Fuzzy Operators for Confidence Modelling in Automotive Safety Applications

Ullrich Scheunert, Philipp Lindner, Eric Richter, Gerd Wanielik

Chemnitz University of Technology
09107 Chemnitz,
Germany
ullrich.scheunert@etit.tu-chemnitz.de;
philipp.lindner@etit.tu-chemnitz.de
eric.richter@etit.tu-chemnitz.de
gerd.wanielik@etit.tu-chemnitz.de

Abstract: The fusion of data from different sensorial sources is the most promising method to increase robustness and reliability of environmental perception today. The paper presents an approach for using fuzzy operators for the hierarchical fusion of processing results in a multi sensor data processing system for the detection of vehicles in road environments. Tracking and fusion of intermediate results are performed in several levels of processing (signal level, several feature levels, object level). To produce higher level hypotheses on the basis of lower level components, grouping rules using certain assignment decisions are used. One example is given for the fusion of image and radar data in a vehicle detection algorithm used in a driver assistance system.

1 Introduction

The use of confidence measures is motivated by the need of scientists and engineers to be able to evaluate and assess their degree of belief or trust in preliminary and final processing results.

Confidence measures can be seen in general as measures about the suitability of a measurement according to a certain type of previous knowledge: Therefore confidence can be only obtained by at first assigning the measurement to a previous knowledge proposition or a data model. Evidence for or against the related data model can be obtained by comparing the model with the measurement data assigned to it. Evidence in combination with an evaluation of the quality of correspondence between the data and the model represent the confidence. To obtain confidence values for the given data one can use mapping functions to model the relation between this particular information and its amount of evidence assigned to it.

The derivation of a hierarchical classification system is based on the experiences with a normal one step multidimensional membership function of the Potential function type and the analysis of the tree properties of an according hierarchical system is described in section 2. This leads to a modification of the membership function as well as to a modified accumulation operator for the sub-classification results that is derived from the commonly known Hamacher operator [2]. Section 3 shows the results of a hierarchical classification system which is successfully used in a vehicle detection application.

2 Membership function and fusion operator

Fuzzy membership functions are one possible way to model the relation between features and the evidence/confidence value assigned to it. In our case the potential function type was chosen in combination with a suitable fuzzy operator to meet the requirements for its use in a multi level fusion procedure [10].

As starting point of the investigations the definition of a one-dimensional Potential function is taken. The parameters of the functions define the position m, the width c and the sharpness d (see [1], [3]).

$$\mu^A = \frac{1}{1+\left(\frac{|m_A - x_A|}{c_A}\right)^{d_A}}$$

$$\mu^B = \frac{1}{1+\left(\frac{|m_B - x_B|}{c_B}\right)^{d_B}}$$

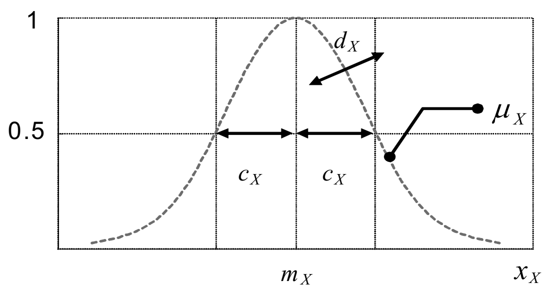

Figure 1: Potential function (one dimensional)

With x as a certain feature of the object of interest a membership value μ can be associated to it. The value of μ defines the degree of evidence which points toward x being affiliated with a particular assumption. With the words of classification problems this relation can be expressed as μ describing the membership value for a feature x belonging to a certain class of a classifier. To combine different membership values or evidence logical operators can be used. These can be operators e.g. of disjunctive or conjunctive type. In particular the **Weighted Modified Hamacher Operator (WMHO)** and a **weighting factor** [3] are introduced in our approach [10]. Using this operator multiple membership values can be fused to yield the overall membership value or evidence pointing towards a higher level assumption.

$$[a, w_a]\,\mathrm{k}^{\cap}_{HG\kappa}\,[b, w_b] = \tag{1}$$

$$\left[\frac{1}{\frac{1}{(1-\kappa)+\kappa\,(w_a + w_b)}\left(\frac{(1-\kappa)+\kappa\, w_a}{a} + \frac{(1-\kappa)+\kappa\, w_b}{b} - (1-\kappa)\right)}, (w_a + w_b)\right]$$

3 Example

To detect the object of interest – vehicles – information of radar and image sensors are used and combined to yield a more reliable detection result. First the radar data – detections with information about strength, range and angle of the signal – is transformed to the vehicle coordinate system. Doing this the information can be projected to the image space of the camera. With this data we get a region of interest in the greyscale image to which all image processing steps are applied to (see bright rectangle in Figure 2).

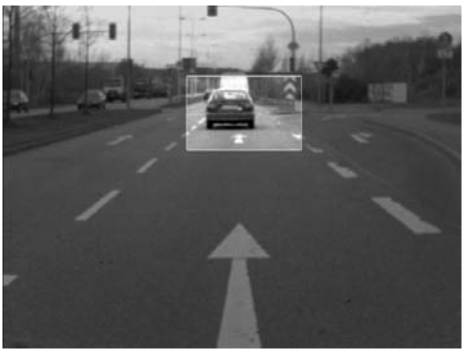

Figure 2: Region of interest created by analyzing data of a long range radar sensor

Figure 3: Example for the result of a Hough transform after LOC processing to extract line features (yellow lines thickened for visibility reasons)

The radar based region of interest in the image is processed with a local orientation coding (LOC) operator to find distinctive image features like edges and line like structures. The Hough Transform is used afterwards to detect horizontal structures in the data created by the LOC operator.

An accumulation of horizontal lines in the radar based image ROI is treated as strong evidence for the existence of an object with the features of interest - a vehicle. The horizontal structures are now combined to create a refined region of interest and an object hypothesis. This is in addition to the radar data which can support the image processing with coarse x-y information only due to the physical limitations of this kind of sensors. To continue the approach to treat the detections (horizontal line) as evidence for the object of interest we are combining the single lines to higher order primitives, e.g. to the bounding rectangle of the combined horizontal lines. The aim is to identify the vehicles back whose extent is described by the bounding rectangle. This area is here represented and supported by stacked horizontal line features.

To find this higher order structures a hierarchical detection and classification procedure using potential functions and the weighted modified Hamacher operator are used. The step for finding first appropriate horizontal line segments and then assigning additional segments to the first horizontal one is shown in Figure 4. To evaluate the line segments and the higher order structures for the detection the potential functions in Figure 5 are created. The parameters *position*, *width* and *sharpness* of these functions have been chosen by evaluating the distribution of the image features of interest in a set of test images.

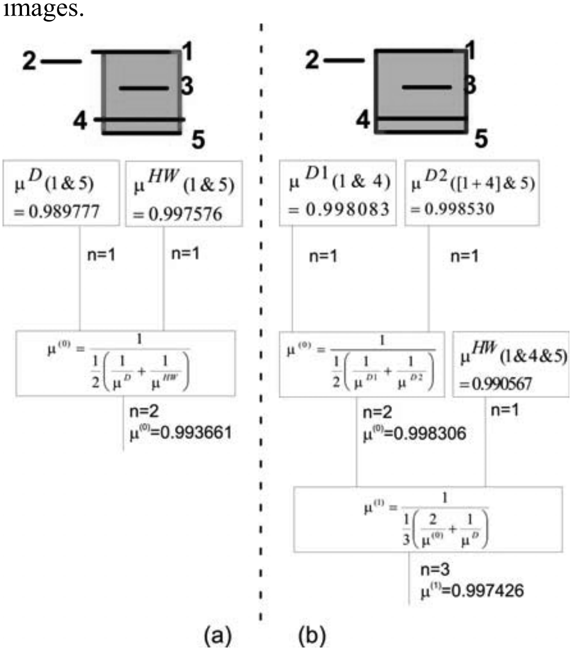

Figure 4: Classification and confidence measures for object recognition example with the modified hamacher operator to calculate $\mu^{(0)}$ and $\mu^{(1)}$; for line numbers see also Figure 3

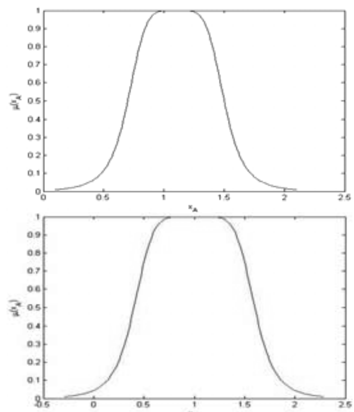

Figure 5: Potential function for the classification of the line segments in the example

The combination of multiple line segments is evaluated by assigning a membership-value μ^{D} to it which expresses the assignment to the class "good matching (overlapping) horizontal lines" in terms of the overlapping of multiple lines (in relation to the line widths, see Figure 4: e.g. line 2 does not overlap with line 1; line 1 and 5 do overlap to almost 100%). This is done for each line combination in the image. The particular feature was chosen because all horizontal lines at the vehicles back are in the best case overlapping to nearly 100%. By assigning membership values the quality of the overlapping can be expressed. The second feature which is evaluated is the bounding rectangle of the combined line sets. A certain height/width ratio is treated as strong evidence for the object hypothesis *vehicle* (see Figure 5 (top), membership value μ^{HW}).

The combination of the lines and their assigned membership value is done by the weighted modified Hamacher operator. This results in a combined membership value, e.g. $\mu^{(0)}$ in Figure 4(a). The membership value $\mu^{(1)}$ in Figure 4(b) is the final result for the combination of the lines 1&4&5. The bounding box (blue) of these lines is chosen to be the candidate with the most confidence in the hypothesis *vehicle* since the evidence pointing towards it with $\mu^{(1)}$ = 0.997426 and the weight n=3 is the highest compared to other combinations e.g. like the one in Figure 4(a). (The weight n of the membership value is a value to express the number of sub-classifications).

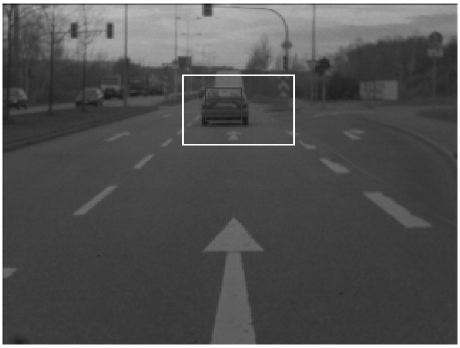

Figure 6: Radar ROI (white) and the final result → the refined image-feature based ROI (blue)

Additional line segments (like line 2 or 3) have been automatically skipped because their classification results and the combined membership values did not perform very well and fell below a threshold.

The resulting rectangle (Figure 4(b)) as a higher level structure is now used to refine the position of the vehicle hypotheses. Since the radar can only provide coarse position information – especially in the horizontal direction – the evaluation of image based features has significantly improved the detection results (see Figure 6).

4 Conclusions

The fusion of radar and image data and the incorporated use of confidence measures proved to lead to very promising and improved detection results. By evaluating the confidence values it was possible to rate the final and intermediate detection results. Using this information a backloop could be induced to retune the classification procedure. This will be part of the future work in combination with the introduction of additional features and the extended fusion on multiple levels.

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