Handling Uncertainty in Context-Aware Driver Assistance Systems

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Abstract— **In this paper we discuss types of imprecision that are important for a tactical driver assistance system during its reasoning process. Methods for handling imprecision are presented using a previously developed overtake assistant as a showcase. The ideas for handling imprecision are demonstrated using several examples, together with the application of different approaches for different types of uncertainty. All presented solutions rely on simple efficient mathematical models, allowing for easy integration into the reasoning process without performance loss, while still yielding natural and useful quality assessments for sensed traffic information.**

I. Introduction

With the ongoing progress for onboard-sensing systems, more information about the driving environment is available to the vehicle. As a result the tasks handled by driver assistance systems (DAS) are getting more complex. DAS have emerged from the purely operational control level to the tactical level, where short-term driving decisions are made. Despite the technological progress of sensing systems, the gathered environment information will never be fully certain. This is the case with any system that represents information about the real world. While traditional DAS, like the anti-lock brake system (ABS), are less concerned with this problem, imperfect environment information is a major concern of tomorrow's systems. Their whole reasoning process for deriving a recommendation depends on the quality of the available information. In this paper we will discuss different types of imperfection and methods for handling them within the context of DAS. We use an overtaking support system as showcase, which has already been presented in [1]. We will demonstrate how non-complex mathematical methods can be used to derive quality measures for the objects involved in a tactical reasoning process.

Since overtaking is one especially difficult driving maneuver, it is a good candidate for driver assistance. Restrictions on the overtaking process can be represented as a series of speed/distance constraints that have to hold for a positive recommendation. Restrictions are concerned with the presence/absence of oncoming traffic, speed limits etc. The reasoning process depends on the quality of the available context information. Eventual doubt about the available information must be considered. The major types of imperfect information in a DAS are *uncertainty*, *ignorance* and *inaccuracy*. Depending on the type of imprecision, different methods are available for dealing with it. In the context of intelligent DAS we will show how a probabilistic approach can be used for dealing with uncertainty, while ignorance is best handled with evidence theory. For inaccuracy, we will investigate the tolerable degree. Small errors in distance/speed measurements are negligible for calculation of overtaking time-spans. However, larger errors can change the final overtaking recommendation and must be considered. Finally, we are going to discuss a simple consolidation approach for obtaining an overall quality value for every constraint. This value can be communicated to the driver. Conclusively, imperfect object information can be easily handled by a DAS in order to assess the quality and usefulness of a derived driving recommendation.

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II. Related Work

The authors of [2] present a fuzzy-logic based virtual rumble strip that should replace the need for static rumble strips. The alarm threshold is implemented with a time-to-lane-crossing approach. A combination of qualitative relative lateral vehicle-position values and the square of the current speed (as a measure for the lateral kinetic energy) serve as input for a fuzzy-logic rule base. The rule base determines the necessary adjustment for the pre-defined alarm threshold. The output is a qualitative value for threshold adjustment.

The authors of [3] present an approach for a fuzzy-logic control component that helps automating an operational overtaking maneuver for autonomous vehicles. The system uses fuzzy controllers for mimicking human behavior and reactions while steering through an overtaking maneuver.

A general framework design for intelligent DAS based on Dynamic Bayesian Networks is discussed in [4]. In this approach, a driver's affective state is inferred from a variety of input variables like eye movement, gaze, facial expression etc. Variables are determined by different sensing systems. The user states are the possible hypotheses that are tested for fulfillment. The decision when to provide assistance is then determined by weighing all affective state probabilities and comparing the result to a preset threshold.

All those projects focus on the operational control of the vehicle or on prediction of the driver behavior. In contrast, our paper discusses imprecision of the sensed environment information. We use efficient mathematical approaches in the reasoning process in order to improve and exploit the quality measure assigned to a sensed traffic object. We concentrate on short-term driving decisions on a tactical level.

III. UNCERTAINTY

Uncertainty is one major kind of imperfection that is going to be encountered in a DAS. The available information about a traffic object, which has been gathered by an on-board sensing system, may be wrong. For example, the camera of an overtaking assistant might recognize a speed limit sign of 100 km/h. This could probably prevent a positive overtaking recommendation. Within the spatial context of a highway, this sign is a rather likely event and therefore can be assigned a high probability. In a city the probability of a speed limit this high will be much lower.

According to [5] we can distinguish between *objective* and *subjective uncertainty*. Theoretically, the number of all 100 km/h speed limits on highways and elsewhere could be counted. The probability can then directly be determined from the result. This would fall under the category of objective uncertainty. We can also have additional information about the quality and reliability of the sensing system. The information can be gathered from test runs, where for example the success rate of the classification algorithm is measured. We may know that the classification algorithm is right in 90 out of 100 cases. Therefore we can assign our sensed speed limit object a probability of 90%. This belief in the agent, in our case the camera, is subjective uncertainty. The same is true for basically all information gathered by a DAS. On one side, uncertainty can be the unlikeliness of an event within a given context. On the other side, the reliability of a source can influence the certainty assigned to a piece of knowledge about a fact. Knowledge about the error rate of a certain source can be exploited to adjust the probability assigned to a given information.

When the same object is sensed by different sources, their single probability measures can be combined. This idea differs from the area of multi-sensor data fusion. There, a hypothesis for a certain traffic object is derived from combining information from different sensors and no sensor is able to provide the necessary information alone.

We can now exploit conditional probability in the reasoning process. We combine the known success rate of a sensing system with a reliability value about the system. The success rate $P(A)$ of a sensing system is a quality measure for the image processing algorithm. For the example, let us assume $P(A) = 0.95$. The reliability $P(B)$ indicates the probability of a system failure. It is self-evident that the success rate depends on the system to work correctly. If the system delivers e.g. a blurred image, the success rate for recognizing the correct traffic sign will drop. A simple example will demonstrate this. Suppose that there are two different and independent sensing systems for speed limit sign recognition:

- System X: success rate 95%, reliability 98%
- System Y: success rate 95%, reliability 80%

Both have the same success rate, but system Y has a lower reliability. We can now calculate the conditional probability for the speed limit sign to be recognized, provided that the sensing system works correctly, as $P(A|B)$ using Bayes' theorem. For this, we first have to determine the conditional probability $P(B|A)$ for the system to work correctly, provided that the traffic sign has been recognized. By definition this is

$$P(B|A) = \frac{P(B \wedge A)}{P(A)}$$

As a general consideration, the probability $P(B \wedge A)$ for both events to occur is lower than the probability for each event occurring alone in any case. So, we can roughly estimate $P(B \wedge A)$:

- System X: $P(B \wedge A)$ = 0.89, so $P(B|A)$ = 0.95
- System Y: $P(B \wedge A)$ = 0.7, so $P(B|A)$ = 0.74

Afterwards the conditional probability $P(A|B)$ is obtained for each system using Bayes' theorem:

- System X: $P(A|B)$ = 0.91 = 91%
- System Y: $P(A|B)$ = 0.879 $\approx$ 88%

The example demonstrates the influence of the lower reliability of system Y on the overall quality measure of the detected traffic sign. Both systems have the same success rate. Since system Y can be expected to fail more often, its conditional probability $P(A|B)$ is lower. Both the success rate and the reliability value are usually available for onboard-sensing systems, so why not use them to adjust the actual quality of the given information? It can be done without complicated reasoning methods; a Bayesian approach already gives valuable additional information.

We can also exploit statistical context information as a probability measure for a traffic sign. The most common speed limit signs are: $\{10, 30, 50, 60, 70, 80, 100, 110\}$. The unconditional probability for the sign s_1 being a 100 km/h sign is therefore $\frac{1}{8}$ = 0.125. The unconditional probability for being on a highway h when driving on a street in Carinthia is $\frac{242\ 504}{8\ 523\ 644}$ = 0.0285 (figures from [6], traffic densities are not considered). The probability that both conditions are true - being on a highway and sensing a 100 km/h speed limit - must be even lower. Let us assume it to be $P(h \wedge s_1) = 0.025$. Then, the conditional probability $P(h|s_1)$ for being on a highway, given that a 100 km/h speed limit has occurred, is

$$P(h|s_1) = \frac{P(h \wedge s_1)}{P(s_1)} = 0.2$$

Now the more interesting case, the conditional probability $P(s_1|h)$ of a 100 km/h speed limit, given that we are on a highway, can be calculated:

$$P(s_1|h) = \frac{P(h|s_1) \cdot P(s_1)}{P(h)} = 0.8772 \approx 88\%$$

Statistical measures about the road network structure are easily obtainable from governmental institutions. However, there are no central public sources about traffic objects and their geographical location yet. While it is self-evident that most 100 km/h speed limit signs are on a highway (and some are on semi-motorways), determination of the conditional probability of both h and s_1 is difficult. Using subjective probabilities when considering context information is a much simpler approach. As just said, we know that the probability for a 100 km/h speed limit sign being on a highway is high. Instead of using statistical measures (which we usually do not have), we can assign a subjective probability of 90% to $P(s_1|h)$ (exploiting our human expertise knowledge about driving) and use it for backing up the probability of the traffic sign, together with the 95% success rate $P(A)$ of the sensing system:

$$P(s_1) = 1 - (\overline{A} \cdot \overline{P(s_1|h)}) = 0.995 = 99.5\%$$

Thus, the generally known information about 100 km/h speed limit signs on highways can be used to improve the quality of the traffic object information. Statistical measurements about road signs and street networks are not needed. This information becomes even more important when the subject vehicle is currently on a rural road or city. In this case, the converse probability $\overline{P(s_1|h)}$ is 1 and the adjustment does not back up the original quality measure of the sensing system at all. If such a conflict occurs, the probability adjustment alone is insufficient. The spatial context rules out the statement of the sensing system. We can assume that the measure falls within the 5% error rate of the camera. Therefore, the quality assigned to the traffic sign must be degraded.

The considerations made can be applied to all sensed traffic objects from the DAS environment. The overall quality measure assigned to the object is adjusted according to the available information and then considered during the reasoning process, as will be demonstrated in section VI.

IV. Ignorance

Ignorance in a DAS means that there are objects in the driving environment, which cannot be sensed exactly or are just not known. Using again the example with speed limit signs, a sensing system can be sure that the detected sign is a speed limit, but it may not be able to tell if the allowed speed is 70, 100 or 110 km/h. This form of ignorance is hard to represent with Bayesian probability, which requires hypotheses to be atomic. Also, with Bayesian reasoning the condition holds that in case of low support of a hypothesis, support of the hypothesis' converse is automatically high. This is not necessarily true in reality. More often, it will happen that a system just knows nothing about the opposite of a given hypothesis. Evidence theory [7] provides a general model for handling ignorance, which overcomes problems of the Bayesian approach.

A basic belief mass m is assigned to a proposition A, which is either a single element or a set of elements from a given frame of discernment Ω. The possibility of assigning belief masses to sets of elements allows for representation of ignorance. We can be quite sure that a sign will be either a 70 km/h or a 100 km/h limit. Besides, we don't have further information. Low support for a proposition is a non-commitment to the remaining propositions of Ω. We may be sure that the speed limit sign is unlikely to be 70 km/h, but beside that information it can be everything from Ω. Instead of supporting the converse hypothesis, remaining belief is assigned to Ω. Two values are important in evidence theory: *belief* and *plausibility*. Belief $Bel(A)$ gives a measure of the extend to which a proposition is definitely supported by all assigned belief masses m. However, the remaining evidence must not necessarily disprove the proposition. Plausibility $Pl(A)$ of a proposition indicates the extend to which the given evidence fails to refute a proposition. Both measures together provide a credibility interval for a hypothesis, with $[1, 1]$ representing absolute certainty for a proposition and $[0, 1]$ representing total ignorance. Belief assignments from two different independent sensing systems m_1 and m_2 can be combined using Dempster's rule of combination:

$$(m_1 \oplus m_2)(C) = \frac{\sum_{A \cap B = C} m_1(A) \cdot m_2(B)}{1 - \sum_{A \cap B = \varnothing} m_1(A) \cdot m_2(B)}$$

C is the new resulting proposition. To continue our example, assume that sensing system X gives the following belief measures:

- $m_X(\{70, 100\}) = 0.95$
- $m_X(110) = 0.05$

This means, X is sure that the sign is either a 70 or 100 km/h limit, but it does not completely rule out the possibility of the sign being a 110 km/h limit. Sensing system Y gives the belief measures

- $m_Y(\{100, 110\}) = 0.8$
- $m_Y(\Omega) = 0.2$

System Y is quite sure that the sign is a 100 or 110 km/h limit and does not give any further belief information. The remaining 0.2 are assigned to Ω. The two belief measurements m_X and m_Y are now combined using Dempster's rule of combination:

- $m_{\text{X,Y}}(100) = 0.76$
- $m_{\text{X,Y}}(\{70, 100\}) = 0.19$
- $m_{\text{X,Y}}(110) = 0.05$

Further calculation of belief and plausibility then gives the credibility interval for each proposition:

- $\{100\} : [0.76, 0.95]$
- $\{70, 100\} : [0.95, 0.95]$
- $\{110\} : [0.05, 0.05]$

It can be concluded that the support for our sign being a 100 km/h speed limit is high. So it was likely recognized correctly. Even if no system made a sure statement, we can easily obtain a belief measure for the sign with evidence theory, thus handling the sensing systems' ignorance. Belief measures are subjective values and should not be confused with a probability measure, which typically has some statistical basis (with the exception of subjective probability). In case of a DAS, it is likely that we have to make a decision based on the given credibility intervals. For this, there are methods for transforming belief and plausibility to probability values. Examples are the generalized insufficient reason principle or interpretation of belief and plausibility as lower/upper bound of a probability interval [7]. Belief can also be further conditioned on the given context information

[8]. Let us assume for simplicity that we have the additional information that the vehicle is on a highway and that a 70 km/h speed limit does not occur on a highway for sure. From the new evidence E we can conclude that the sign must be either 100 or 110, so $E = \{100, 110\}$. One method to revise the given belief with the new evidence is to keep all data that *possibly* agrees with the sure evidence E and make the existing data consistent with it. This would mean to take the 70 km/h speed limit out of the second proposition $m(\{70, 100\})$, but to keep the 100 km/h limit. The resulting new proposition $m(100)$ is then consistent with E. A new mass distribution is obtained with [8]

$$m_E(A) = \begin{cases} \frac{\sum\limits_{E \cap C = A} m(C)}{1 - \sum\limits_{C \cap E = \varnothing} m(C)}, & \text{if } A \subseteq E \\ 0, & \text{otherwise} \end{cases}$$

The revised mass distribution for our example is then accordingly

- $m_E(100) = 0.95$
- $m_E(110) = 0.05$

With changing belief assignments we also have to revise the belief and plausibility measures.

$$Bel_{mE}(A) = \frac{Bel_m(A \cup \overline{E}) - Bel_m(\overline{E})}{1 - Bel_m(\overline{E})}$$

$$Pl_{mE}(A) = \frac{Pl_m(A \cap E)}{Pl_m(E)}$$

The new credibility intervals are then

- $\{100\} : [0.95, 0.95]$
- $\{110\} : [0.05, 0.05]$

During revision, the belief in the hypothesis for the 100 km/h sign increases and the credibility interval narrows down. The small chance for the 110 km/h sign remains. Again, this method provides a quality measure for a traffic object without negative influence on the reasoning performance.

V. Inaccuracy

The overtake support system presented in [1] uses numerical values for speed and distance measurements. Inaccuracies are likely to occur while sensing those. However, it can be easily demonstrated that small measurement errors are negligible and do not make a difference for the overall recommendation.

Assume that we have an onboard-sensing system which has a 5% error for distance and speed measurement. We can calculate the necessary time needed to complete an overtaking maneuver from given speed/distance values of the subject and the front vehicle, as well as the desired overtaking speed. For the exact algorithms we refer the reader to [1]. As an example, assume an overtake time of 7.5044 seconds for a distance of 68.61 meters, with the front vehicle's speed $v_f = 67$ km/h, the current speed of the subject vehicle $v_0 =$ 96 km/h and a desired overtaking speed $v_1 = 100$ km/h. A 5% measurement error for the given distance value results in a disturbance of ± 3 m. Recalculation of the overtake times for 65 resp. 71 m gives a time interval of [7.11, 7.765]. Either way, the time difference resulting from the error is less than half a second. Inaccuracies also have to be considered for the distance measurement to an eventual oncoming vehicle. With an oncoming speed of 73 km/h and a distance of 367 m, the original time until the meeting point is 7.641 sec. A 5% error gives a disturbance of ± 18 m. The recalculated overtaking times give the time interval [7.266, 8.015]. Again the deviation is less than half a second. Even the best case error, -5% deviation for the overtake time and +5% deviation for the oncoming time, would still not change the correct negative overtake recommendation, so the error can be neglected.

With a 10% error, the situation is already different. 10% means ± 7 m deviation for the overtake distance and ± 37 m deviation for the oncoming distance. Recalculation then gives an overtake time interval of [6.67, 8.3] seconds and an oncoming time interval of [6.87, 8.41] seconds. The best case scenario now leads to a change in the final decision and gives a positive high-risk overtake recommendation, instead of the correct negative one. Therefore, a 10% error is non-negligible. A safe way of handling measurement errors $>$ 5% is to take the longest overtaking time and the shortest oncoming time (worst case) and relate these two to each other in the reasoning process. It can possibly happen that a negative overtake decision for the worst case would be a positive recommendation for the best case (shortest overtake time and longest oncoming time). However, since a false positive is more dangerous with regard to overtaking than a false negative, the safer way must be preferred for larger measurement errors.

For speed measurements a 5% error in the given example results in a speed difference of ± 0.93 m/s (approx. 3 km/h) for the front vehicle and thus in an overtake time interval of [6.67, 8.42]. This already gives a deviation of $>$ 0.5 seconds, but is still less than one second. By contrast, a 5% measurement error in the speed of the oncoming vehicle results in a difference of ± 1.014 m/s and in an oncoming time interval of [7.48, 7.8], which is a much smaller deviation from the correct value.

Speed measurement errors for the front vehicle speed v_f have more influence on the success of the overtaking maneuver than speed deviations of the oncoming vehicle, because of the relative movement of the vehicles to each other. Fig. 1 depicts this graphically. The solid line represents the own vehicle's path, the dashed line the front vehicle's path and the dotted line the oncoming vehicle's path. It can be immediately seen in the figure that a negative speed deviation decreases the overtaking time by a larger extend than it does for the oncoming time. The same is true for a positive speed deviation - the relative speed between the own and front vehicle is decreased, which in turn slows down the overtaking process. For the oncoming vehicle, the influence of the speed deviation on the meeting time is much smaller. However, the front vehicle is usually nearer to the own vehicle's sensing system, which increases the measurement accuracy. For the larger distances to oncoming

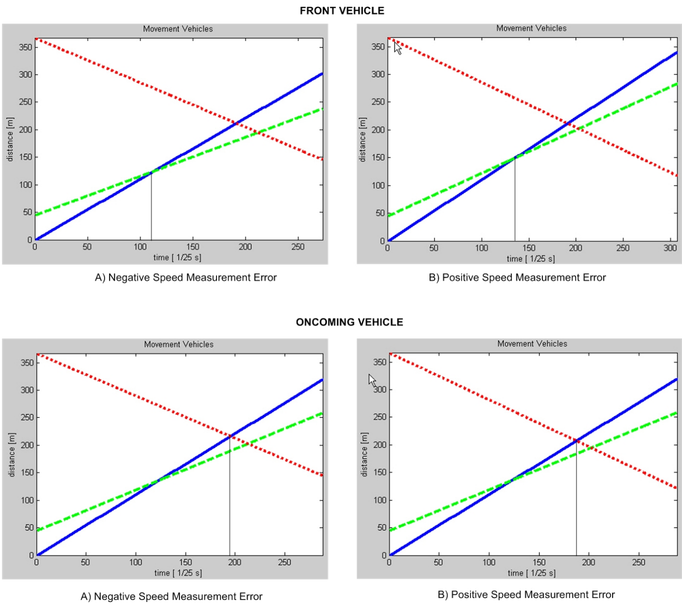

Fig. 1. Influence of speed measurement deviations on the overtaking maneuver

vehicles the inaccuracy is higher, but has less influence on the overtaking recommendation, as has just been shown. Thus, for the front vehicle, we must set a smaller threshold for an acceptable speed measurement error than for an oncoming vehicle. With decreasing distance between the oncoming and the own vehicle, the accuracy of the speed measurement increases, resulting in a smaller error.

Modern laser/radar systems already have a distance measurement range of 0.3 to 200 meters and achieve accuracies in the range of centimeters [9]. Speed measurements can be done up to 250 km/h, with a claimed deviation of 0.1 km/h [10]. With the additional support of differential GPS and car-to-car-communication, obtaining of speed/distance values for farther away vehicles is unproblematic. Also, the measurement range for future on-board systems can be expected to increase. Present stationary radar systems already achieve measurement ranges of up to 1 000 meters between the system and the monitored vehicle [11].

VI. Combining Quality Measures During Reasoning

The past sections showed how to handle imprecise object information with non-complex methods. The reasoning process must now consolidate the available quality information for several traffic objects to achieve an overall quality assessment of the final decision.

Several constraints, like ban-on-passings, oncoming vehicles, etc. are involved in an overtaking decision. Every constraint depends on different attribute values and some of them influence all overtake constraints. The obtained quality values of the attributes must be combined for a quality assessment of the whole constraint. The motivation behind this is that there may be single constraints with unreliable information, while for all others good quality information is available. Deriving a single assessment for the whole decision means that one bad quality constraint would negatively influence the quality statement for the whole decision, even if the information about the remaining constraints is reliable. So, instead of degrading the final decision, a single quality value is assigned to every constraint. Those with unreliable information are singled out.

The attributes for the speed of the subject and the front vehicle, the distance between the two vehicles, and the allowed overtaking speed are the most important values. The overtake time is obtained from them, which in turn influences nearly every overtaking constraint. Therefore, the quality values assigned to these attributes, together with the other values used in a specific constraint, will increase or decrease the quality of the overall constraint. In the previous sections we have shown that imprecision has different degrees of implication, depending on the attribute value under concern. Imprecision for speed and distance of the front vehicle heavily influences the resulting overtake time. Imprecisions in speed/distance of the oncoming vehicle have lesser effects on the overtaking constraint. To obtain a realistic result for the overall constraint, a poor quality value for an important attribute must have higher influence on the final result than for a less important attribute. A simple weighting factor approach can be used to reflect this considerations. As an example, take the following six attribute values ($a = |6|$) together with their weight w and assume that their quality assessments q have been derived with the methods described in the previous sections:

- own speed v_0: w = $\frac{1}{6}$, q = 0.99
- front vehicle speed v_f: w = $\frac{1.5}{6}$, q = 0.95
- distance to front vehicle d_0: w = $\frac{1.5}{6}$, q = 0.98
- speed limit l: w = $\frac{1}{6}$, q = 0.98
- oncoming vehicle speed v_{onc}: w = $\frac{0.5}{6}$, q = 0.97
- distance to oncoming vehicle d_{onc}: w =$\frac{0.5}{6}$, q = 0.95

The weighting reflects the importance of the attribute on the constraint calculation. The final quality result $q(c)$ for the constraint then be obtained by combining the quality values of the attributes and by adjusting them with the weighting factor:

$$q(c) = \sum_{i=1}^{|a|} q(i) \cdot w(i) = 0.9723 \approx 97\%$$

With the additional weights, the importance of an attribute value's quality measure can now be seen clearly. If the quality of an important attribute is poor, the overall constraint quality is more affected. A quality value of 60% instead of 95% for the speed of the front vehicle would for example degrade the final quality value to $\approx$ 88.5%. In comparison, a decrease in the quality value of a less important attribute still decreases the quality of the overall result, but to a smaller degree. For example, if we decrease the quality of d_{onc} to 60%, the final result is given with 94%. This approach yields a natural quality value for the overall constraint. The imprecision of all involved attribute values is taken into account according to their importance for the final decision.

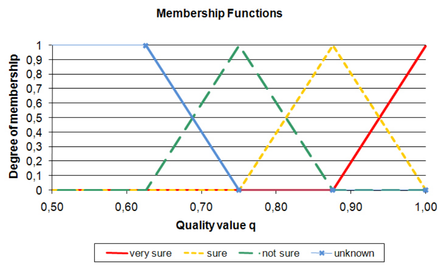

Fig. 2. Piecewise linear membership functions for fuzzy quality classification

The quality values of constraints should be communicated to the driver for assessment of the recommendation. For this, the numerical quality result is transformed to a natural language value. Since there is already so much other information that a driver must consider, a natural language value or an additional color bar will reduce the cognitive workload. Interpreting a numerical percentage value requires considerable more thinking by the human driver. We use four classes for the fuzzy classification of the quality value: *very sure, sure, not sure, unknown*. Four values give a finer classification spectrum in comparison to a three-value approach, e.g. *sure, not sure, unknown*. It can already make a difference for the driver, if the presented values for a constraint are given as *very sure* instead of just *sure* quality. A quality value which is even lower than *not sure* means that the given information is in fact *unknown*. Classification of the numerical quality value is done with a piecewise linear membership function approach within the interval [0,1], using a stepwidth of 0.125 for the first three quality classes:

$$\mu_1 = \mu_{\textit{very sure}} = 1 \text{ at } 1$$
$$\mu_2 = \mu_{\textit{sure}} = 1 \text{ at } 0.875$$
$$\mu_3 = \mu_{\textit{not sure}} = 1 \text{ at } 0.75$$
$$\mu_4 = \mu_{\textit{unknown}} = 1 \text{ at } 0.625 \text{ and below}$$

The membership functions are graphically shown in figure 2. The membership of a quality value q belonging to either class c_i or c_{i+1} is then determined with

$$\mu_i(q) = Y_i + \frac{q - X_i}{s} \cdot (Y_{i+1} - Y_i)$$
$$\mu_{i+1}(q) = 1 - \mu_i(q)$$

where Y_i is the lower boundary of the membership interval, Y_{i+1} is the upper boundary of the membership interval, X_i is the lower boundary of the class interval c_i and s is the stepwidth. For the above example with a decreased quality for v_f, an overall quality measure of 88.5% was obtained. This value falls between the classes *very sure* and *sure*, with a membership $\mu_{\textit{sure}} = 0.92$ and $\mu_{\textit{very sure}} = 0.08$. In case of a poor quality for the less important attribute d_{onc}, the overall quality value was 94%. It falls into the same membership classes, but now with a higher membership value for *very sure* ($\mu_{\textit{sure}} = 0.4544, \mu_{\textit{very sure}} = 0.5456$).

In order not to overload the driver, the quality information can be kept quiet, as long all constraints have a very high quality value. As soon as there are derivations for the highest quality value for one or more constraints, the exceptional constraints must be communicated.

VII. Conclusions

For driver assistance systems (DAS) safety is always the first and foremost aspect. A support system must be able to know its own limits. It should admit ignorance when necessary and inform the driver about the quality of its decision. Despite the progress made in sensing systems and collaboration between vehicles/infrastructure, it is extremely unlikely that the available context information will always be fully reliable. Our work pays tribute to this fact. We investigate some of the major types of imperfect environment information that can occur in a DAS during the reasoning process and possible solutions for handling them. Using a previously developed overtake support system for demonstrational purposes, the main ideas for tackling imprecise information are demonstrated. The application of different approaches for different types of uncertainty is outlined with several examples. All of the presented solutions rely on simple, efficient mathematical models, so they can be integrated into the already complex task of decision making without cutting down the system's performance, while still yielding natural and useful quality assessments.

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