection of pedestrians has arisen as a part in the automotive safety research.

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Information is provided about the sensors used and an explanation of how they are set up during this work. Methods used for classifying objects are given and the assumptions made about pedestrians in this system. A basic tracking algorithm is used to track radar detected objects in order to provide the fusion system with better data. The approach chosen for the sensor fusion is a central-level fusion where the probabilities for a pedestrian from the radars and the thermoelectric infrared sensors are combined using Dempster-Shafer Theory and accumulated over time in the Occupancy Grid framework. Theories that are extensively used in this thesis are explained in detail and discussed accordingly in different chapters.

Finally the experiments undertaken and the results attained from the presented system are shown. A comparison is made with the previous detection system, which only uses thermoelectric infrared sensors and of which this work continues on. Conclusions regarding what this system is capable of are drawn with its inherent strengths and weaknesses.
Acknowledgements

This thesis is submitted for the degree of Master of Science in Applied Physics and Electrical Engineering at Linköping Institute of Technology, Linköping, Sweden.

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My gratitude also goes to my supervisor at Linköping University, Lic. Eng. Thomas Schön for the help he has provided despite the long distance.

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Ulm, May 2005
Shahin Rouhani
Notation

In this section the notational conventions used for mathematical symbols, operators and abbreviations are presented. Where the same symbols are used for different items it is asserted that no confusion can arise.

Symbols

\(\emptyset\) An empty set
\(2^\emptyset\) Power set, i.e. all possible union of propositions, \(2^n\)
\(A\) Single proposition or a union of propositions
\(A_i\) Single proposition
\(a_{veh}\) Acceleration of the test vehicle
\(B\) Single proposition or a union of propositions
\(B_i\) Single proposition
\(C\) Proposition Cold object in the Dempster-Shafer combinations and also used to signify "Cell" when used as index
\(D_x\) Number of cells in the x-direction for the object fusion area
\(D_y\) Number of cells in the y-direction for the object fusion area
\(E\) Event
\(F\) Used to signify "Fused cell" when used as index
\(g_{init}\) Gate for a radar object in the tracker with an initial state
\(g_{cont}\) Gate for a radar object in the tracker with a tentative or confirmed state
\(g_{miss}\) Gate for a radar object in the tracker with a missed state
\(g_r\) Gate for the fusion of two radar targets
\(H_i\) Mutually exclusive and exhaustive hypotheses
\(H\) Proposition Hot object in the Dempster-Shafer combinations
\(k\) Contradiction in Dempster-Shafer Theory
\(l_{xy}^t\) Accumulated probability at time \(t\) in a cell with position \(xy\) in the Occupancy Grid
\(M\) Number of cells with probability over the threshold for detection
\(N\) Proposition No object in the Dempster-Shafer fusion and also
number of mutually exclusive and exhaustive hypothesis $H_i$

$n$  Number of mutually exclusive and exhaustive propositions $A_i$

$O_{xy}$  Occupied state in a cell with position $xy$ in the Occupancy Grid

$P$  Proposition used to exemplify pedestrian

$R$  Used to signify "Radar" when used as index

$r_t$  Measurement at time $t$

$r_t$  Measurements up to time $t$

$T$  Sample period and also used to signify "Thermopile" when used as index

$v$  Velocity of an object in general, it is signified with index what kind of object

$v_{ped,\text{max}}$  Maximum velocity of a pedestrian

$x$  x-coordinate for an object in general, can appear as index or together with $y$, $xy$

$X$  Single proposition or a union of propositions

$y$  y-coordinate for an object in general, can appear as index or together with $x$, $xy$

$z$  World state in the Occupancy Grid

$\alpha$  xy-position of a radar target which is the output from the radars, can also appear as $\alpha_t$ meaning the position at time $t$

$\beta$  xy-position of a radar object which is the output from the tracker, can also appear as $\beta_t$ meaning the position at time $t$

$\delta_t$  Movement vector for the radar object at time $t$

$\lambda_{t+1}$  Predicted position for the radar object at time $t + 1$

$\mu_x$  Radius in x-direction for the different gates

$\mu_y$  Radius in y-direction for the different gates

$\rho$  Reflectivity of an object attained from the radar

$\rho_{ped,\text{max}}$  Maximum reflectivity from a pedestrian

$\sigma_{MERGE}$  Lower threshold used for merging a larger segmenting area

$\sigma_{SEED}$  Threshold used for the accumulated probabilities to exceed for a detection to arise

$\tau$  Used as index for the radar target fusion area

$\theta$  Frame of discernment, i.e. uncertainty

Operators

$\in$  Belongs to

$\subset$  Subset of

$\cup$  Union

$\cap$  Intersection

$\oplus$  Dempster-Shafer combination
\[ \sum \quad \text{Sum} \]
\[ \bar{A} \quad \text{Not A} \]
\[ Bel(A) \quad \text{Belief of A} \]
\[ m(A) \quad \text{Probability mass function for A} \]
\[ P(A|B) \quad \text{Probability of A given B} \]
\[ p(A|B) \quad \text{Probability density function for A given B} \]
\[ Pl(A) \quad \text{Plausibility of A} \]

**Abbreviations**

- BPT: Bayesian Probability Theory
- DST: Dempster-Shafer Theory
- FOV: Field Of View
- MTT: Multiple Target Tracking
- OG: Occupancy Grid
- ROI: Region Of Interest
- STT: Single Target Tracking
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Chapter 1

Introduction

In this chapter a background to why detection of pedestrians has arisen as a focal point in the research is given. Some of the research available in the area has been cited and a brief introduction of the sensors used is made. The objective of this thesis is outlined together with a formulation of the problems dealt with. Finally, a readers guide is provided.

1.1 Background

During the last decades, great steps have been taken to decrease passenger fatality in cars. Systems such as ABS and airbags have been developed for this purpose alone. But not much effort has been put into pedestrian safety. In traffic today, pedestrians are one of the most endangered participants and in recent years, there has been an increased demand for pedestrian safety from the European Enhanced Vehicle safety Committee (EEVC).

A sample from statistical data [5] is shown in Figure 1.1 which shows that the most accidents including pedestrians occur with passenger cars. The most important reason for this is of course that most vehicles travelling on roads today are passenger cars. But this still implies that measures have to be taken to aid drivers of vehicles and especially drivers of passenger cars.

The European New Car Assessment Programme (EuroNCAP) has thereby developed tests where pedestrian safety is rated. In these tests a simulation of the impact towards knee/lower leg, hip/upper leg and the head is performed which are the most vulnerable areas in a frontal accident. Figure 1.2 gives an illustration of these tests.

Research (Cavallero et al. [10], Matsui et al. [23], Yoshida et al. [35]) has shown that injuries towards the head cause the highest number of casualties. Thus, the most research towards improving the safety and relieving pedestrian injuries and casualties has so far pointed towards changing the design on the front of the car as shown in Figure 1.3 or a method of raising the bonnet of the car, Fredriksson et al. [13]. These methods serve the purpose of reducing the impact velocity of the body and specifically the head. Since the head is swung on to the bonnet with
Figure 1.1. Pedestrian fatalities versus category of impacting vehicle [7].

high force, creating more space between the bonnet and the engine block beneath it, which is usually what causes the severest damages, also creates a greater chance for survival.

Safety measures like raising the bonnet of the car would of course serve its purpose more if a decision could come before impact and with that maybe other measures could be taken. Therefore, a general awareness of the environment around the car is necessary and more specifically, there is a need to classify and detect pedestrians since safety measures like the ones mentioned, only should occur for pedestrians. Research is in progress for this purpose and the main problem is in classifying the pedestrian. In the field of image processing there is extensive research made (Gavrila et al. [18], Viola et al. [35], Zhao and Thorpe [39]) with some applications for the automotive industry, but there is still no complete solution for

Figure 1.2. Three different EuroNCAP tests for pedestrian safety.
1.2 Sensor Fusion

Using a single sensor, monitoring of objects can only occur with a precision that depends on the sensor characteristics. By using multiple sensors to observe a target, multiple viewpoints can be obtained with extended coverage both spatially and over time. Ambiguity can be reduced and a more precise estimate of the object kinematics attained than that which is possible through the best individual sensor.

In this thesis, a new sensor system is presented based on passive infrared sensors, thermopiles, and active radar sensors. These are combined with the aid of probabilistic theory. The advantage of this system being the ability to detect pedestrians with a reasonable price compared to other systems. To combine thermopiles with radar sensors, which have a larger field of view allows for a larger reliable detection area. Also the operating physics behind the different sensor types allows for a classification of the detected objects.

1.3 Choice of Sensors

There are numerous different available sensors for a pedestrian detection application and why the actual sensors in use were chosen, is to large extent a matter of cost. Both computational and monetary. However, there is also other reasons for the choice of sensors.

A laser-scanner is able to provide long-range information with high angular resolution and the results are very accurate. There has been research made with laser-scanner for the purpose of pedestrian detection, Fürstenberg et al. [15] [16]. The pedestrians were detected, but only when they were walking. Using a laser-scanner would probably yield better results since it is a more accurate sensor
overall. However, it is also by far a more expensive choice than radar and thermopile. An ordinary camera brings high computational cost as there is extensive need for image processing. In environments with high clutter, like rain and snow, it is very hard if not impossible to detect objects and then specifically pedestrians. It thereby suffers from the same problems as the driver of the vehicle.

Thermopiles presents a low cost alternative and since they operate in a passive manner, without illuminating the environment, there are no regulation demands to be met. They detect hot objects in a range of 0 to 10 meters depending on the temperature contrast between the object and the surrounding. Furthermore, they are not highly sensitive to environmental clutter. This makes the thermopiles a very feasible proposition for pedestrian detection. The short range radar is better adapted than a longer range radar since it has a view range of 0 to 30 which is quite adequate. Also, the radar is widely used in different tracking applications.

However, as will be shown, thermopiles can yield false detections which can be removed with the aid of radars and vice versa. This means a combination between radars and thermopiles has a high potential as a pedestrian detection system. It would also constitute a very low cost alternative which is achievable in production in the near future.

1.4 Objective

The objective of this work is to detect pedestrians in front of a vehicle and also to minimize any missed detections or false alarms. There has already been extensive work performed with thermopiles for this sole purpose and this thesis is based on that work. Linzmeier et al. 21 22 23 and Vogt 26. Prior there has been simulation tests with these sensors in a pedestrian detection application done by Beyer and Hahn at the Fraunhofer Institute in Munich, Germany 27.

1.5 Problem Formulation

The initial problems occur with the thermopiles not knowing the distance to the target. From only the voltage output of the thermopiles there has to be signal processing done to retrieve a position. However, this is not possible with only one thermopile. Therefore there has to be several thermopiles with overlapping field of views (see Figure 22). By knowing the positions of the thermopiles used and thereby knowing the positions of the overlapping field of views, a position estimate can be calculated. For higher number of overlapping field of views a more accurate estimate can be obtained.

However, pedestrians are not the only objects emitting infrared radiation. Lampposts, cars and many other objects are also emitting radiation captured by infrared sensors. Furthermore, the human body does not emit heat uniformly and the amount of radiation also depend on the time of day and the dress of the person.

The radar works differently compared to the thermopile in the sense that it does not differentiate between hot and cold objects or even between objects in
1.6 Reader’s Guide

This section is given as an aid to the reader when guiding through the different sections in this thesis.

1.6.1 Conventions

Throughout this thesis, radar targets is used as a convention for the radar output. Meanwhile, radar objects refer to tracked radar targets attained after the tracking procedure in Chapter 3. This has been emphasized when necessary. All other conventions should not cause any confusion. If questions arise it is recommended to refer to the index or the section on notations.

1.6.2 Thesis Outline

This thesis consists of 8 chapters and 1 appendix. Especially readers with prior knowledge about the topic treated are helped by reading through the guidelines below.

Chapter 2: System Overview

This chapter provides information about the sensors used and an overview of how they are set up in this work. Methods used for classifying objects are given and the chapter ends with assumptions made about pedestrians in this system.

It is recommended to read through this chapter if the reader lacks prior knowledge about the sensors used and their setup. Otherwise, Sections 2.4.2 and 2.5 are the most important.

Chapter 3: Target Tracking and Data Association

In this chapter an overview of a typical tracking system is provided and the foundation in a tracking algorithm. A brief literature survey is given. The tracking procedure used in this work is further presented with results. The chapter ends with a discussion regarding other possible methods.

If the reader is already acquainted with basic tracking methods and their results, overviewing Sections 3.2 and 3.3 which are specific for this work is sufficient.
Chapter 4: Sensor Fusion for Pedestrian Detection

General sensor fusion approaches are explained in this chapter with an insight into the difficulties and benefits. An introduction to the common way of categorising sensor fusion is provided. With a starting point in this, an explanation of the sensor fusion architecture used in this work is given. Furthermore, an overview of the data fusion procedure is given to ease the understanding of later chapters.

Only Sections 4.3 and 4.4 are specific for this system and thus, other sections are not necessary for a reader with prior knowledge on this topic.

Chapter 5: Data Fusion using Dempster-Shafer Theory

This chapter starts with acquainting the reader to basic probability theory and to Dempster-Shafer Theory which is the data fusion process used in this work. Although, it is assumed that the reader has some understanding of probability theory. There is also an example provided to show when these approaches are equal. An extensive explanation is made of how the specific data fusion equations in this system are derived. Furthermore, some application specific attributes are explained incorporating the data fusion equations.

The reader with prior knowledge on Dempster-Shafer Theory can start on Section 5.5.

Chapter 6: Occupancy Grid

Information gathered in one sample, have to be processed over time and this is explained further in this chapter. The Occupancy Grid is the selected approach and therefore a complete derivation is given. Two examples have been used to ease the understanding of the process. Following this is an adaption of the grid and application specific procedures. It is shown how the final position of the pedestrian is obtained and a discussion regarding the Occupancy Grid ends the chapter.

Sections 6.2.4 and 6.2.5 could be ignored by a reader already comfortable with the formalities surrounding the Occupancy Grid.

Chapter 7: Experiments and Results

In this chapter the experiments undertaken and the results attained from the presented system are shown. A comparison is made with the previous thermopile system of which this work rests.

Chapter 8: Concluding Remarks

Conclusions regarding what this system is capable of are drawn in this chapter with the inherent strengths and weaknesses. The chapter concludes with some recommendations regarding the direction for future research.
Appendix

The purpose of this appendix is to simplify for the reader not acquainted with the Occupancy Grid and how the equations are derived. Thus, the notations used in Section 5.2.3 will also be used here.
Introduction
Chapter 2
System Overview

This chapter provides information about the sensors used and an overview of how they are set up in this work. Methods used for classifying objects are given and the chapter ends with assumptions made about pedestrians in this system. It is recommended to read through this chapter if the reader lacks prior knowledge about the sensors used and their setup. Otherwise, Sections 2.4.2 and 2.5 are the most important.

2.1 Introduction

This system has been developed at Daimler-Chrysler AG, research center Ulm, with the intent of accurately being able to detect pedestrians before an accident occurs. It makes use of short-range radars and thermoelectric infrared sensors (thermopiles) for detecting pedestrians. This will be further explained below but a good overview of the thermopile system is given in Linzmeyer et al. [21] and Vogt [56]. Sensors have been arranged on the front of the vehicle to achieve optimal coverage of the ROI\(^1\), which is the area in front of the vehicle where it is possible for a pedestrian to enter an accident situation. More details regarding can be found in Linzmeyer et al. [22].

To attain an overview of the fusion approach in this work and to ease the understanding of this chapter, it is recommended to view Figure 1.1 on page 9 before moving on. From this it should be recognised that the fusion will be performed by assigning probabilities to the readings from the sensors utilised. These are then combined with Dempster-Shafer Theory and accumulated in the Occupancy Grid framework to a probability for a pedestrian. This is more detailed in Chapters 4 and 5.

\(^{1}\)Region Of Interest is abbreviated ROI and refers to the region where it is most likely for an accident with a pedestrian to occur if one is residing there.
2.2 Experiment Setup

During this work, ten thermopiles and two radars have been used. The sensors and their setup on the test vehicle can be viewed in Figure 2.1 The thermopiles have been placed in two boxes, with five thermopiles in each box. These boxes are then placed on each side, on the front of the vehicle. Inside the boxes, the thermopiles are in turn placed with a certain relative angular difference to each other, to achieve an optimal coverage of the ROI with overlapping FOV\(^3\). To find this sensor arrangement a cost function has been derived and the method chosen for finding a solution to the optimal problem is called *simulated annealing* \(^2\). The radar sensors are also placed on each side of the vehicle, more specifically, one on each side. These are also built in to the front bumper of the vehicle and are thereby out of view.

It should also be known that in this system the sample period is 40ms.

2.3 Thermopiles

The physical capabilities of the thermopiles, like detection range and angle are given in Figure 2.2. View range of the thermopiles is up to 10 meters and the angle of FOV is 7\(^\circ\), which gives a combined FOV of about 50\(^\circ\) for all ten thermopiles. It should be noted that this setup is made for a detection optimisation at around 4 meters.

Thermopiles detect objects, i.e. give a voltage output depending on the thermal, or infrared radiation transmitted to the receiver. The physics behind the procedure is known as the *Seebeck effect*\(^4\) See Linzmayer et al. [21] or a physics handbook, e.g. [28]. It should be noted here that a thermopile receive thermal radiation from the whole FOV and give a signal output accordingly. Meaning that for an object to be detected, e.g. a pedestrian, it must have a radiation

\(^3\)FOV is an abbreviation of Field Of View and refers to the area in which sensors possibly give an output and thereby make a detection.

\(^4\)Discovered in 1821 by physicist Thomas Johann Seebeck (1770-1831) and refers to the effect of when two connected junctions of dissimilar metals with different temperatures, cause a potential to appear between them. It is considered the most accurate measurement of temperature.
2.3 Thermopiles

![Diagram of Thermopiles Field of View]

**Figure 2.2.** Thermopiles’ field of view. Overlaps from different sensors is signified by a darker shade. In these areas a more accurate position estimate can be obtained.

contrast to the background. Also affecting the signal output is the vertical area of the object facing the sensors and covering the vertical FOV. Furthermore, the distance between the object and the sensors influence the readings. Hence, the closer a pedestrian is and the larger the area of the FOV it covers, the better is the signal received, Linzmeier et al. [21]. From the manufacturer [29, 30] a good overview on thermopiles can be attained with more information about the electrical and mechanical data.

2.3.1 Signal Interpretation

Classification of pedestrians by the thermopile sensors alone is made through pattern classification methods using the signal gradient, ambient temperature, steering angle and vehicle velocity. All these quantities make up prior statistic known through measurements. From this, a probability from the thermopiles for there being a pedestrian present is obtained. This is illustrated in Figure 2.2. Here it is important to remember the fact that the sensor models are assumed to be uniform over the FOV for a thermopile sensor, which is a simplification of the actual circumstances. Although it does not decrease the performance of the system noticeably. Linzmeier et al. [25] and Vogt [36] explain further about the signal interpretation methods used and how probabilities to the thermopiles signals are assigned. What is used in this thesis is the output of that work, as detailed in Table 2.1.
2.3.2 Thermopile Output

Because of the attribute of detecting dependent on the thermal radiation received, thermopiles do not detect cold\(^4\) objects at all. This means that the sensor cannot distinguish between a cold object and when there is no object present. Furthermore, it cannot distinguish between pedestrians and other warm\(^5\) objects. Due to these facts, the sensor can provide the means to differ between the features shown in Table 2.1 and to later assign probabilities to propositions explained in Chapter 3.

<table>
<thead>
<tr>
<th>Thermopile features</th>
<th>Notations in Section 5.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>A pedestrian or another hot object is detected</td>
<td>$H$</td>
</tr>
<tr>
<td>No object or a cold object is detected</td>
<td>$C \cup N$</td>
</tr>
<tr>
<td>Inconclusive measurement</td>
<td>$\theta_T$</td>
</tr>
</tbody>
</table>

Table 2.1. Thermopile features

2.4 Radars

The radar sensor is a 24GHz short-range radar and in general it is able to detect objects that reflect electromagnetic waves. The physical capabilities of the radars can be seen in Figure 2.3. The view range of the radars is 30 meters and the field of view is 60°, which gives a FOV of about 70° when both radars are combined.

Radars are not directly able to discern between pedestrians and other objects. However, information can be gathered to classify objects to some extent. Worth

\(^4\)With cold here is meant a temperature equal or below the current ambient temperature.

\(^5\)With warm or hot here is meant a temperature equal or above a pedestrian's, assumed the pedestrian's temperature is higher than the current ambient temperature.
remembering here is the fact that the radars provide targets with a position and different attributes. It is the targets that have to be processed and given as input to the fusion system.

2.4.1 Preprocessing of Targets

The preprocessing performed on the radar targets is detailed in Figure 2.6. Here

---

\footnote{The output given from the radars before any preprocessing has occurred will be referred to as a target throughout this thesis.}
it can be seen that some measures have been taken to stabilise the output from the radars and to acquire more information about the physical object before fusing with the thermopiles. By tracking the output from the radars as explained in Chapter 3 the output becomes more stable since occasional ghosts, i.e. false detections, can be disregarded. When referring to radar objects in this thesis, it is the output from the tracking which is referred to.

Also a reflectivity measure for the object in question is given with the target output which provides another tool for classifying the object.

2.4.2 Radar Amplitudes

Also influencing the object probability from the radars is the reflectivity\footnote{Further explanations about reflectivity will not be made in this thesis since the quantity referred to is already processed when used in this system. For interested readers, reflectivity can be found in most handbooks for physics, e.g. \cite{25}.} of the object, here called \textit{amplitudes} and denoted $\rho$. Before explaining further about this measure there are some points to consider. It is not a continuous reflectivity value the radar provides regarding an object. Rather, it is discrete and in quantity steps of two which can be seen in Figures \ref{fig:amplitude4} and \ref{fig:amplitude3}. Despite this, the amplitudes yield satisfying results in this system.

When pedestrians are detected, it usually occurs with a lower amplitude than for metallic objects. Lower amplitude meaning also a lower reflectivity and respectively for high amplitudes. However, the amplitude also depends on the distance to the object. For very short distances there are no differences between the two classes, but the differences increase with distance. It should be noticed here that it is only the maximum possible amplitude at different distances that varies for pedestrians and metallic objects, it is very conceivable that there might be overlaps in amplitude values for the different classes. So a full cut classification at all times is not possible.

Another matter to consider is the fact that what is interesting in this system is not only the difference in amplitude between pedestrians and metallic objects. Rather the difference between all other objects, and pedestrians. Other objects could be anything conceivable in the environment, e.g. organic or plastic material. Then the overlapping area of the amplitudes becomes more considerable as seen by comparing the amplitudes for pedestrians in Figure \ref{fig:amplitude2} with the amplitudes for all other objects, see Figure \ref{fig:amplitude3}. These figures show the radar amplitudes for a considerable amount of measurements. From this statistical data, it is possible to derive a probability for the object being a pedestrian. But doing so in the area where the amplitudes overlap, the probability for a pedestrian would be around 0.5. For this system this is not a feasible solution, since giving the radar objects a probability of 0.5 provides no extra information regarding the object. This implies that the system is relying on the thermopiles for detection.

Although, there is still the possibility to use the amplitude in such a way that, when it exceeds a certain limit at different distances $x$, it is with high probability, not a pedestrian. This limit is shown in Figure \ref{fig:amplitude1} where the maximum amplitudes for a pedestrian $p_{\text{ped, max}}$, for every meter is found and a function is approximated...
Figure 2.6. Radar amplitudes only for pedestrians. The values are acquired through a considerable amount of measurements. Especially notice the maximum value possible and compare with the maximum value for other objects.

Figure 2.7. Radar amplitudes for all other objects than pedestrians. The values are acquired through a considerable amount of measurements. Especially notice the maximum value possible and compare with the maximum possible value for pedestrians.
that interpolates through these points. This function is then raised with an offset to be the maximum at each point. Since the radars’ resolution is in centimeters the function is also given in this resolution.

$$\rho_{\text{ped, max}} = \begin{cases} 
9.9771 + 22.1695 \cdot e^{-0.001 \cdot x} & \text{for } 0 \leq x \leq 2000 \\
0 & \text{for } 2000 < x
\end{cases} \quad (2.1)$$

Thereby, it can be used as a comparative limit for every objects amplitude, to decide if it is a pedestrian.

$$\rho_{\text{ped}} \not< \rho_{\text{ped, max}} \quad (2.2)$$

If an object’s amplitude is below this limit for four samples in a row, it can once again attain a high probability for pedestrian.

### 2.4.3 Radar Output

In effect the radar sensor provides four features for discerning a pedestrian. These are presented in Table 2.7. Here it can be seen that no differentiation is made between objects with high reflectivity and when there is no object present. This is because for the purpose of classifying and detecting pedestrians there is only the need to differentiate pedestrians from all other objects that is necessary.

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8The interpolation performed here will not be discussed further since it is not an important part of this work. Worth noting is that the function chosen should yield a proper approximation for the values it interpolates through.
2.5 Assumptions about Pedestrians

<table>
<thead>
<tr>
<th>Radar features</th>
<th>Notations in Section 5.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Object with low reflectivity is detected, hot or cold</td>
<td>$H \cup C$</td>
</tr>
<tr>
<td>Object with high reflectivity is detected, hot or cold</td>
<td>$N$</td>
</tr>
<tr>
<td>No object detected</td>
<td>$N$</td>
</tr>
<tr>
<td>Inconclusive measurement</td>
<td>$\theta_R$</td>
</tr>
</tbody>
</table>

Table 2.2. Radar features

2.5 Assumptions about Pedestrians

Assumptions made about what is assigned a pedestrian, in context of the explanations made above on how the sensors perceive objects, are detailed in Table 2.3. What is meant with a low radar reflectivity is derived from the radar amplitudes

<table>
<thead>
<tr>
<th>Assumptions about Pedestrian</th>
<th>$\approx 37,^\circ C$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Warm temperature</td>
<td>$0 - 27 \text{km/h}$</td>
</tr>
<tr>
<td>Static or moving with a low speed</td>
<td>$P_{ped} \neq P_{ped,max}$</td>
</tr>
</tbody>
</table>

Table 2.3. Assumptions about pedestrians

and if the object is warm or not is detected by the thermopiles. The highest speed for a pedestrian is with high probability not above 20 km/h and certainly not above 30 km/h. $27 \text{km/h}$ is chosen because of our grid resolution, explained in Chapter 5. It should be remarked that this way of assignment is a simplification of the actual circumstances. However, as will be shown, this is enough to carry this approach far.
Chapter 3

Target Tracking and Data Association

In this chapter an overview of a typical tracking system is provided and the foundation in a tracking algorithm. A brief literature survey is given. The tracking procedure used in this work is further presented with results. The chapter ends with a discussion regarding other possible methods. If the reader is already acquainted with basic tracking methods and their results, overviewing Sections 3.3 and 3.5 which are specific for this work is sufficient.

3.1 Introduction

In tracking systems, the designer must choose, based on knowledge and prior experience, the techniques that are best suited to the particular application. Used in this application, is a relatively simple tracking system to accommodate the needs of the system. The main purpose of which is to provide the fusion system with better data, i.e. filter out false radar detections. Meanwhile the topic here is a vastly explored and widely applied one judging by the research readily available and the different tracking designs can be very complex. For this reason, a brief survey of the literature is given below.

3.2 Brief Literature Survey

Throughout the literature there is usually a separation between STI and MTT systems. Different tracking methods is discussed by Gad et al. [17] and the paper provides an overview of various issues involved in a network centric sensor data fusion environment. While Blackman and Popoli [3] and Bar-Shalom [2] give a deeper view into the design of tracking and data association systems.

1STT is used as an abbreviation for Single Target Tracking systems in the literature.
2MTT is used as an abbreviation for Multiple Target Tracking systems in the literature.
The Kalman Filter (Kalman, 1960) is now widely used within tracking applications since its introduction into tracking in 1969 (Nahi [27]). For modern MTT schemes, this can to large extent be credited to Bar-Shalom and Tse [3] and to Singer and Stein [33]. Today there are complex approaches either with (Llinas et al. [24]) or without (Hen et al. [11]) the Kalman Filter. The book written by Gustafsson et al. [19] explains, besides general signal processing methods, the Kalman filter in a nice way.

3.3 Data Association

Association area is a term used to refer to the surroundings of a target associated with it while a gate is defined as the exterior bounds of that area. The problem of being able to say which new measurement matches with which old measurement from earlier samples is referred to as a data association problem. Difficulties lie in determining the size of the association area since making the area too small could result in a missed track and the opposite could result in false associations.

![Diagram of a typical tracking system]

Figure 3.1. A typical tracking system.

The tracking algorithm is basically composed of three steps between samples: prediction, data association and state update. This algorithm can be found in Figure 3.2 which is the last box in Figure 3.1 depicting a typical tracking system, here with the radar as the chosen sensor. These three steps will be specifically explained below for this system but it should already now be known that this application is a MTT system in a multisensor environment since the two radars can provide several targets in the same sample.

3.4 Tracking Preprocessing

Before the actual tracking algorithm starts in every sample, the radar targets are also preprocessed in every sample and possibly fused into one target to allow for a simpler tracking.
3.4 Tracking Preprocessing

When a radar target appears in every sample, a search is made inside a gate, $g_r$ surrounding the target, looking for another target from the other radar. The size of the gate, $\mu_{rx}$ and $\mu_{ry}$ are tested and validated by the results of the tracker. If another target is detected inside this gate, they are associated and fused into one target. The position of the new target, $\alpha_{12}$ is then the mean value of the two previous positions, $\alpha_1$ and $\alpha_2$.

$$\alpha_{12} = \frac{\alpha_1 + \alpha_2}{2}$$ (3.1)

Notice that this is only performed if it is two different radars detecting targets close by each other. While if it is the same radar, it is assumed to be different physical objects and the targets are not fused. Figure 3.3 shows a situation where two targets from different radars are close enough for fusing.

**Figure 3.3.** Association area(ellipse) for two radar targets(squares) from different radars.

Thereby this also gives a higher probability for there being an object since the two targets can actually be the same physical object.
3.5 Tracking of Radar Targets

Important to notice in this section are the different notations used. Objects are radar targets from previous samples with different states and are denoted $\beta$. While targets are the radar targets from the latest measurement denoted $\alpha$. Targets will not here be differentiated between fused or not, as explained in the previous section. Furthermore, $\alpha_x$ means the radar target’s $x$-coordinate and $\alpha_y$ the $y$-coordinate. When indexes are left out it is the $xy$-position that is meant and index $t$ refers to the position at time $t$.

When a new physical object appears, e.g., a pedestrian, and is detected as a target by the radars, an object is initialised at the position of the measurement.

$$\beta_t = \alpha_t$$

(3.2)

Thereafter, with a new measurement, a search is performed for targets inside a gate surrounding the initialised object. This initial gate $g_{init}$, or association area, depends on the current speed of the test vehicle, $v_{veh\cdot t}$ and the maximum speed assumed our pedestrian can have, $v_{ped\cdot max}$ which is the same in either direction.

$$g_{init} = \frac{(\beta_{x,t-1} - \alpha_{x,t})^2}{\mu_x^2} + \frac{(\beta_{y,t-1} - \alpha_{y,t})^2}{\mu_y^2} \leq 1$$

(3.3a)

where

$$\mu_x = (v_{veh\cdot x\cdot t} + v_{ped\cdot max}) \cdot T$$

(3.3b)

$$\mu_y = (v_{veh\cdot y\cdot t} + v_{ped\cdot max}) \cdot T$$

(3.3c)

The value $T$ refers to the sample period. If there is a target inside this gate, the target is associated to the object and the motion vector, $\delta$ is computed as the difference between the two positions.

$$\delta_t = \alpha_t - \beta_{t-1}$$

(3.4a)

$$\beta_t = \alpha_t$$

(3.4b)

Meanwhile if there is more than one target inside the gate, the closest one is associated and the motion vector is the difference between this target’s and the object’s position, see Figure 3.3. This motion vector gives the likely position for this object, i.e., a prediction $\lambda$, in the next sample.

$$\lambda_{t+1} = \beta_t + \delta_t$$

(3.5)

Thus, with the new sample, the new association area, $g_{cont}$ is placed around the predicted position and depends on the assumed maximum speed our pedestrian can have, since the test vehicle movement is already included in the prediction, and on an assumed acceleration from the test vehicle, $a_{veh}$.

$$g_{cont} = \frac{(\lambda_{x,t} - \alpha_{x,t})^2}{\mu_x^2} + \frac{(\lambda_{y,t} - \alpha_{y,t})^2}{\mu_y^2} \leq 1$$

(3.6a)

where

$$\mu_x = (a_{veh\cdot x} \cdot T + v_{ped\cdot max}) \cdot T$$

(3.6b)

$$\mu_y = (a_{veh\cdot y} \cdot T + v_{ped\cdot max}) \cdot T$$

(3.6c)
3.5 Tracking of Radar Targets

\[ a_{\text{veh}} \cdot T \approx 0. \] (3.7)

This allows for a smaller association area and rightfully so since there now is a prediction available. If there is one target inside the gate surrounding that position, the object has successfully been tracked and the algorithm starts over with (3.4). This is displayed in Figure 3.5 where the small circle is the prediction and the solid arrow is the new motion vector. When there are several targets inside the gate,

\[ \delta_t = \delta_{t-1} \] (3.8a)
\[ \beta_t = \beta_{t-1} + \delta_{t-1} \] (3.8b)
This gives the new prediction as
\[ \lambda_{t+1} = \lambda_t + \delta_t = \lambda_{t-1} + \delta_{t-1} + \delta_t. \] (3.9)

With this, there is also the need for a larger association area when a new measurement is available.

\[ g_{\text{miss}} = \frac{(\lambda_{x,t} - \alpha_{x,t})^2}{\mu_x^2} + \frac{(\lambda_{y,t} - \alpha_{y,t})^2}{\mu_y^2} \leq 2 \] (3.10a)

where
\[ \mu_x = v_{\text{ped, max}} \cdot T \] (3.10b)
\[ \mu_y = v_{\text{ped, max}} \cdot T \] (3.10c)

If the radar object can be associated with a radar target in this sample, the algorithm continues with (3.4). Otherwise, another attempt is made to continue with (3.8) until it is no longer feasible and the object is deleted.

It should be noted here that the tracking preprocessing is equivalent to allowing association of two targets, one from each radar, if within the association area. Then the new position of the radar object would be in between the two associated targets with corresponding gate parameters, prediction and motion vector.

### 3.6 Result

It is up to the designer of the tracking system to decide the number of samples needed for the radar object to change between states. The radar objects used for fusion with the thermopiles have been tracked for four samples in a row to reach a confirmed state. If a missed track occurs before it reaches a confirmed state the object is deleted and if it has reached a confirmed state the track has to be missed three times in a row for the object to be deleted. This allows for filtering out any false detections from the radars that might otherwise have been used for fusing. Also, it is used for applying an object motion compensation to the Occupancy Grid further explained in Section 5.3.2.

Results from a track scenario where parameters are
\[ \mu_{\tau_x} = 36 \text{cm} \quad \text{and} \quad \mu_{\tau_y} = 75 \text{cm} \] (3.11)
and the test vehicle is driving straight towards a standing pedestrian can be viewed in Figure 5.3. Here it can be seen that the tracked radar object has a position in the middle of the two radar targets because of the tracking preprocessing (3.1). The chosen parameters were the smallest showing these satisfying results for this scenario. Why \( \mu_{\tau_y} \) has to be larger than \( \mu_{\tau_x} \) can only be assigned to noise on the output of the radar targets.

### 3.7 Discussion

In this application gate computations are not performed except for the difference in gate sizes dependent on which tracking state the radar object is in. The Kalman
filter could be applied for the same purpose and probably with satisfying results. Although the results would not yield noticeably better fusion results for the complete system in the end since a design feature of the fusion system is the fusion of radar object probabilities not only at the position of the object, but also in a surrounding area. This is detailed in Section 3.3.1 and allows for some inaccurate object position estimates after the tracking procedure.

The main problem arises with false associations of measurements. This means physical objects that disappear out of the FOV of the radars or for some reason not detected and thus also should disappear in the system, still survive because another physical object detected by the radars as a target resides inside the previous objects gate.

Also, the Kalman filter is usually utilized for the complete fusion process while the fusion is performed in the Occupancy Grid for this application.

With these requirements on performance of a tracking system in this complete fusion system and the design features possible to apply in the fusion system, the choice was made to use a simpler tracking approach.
Figure 3.6. Upper graph shows the positions of the radar targets while the lower graph shows the positions of the tracked radar object. Notice that the radar object has a position in the middle of the two radar targets.
Chapter 4

Sensor Fusion for Pedestrian Detection

General sensor fusion approaches are explained in this chapter with an insight into the difficulties and benefits. An introduction to the common way of categorising sensor fusion is provided. With a starting point in this, an explanation of the sensor fusion architecture used in this work is given. Furthermore, an overview of the data fusion procedure is given to ease the understanding of later chapters. Only Sections [4.3] and [4.4] are specific for this system and thus, other sections are not necessary for a reader with prior knowledge on this topic.

4.1 Introduction

The problem of combining information regarding an object, or several objects, and the surrounding environment is commonly referred to as the sensor fusion problem when the information considered is provided on different levels of abstraction. When discussing multiple sensor networks and setups, three different sensor fusion categories are mentioned, complementary, competitive and cooperative.

These categories are not mutually exclusive but each sensor network configuration can consist of two or more categories with the advantage that methods can be found to match the actual application. Different categories and sensor fusion approaches are more thoroughly introduced and discussed by Brooks and Iyengar [9] and Klein [20].

4.2 Sensor Fusion Possibilities

Complementary sensors do not depend on each other directly but can be merged to form a more complete picture of the environment. Furthermore, there should not be any conflicting information present in the measurements.

Competitive sensors provide equivalent information about the environment in the sense that they operate and detect at the same abstraction level. For example
infrared sensors detect objects depending on the emitted thermal radiation. However, the readings can still be conflicting which makes it a challenging problem. Although such a setup of multiple units can tolerate the failure of one unit.

Cooperative sensors work together to drive information that neither sensor alone could provide and therefore this type of fusion is dependent on details of the physical devices involved and cannot be approached as a general problem.

When different fusion methods are discussed, they are mainly divided into sensor-level fusion, Figure 4.1 and central-level fusion, Figure 4.2. The sensor-level approach is to pre-process sensor data, possibly having actual object positions as input, and fuse these into one target position and type. This is usually also referred to as a high-level fusion since the sensor data is highly pre-processed and therefore has a high abstraction level. Whilst in a central-level fusion approach, the input to the system would be the raw sensor data. Therefore it is also referred to as low-level fusion. This means that for a central-level fusion approach, there is more information available from the sensors, than if the same problem would be addressed with sensor-level fusion. It would probably also incur more computational cost. But of course, there is no saying that a combination of the two approaches or a compromise between the two, is not possible.
4.3 Sensor Fusion Architecture

The approach chosen for the fusion of data in this work can be referred to as central-level fusion and is outlined in Figure 4.2.

Because of the pre-processing performed on the sensor data, before the fusion starts, it already has a certain abstraction level, although all available data is centrally fused on the Occupancy Grid. Meanwhile, the sensor setup in this work can be considered a cooperative and complementary sensor network as the combined data from the different independent sensors would be unavailable from the individual sensors alone. Also, radars and thermopiles complement each other since they give information belonging to different physical properties of an object, like hot or cold (see Chapter 2).

4.4 Data Fusion

When fusing radar targets with the thermopiles' output, it is necessary to consider the sensors' uncertainty level. By doing that, a better final result is attained and therefore the Dempster-Shafer Theory has been utilised in this work. It works with belief functions and is different from standard Bayesian theory. With the use of Dempster-Shafer Theory, a combination of the probabilities from thermopiles and radars are done for each cell in the Occupancy Grid. It will be assumed to not have a detection from the fusion system unless both radars and thermopiles give a detection, i.e. a high probability in the same area. This to increase the reliability of the system. In the Occupancy Grid, each new probability from every new measurement, is combined with the old ones using recursive Bayesian estimation. After the Occupancy Grid calculations, a position is derived through segmentation of the cell probabilities. Meanwhile we also arrive at an object type with the same Dempster-Shafer equations. The beauty of the approach in this work lies in the same fact, that there is no need to separate between object type and object position determination. The whole fusion approach is detailed in Chapters 5.1 and 5.2.

Another benefit of this approach is as mentioned earlier, that all information available from the system is utilised. In the sense that fusion of thermopile and radar probability is performed in every grid cell. One could possibly argue, that more information could be achieved by going down to raw sensor data and working with actual sensor output, but that is hardly applicable here. The opposite would be to work with an object position output from the thermopiles respectively the radars, fusing them into one. Additional to that, have a probability for the different

---

1A multidimensional random field used to model the surroundings with sensor readings. By using a probabilistic segmented representation of spatial information, the Occupancy Grid maintains stochastic estimates of the occupancy state of the cells. Presented in detail in Chapter 5.2.
2A mathematical theory for evidential reasoning developed by Arthur Dempster and Glenn Shafer and usually referred to as the Dempster-Shafer Theory. Further presented in Chapter 5.
3In this thesis it is assumed that the reader has prior knowledge about Bayesian theory, but a short presentation is made in Section 5.2.
4A segment in the Occupancy Grid. See Section 5.2.
object types and fusing them. The upside of the latter is of course the need for less computation.

Figure 4.3. Outline of the sensor fusion architecture used in this system.
Chapter 5

Data Fusion using
Dempster-Shafer Theory

This chapter starts with acquainting the reader to basic probability theory and to Dempster-Shafer Theory which is the data fusion process used in this work. Although, it is assumed that the reader has some understanding of probability theory. There is also an example provided to show when these approaches are equal. An extensive explanation is made of how the specific data fusion equations in this system are derived. Furthermore, some application specific attributes are explained incorporating the data fusion equations. The reader with prior knowledge on Dempster-Shafer Theory can start on Section 5.5.

5.1 Introduction

Usually it has to be distinguished between the problems of determining an object’s type versus its position. However, as already mentioned, it is not necessary for this approach since the probability for a pedestrian is computed and accumulated over time in the Occupancy Grid. In this chapter it will become evident how the probability for a pedestrian is reached. It is assumed that the reader has some understanding of Bayesian Probability Theory (BPT). A comparative analysis between BPT and Dempster-Shafer Theory (DST) is given to show in which aspects they differ and for which cases they give the same result. But first a short overview of BPT is given and a more extensive explanation surrounding DST. For further reading regarding these topics in a fusion framework, Klein [20] and also Waltz and Linas [37] are well suited.

5.2 Bayesian Probability Theory

For BPT there are many textbooks to be found, e.g. Blom [7], that give deeper and more thorough explanations than can be found here. Although a thorough
derivation of the Bayesian Estimation Process for the Occupancy Grid is given in Chapter 9.

BPT is based on a set of mutually exclusive and exhaustive hypotheses \( H_1, H_2, \ldots, H_N \) which are connected to an event \( E \). For this application \( H_i \) represents the existence of an object of type \( i \) and \( E \) is a measurement. A foundation for this approach is Bayes' Theorem.

**Theorem 5.1 (Bayes’ Theorem)** For \( H_i \) and \( E \) it holds,

\[
P(H_i|E) = \frac{P(E|H_i) \cdot P(H_i)}{P(E)} \tag{5.1a}
\]

or equivalently

\[
P(H_i|E) = \frac{P(E|H_i) \cdot P(H_i)}{\sum_{i=1}^{N} P(E|H_i) \cdot P(H_i)} \tag{5.1b}
\]

Here it can also be seen that

\[
P(E) = \sum_{i=1}^{N} P(E|H_i) \cdot P(H_i) \tag{5.2}
\]

is the probability for the measurement, but as seen above, acts as a normalisation factor. It should be added that the total probability equals one.

\[
\sum_{i=1}^{N} P(H_i) = 1 \tag{5.3}
\]

An explanation of the different probabilities is perhaps valid here.

\[
P(H_i|E) = \text{the a posteriori probability of } H_i \text{ being true, given the event } E
\]

\[
P(H_i) = \text{the a priori probability of } H_i \text{ being true}
\]

\[
P(E|H_i) = \text{the probability of observing } E \text{ given } H_i \text{ is true}
\]

Each sensor observes an object property and provides an object type declaration. This declaration is a hypothesis \( H_i \) about the object type \( i \), given a measurement \( E \). The nature of the connection between the two depends on the sensor and the underlying algorithm.

To combine several sensors, additional information is needed which is not always easily determined. It has to be established, given a hypothesis \( H_i \), how likely the sensor actually declares the object to be of type \( i \), \( P(E|H_i) \). It is an a priori knowledge of the reliability in our measurements. Furthermore, the a priori probability of an object of type \( i \), \( P(H_i) \), is needed. Thereafter the evidence can be combined with Theorem 5.1 which provides a joint probability for an object of type \( i \) given evidence \( E_1 \) by sensor 1, \( E_2 \) by sensor 2 and so on for an arbitrary amount of sensors,

\[
P(H_i|E_1 \cap E_2 \cap \ldots).
\tag{5.4}
\]

To summarize, the disadvantages of BPT are shown in Table 5.1.
### 5.3 Dempster-Shafer Theory

The Dempster-Shafer Theory of evidence is based on the work of Arthur Dempster [12] who laid the foundation in a series of articles in the 1960’s. It was further developed by Glenn Shafer who established a mathematical framework in 1976 [31]. Thereby it has earned its name and is sometimes also called the Dempster-Shafer Evidential Theory. In [32] Shafer further discusses DST, but more concerning the interpretation of the approach. DST is a generalization of the Bayesian theory in the way that it allows for the distribution of support not only to a single hypothesis, but also to a union of hypotheses. This is a more intuitive way of assigning probabilities since humans usually have a degree of uncertainty in their statements. The Dempster-Shafer and Bayesian methods produce identical results when all of the hypotheses are singletons and mutually exclusive. In the following section the general definitions of Dempster-Shafer Theory will be described and it will be explained how assigning probability to unions of hypotheses can model uncertainty.

#### 5.3.1 Introduction of Uncertainty

DST assumes a set of \( n \) mutually exclusive and exhaustive events, also called propositions like \( A_1, A_2, \ldots, A_n \). They are collectively called the frame of discernment

\[
\theta = \{A_1, A_2, \ldots, A_n\}
\]

where \( n \) is the number of propositions available. The number of all possible propositions and their combinations, including the empty set, is then \( 2^n \). Usually this set of all possible combinations is called the power set and denoted by \( 2^\theta \).

\[
2^\theta = \{\emptyset, \{A_1\}, \{A_2\}, \ldots, \{A_n\}, \{A_1, A_2\}, \{A_1, A_3\}, \ldots, \{A_1, A_2, \ldots, A_n\}\}
\]

The basic idea of DST is a probability mass \( m(A_i) \) which is distributed amongst those propositions, or their unions. Thus, a sensor can assign a probability mass to the proposition that either \( A_1 \) or \( A_2 \) is true, denoted \( m(A_1 \cup A_2) \). This is a major difference to the Bayesian method, where all hypotheses have to be singletons. To further explain this, one definition has to be made.
Definition 5.1 Probability mass distribution $m$ assigns a value between 0 and 1 to a proposition or a union of propositions

$$m : 2^\theta \to [0, 1]$$

so that it satisfies the axioms

$$0 \leq m(A) \leq 1$$
$$m(\emptyset) = 0$$
$$\sum m(A) = 1$$

where $A \in 2^\theta$.

It should be noted that probability mass assigned to $\emptyset$ from $\{\emptyset\}$, represents the statement "any proposition could be true" and is therefore a measure of uncertainty. If all probability mass is assigned to $m(\emptyset)$, i.e. $m(\emptyset) = 1$, there is a complete uncertainty about all propositions. In other words, no information at all. It is conceivable that a situation may arise, where it is impossible for a sensor to gather any information. These situations can now easily be taken care of by using this fact.

5.3.2 Plausibility and Belief

To reach an adequate summary of the support for a proposition or union of propositions $A$ from the evidence available, one has to include at least two measures. How well $A$ is supported, $m(A)$, and how well $\overline{A}$, meaning "not $A$", is supported, $m(\overline{A})$. Therefore two concepts are introduced in DST.

Definition 5.2 A Belief function is defined by

$$Bel(A) = \sum_{B \subseteq A} m(B), \quad \text{for all } A, B \in 2^\theta$$

and is drawn from the sum of all probability masses that are subsets of the probability mass in question. Literally speaking, it is the sum of all evidence that are supporting the proposition or one of its subsets. This means an evidence for $A_1$ is also an evidence for $A_1 \cup A_2$.

Definition 5.3 A Plausibility function is defined as

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B) \quad \text{for all } A, B \in 2^\theta$$

the sum of all probability masses that are not contradictory to the proposition.

From this it follows that Belief and Plausibility are related to one another as

$$Bel(A) = 1 - Pl(\overline{A}) \quad (5.7a)$$
$$Pl(A) = 1 - Bel(\overline{A}) \quad (5.7b)$$
and further illustrated in Figure 5.1. The interval \([\text{Bel}(A), \text{Pl}(A)]\) is referred to as the uncertainty interval. It can be interpreted as a lower and upper boundary on the "true" probability of \(A\).

![Figure 5.1. Concepts in Dempster-Shafer Theory](image)

### 5.3.3 Combination of Evidence

If there is more than one information source, e.g., sensor, in a system, the individual pieces of evidence from the different sensors can be combined using Dempster’s rule of combination assuming that the evidence is gathered independently. This means for example that sensors cannot influence each other but it does not mean, sensors may not react on the same event.

**Definition 5.4** The **combined mass function** is denoted by \(m_1 \oplus m_2\) where \(m_1\) and \(m_2\) are two different mass functions associated with the same proposition space, \(2^\theta\). Let \(X\) be the proposition or union of propositions under question, then the combination is defined as

\[
m_1 \oplus m_2 (X) = \begin{cases} \frac{\sum_{A_i \cap B_j = X} m_1(A_i) \cdot m_2(B_j)}{\sum_{A_i \cap B_j = \emptyset} m_1(A_i) \cdot m_2(B_j)} & \text{for } X \neq \emptyset, \\ 0 & \text{for } X = \emptyset, \end{cases}
\]

for all \(A_i\) and \(B_j \in 2^\theta\) and is also denoted as the Belief of \(X, \text{Bel}(X)\).

This equation can be interpreted literally as the mass of all supportive evidence divided by the mass of all possible evidence. The denominator of this equation is a normalisation factor and will here be denoted as \(1 - k\).

\[
k = \sum_{A_i \cap B_j = \emptyset} m_1(A_i) \cdot m_2(B_j) \tag{5.8}
\]

The variable \(k\) is a measure for the contradiction between the two sources and represents the mass that would be assigned to the empty set. In cases where the contradiction is very high, i.e., \(k \approx 1\), the result of the combination becomes
unreliable. It is evident that cases of complete contradiction, \( k = 1 \), must be avoided, as the combined probability mass is not defined for this case. These facts about the contradictions must be kept in mind when a system using DST is built.

The numerator, as mentioned above, is the mass of all supportive evidence. More specifically, all elements of \( 2^\theta \) that \( X \) is a subset of, are taken into account and the combined mass is found by building the sum of all possible combinations of these elements. If more than two sources have to be taken into account, the first two can be combined as stated above. The next has to be combined with the result of the first combination and so forth.

To summarize, the disadvantages of DST are shown in Table 5.2.

<table>
<thead>
<tr>
<th>Disadvantages of DST</th>
<th>( n ) mutually exclusive propositions ( \Rightarrow 2^n ) combinations</th>
<th>( k \rightarrow 1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Could be highly complex, i.e. involve a high computational load</td>
<td>( \theta = {P, \overline{P}} )</td>
<td>( 2^\theta = {P, \overline{P}, \theta} )</td>
</tr>
<tr>
<td>Handling of extremely contradicting evidence</td>
<td>( \theta = {P, \overline{P}} )</td>
<td>( 2^\theta = {P, \overline{P}, \theta} )</td>
</tr>
</tbody>
</table>

**Table 5.2. Disadvantages of Dempster-Shafer Theory**

### 5.4 Comparison between Bayes and Dempster-Shafer

As mentioned before, BPT and DST yield the same results for mutually exclusive events. For two mutually exclusive events \( P \) and \( \overline{P} \), for example "Pedestrian" and "not Pedestrian", the frame of discernment is easily written and with that the power set.

\[
\theta = \{P, \overline{P}\} \quad \quad \quad \quad \quad \quad \quad (5.9a)
\]

\[
2^\theta = \{P, \overline{P}, \theta\} \quad \quad \quad \quad \quad \quad \quad (5.9b)
\]

Consider the combination of two mass functions \( m_1 \) and \( m_2 \) from sensor \( s_1 \) and sensor \( s_2 \) respectively. Then the belief in the combined mass function is computed as

\[
Bel(P) = \frac{m_1(P) \cdot m_2(P) + m_1(\theta) \cdot m_2(P) + m_2(\theta) \cdot m_1(P)}{1 - k}
\]

\[
= \frac{m_1(P) \cdot m_2(P) + m_1(\theta) \cdot m_2(P) + m_2(\theta) \cdot m_1(P)}{1 - m_1(P) \cdot m_2(P) + m_2(P) \cdot m_1(P)} \quad \quad \quad \quad (5.10a)
\]

and the combined belief in \( \theta \) and \( \overline{P} \) as

\[
Bel(\theta) = \frac{m_1(\theta) \cdot m_2(\theta)}{1 - k}
\]

\[
Bel(\overline{P}) = \frac{m_1(\overline{P}) \cdot m_2(\overline{P}) + m_1(\theta) \cdot m_2(\overline{P}) + m_2(\theta) \cdot m_1(\overline{P})}{1 - k} \quad \quad \quad \quad (5.10b)
\]
which is all that is needed for the computations to become complete. To give an
overall picture, the plausibility for $P$ is also shown.

\[ Pl(P) = 1 - Bel(\overline{P}) = Bel(P) + Bel(\theta) \quad (5.10d) \]

If the two events $P$ and $\overline{P}$ are also exhaustive one of the major differences between
DST and BPT, hypotheses that are not singletons, do not exist. When this simplification is applied to (5.7), it becomes evident that belief and plausibility are equal for such a case.

\[

Bel(P) = \frac{m_1(P) \cdot m_2(P)}{1 - k} \quad (5.11a)
\]

\[

Bel(\theta) = 0 \quad (5.11b)
\]

\[

Bel(\overline{P}) = \frac{m_1(\overline{P}) \cdot m_2(P)}{1 - k} \quad (5.11c)
\]

\[

Pl(P) = 1 - Bel(\overline{P})
= Bel(P) + Bel(\theta) = Bel(P) \quad (5.11d)
\]

The fact that this is also numerically identical is shown in Example 5.1.

---

**Example 5.1: Comparison between BPT and DST**

By comparing the combined belief when events are mutually exclusive and exhaustive,

\[

Bel(P) = \frac{m_1(P) \cdot m_2(P)}{1 - m_1(P) \cdot m_2(P) + m_2(P) \cdot m_1(P)}
= \frac{m_1(P) \cdot m_2(P)}{m_1(P) \cdot m_2(P) + m_1(\overline{P}) \cdot m_2(P)} \quad (5.12)
\]

with the result of a Bayesian combination

\[

P(H_P|E_1 \cap E_2) = \frac{P(E_1 \cap E_2|H_P) P(H_P)}{\sum_j P(E_1 \cap E_2|H_j) P(H_j)} \quad (5.13)
\]

where $H_P$ is the hypotheses for there being a pedestrian. Now assume equal prior likelihood for all hypothesis

\[

P(H_j) = 0.5 \quad (5.14)
\]

and with conditional independence in the measurements

\[

P(H_j|E_1 \cap E_2) = P(H_j|E_1) \cdot P(H_j|E_2) \quad (5.15)
\]

the Bayesian combination follows.

\[

P(H_P|E_1 \cap E_2) = \frac{P(H_P|E_1) \cdot P(H_P|E_2)}{P(H_P|E_1) \cdot P(H_P|E_2) + P(H_P|E_1) \cdot P(H_{\overline{P}}|E_2)} \quad (5.16)
\]

The results of (5.15) can easily be identified with those of (5.12) where $P(H_P|E_i)$ and $m_i(P)$ are each others equals for $i = 1, 2$. 

5.5 Deriving Probability for a Pedestrian

Using the Dempster-Shafer Theory, for fusing the probabilities from thermopiles and radars give advantages since it allows for an easy way to include the uncertainty from sensor output which means it is possible to give more weight to more certain measurements. More importantly, it also makes it possible to combine sensors that detect different items, or different properties of an item, since the events do not have to be mutually exclusive and exhaustive.

For this application it means, since thermopiles only differentiate between the set consisting of one proposition, \(\{\text{hot object}\}\), and the set consisting of two propositions, \(\{\text{cold object, no object}\}\), they cannot differentiate between the propositions \(\text{cold object}\) and \(\text{no object}\). While radars differentiate between the set consisting of two propositions \(\{\text{hot object, cold object}\}\) and the set consisting of one proposition, \(\{\text{no object}\}\). It thereby means they cannot distinguish between the propositions \(\text{cold object}\) and \(\text{hot object}\).

This is also shown in the notations below which are given for use in the equations in this section. Throughout here index \(T\) will refer to the thermopiles, index \(R\) refer to the radars, index \(C\) refer to the cells and index \(F\) refer to cells that are multiply fused.

\[
\begin{align*}
H : & \text{ hot object } \quad C : \text{ cold object } \quad N : \text{ no object } \\
\theta : & \{H, C, N\} \\
m_T : & \text{ thermopiles' mass function } \quad m_R : \text{ radars' mass function } \\
m_T = & \begin{bmatrix} \text{ Bel}_T(H) \\ \text{ Bel}_T(C, N) \\ \text{ Bel}_T(\theta_T) \end{bmatrix} \quad m_R = \begin{bmatrix} \text{ Bel}_R(H, C) \\ \text{ Bel}_R(N) \\ \text{ Bel}_R(\theta_R) \end{bmatrix}
\end{align*}
\]

To differentiate between these three propositions, the possibility to compute probabilities for the propositions exclusively comes to hand and most importantly for \(H\) which is interesting for this application. But to start with when setting up the combination equations for radars and thermopiles, there are some things to consider regarding the propositions or unions of propositions in the power set.

\[
\theta^2 = \{H, C, N, \{H, C\}, \{H, N\}, \{C, N\}, \theta\}. 
\tag{5.17}
\]

Firstly it should be noted that there is no contradiction between the radars' \(\{H, C\}\) and the thermopiles' \(\{C, N\}\) since there is a conjunction between the sets which is not the null set, namely proposition \(C\).

\[
\{C\} = \{H, C\} \cap \{C, N\} 
\tag{5.18}
\]

So the only contradiction according to \[(5.8)\] is between \(H\) and \(N\). Secondly, it should be noticed for example, that the conjunction between \(\{\theta\}\) and \(\{H, C\}\) is not exclusively a support for proposition \(H\) but also for \(C\).

\[
\{H, C\} = \{H, C\} \cap \{\theta\} 
\tag{5.19}
\]

With this in mind and by using Definition \[(5.4)\] the fusion equations for each cell in the grid can be computed.
5.5 Deriving Probability for a Pedestrian

5.5.1 Fusion Model

Meanwhile, for each cell in the grid with a radar object at the same position, a fusion between thermopiles' probabilities and radars' probabilities occurs. Fusion is made for the surrounding cells with a Gaussian distribution applied on the radar object's probability. See Figure 5.2. Meaning that wherever there is a radar object without a high amplitude\(^1\), it is fused with the thermopiles with a high probability for pedestrian, proposition \(H\), and with surrounding probabilities for pedestrian descending to zero inside a valid area. Thus, outside this area where there is no other object, the thermopile probabilities are fused with a low probability for pedestrian. This area with parameters \(D_x\) and \(D_y\) is validated by the final results of the fusion process, but it should be known that making the area too small implies an accurate sensor since thermopiles and radars have to detect at the same position to give a fusion detection.

\[k_C = m_T(H) \cdot m_R(N).\]  \(\text{(5.20)}\)

\(^1\)See Section 5.2.2

\[\text{Figure 5.2. Gaussian distribution for the radar object probabilities. Cells surrounding a radar object's position are also fused, but with lower probabilities the further away from the actual position it is.}\]
\[
\begin{align*}
Bel_C(H) &= \frac{m_T(H) \cdot m_R(H, C) + m_T(H) \cdot m_R(\theta_R)}{1 - k_C} \quad (5.21a) \\
Bel_C(C) &= \frac{m_T(C, N) \cdot m_R(H, C)}{1 - k_C} \quad (5.21b) \\
Bel_C(N) &= \frac{m_T(C, N) \cdot m_R(N) + m_T(\theta_T) \cdot m_R(N)}{1 - k_C} \quad (5.21c) \\
Bel_C(\theta_C) &= \frac{m_T(\theta_T) \cdot m_R(\theta_R)}{1 - k_C} \quad (5.21d) \\
Bel_C(H, C) &= \frac{m_T(\theta_T) \cdot m_R(H, C)}{1 - m_T(H) \cdot m_R(N)} \quad (5.21e) \\
Bel_C(C, N) &= \frac{m_T(C, N) \cdot m_R(\theta_R)}{1 - m_T(H) \cdot m_R(N)} \quad (5.21f)
\end{align*}
\]

With these, all sets in the power set have been computed. Except for the contradiction of course. Notice that \(5.21a\) and \(5.21b\) make up two additional uncertainties but more specific than \(5.21d\) since these can be placed to two propositions instead of three.

For this application, the result from \(5.21a\) is the one interesting. Meanwhile \(5.21b\) - \(5.21f\) come into use when there are radar object fusion areas overlapping because of two or more objects having a position close to each other. Thereby these cells where they overlap become fused twice or more with the radar in the same sample, depending on how many objects’ fusion areas are overlapping. This is of course also dependent on the size of the fusion area. An example is shown in Figure 5.3 for two fusion areas overlapping.

![Figure 5.3](image)

**Figure 5.3.** Fusion in cells with overlapping (marked) fusion areas (squares) for different objects (circles) have to be treated differently.

For these occasions it has to be remembered which cells already have been
5.5 Deriving Probability for a Pedestrian

fused in this sample. Because of these cells’ mass function,

\[
m_C = \begin{bmatrix}
  Bel_C(H) \\
  Bel_C(C) \\
  Bel_C(N) \\
  Bel_C(H,C) \\
  Bel_C(C,N) \\
  Bel_C(\theta_C)
\end{bmatrix}
\]

which are the result of the earlier fusion, the fusion equations have changed. Notice that \( m_C \) includes every set in the power set except for the previous contradiction, \( k_C \).

\[
Bel_F(H) = \frac{m_C(H) \cdot m_R(H,C) + m_C(H) \cdot m_R(\theta_R)}{1 - k_F} \tag{5.22a}
\]

\[
Bel_F(C) = \frac{m_C(C) \cdot m_R(H,C) + m_C(C,N) \cdot m_R(H,C) + m_C(C) \cdot m_R(\theta_R)}{1 - k_F} \tag{5.22b}
\]

\[
Bel_F(N) = \frac{(m_C(N) + m_C(C,N)) \cdot m_R(N) + m_C(\theta) \cdot m_R(N) + m_C(N) \cdot m_R(\theta_R)}{1 - k_F} \tag{5.22c}
\]

\[
Bel_F(H,C) = \frac{m_C(H,C) \cdot m_R(H,C) + m_C(H,C) \cdot m_R(\theta_R) + m_C(\theta_C) \cdot m_R(H,C)}{1 - k_F} \tag{5.22d}
\]

\[
Bel_F(C,N) = \frac{m_C(C,N) \cdot m_R(C,N) + m_C(C,N) \cdot m_R(\theta_R) + m_C(\theta_C) \cdot m_R(C,N)}{1 - k_F} \tag{5.22e}
\]

\[
Bel_F(\theta_F) = \frac{m_C(\theta_C) \cdot m_R(\theta_R)}{1 - k_F} \tag{5.22f}
\]

Where \( k_F \) refers to the new contradiction

\[
k_F = (m_C(H) + m_C(C) + m_C(H,C)) \cdot m_R(N) + m_C(N) \cdot m_R(H,C). \tag{5.23}
\]

As stated above, in these equations there no longer is a mass function for the thermopiles involved but rather the results from (5.21)

So finally in a cell the probability for a pedestrian is given by either (5.21a) or (5.22a) depending on if the cell is fused more than once. This is then used in each cell for the Occupancy Grid computations, explained as the inverse sensor model in Section 5.7.3 to derive a position for the pedestrian over time.

With this approach it is also possible to display and follow cold objects, like lampposts or other obstacles, in the same manner since it is possible to differentiate those with the equations above. But the signal processing algorithms have to be adjusted to make this possible.
Chapter 6

Occupancy Grid

Information gathered in one sample, have to be processed over time and this is explained further in this chapter. The Occupancy Grid is the selected approach and therefore a complete derivation is given. Two examples have been used to ease the understanding of the process. Following this is an adaption of the grid and application specific procedures. It is shown how the final position of the pedestrian is obtained and a discussion regarding the Occupancy Grid ends the chapter. Sections 6.2.4 and 6.2.5 could be ignored by a reader already comfortable with the formalities surrounding the Occupancy Grid.

6.1 Introduction

Occupancy Grid (OG) was first introduced by Alberto Elfes and Hans Moravec at Carnegie Mellon University in 1984 as a multidimensional random field to model the surroundings of mobile robots using sonar sensors [1]. By using a probabilistic segmented representation of spatial information, the OG maintains stochastic estimates of the occupancy state of the cells. These estimates are obtained by applying probabilistic sensor models on sensor readings and therefore this approach takes into account, in contrast to other methods, the uncertainty of sensor derived data. Bayesian estimation procedures then integrate measurement data from different time, location and sensors to arrive at a more reliable decision. This chapters emphasis will be about this task. Bergman [1] discusses more generally concerning recursive Bayesian estimation and an approach using Point Mass Filters is presented. Another complete derivation specifically surrounding OG has been made by Thrun [31]. OG applications, today also called Evidence Grids, are widely used in areas of navigation, mapping, positioning and collision avoidance systems.

6.2 Method

Generally the OG representation is a two or three dimensional space, divided into cells, where each cell stores a probabilistic estimate of its state. In different
applications the states for each cell can vary depending on the task at hand, e.g. {red, blue, yellow}, {tree, stone} or {pedestrian, no pedestrian}. Figure 6.1 is an example from an OG with raised and lowered probabilities.

![Occupancy Grid](image)

**Figure 6.1.** Example from an Occupancy Grid. The raising and lowering shown are the probabilities in each cell.

### 6.2.1 For Pedestrian Detection

Figure 6.2 shows how the OG is set up for this application. The grid size is $7 \times 3$ meters and the cell sizes, signified by $d_x$ and $d_y$ in the figure, are $10 \times 10$ centimeters. With the vehicle movement, there is a shifting of the accumulated grid probabilities performed so that objects that are static, move on the OG when the vehicle is moving.

\[
\begin{align*}
(xy)_{t+1} &= (xy)_t - v_{veh,t} \cdot T \\
I_{xy}^{t+1} &= I_{xy}^t
\end{align*}
\]  

(6.1a)  

(6.1b)

Here $(xy)_t$ signifies the cell position at sample $t$, $v_{veh,t}$ the vehicle’s velocity and $T$ the sample period. While $I$ is the accumulated grid probability and derived below.
6.2 Method

6.2.2 Illustrative Example

Example 6.1 is an introduction to the usefulness of OG applications. Here, discussed in one dimension with a range sensing vector only detecting binary discrete states. But this reasoning can, with some extra effort, be expanded into multidimensional space and numerous states. For details around the example see [13].

---

Example 6.1: Occupancy Grid use in one dimension

$O(x)$ is a discrete state stochastic process with $x$ being a range vector defined over a set of discrete spatial coordinates $x = (x_1, x_2, \ldots, x_n)$ with states typically being occupied or empty. These cell states are exclusive and exhaustive and consequently, here the OG corresponds to a discrete state binary random range. To be able to apply Bayesian estimation procedures there must be an inverse sensor model at hand. This is discussed in Section 6.2.3.

For an one dimensional ideal sensor, doing one measurement throughout the whole range $x$, the occupancy probability profile can be seen in Figure 6.3. Where

![Figure 6.3. One dimensional ideal sensor.](image)

there has already been a sensor reading detecting no object, the probability is zero. When detecting an object the probability immediately reaches one. Behind the object where the sensor cannot reach, or, depending on point of view, where the sensor has not yet made any readings, the probability is equal to 0.5 which means nothing is known and this will not effect the values while updating. Figure 6.4 shows the same concept for a Gaussian sensor but now with multiple measurements. With every measurement, the probability increases since the Bayesian estimation process, shown in Section 6.2.4, is used to combine old measurements with new ones, but it starts at a lower peak value than the ideal sensor and never reaches probability value one.

This example shows that with a Gaussian sensor and only one measurement, there is no way to reach the results of an ideal sensor but by using several measurements and the Bayesian estimation process, the results of one are approached.
6.2.3 Inverse Sensor Model

Sensor models can be evaluated by determining, given world state in a number of readings, how many times do the sensor data coincide with this. Doing this for repeated number of times and situations gives us our stochastic sensor model defined by a probability density function relating reading $r$, to the world state $z$, like $p(r|z)$. Of course the sensor model can also be derived formally through prior knowledge of measurement parameters such as mean value, standard deviation error e.t.c. The inverse sensor model, $p(z|r)$, is then used in the Bayesian estimation process to determine the cell state probabilities. Inverse because it maps sensor measurements back to its causes.

In this application, what serves as the sensor model in the OG is the fusion between thermocouples and radars from the latest sample, (6.21a) or (6.22a). This is received as a probability directly, rather than a probability density function, and is therefore denoted $P(O|r)$. Probability that the cell is occupied given the measurement. This is further explained below, along with the notations used.

6.2.4 Bayesian Estimation Process

To assign the state of a cell being occupied $O_{xy}$ is used and $\overline{O}_{xy}$ if empty, not occupied, where subscript $xy$ stands for the position of the cell in the grid. Since this is based on Bayesian theory and the states are mutually exclusive and exhaustive, (6.2b) holds for any conditioning variable "n".

\[
P(O_{xy}) + P(\overline{O}_{xy}) = 1 \quad (6.2a) \\
P(O_{xy}|\cdot) + P(\overline{O}_{xy}|\cdot) = 1 \quad (6.2b)
\]

The sequential updating formulation of the Bayesian estimation process is used to determine the cell occupancy probabilities. Given a current estimate of the state
of a cell

\[ P(O_{xy}|r_t) \]  

(6.3a)

that is based on all earlier sensor readings,

\[ r_t = \{r_1, \ldots, r_t\} \]  

(6.3b)

the improved estimate is derived, based on a new reading \( r_{t+1} \) and with the use of Bayes’ theorem for multiple events shown by (6.3) and derived in Appendix \( \Delta \)

\[
P(O_{xy}|r_t) \cdot P(O_{xy}|r_{t+1}) = P(O_{xy}|r_t, r_{t+1})
\]

\[
= \frac{P(r_{t+1}|r_t, O_{xy}) \cdot P(O_{xy}|r_t)}{P(r_{t+1}|r_t)}
\]

(6.4)

Therefore, (6.4) is true with the assumption that the readings are conditionally independent given knowledge of each individual grid cell \( O_{xy} \), regardless of the occupancy of neighboring cells,

\[ P(r_{t+1}|r_t, O_{xy}) = P(r_{t+1}|O_{xy}) \]  

(6.5)

which is an extensive assumption but convenient since it allows important simplifications.

\[
P(O_{xy}|r_{t+1}) = \frac{P(r_{t+1}|O_{xy}) \cdot P(O_{xy}|r_t)}{P(r_{t+1}|r_t)}
\]

(6.6)

By applying Bayes’ theorem for two conditionally dependent events, Theorem [6.1] but this time on the prior probability \( P(r_{t+1}|O_{xy}) \), (6.7) is finally reached.

\[
P(O_{xy}|r_{t+1}) = \frac{P(O_{xy}|r_{t+1}) \cdot P(r_{t+1}|O_{xy}) \cdot P(O_{xy}|r_t)}{P(O_{xy}) \cdot P(r_{t+1}|r_t)}
\]

(6.7)

6.2.5 Odds Calculations

In order to make the need for prior knowledge about probabilities less, the odds are determined. This means the ratio between \( P(O_{xy}|r_{t+1}) \) and \( P(O_{xy}|r_{t+1}) \) is derived and therefore \( P(O_{xy}|r_{t+1}) \) is derived analogous to (6.7).

\[
\frac{P(O_{xy}|r_{t+1})}{P(O_{xy}|r_{t+1})} = \frac{P(O_{xy}|r_{t+1}) \cdot P(O_{xy}|r_{t+1}) \cdot P(O_{xy}|r_{t+1})}{P(O_{xy}) \cdot P(O_{xy}) \cdot P(O_{xy})}
\]

(6.8)

For the updating calculations to become less computationally demanding the logarithm is utilised and also for readability following notational simplifications are made,

\[
l_{xy}^{t+1} = \log \frac{P(O_{xy}|r_{t+1})}{1 - P(O_{xy}|r_{t+1})}
\]

(6.9a)

\[
l_{xy}^{t} = \log \frac{P(O_{xy}|r_{t})}{1 - P(O_{xy}|r_{t})}
\]

(6.9b)
which then gives

\[ b_{xy}^{t+1} = \log \frac{P(O_{xy}|r_{t+1})}{1 - P(O_{xy}|r_{t+1})} + \log \frac{1 - P(O_{xy})}{P(O_{xy})} + r_{xy} \tag{6.10} \]

and here the recursiveness of the formula is easily seen. To show that only two probabilities actually need to be known, (6.23) and (6.24) have also been included in (6.10). Now, the only two factors left are the prior probability of occupancy \( P(O_{xy}) \) and \( P(O_{xy}|r_{t+1}) \) which is the probability of occupancy conditioned on the measurement \( r_{t+1} \), also explained in Section 6.2.3 as the inverse sensor model. Finally, we obtain a discrete world model using optimal estimators to assign discrete cell states, such as occupied or empty.

To illustrate the previous discussion example 6.2 is used. Here the Bayesian estimation process is used to combine two sensor readings instead of previously accumulated readings with a new sensor reading.

---

**Example 6.2: Bayesian estimation in Occupancy Grid**

Two sensors estimate the occupancy of one cell. Left sensor measures \( s_l = r_1 \) and right sensor measure \( s_r = r_2 \). From the sensor model there are equal a priori probabilities.

\[ P(O) = P(\overline{O}) = 0.5 \tag{6.11} \]

Sensor one's occupancy value for the cell

\[ P(O|r_1) = 0.7 \tag{6.12a} \]

\[ P(\overline{O}|r_1) = 1 - P(O|r_1) = 1 - 0.7 = 0.3 \tag{6.12b} \]

\( \text{Max} \{0.7, 0.3\} \Rightarrow \text{occupied} \)

Odds for the values is 0.7/0.3 ≈ 2.3 : 1

Sensor two's occupancy value for the cell

\[ P(O|r_2) = 0.75 \tag{6.13a} \]

\[ P(\overline{O}|r_2) = 1 - P(O|r_2) = 1 - 0.75 = 0.25 \tag{6.13b} \]

\( \text{Max} \{0.75, 0.25\} \Rightarrow \text{occupied} \)

Odds for the values is 0.75/0.25 ≈ 3 : 1

Combining these occupancy values for the cell according to (6.7) gives

\[ P(O|r_1, r_2) = 0.7 \cdot 0.5 \cdot 0.75 = 0.26 \tag{6.14a} \]

\[ P(\overline{O}|r_1, r_2) = 0.3 \cdot 0.5 \cdot 0.25 = 0.038 \tag{6.14b} \]

\( \text{Max} \{0.26, 0.038\} \Rightarrow \text{occupied} \)

Odds for the decision are 0.26/0.038 ≈ 6.8 : 1

Which shows that when sensors give coherent occupancy values, the occupancy
6.3 Grid Adaption

probability for the cell increases when combining them. But for contradictory values the result is different.

Sensor one's occupancy value for the cell

\[
P(O|r_1) = 0.65 \quad (6.15a)
\]
\[
P(\overline{O}|r_1) = 1 - P(O|r_1) = 1 - 0.65 = 0.35 \quad (6.15b)
\]

\(\text{Max} \{0.65, 0.35\} \Rightarrow \text{occupied}\)

Odds for the values is \(0.65/0.35 \approx 1.3 : 1\)

Sensor two's occupancy value for the cell

\[
P(O|r_2) = 0.25 \quad (6.16a)
\]
\[
P(\overline{O}|r_2) = 1 - P(O|r_2) = 1 - 0.25 = 0.75 \quad (6.16b)
\]

\(\text{Max} \{0.25, 0.75\} \Rightarrow \text{not occupied}\)

Odds for the values is \(0.25/0.75 \approx 1 : 3\)

Combining these occupancy values for the cell gives

\[
P(O|r_1, r_2) = 0.65 \cdot 0.5 \cdot 0.25 = 0.081 \quad (6.17a)
\]
\[
P(\overline{O}|r_1, r_2) = 0.25 \cdot 0.5 \cdot 0.75 = 0.094 \quad (6.17b)
\]

\(\text{Max} \{0.081, 0.094\} \Rightarrow \text{not occupied}\)

Odds for the decision are \(0.081/0.094 \approx 1 : 1.2\)

Here we receive a lower probability and odds after combination, which shows correctly, that we cannot be sure about the occupancy of the cell.

6.3 Grid Adaption

To apply the grid to the specific objective of detecting pedestrians some adoptions have to be made. Since pedestrians can pass through the FOV of the sensors and thereby over the OG within very few samples there is a need to make the grid respond faster, i.e. yield a detection before the pedestrian has passed outside the OG or more importantly, before an accident occurs. Thus, the following adaption to (6.1d) has been made

\[
t_{xy}^{t+1} = L \cdot \left( \log \frac{P(O_{xy}|r_{t+1})}{1 - P(O_{xy}|r_{t+1})} + \log \frac{1 - P(O_{xy})}{P(O_{xy})} \right) + t_{xy}^{t} \quad (6.18)
\]
where \( L \) is a scalar and allows for raising and lowering of the grid level, i.e. allowing the system to respond faster or slower. It will be used as a design parameter. Assuming equal a priori probabilities

\[
P (O) = P (\overline{O}) = 0.5
\]  
(6.19)

the recursive formula is now shown by (6.20).

\[
l_{xy}^{t+1} = L \cdot (\log (P (O_{xy} | r_{t+1})) - \log (1 - P (O_{xy} | r_{t+1}))) + l_{xy}^t
\]  
(6.20)

A further measure applied is a floor for the accumulated probabilities which they cannot go below.

\[
l_{xy}^{t+1} = \begin{cases} 
    l_{xy}^t + 1 & \text{for } l_{xy}^t > 0 \\
    0 & \text{for } l_{xy}^t \leq 0
\end{cases}
\]  
(6.21)

This gives more control over the accumulated probabilities in the OG since they can decrease to a very low level when there is no object present for numerous samples in a row. A snapshot from the OG in this system is displayed in Figure 6.5.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure6.5.png}
\caption{Example from the Occupancy Grid in this system with one pedestrian in the field of view. The raising shown are the probabilities in each cell when the vehicle is driving towards it. Center of the vehicle is at coordinates (0,0).}
\end{figure}

### 6.3.1 Inverse Sensor Model

The recursive Bayesian estimation for the OG is performed as described earlier, except for one difference. Measurements have shown that the radars do detect
physical objects behind other physical objects in this system. An example of such a case is displayed in Figure 6.6, where a pedestrian is standing behind a pillar with the vehicle driving towards them. This is also the reason why the radar object

Figure 6.6. Radar objects (circles) can be viewed on the left and the actual experiment situation with a pedestrian behind a pillar, on the right.

fusion is not modeled as in Example 5.1 but rather as explained in Section 5.3 and shown in Figure 5.2.

6.3.2 Object Motion Compensation

Another reason to track the radar targets is the fact in which the OG works. Since it works under the assumption that it is a static world, the probabilities for a moving object is not traveled along with the object when it moves across the grid. This makes the probabilities to rise slower and thereby the decision on whether it is a pedestrian or not, comes later or not at all. Thus the logarithmically accumulated fused probability, (5.10) for there being a pedestrian, is allowed to
travel along with the radar object ego movement. Meaning the objects relative movement to the vehicle since the grid is later shifted with the vehicle’s movement, 6.1.

\[ p_{\beta, t+1}^{rel} = p_{\beta, t+1} \]  

(6.22a)

where

\[ \beta_{rel} = \beta - v_{veh} \cdot T \]  

(6.22b)

is the position of the radar object with only the relative movement of the object considered. An example of this is shown in Figure 6.7. Moving multiple cells around the object, instead of only the actual cell that holds the object’s position, is performed for the same reasons as for applying a fusion area explained in Section 5.3. Size of the area, i.e. number of cells, chosen in which the probabilities are to be moved will be the same as for the radar object fusion area in the mentioned section. Meaning parameters \( D_x \) and \( D_y \). This comes naturally at hand since this is the area designated to the object. Thereby, the fused probabilities from ther-

![Figure 6.7](image-url)

**Figure 6.7.** Grid adaptation by compensating for the radar object(circle) movement. Area(marked) in which the probabilities are moved is the same as the radar object fusion area.

mopiles and radars in the latest sample, will be accumulated with the previously accumulated values for the pedestrian, at the correct position. It should also be ascertained that the area moved is comparatively large to the largest shift possibly done. This allows for some discrepancy in the shifting.

Although the possibility to shift the accumulated occupancy probability in the grid cells with the movement of the pedestrian should be handled very carefully since it makes the decreasing of the probability slower, when there is no object there anymore. Also the tracking should have reached a confirmed state since the tracking is heavily relied upon here. It should also be noted that this is performed only for pedestrians. Which means, as stated in Section 2.3 an assumption is made that the pedestrian always moves with a low speed, or not at all. This would mean a maximum movement of 30 cm in one sample, corresponding to not more than three grid cells.
6.4 Positioning

To position an object on the OG by taking the highest peak of the accumulated probabilities would be the simplest approach, but this is not sufficient for this system. First of all a decision should not be made as soon as probabilities rise, i.e. a peak in the probabilities is available, since this would yield many false detections. Secondly, a situation could arise where two pedestrians exist on the OG simultaneously. Then the pedestrian with the highest probability would be the only one detected. An example is shown in Figure 6.8. Thus, the need for a threshold and a segmentation procedure arises.

![Figure 6.8](image)

**Figure 6.8.** Example from the Occupancy Grid in this system with two pedestrians in the field of view. The raisings shown are the probabilities in each cell. Notice that one peak is lower than the other and thus, only the highest peak would be detected as a pedestrian if only the highest probability would be sought after when making a decision.

6.4.1 Segmentation

To find an exact position of one or more pedestrians on the grid, there is a need to segment the accumulated probability mass on the grid to a smaller area belonging to one pedestrian and thereafter locating the exact position of the pedestrian. The segmentation procedure is started when one of the grid cells’ accumulated probability mass $t_{xy}$ reaches a level which exceeds a preset threshold at time $t$. An example is shown in Figure 6.9. When this occurs, a recursive segmentation is started to find the whole area of the pedestrian. Recursive in the sense that it calls every neighboring cell of all cells with an accumulated probability above a
threshold, not recursive over time. Algorithm 6.1 shows this procedure which is done for each cell in every sample.

**Algorithm 6.1: Recursive Segmentation**

1. If $t^t_{x,y} > \sigma_{SEED}$ and $(x,y)$ is not already segmented
2. Denote $(x,y)$ as segmented
3. Check the neighbor of this cell $(x+i,y+j)$ where $i = -1,0,1$ and $j = -1,0,1$
4. If $t^t_{x+i,y+j+j} > \sigma_{MERGE}$ and $(x+i,y+j)$ is not already segmented
5. Go to 2 if true, otherwise go to 3

Here $\sigma_{SEED}$ is the actual threshold the probabilities need to exceed, to be able to say that there is a pedestrian detected. From the cell where the detection occurred, a search is started for neighboring cells with an accumulated probability mass higher than a threshold $\sigma_{MERGE}$. Every cell has eight neighbors if it is not on the edge of the grid. To achieve a better result, the threshold is lower when trying to find neighboring cells to merge with the cell where the original detection was made. This is done because a larger area to find the center of gravity on, yields only better results. For each new cell that is found to be over this second threshold, a search is started in the same way.

**Figure 6.9.** Raised probabilities for two pedestrians in this system with a set threshold.
6.5 Discussion

If a situation appears as in Figure 6.29 there would be two initial detections and with that finally two different segments. Thereby a segment for each pedestrian is achieved and now, with this at hand, an exact positioning of the pedestrian has to be made.

6.4.2 Probability Mass Center

By weighting the cell position with the accumulated probability mass in each segmented cell, a center of the probability mass is found for the segment. The origo for these calculations will of course be the origo for the grid cells since a position on the grid is the desired result. Meanwhile, the total accumulated probability mass from all the cells in the segment, \( l_{TOT} \), is used to weight all other accumulated probabilities in the segment. Index \( M \) is a positive integer and denotes the number of cells found above the threshold belonging to the same segment.

\[
(x, y)_{PMC} = \sum_{k=1}^{M} \frac{l_k}{l_{TOT}} \cdot (x, y)_k
\]  

(6.23)

This procedure is shown in Figure 6.10 where the probability mass center is depicted with a cross as the position of the pedestrian on the grid.

6.5 Discussion

OG is an useful tool during mapping, pedestrian detection and other applications. With the moderate mathematics it incorporates it can also be said that it is not hard to apply and does not take up much computational power. Although, one assumption made in this chapter should raise discussion. To attain (6.6) on Page 46 the following is assumed,

"readings are conditionally independent given knowledge of each individual grid cell \( O_{xy} \), regardless the occupancy of neighboring cells"  

and it is shown formally in (6.6). This assumption is made for a static world but since sensor measurements include multiple grid cells, all of these have to be known for obtaining independence. It is a common assumption in OG applications and is validated by the fact that it has worked and still does. In [21], the author makes a comprehensive discussion surrounding this assumption and suggests an alternative approach where a forward sensor model is used instead of the inverse sensor model. But this approach suffers from extensive computation times due to the existing optimization problem. Therefore the shifting of the probabilities in the OG is performed. This could certainly be debated since the OG in this system works on a static world assumption. But it allows for consideration of the movement of the object in a simple and computationally low cost manner. It is very likely that an OG that considers a dynamic world would be an improvement here, but for automotive applications, with cycle times of a few milliseconds, such an approach cannot be applied.
Figure 6.10. The segmentation procedure can be seen from left to right. The accumulated probabilities (left) are segmented to an area where the probabilities are above the different thresholds (middle) and the probability mass center of the area is finally shown with a cross (right) as the position of the pedestrian.
Chapter 7

Experiments and Results

In this chapter the experiments undertaken and the results attained from the presented system are shown. A comparison is made with the previous thermopile system of which this work rests.

7.1 Introduction

For validating the results in this work, a comparison with the previous detection system, consisting of only the thermopiles, will be performed. It is also interesting how well the fusion system copes with ordinary situations that can occur during city driving. It will be shown that the fusion system of thermopiles and radars far exceed the performance of only the thermopile system. There will be less false and missed detections and the system reaction speed will be considerably faster. The remaining problems of the system will be shown to furthest possible extent with the acquired measurements and a differentiation between experiment cases with unique ambient temperatures will be done.

The tables below show how many samples it takes for the fusion system and separately for the thermopile system, to detect the pedestrian in the measurement. Values given are the number of samples and time to target counted from the sample when the pedestrian enters the grid, if nothing else is said. The distance measure will always be the distance between pedestrian and vehicle at time of detection. Except for Tables 7.6 and 7.8 the last row in the tables is an average over the given measurements.

7.2 Design parameters

The design parameters available for tuning the system have been changed and validated during this work. They have been found to mostly affect the detection speed of the system, which could also be expected. The final values for the parameters are shown in Table 7.4 and these are the ones used during the experiments below. No results will be shown for other values assigned to these parameters since
it is not found interesting for the final detection system. Rather, emphasis will be given to the detection performance of the system, but a discussion about the different parameters will be held.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Used values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_x$</td>
<td>11</td>
</tr>
<tr>
<td>$D_y$</td>
<td>11</td>
</tr>
<tr>
<td>$L$</td>
<td>8000</td>
</tr>
<tr>
<td>$\sigma_{\text{SEED}}$</td>
<td>30000</td>
</tr>
<tr>
<td>$\sigma_{\text{MERGE}}$</td>
<td>56000</td>
</tr>
</tbody>
</table>

Table 7.1. The different parameters available in this system and their values during the measurements shown in this chapter.

These parameters signify accordingly that

- the fusion area is chosen to $11 \times 11$ cells centered on the position of the radar object,
- the level of the reaction speed of the system is set to 8000,
- the detection threshold is set to 80000,
- and the threshold for merging a larger segmentation after detection is set to 56000.

$D_x$ and $D_y$ are mostly important if the radar and thermopiles outputs are not aligned. Making these values very small would mean relying heavily on the position estimation of the sensors and thereby not being able to make a detection if the outputs are misaligned. It should also be noticed that with these values, if radar targets are fused as explained in Section 5.1 the original positions of the radar targets, $\alpha_1$ and $\alpha_2$ are inside this area.

Raising or lowering $L$, $\sigma_{\text{SEED}}$ or $\sigma_{\text{MERGE}}$ only effects the speed of the detection. Raising $L$ would be the same as lowering the threshold $\sigma_{\text{SEED}}$. Maybe some false detections, like warmer objects passing through the FOV, could be avoided by lowering the reaction speed of the system. However, it would still not be a full out solution to a situation where a possible collision with a warm object occurs since the object is then in the FOV for enough time to be detected, if not classified as not being a pedestrian.

### 7.3 Pedestrian Detection

In the three first experiment situations with results detailed in Table 7.2, the pedestrian is standing still with the vehicle driving towards it and slowing down from 30km/h to a complete halt at the position of the pedestrian. The scenario is displayed in Figure 7.1. It will not be differentiated between a pedestrian standing in the middle, left or right in front of the vehicle since the results are similar for
these cases. But a differentiation will be made for the different ambient temperatures. It should be remembered here that the pedestrian enters the grid at the furthest distance possible, 7m, which allows many processing cycles.

![Image of cars and pedestrian](image)

**Figure 7.1.** Simple experiment scenario with the vehicle driving towards a standing pedestrian.

The first set of measurements in Table 7.2 are performed in an ambient temperature of 0°C and show that the fusion system needs around 9 samples to detect a pedestrian counted from when it enters the grid. The comparison with the thermopile system alone show that the fusion system is more than two times faster.

<table>
<thead>
<tr>
<th>Fusion system detect. (sample)</th>
<th>Fusion system detect. [ms]</th>
<th>Fusion system detect. [m]</th>
<th>TP system detect. (sample)</th>
<th>TP system detect. [ms]</th>
<th>TP system detect. [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>200</td>
<td>6.1</td>
<td>12</td>
<td>480</td>
<td>4.9</td>
</tr>
<tr>
<td>9</td>
<td>360</td>
<td>5.0</td>
<td>26</td>
<td>1040</td>
<td>1.1</td>
</tr>
<tr>
<td>12</td>
<td>480</td>
<td>5.0</td>
<td>23</td>
<td>920</td>
<td>3.7</td>
</tr>
<tr>
<td>9</td>
<td>347</td>
<td>5.4</td>
<td>20</td>
<td>813</td>
<td>3.2</td>
</tr>
</tbody>
</table>

**Table 7.2.** Experiment situation with the vehicle driving towards a standing pedestrian in an ambient temperature of 0°C. Comparison made between a detection system consisting of only thermopiles and the fusion system detailed in this work. The values are at detection and counted from when the pedestrian enters the grid. The last row is the average over the measurements.

Results from measurements in Table 7.2 displays a reaction speed of 8 samples for the fusion system to detect a pedestrian, which is within measurement deviations when compared to the previous measurements. Also, the comparison with the thermopile system shows that the fusion system is still two times faster. These measurements are performed in an ambient temperature of 7°C.

When also looking at Table 7.3 which show measurements that are obtained in an ambient temperature of 15°C, it is noticeable that the number of samples needed for a detection increases with the ambient temperature. Although the fusion system is still significantly faster than its predecessor.

Figure 7.2 displays an experiment situation with the pedestrian walking out behind a standing metallic vehicle and moving across the FOV of the sensors at a normal walking velocity. This, while the vehicle is driving straight towards it and slowing down from 25km/h to 5km/h when passing the pedestrian.

From the results in Table 7.3 it should be noticed that there is no decrease in performance when the pedestrian appears later, e.g. behind a vehicle, and
### Table 7.3. Experiment situation with the vehicle driving towards a standing pedestrian in an ambient temperature of \(T\) °C. Comparison made between a detection system consisting of only thermopiles and the fusion system detailed in this work. The values are at detection and counted from when the pedestrian enters the grid. The last row is the average over the measurements.

<table>
<thead>
<tr>
<th>Fusion system detect. (sample)</th>
<th>Fusion system detect. [ms]</th>
<th>Fusion system detect. [m]</th>
<th>TP system detect. (sample)</th>
<th>TP system detect. [ms]</th>
<th>TP system detect. [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>280</td>
<td>5.5</td>
<td>10</td>
<td>400</td>
<td>3.5</td>
</tr>
<tr>
<td>10</td>
<td>400</td>
<td>4.5</td>
<td>12</td>
<td>480</td>
<td>3.5</td>
</tr>
<tr>
<td>6</td>
<td>240</td>
<td>5.5</td>
<td>13</td>
<td>520</td>
<td>3.5</td>
</tr>
<tr>
<td>7</td>
<td>280</td>
<td>5.5</td>
<td>16</td>
<td>640</td>
<td>3.5</td>
</tr>
<tr>
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<td>320</td>
<td>5.5</td>
<td>17</td>
<td>680</td>
<td>3.5</td>
</tr>
<tr>
<td>6</td>
<td>240</td>
<td>5.5</td>
<td>13</td>
<td>520</td>
<td>3.5</td>
</tr>
<tr>
<td>5</td>
<td>200</td>
<td>5.5</td>
<td>23</td>
<td>920</td>
<td>2.2</td>
</tr>
<tr>
<td>11</td>
<td>440</td>
<td>4.5</td>
<td>21</td>
<td>840</td>
<td>2.2</td>
</tr>
<tr>
<td><strong>8</strong></td>
<td><strong>300</strong></td>
<td><strong>5.3</strong></td>
<td><strong>16</strong></td>
<td><strong>625</strong></td>
<td><strong>3.2</strong></td>
</tr>
</tbody>
</table>

Table 7.4. Experiment situation with the vehicle driving towards a standing pedestrian in an ambient temperature of 15°C. Comparison made between a detection system consisting of only thermopiles and the fusion system detailed in this work. The values are at detection and counted from when the pedestrian enters the grid. The last row is the average over the measurements.

<table>
<thead>
<tr>
<th>Fusion system detect. (sample)</th>
<th>Fusion system detect. [ms]</th>
<th>Fusion system detect. [m]</th>
<th>TP system detect. (sample)</th>
<th>TP system detect. [ms]</th>
<th>TP system detect. [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>680</td>
<td>3.5</td>
<td>30</td>
<td>1200</td>
<td>2.5</td>
</tr>
<tr>
<td>10</td>
<td>400</td>
<td>5.0</td>
<td>18</td>
<td>720</td>
<td>3.5</td>
</tr>
<tr>
<td>11</td>
<td>440</td>
<td>5.0</td>
<td>20</td>
<td>800</td>
<td>3.5</td>
</tr>
<tr>
<td>22</td>
<td>880</td>
<td>3.0</td>
<td>23</td>
<td>920</td>
<td>3.0</td>
</tr>
<tr>
<td><strong>15</strong></td>
<td><strong>600</strong></td>
<td><strong>4.4</strong></td>
<td><strong>23</strong></td>
<td><strong>910</strong></td>
<td><strong>3.1</strong></td>
</tr>
</tbody>
</table>
that the fusion system handles such a situation nicely. These measurements were performed in an ambient temperature of 15°C.

<table>
<thead>
<tr>
<th>Fusion system detect. (sample)</th>
<th>Fusion system detect. [ms]</th>
<th>Fusion system detect. [m]</th>
<th>TP system detect. (sample)</th>
<th>TP system detect. [ms]</th>
<th>TP system detect. [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>520</td>
<td>4.5</td>
<td>33</td>
<td>1320</td>
<td>2.0</td>
</tr>
<tr>
<td>9</td>
<td>360</td>
<td>4.0</td>
<td>20</td>
<td>800</td>
<td>3.0</td>
</tr>
<tr>
<td>20</td>
<td>800</td>
<td>4.5</td>
<td>32</td>
<td>1280</td>
<td>3.5</td>
</tr>
<tr>
<td>14</td>
<td>560</td>
<td>4.5</td>
<td>28</td>
<td>1133</td>
<td>2.8</td>
</tr>
</tbody>
</table>

Table 7.5. Experiment situation with the vehicle driving towards a pedestrian crossing the FOV after coming out behind a standing vehicle in an ambient temperature of 15°C. Comparison made between a detection system consisting of only thermopiles and the fusion system detailed in this work. The values are at detection and counted from when the pedestrian enters the grid. The last row is the average over the measurements.

Table 7.6 shows the results from one experiment situation with three pedestrians standing with a relative distance to each other. Meanwhile the vehicle is driving towards them at 20 km/h and performing evasive turns, but never coming to a complete halt until reaching the third and final pedestrian. This scenario is displayed in Figure 7.3 and during these measurements, the ambient temperature was around 0°C. Seen here is that the thermopile system has difficulties when the vehicle is doing turns. Thus, it only detects the last pedestrian which the vehicle is driving straight towards. Although, with the fusion system, there are still very satisfying results.
Figure 7.3. Experiment scenario with three standing pedestrians and the vehicle driving
towards them and performing evasive turns until coming to a complete halt in front of
the last pedestrian.

<table>
<thead>
<tr>
<th>Ped. #</th>
<th>Fusion system detect. (sample)</th>
<th>Fusion system detect. [ms]</th>
<th>Fusion system detect. [m]</th>
<th>TP system detect. (sample)</th>
<th>TP system detect. [ms]</th>
<th>TP system detect. [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>14</td>
<td>560</td>
<td>4.9</td>
<td>MISSED</td>
<td>MISSED</td>
<td>MISSED</td>
</tr>
<tr>
<td>2</td>
<td>16</td>
<td>640</td>
<td>4.5</td>
<td>MISSED</td>
<td>MISSED</td>
<td>MISSED</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>400</td>
<td>5.2</td>
<td>28</td>
<td>1120</td>
<td>3.8</td>
</tr>
</tbody>
</table>

Table 7.6. Experiment situation with the vehicle driving towards three standing pedes-
trians and performing evasive turns in an ambient temperature of 0°C. The results are
from one measurement displayed in Figure 7.3. Comparison made between a detection
system consisting of only thermopiles and the fusion system detailed in this work. The
values are at detection and counted from when the pedestrian enters the grid.

7.3.1 Limitation

There is a limitation with this system that should be noted. When two pedestrians
are standing within a distance of one meter from each other, they will not be
detected as two different pedestrians, but rather appear as one pedestrian with
a position in between the two. This is because of the parameters chosen for the
fusion model explained in Section 5.3.1 When the two different radar objects are
fused with overlapping fusion areas, these two areas will rise above the threshold
merged as one area. Displayed in Figure 7.4 are the probabilities from a scenario
when the vehicle is driving towards two pedestrians standing still with a mutual
distance of less than one meter, see Figure 7.4.

Figure 7.4. Experiment scenario with two pedestrians standing at a short mutual dis-
tance and the vehicle driving towards them.

With this, the question arises of the necessity for a pedestrian detection system
to differentiate between one or multiple pedestrians when these are standing at
a short mutual distance. During the design of this system it was not considered
necessary since the actual detection already has been attained.
7.3.2 Robustness

During numerous measurements, some faults occurred with the radars. Or rather, the radars detected the pedestrian very late, i.e. when the pedestrian already had entered the grid. A few of these measurements are displayed in Table C.7 for the purpose of showing that a late radar detection can still, very fast, result in a proper detection. It is also shown at what distance from the vehicle the late detection occurs. The values over time are counted from when the radar detection occurs and the pedestrian’s distance to the vehicle when detection by the thermopile system occurs is also shown. Of course, this value is not influenced by the late radar detection.

These measurements show that the system can make a decision on a pedestrian within very few samples if necessary.

There were also faulty measurements obtained where the thermopiles attained a faulty ambient temperature reading. This will cause the output of the signal processing algorithms of the thermopiles to yield a false output. During most of these measurements, the fusion system still made a detection at a satisfying distance while the thermopile system had missed detections.

7.4 Urban Area Driving

To test the system in more real life scenarios, longer measurements were undertaken in urban areas with heavy traffic. The main purpose of which was to yield a measure for the false detection rate of the system. Results are given in Table C.8.
Table 7.7. Different measurements with a late radar detection, here also shown at what distance from the vehicle it occurs. The values over time are at detection and counted from when the radar detection occurs. Also the pedestrian’s distance to the vehicle when detection by the thermopile system occurs is shown. The last row is the average over the measurements.

<table>
<thead>
<tr>
<th>Radar detect. [m]</th>
<th>Fusion system detect. (sample)</th>
<th>Fusion system detect. [ms]</th>
<th>Fusion system detect. [m]</th>
<th>TP system detect. [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.0</td>
<td>5</td>
<td>200</td>
<td>3.0</td>
<td>1.5</td>
</tr>
<tr>
<td>4.5</td>
<td>3</td>
<td>120</td>
<td>4.0</td>
<td>3.5</td>
</tr>
<tr>
<td>5.0</td>
<td>5</td>
<td>200</td>
<td>4.2</td>
<td>3.0</td>
</tr>
<tr>
<td>4.5</td>
<td>4</td>
<td>173</td>
<td>3.7</td>
<td>2.7</td>
</tr>
</tbody>
</table>

Table 7.8. Experiment situation with the vehicle driving around in an urban area with an ambient temperature of 20°C. Comparison made between a detection system consisting of only thermopiles and the fusion system detailed in this work.

<table>
<thead>
<tr>
<th>Experiment length (sample)</th>
<th>Experiment length (time)</th>
<th>Fusion system detect. (#false)</th>
<th>Fusion system detect. (#missed)</th>
<th>TP system detect. (#false)</th>
<th>TP system detect. (#missed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>16183</td>
<td>10min 48s</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Here it is seen that the fusion system is more likely to give false detections while the thermopile system also yields missed detections. This since the thermopile system is designed to react slower to not yield so many false detections, which otherwise occurred repeatedly. Meanwhile the fusion system is designed for a more dynamic world, meaning fast detections if necessary. It should also be noted that the false detections from the fusion system are because the amplitudes do not give a full out classification. The amplitude of a metallic object does not always exceed the amplitude limit derived in Section 2.4.2 and thus, cannot be differentiated from a pedestrian when the metallic object has a heated surface.

7.5 Miscellaneous

Since this system is designed for the purpose of pedestrian detection, it should be interesting to see how it reacts to animals or bicyclists. There has only been one measurement done of each and the scenarios are displayed in Figure 7.10. For these two situations there were no detections made. This could be because of two factors. Either the area of the object facing the thermopiles is too small or the object has a position too high or too low, relative to the sensors.
Figure 7.6. Dog in the FOV(left) and bicyclist in the FOV(right).
Chapter 8

Concluding Remarks

Conclusions regarding what this system is capable of are drawn in this chapter with the inherent strengths and weaknesses. The chapter concludes with some recommendations regarding the direction for future research.

8.1 Conclusion

The results presented in this work are not enough to make any far reaching conclusions even though it should be remembered that the results are from authentic measurements as opposed to simulations. It also proves that there is a need for further testing of this system to validate the results provided.

The system presented can be said to always detect objects when the object is in the field of view of the sensors and approaching the vehicle. While a full out classification whether or not it is a pedestrian is possible when the ambient temperature allows for a difference in thermal radiation between the pedestrian and the background. However, when the ambient temperature is too similar to the temperature range of a pedestrian, meaning $30 - 45^\circ C$, it is physically impossible to detect pedestrians.

The false detections typically occurs when hot organic objects, like large stones or trees passes through the field of view. These objects usually have a lower reflectivity and can therefore not be distinguished from pedestrians when they are also heated up by the sun. Meanwhile, hot vehicles can be distinguished from pedestrians when not entering the field of views late, i.e. close to the vehicle. Since they have a higher reflectivity because of their metal surface and thus, can also be detected at a longer distance than pedestrians.

It should be noted that when a misalignment of the radars and thermopiles position estimate remain throughout the pedestrian movement across the grid, there will be no detection. This is a property that was desired during the design of the system since the sensors should agree that there is an object present and at what position. However, in turn it gives this limitation.

The radars have yet to miss detecting an object, even if some detections can appear very late. Although, it does provide some false detections that have to be
handled when including radars in a sensor fusion system.

Thermopiles will always have the restriction of only being able to detect pedestrians when there is a thermal radiation contrast between the pedestrian and the background. Which means that in an ambient temperature range of a pedestrian's temperature, thermopiles are rendered useless. This makes the thermopiles not being able to give an overall solution to the detection problem. A solution to this problem could of course be to replace it with another sensor for this temperature range. Although, it should also be considered how often the actual temperature range comes in to question. For the price of which the thermopiles are available and with the performance it yields after some signal processing, it is the authors view that they are definitely worth further research.

8.2 Further Work

According to the author sensor fusion seems to be the only systematic way of dealing with the problem of detecting pedestrians. It yields a more complete view of the vehicle surroundings than is possible with any single sensor available on the market today.

A laser-scanner would probably yield better results since it is a more accurate sensor with less false detections. There is also the possibility to more extensively classify the objects, compared to what has been shown possible using radars. This would maybe give the possibility to differentiate between pedestrians and other organic material.

Sensor fusion between thermopiles and ordinary cameras could also be a thought-worthy option. Maybe a full out detection and classification could be reached at least for environmental conditions without high clutter, like snow or rain.
Bibliography


Appendix A

Bayes’ Theorem

The purpose of this appendix is to simplify for the reader not aquainted with the Occupancy Grid and how the equations are derived. Thus, the notations used in Section 6.2.4 will also be used here.

Bayes’ theorem for multiple events is

\[ P(O_{xy}, r_t|r_{t+1}) = P(O_{xy}|r_t,r_{t+1}) \cdot P(r_t|r_{t+1}) \quad (A.1) \]

and since events are associative

\[ P(r_t, O_{xy}|r_{t+1}) = P(r_t|O_{xy},r_{t+1}) \cdot P(O_{xy}|r_{t+1}) \quad (A.2) \]

putting \((A.1)\) and \((A.2)\) equal gives

\[ P(O_{xy}|r_t,r_{t+1}) = \frac{P(r_{t+1}|r_t,O_{xy}) \cdot P(O_{xy}|r_t)}{P(r_{t+1}|r_t)} \quad (A.3) \]

which is Bayes’ theorem for multiple events in the desired form.
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