Selecting Adequate Aerial Perceptual Functions with Fuzzy Logic

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Abstract—**The increasing interest in higher automation of unmanned aerial vehicles (UAV) rises the challenge of implementing sophisticated perception functions. Since such functions, whether being used for navigational (e.g., sense & avoid) or surveillance purposes (e.g., object detection & tracking), are heavily influenced by environmental conditions. Hence, a careful selection and parametrization of the perception functions during flight is required to maintain perceptual efficiency on-board the UAV. This paper introduces a method to predict the performance of perception functions, allowing a ranking for algorithm selection. The proposed method uses expert knowledge to model the influence of the environment on the perception functions using fuzzy logic. An evaluation of the proposed method is performed with an aerial vehicle detection algorithm on an imagery dataset, generated from virtual simulation, taking into account fog density and cloud cover. The results show that the method can predict the algorithms performance in general and has the advantage of expressive modelling of the expert knowledge.**

Keywords-Perception functions; fuzzy logic; algorithm selection; algorithm ranking; expert knowledge.

I. INTRODUCTION

The automation of unmanned aerial vehicle (UAV) navigation and guidance is an active research area. Further, the on-board analysis of mission sensor data is needed for environmental awareness and reconnaissance and surveillance missions. The anticipated benefit of higher levels of automation of UAVs is seen by reducing costs, being able to control multiple UAVs by a single operator, and deploying UAVs in areas where no infrastructure for communication and navigation is available.

Mature data processing algorithms for UAV mission sensors are designed for specific use cases, for example often in the domain of object detection and tracking. Therefore, the algorithms regularly produce reliable results only under certain constraints. However, during UAV missions, the environment can change considerable for example in terms of ground surfaces, field of view, lighting conditions and atmospheric effects, influencing the sensor data quality, as well as the performance of data processing algorithms. Hence, a management of sensors and sensor data processing algorithms is advisable to assure the quality of the automated sensor data evaluation in the aforementioned application domains.

For this purpose, a respective system concept was introduced in [1], namely the Sensor & Perception Management System (SPMS). Thereby, the SPMS selects appropriate sensor types, e.g., electro-optical (EO), infrared (IR), and light detection and ranging (LIDAR), and applies adequate sensor data processing algorithms to accomplish certain perception tasks, such as object detection, tracking, and obstacle recognition. Selecting and parametrizing perceptual capabilities according to the current environmental situation eventually results in maintaining algorithm performance.

We developed a method to predict the quality or performance of such perceptual capabilities of the SPMS, allowing the ranking and selection of the best suited algorithms. In Section II, the related work is briefly shown and Section III presents an algorithm selection method using a weighting function based on fuzzy logic and compares its performance prediction for a selected vehicle detection algorithm with ground-truth obtained from an evaluation dataset. The results of our method are presented and discussed in Section IV. Section V closes the paper with a conclusion and future work.

II. RELATED WORK

Rice [2] formulated a general concept for the problem of selecting an algorithm from a set of algorithms. Using a case base, which contains cases from learning or observing successful executed tasks with their solution, is as a general methodology for algorithm selection and was proposed by [3]. A similarity measurement [4] compares the new task with the case base using the tasks problem description to select the appropriate solution.

Hochgeschwender et al. [5] addressed the problem of selecting marker detection algorithms, based on image interest point detection, under different illuminations in an indoor scenario to maximize detection performance. During a training phase, the performance of the algorithms is evaluated and image histograms, as well as respective algorithm parameters, are stored whenever the performance seems reasonable. The selection algorithm uses the Kullback-Leibler divergence as measurement to compare the current image histogram with the saved ones to rank the algorithms.

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An automatic selection approach for color constancy algorithms is proposed in [6]. They extract simple features from images and using a Mamdani-type fuzzy inference system to reason about the appropriate algorithm. Thereby, the fuzzy rules and sets are learned from example.

In [7], an approach for selecting sensor processing algorithms with Bayesian networks is proposed. Here, the environmental and sensor requirements of the algorithms, as well as their implementation quality, is modelled to estimate the performance of the algorithms.

A meta-learning approach is used by [8][9] for ranking the algorithms with a relative score, in respect of the algorithm with the highest score. They extract meta-features (e.g., mean illumination or noise-signal ratio of an imagery dataset) and evaluate the performance of the algorithms from the learning datasets. Afterwards, a meta-learner uses the performance and meta-features to derive a model, enabling the computing of relative performances of the algorithms on a new dataset. This method allows the automatic learning of an algorithm selection mechanism without the need for explicit expert knowledge as required in the here presented method. However, a sophisticated learning dataset must be provided to achieve reliable results.

Other approaches [10]–[12] also model the algorithms constraints with expert knowledge and apply machine inferencing about the availability of the algorithms [13]. Our approach now uses the idea of modelling the environmental impact with probabilities [7], since they can be considered as not completely observable. It is realized with fuzzy logic where expert knowledge is mapped to fuzzy rules. The notation and concept introduced by [2] is used in this paper.

III. METHOD

The selection of an algorithm requires a ranking metric. In the proposed method, a weighting function predicts the performance of the algorithm with respect to a given perceptive task (e.g., vehicle detection), in dependency of a feature vector describing the actual environment state. The weighting function returns a normalized value, describing how successful a certain algorithm can be applied. Fig. 1 shows an overview of the proposed algorithm selection method. The selection function takes the algorithm set and the environment state vector to choose an algorithm with a parameter set, in dependency of the calculated performance. Expert knowledge declare the impact of the environment state vector on the algorithms performance.

The algorithm selection s requires features f_x to compute the performance of the algorithms in a set A, where each algorithm $a_i \in A$ has parameter sets $p_j \in a_i$. The following formula expresses the algorithm selection function:

$$a_i(p_j) = s(f_x, A) \tag{1}$$

with x denoting a candidate from the problem space and $f_x = \{x_0, \ldots, x_{K-1}\}$ the extracted features. K is the number of feature elements. The weighting function w computes the

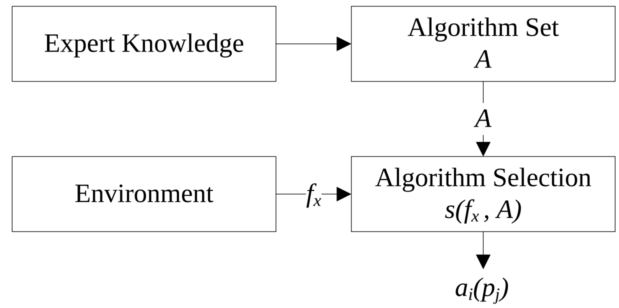

Figure 1. Algorithm selection method using expert knowledge to predict the algorithms performance.

predicted performance for one specific algorithm within one specific parameter set. The maximum performance of an algorithm a_i considering its parameter sets results from

$$\max_{p \in a_i} \left(w\left(f_x, a_{i,p}\right) \cdot q\left(a_{i,p}\right) \right) \tag{2}$$

where the variable q states the quality, or general usability, of the algorithm for a given parameter set. For example, the quality of an object detection algorithm can be measured by its average precision.

In [1][14] the concept for sensor and perception management (SPM) was introduced, presenting the idea of having a set of dedicated *perception chains*, each being a combination of several algorithms a_i to fulfill a specific perception task. An example perception chain could consist of a *segmentation stage*, followed by *interest point detection* and eventually a *classification algorithm*. This work is part of such SPM concept and therefore the equation (2) extends to

$$\sum_{a_i \in c_m} \left(\max_{p \in a_i} \left(w\left(f_x, a_{i,p}\right) \cdot q\left(a_{i,p}\right) \right) \right) \frac{1}{N} \tag{3}$$

where $c_m \in C$ is a perception chain containing algorithms a_i from A. $C = \{c_o, \ldots, c_m, \ldots, c_M\}$ comprises all perception chains designed for a perception task and N is the number of algorithms in c_m. The selection function calculates the perception chain performance, using equation (3), and returns the perception chain with the highest performance, including the related parameter sets.

The computation of the algorithms performance within the weighting function requires a method to compute the impact of the feature vector f_x on the algorithm's $a_{i,p}$ performance. A classical assessment of the impact of the feature vector from examples would require a large dataset with aerial imagery, however existing ones [15]–[17] are lacking the necessary environmental variations. As an alternative approach, here, experts assess the impact of

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Figure 2. Example images from the dataset: In the first row, the cloud cover increases from the left to right. The illumination decrease slightly and the shadows are more blurred while the cloud cover increases. In the second row, the fog density increases from left to right and the contrast declines.

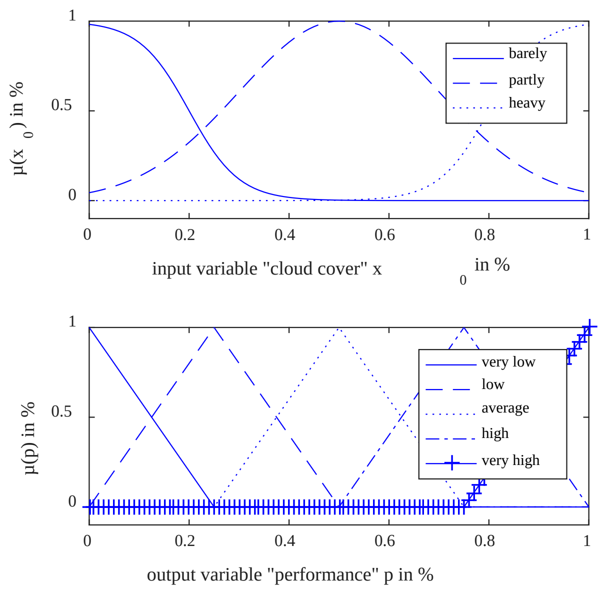

Figure 3. Fuzzy membership functions of cloud cover and performance variable: The y-axis denotes the degree of membership. Note that cloud cover and fog density are modelled equally.

environmental features from their experience and knowledge. Here, the notation of *if-then fuzzy logic rules* were chosen, because it is human understandable and machine-processible. In addition, since the environment is not completely observable, the *if-then fuzzy logic rule* notation is capable of modelling vague knowledge. Such fuzzy inference system requires the *fuzzification* of the input values from the feature vector by membership functions.

In a given toy problem, two input variables were selected for describing ambient environmental features, the *cloud cover* $x_0 \in f_x$ and the *fog density* $x_1 \in f_x$, since they affect illumination, shadow intensity and significance of gradients in images. For illustration, Fig. 2 shows the cloud cover input and the performance output value with their membership functions.

The fuzzy rules activate the related membership function, whereby the input value of x_0, e.g., the cloud cover measurement, determines the membership degree $\mu(x_0)$. For example, the rule *"if cloud cover is heavy then performance is average"* activates the cloud cover membership function *"heavy"*, for $x_0 = 0.8$ resulting in $\mu(x_0) = 0.5$. Afterwards, the membership function *"average"* of the output variable performance receives the same degree of membership. A *deffuzification* step computes the center of the area under the *"average"* curve, cut off by the degree of membership line. For multiple input values, the center of the union of the areas is calculated to obtain the performance value. This work uses the Mamdani-type fuzzy inference [18], because of its expressional power which allows a clean modelling of expert knowledge as examined by [19].

IV. Evaluation and Discussion

On the basis of an aerial vehicle detection algorithm, developed by [20], an evaluation of the proposed method is performed. The vehicle detection algorithm uses weak classifiers in a cascade to detect vehicles with Haar-like image features and local binary pattern features. The variables describing the environment are the cloud cover and fog density of the scene as mentioned above. First, the average performance of the algorithm is determined with a ground-truth evaluation dataset obtained in virtual simulation, using Virtual Battlespace 3 (VBS3) [21]. The average performance is then compared with the output of the modelled fuzzy inference system to evaluate the precision of the weighting function.

The dataset includes 22 scenarios from one VBS3 map with fixed cloud cover and fog density values from zero to one, where zero defines clear sky or no fog and one defines full cloud cover or dense fog. Fig. 3 shows some example images form the dataset. Each scenario consists of 7500 images in 1920x1080 resolution with annotations of the vehicle locations. The parameters for the image generation are 50 meter distance from camera to the center of the image and an elevation of -45 degrees. These parameters where selected from the evaluation of the algorithm in [20], where the average performance has the highest score. The image generation process scans the scenarios in a grid with randomly selected azimuth angles and each vehicle from azimuth angles ranging from zero to 360 degrees. The vehicles, 50 per scenario, are randomly placed on the map. The vehicle detection algorithm is tested on each scenario to calculate a receiver operating characteristic (ROC) curve to determine the algorithm's average performance, in dependency of the cloud cover and fog density value separately.

The resulting ROC curves from the scenarios are shown in Fig. 4, where the area under the curve is the measurement for the average performance of the vehicle detection algorithm on the related scenario, and the circles mark the optimal operation point for the classifier. The upper plot in Fig. 4 shows the ROC curves for cloud cover and the one below for influences of the fog density. The scenarios to evaluate the cloud cover impact have zero fog density and the scenarios for evaluating the fog density impact have 50 percent cloud cover.

The fuzzy inference system calculates the prediction of the algorithm performance using as input the cloud cover and fog density and as output the performance. In Fig. 2 the membership functions for the fuzzy variables are shown. The fuzzy rules can be read as follows:

- *If fog density is hardly and cloud cover is barely then performance is high*
- *If fog density is hardly and cloud cover is partly then performance is high*
- *If fog density is hardly and cloud cover is heavy then performance is very high*
- *If fog density is moderate and cloud cover is barely then performance is high*
- *If fog density is dense and cloud cover is barely then performance is average*

With increasing cloud cover, the average performance of the algorithm increases from 62 to 71 percent as depicted in the upper graph of Fig. 5. While the cloud cover increases, the appearance of shadows and the illumination decreases. Therefore, the algorithm is obviously robust against illumination changes and shadows. The error between the calculated performance and the predicted performance is 7.6 percent. In the upper graph of Fig. 5 the error is the highlighted area between performance and prediction curve.

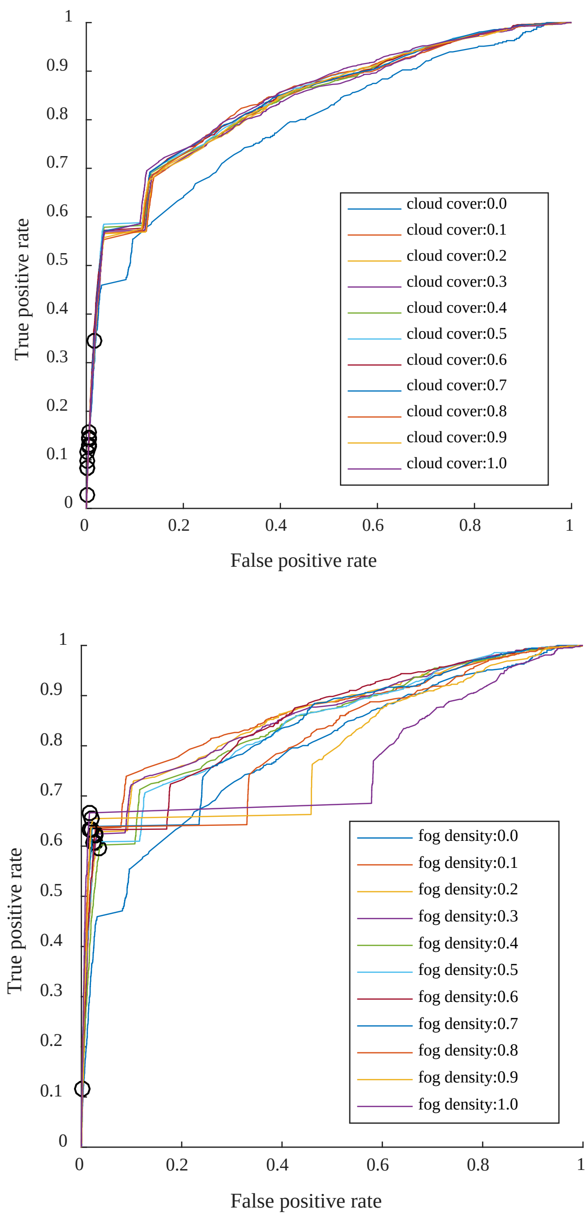

Figure 4. ROC curves of the vehicle detection algorithm for each scenario.

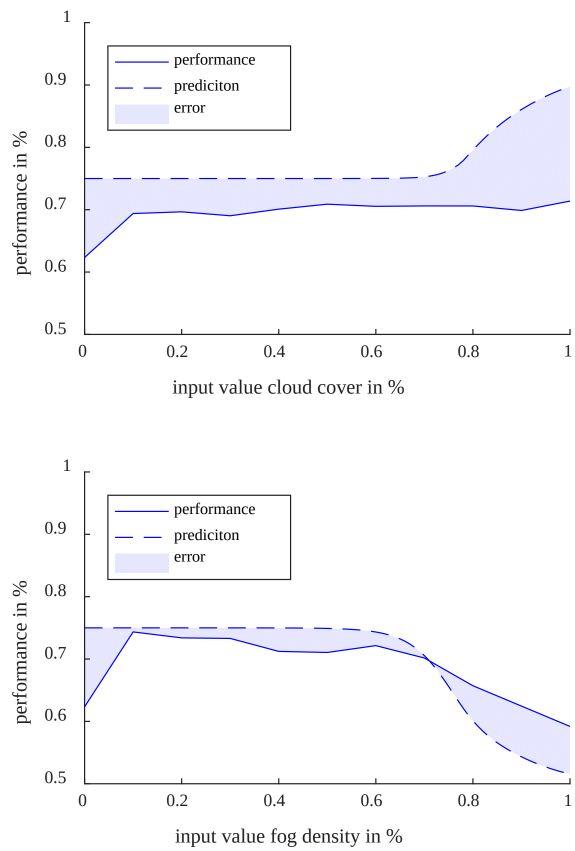

Figure 5. Comparison between evaluated (solid line) and predicted (dashed line) algorithm performance for cloud cover and fog density.

In general, with increasing fog density the average performance decreases, while the image is blurred, reducing the significance of the edges in the image. First, the average performance increases from 62 to 74 percent and then drops to 59 percent. Comparing the calculated performance with the predicted performance results in an error of 0.3 percent (see lower graph of Fig. 5).

It can be observed, that the proposed method can in general describe the trend of environmental impact on the algorithm and is therefore useful for predicting the performance of the algorithm. The advantage of the proposed method is the clear description of the environmental influence, with fuzzy rules from expert knowledge, but the disadvantage is the lack in accuracy between the calculated and predicted performance. The introduction of a greater set of membership functions for the fuzzy variables can increase the accuracy, but it also increases the modelling effort and therefore, detailed expert knowledge is required, but it is unlikely that such detailed knowledge is available. Thus, we recommend a clear set of membership functions.

V. CONCLUSION

The management of perceptual capabilities requires the estimation of the performance of the underlying algorithms in dependency of the environmental state. In this paper, such performance prediction was demonstrated using a fuzzy logic approach. The results show, that it is possible to model the general influence of the environment state at the algorithm performance.

In [6] image features where used to select the best algorithm via learning of an fuzzy inference system. In contrast to our approach, the image data must be available to select the algorithm, while our method can predict the algorithm performance without image data. Tenorth and Beetz [11] use expert knowledge to reason about the appropriate vision algorithm for a personal robot. Unlike our approach, they require detailed expert knowledge. Comparing our method with [5], the modelling of the environmental influences takes less effort, but the performance prediction accuracy is lower. In addition, when expert knowledge is not available, our method cannot be used. Therefore, in a next step, the missing expert knowledge shall be obtained by machine learning approaches to shape the membership function and generate fuzzy rules to enhance the performance prediction accuracy. For future evaluation, a larger scaled dataset will be generated to test learning approaches as well as suitable methods to determine the environmental state vector.

REFERENCES

[1] M. Russ and P. Stütz, “Airborne sensor and perception management: A conceptual approach for surveillance UAS,” in *Proceedings of the 15th International Conference on Information Fusion (FUSION2012)*, pp. 2444–2451, 2012.

[2] J. R. Rice, “The Algorithm Selection Problem,” *Adv. Comput.*, vol. 15, no. C, pp. 65–118, 1976.

[3] A. Aamodt and E. Plaza, “Case-based reasoning: Foundational issues, methodological variations, and system approaches,” *AI Commun.*, vol. 7, no. 1, pp. 39–59, 1994.

[4] P. Cunningham, “A Taxonomy of Similarity Mechanisms for Case-Based Reasoning,” *IEEE Trans. Knowl. Data Eng.*, vol. 21, no. 11, pp. 1532–1543, Nov. 2009.

[5] N. Hochgeschwender, M. A. Olivares-Mendez, H. Voos, and G. K. Kraetzschmar, “Context-based selection and execution of robot perception graphs,” *IEEE Int. Conf. Emerg. Technol. Fact. Autom. ETFA*, pp. 1–4, 2015.

[6] J. Cepeda-Negrete and R. E. Sanchez-Yanez, “Automatic selection of color constancy algorithms for dark image enhancement by fuzzy rule-based reasoning,” *Appl. Soft Comput. J.*, vol. 28, pp. 1–10, 2015.

[7] M. Russ and P. Stuetz, “Application of a probabilistic market-based approach in UAV sensor & perception management,” in *Information Fusion (FUSION), 2013 16th International Conference on*, pp. 676–683, 2013.

[8] Q. Sun and B. Pfahringer, “Pairwise meta-rules for better meta-learning-based algorithm ranking,” *Mach. Learn.*, vol. 93, no. 1, pp. 141–161, 2013.

[9] K. A. Smith-Miles, “Cross-disciplinary perspectives on meta-learning for algorithm selection,” *ACM Comput. Surv.*, vol. 41, no. 1, pp. 1–25, 2008.

[10] G. H. Lim, S. Member, I. H. Suh, S. Member, and H. Suh, “Ontology-Based Unified Robot Knowledge for Service Robots in Indoor Environments,” *Syst. Man Cybern. Part A Syst. Humans, IEEE Trans.*, vol. 41, no. 3, pp. 492–509, 2011.

[11] M. Tenorth and M. Beetz, “KnowRob: A knowledge processing infrastructure for cognition-enabled robots,” *Int. J. Rob. Res.*, vol. 32, no. 5, pp. 566–590, 2013.

[12] M. Tenorth and M. Beetz, “KnowRob—knowledge processing for autonomous personal robots,” *IEEE/RSJ Int. Conf. Intell. Robot. Syst. 2009 (IROS 2009)*, pp. 4261–4266, 2009.

[13] M. Gomez et al., “An ontology-centric approach to sensor-mission assignment,” *Knowl. Eng. Pract. Patterns*, pp. 347–363, 2008.

[14] C. Hellert, D. Smirnov, M. Russ, and P. Stuetz, “A High Level Active Perception Concept For UAV Mission Scenarios,” in *Deutscher Luft- und Raumfahrtkongress 2012*, 2012.

[15] S. Razakarivony and F. Jurie, “Vehicle detection in aerial imagery : A small target detection benchmark,” *J. Vis. Commun. Image Represent.*, vol. 34, pp. 187–203, 2016.

[16] R. Collins, X. Zhou, and S. K. Teh, “An open source tracking testbed and evaluation web site,” *IEEE Int. Work. Perform. Eval. Track. Surveill.*, pp. 17–24, 2005.

[17] F. Tanner et al., “Overhead imagery research data set - An annotated data library & tools to aid in the development of computer vision algorithms,” *Appl. Imag. Pattern Recognit. Work. (AIPRW), IEEE*, pp. 1–8, 2009.

[18] E. H. Mamdani and S. Assilian, “An experiment in linguistic synthesis with a fuzzy logic controller,” *Int. J. Man. Mach. Stud.*, vol. 7, no. 1, pp. 1–13, 1975.

[19] A. Hamam and N. D. Georganas, “A comparison of mamdani and sugeno fuzzy inference systems for evaluating the quality of experience of hapto-audio-visual applications,” *HAVE 2008 - IEEE Int. Work. Haptic Audio Vis. Environ. Games Proc.*, no. October, pp. 87–92, 2008.

[20] G. Hummel, D. Smirnov, A. Kronenberg, and P. Stütz, “Prototyping and training of computer vision algorithms in a synthetic UAV mission test bed,” in *AIAA SciTech 2014*, pp. 1–10, 2014.

[21] P. Morrison, “White Paper: VBS2 Release Version 2.0,” Nelson Bay, Australia, 2012.