Multisensor Data Fusion for Obstacle Detection in Automated Factory Logistics

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***Abstract*—This paper describes data fusion methodologies for obstacle detection in an automation system based on advanced Automatic Guided Vehicles (AGV), used for automated logistics in modern factories. We present the background of the problem, introducing generic aspects of the system architecture designed to cope with the obstacle detection in automated factory logistics; then, we focus on the system specification for the module responsible of integrating data from different sources and providing a global representation of the environment. Finally, we present a comparative analysis among different strategies of multisensor data fusion compliant with the requirements of the described system, highlighting their advantages and drawbacks.**

I. Introduction

Multisensor data fusion deals with the combination of information coming from multiple sources in order to provide a robust and accurate representation of an environment or process of interest. A review and discussion of several data fusion definitions is presented in [1].

The Joint Directors of Laboratories (JDL) [2] defines data fusion as *"A process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats, and their significance. The process is characterized by continuous refinements of its estimates and assessments, and the evaluation of the need for additional sources, or modification of the process itself, to achieve improved results"*.

Multisensor data fusion is a multidisciplinary technology that involves several application domains, such as robotics [3], [4], military application [5], biomedicine [6], [7], wireless sensor network (WSN) domain [8], video and image processing [9]. Significant attention has been dedicated to the field in recent years: a review of contemporary data fusion methodologies, as well as the most recent developments and emerging trends in the research field is presented in [10].

Different criteria can be used for the classification of the data fusion techniques, as discussed in [11]. Considering the abstract level of the employed data, Luo et al. [12] proposed four types of abstraction: signal level, pixel level, characteristic (based on features extracted from images or signals) and symbols (or decision). More generally, we can address three main levels of abstraction: measurements, features and decisions. Another possible classification relative to the data abstraction level concerns:

- Low level fusion: this level deals directly with raw data to improve the accuracy of the individual sources.
- Medium level fusion: it is based on the processing of features or characteristics (dimension, shape, position).
- High level fusion: also known as decision fusion, this level addresses symbolic representation, such as object classes. This level is also known as the feature or characteristic level.
- Multiple level fusion: based on the processing of data provided at different levels of abstraction.

Considering the relation of the information to fuse, Durran-White [13] considers three main categorization for sensor fusion:

- Complementary, where each sensor provides incomplete information about the world and the objective of data fusion is combining these different parts to achieve a more complete and accurate representation.
- Competitive, where information about the same target is provided by two or more sources and the data fusion is employed to increase the reliability and the accuracy, reducing conflicts, noisy and erroneous measurements.
- Cooperative, in which the information provided by different sources is combined into new and, typically, more complex information.

According to point where data fusion is performed it is possible to distinguish three main types of classification architecture: centralized, distributed and hierarchical. In a centralized architecture a single module collects information from all the input sources and makes decisions according to the received raw data. The principal drawbacks of this solution are the possibility of communication bottleneck and the large amount of bandwidth requested to transmit raw data over the network. In a distributed architecture source nodes process independently raw data and provide an estimation of the object status based on only their local views; this information is the input to the multisensor fusion, which provides a fused global view. Hierarchical architectures are combinations of decentralized and distributed nodes, in which the data fusion process is performed at different levels in the hierarchy.

This paper is organized as follows. Section II presents an overview of the problem, describing the system architecture and the main specifications for the multisensor data fusion. Section III presents a comparative analysis among multi-sensor data fusion algorithms compliant with the presented architecture. Finally, concluding remarks are summarized in Section IV.

II. Background of the problem

Nowadays, automation is not yet widespread in factory logistics and usually manually operated forklifts are employed for the transportation of raw materials and final products. The use of manual forklifts involves low efficiency and high energy consumption and, moreover, it is not safe for workers: according to EUROSTAT statistics [14], from 1998 to 2007, in the European Union, more than 3 million work accidents related to transports, warehouse activities and communications took place. This is mainly due to the fact that forklift drivers are prone to errors and not always sufficiently trained. In addition to that, manufacturing environments are often rather cluttered with numerous blind spots. The employing of multiple Automated Guided Vehicles (AGV) is a flexible, cost effective and safe solution for increasing the automation in factory logistics [15].

A. *Definition of the Multisensor System Architecture*

Working in an autonomous guided scenario requires a reliable obstacle detection and recognition system to avoid collision that may lead to accidents and/or damaged goods: for this reason it is important to equip each AGV with a robust on-board multisensor system for environment perception, capable of monitor the entire $360°$ region around the vehicle. This on-board perception system is composed by a safety laserscanner, supplemented by another laserscanner and by an omnidirectional stereo vision subsystem consisting of two omnidirectional lenses and two cameras mounted on the top of the AGV.

To further support a reliable system for object detection, tracking and classification it is important installing, inside the warehouse area, a laser infrastructure-based environment perception system to monitor intersections and blind spots.

Whenever a new plant is built or an existing one is extended or modified it would be necessary to perform a manual re-registration of the relevant points of interest, e.g. pallet positions in the racks and pickup places. To overcome this situation a fundamental aspect is the presence of semi-autonomous plant exploration system, in the form of an advanced AGV, capable of retrieving automatically a 3D representation of the warehouse, highlighting all the structural elements placed inside it: racks, conveyors, poles, walls, windows, doors for humans, gates for AGVs/manual forklifts, pickup places, pallet positions in the racks, block storage/free stacks, maintenance area / battery station, drivable corridors / paths, dedicated / shared walkways for pedestrians, safety zones (e.g. in front of picking places).

B. *Specifications for Multisensor Data Fusion*

The semi-autonomous plant exploration system, the on-board multisensor and the laser infrastructure-based perception systems all support object detection, tracking and classification capabilities. Thus, in a general architecture for automated logistic management the information about the obstacles in the scene may be provided by several sources, involving the possibility of data redundancy, inconsistency, ambiguity, noise, and incompleteness. To overcome this problem it is necessary to define a module that collects all data acquired by the sensors and combines them in a unique and complete representation of the overall system, including the static and dynamic entities that act inside it. This modules, called global live view, allows achieving higher quality information, providing a global updated map representing the static entities (the 3D map of the plant, the route map), the dynamic entities (the current position and velocity of the AGVs, the position and velocity of currently identified objects), the congestion zones and the status of the monitored intersections.

The information provided to the global live view by the infrastructure and on-board perception systems consists of tracked and classified objects, identified with a unique ID. In detail, data regarding each object are:

- position
- orientation
- velocity
- size
    - 2D object: width, length
    - 3D object: width, length, height
- Class of the objects: human, manual forklift, AGV, other dynamic object, static object.
- An assessment regarding the quality and reliability of the classification.

Furthermore, the semi-automated plant exploration system provides the complete map of the plant, which consists of the warehouse blueprint, the generated route map and the occupancy grid mapping.

The global live view is then updated with the information acquired during the operation and a real-time global map is generated. This output is shared with the AGVs' fleet in order to improve their local on-board navigation capabilities and support safe operation. The update rate of the global live view needs to be at least 10 Hz and the maximum time of processing and update should always be less than $150ms$.

It is important to guarantee consistency with respect to the real world: each virtual object represented in the map must have a correspondence to a real object of the world. Therefore, the global live view is expected to perform data fusion to merge data acquired from the different sensors, reducing information redundancy and verifying the presence of data inconsistence and ambiguity. The described system architecture is represented in Fig. 1.

III. Mulisensor data fusion approaches

For the implementation of the global live view, different approaches of multisensor data fusion can be considered. Since the global map will contain mainly information about the static and dynamic obstacles detected in the sensors surrounding

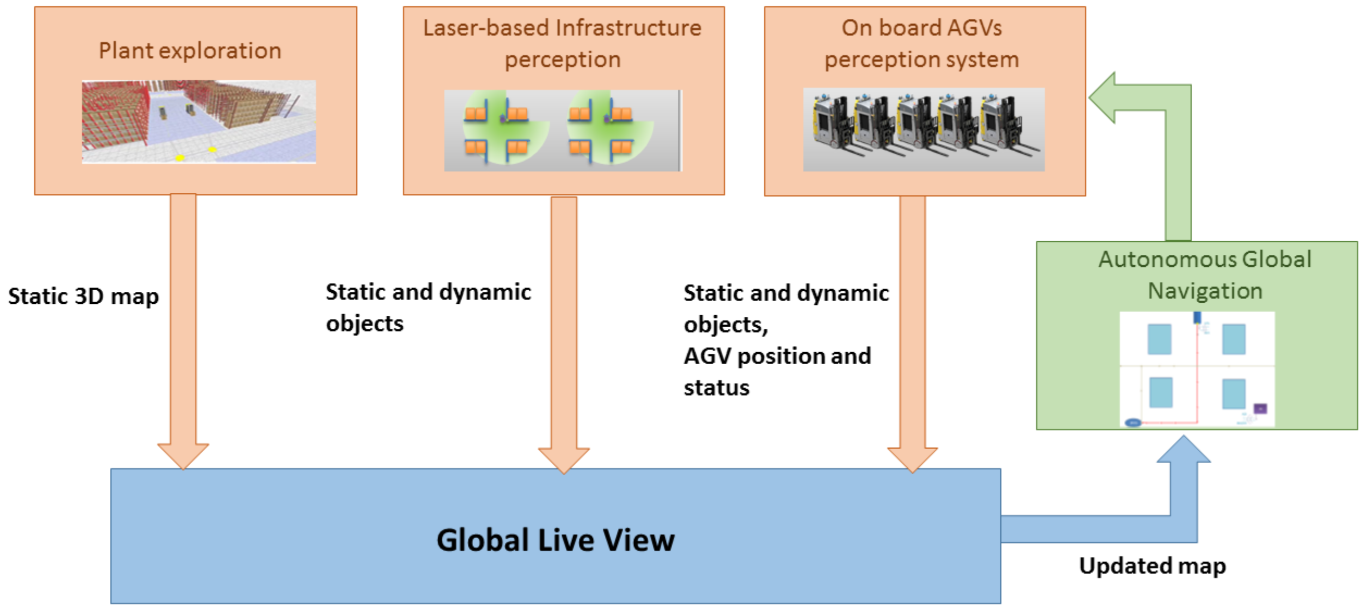

Fig. 1. The general system architecture, designed for obstacle data detection, tracking, classification and fusion.

area, the principal methodologies investigated for multisensor data fusion are focused on obstacle detection. Sensor fusion methods are particularly spread in the obstacle detection field to achieve improved accuracies that could not be guaranteed by the use of a single sensor [16]–[19].

Occupancy grids [20], [21] are the most common low-level sensor fusion strategies employed in robotics to perform detection and tracking of moving objects, simultaneous localization and mapping and local path planning. They allow to automatically generate a discrete map of the environment, representing the area of interest as a grid of two/three dimension cells of equal size. Originally designed for sonar data fusion, occupancy grid approaches have been extended for fusion of stereo and optical flow data [22] and, under certain circumstances, for fusion of monocular camera data [23]. Compared with feature-based approaches [24], grid maps are particularly flexible and robust for the fusion of noisy information; they allow to integrate different kinds of input data in the same framework, considering the inherent uncertainty of each input sensor. Fast inverse models [21], [25], or alternatively, more accurate forward models [26] can be employed as occupancy mapping algorithms for the updating of the grid cells. The major drawback of fixed grid structures is their large memory requirement, especially during their initialization phase. Moreover, the extent of the mapped environment needs to be known beforehand, otherwise, every time the map is expanded, high costly operations must be performed.

Octrees [27] allow to cope with these limitations: they are hierarchical tree-based representations, that delay the initialization of map volumes until measurements need to be integrated. Thus, the map is populated only with volumes that have been measured and the hierarchical structure of the trees can also be used as a multi-resolution representation.

An alternative to grid based methods is the sensor fusion strategy presented in [18] for obstacle detections/classification in an active pedestrian protection system: range data provided by a laser scanner are fused with images coming from a camera, obtaining a set of images representing vehicle and pedestrian candidates. These images are used as input for two pattern classifiers (one for vehicle detection and the other for pedestrian detection) implemented by Support Vector Machine with Gabor filter bank [28].

Despite the accuracy and robustness provided, these approaches require the processing of low level information (images, 3D point clouds, laser raw data) in the data fusion level, thus, it is not suitable for the global live view implementation: in fact, for each obstacle candidate, we assume to process medium level features (ID, age, position, orientation, velocity and size) and high level features (class and classification quality) in order to optimize the data transmission time and reduce the network overhead.

Therefore, according to the system specification, a possible strategy could be based on dealing, separately, the medium level and the decision level data fusion.

A. *Medium level*

In the described architecture, dealing data fusion at medium level means processing the object measurements (ID, age, position, orientation, velocity and size) estimated with uncertainty by:

- the semi-autonomous plant exploration system;
- the on-board multi-sensor systems;
- the laser infrastructure-based perception systems.

Thus, from a medium level point of view we can deal the data fusion problem as a target tracking process, focused on maintaining the state estimates of one or several objects over a period of time. Since object tracking is performed both by the on-board multi-sensor systems of the AGVs and by the laser infrastructure-based perception systems, distributed track fusion methodologies can be employed for the global live view implementation, including both maximum-likelihood [29] and minimum mean square error (MMSE) solutions. According to considerations about reliability, survivability, communication bandwidth and computational resources, distributed processing architectures are more practical solutions than the centralized ones: as highlighted in [17], in a distributed architecture the sources transmit only the target tracks, instead of all measurements and this allows to reduce the cost in computational demand as well as communication bandwidth requirements. The drawback of dividing the tracking task among multiple processors is the possible introduction of correlated errors among the tracks [30]: while measurements of a target from different sensors are generally uncorrelated, different local track estimates for a common target are correlated, requiring additional processing. To cope with the introduction of correlation in the estimation, the cross covariances between track estimates must be computed: since this calculation is computationally expensive, it is possible to employ methodologies based on direct track-to-track fusion [17] or, alternatively, treat the decorrelation of the state estimates [31]. In both cases, local source processors must send to the global level additional information as covariances and corresponding measurement matrices.

An alternative approach for the global live view implementation is the use of a heuristic based on the evaluation of the obstacles occupational area: the principal steps of this solution are represented in Fig. 2. Starting from the bounding boxes delimiting the obstacles detected by the source sensors, the algorithm considers their positions, orientations and occupational overlapping in order to reconstruct a 2D/3D map containing the set of blobs corresponding to the region covered by each candidate. Integrating the information about the velocities and directions estimated for each tracked obstacle, it is possible to discriminate among static and dynamic obstacles. Then, split and merge techniques [32] can be employed to resolve conflicts in the discrimination between blobs that may represent different views of the same object or, alternatively, separated elements. If necessary, the information representing the fused obstacles could be integrated in a grid map on which free space and unknown regions can be modeled, supporting the implementation of path planning and navigation functions.

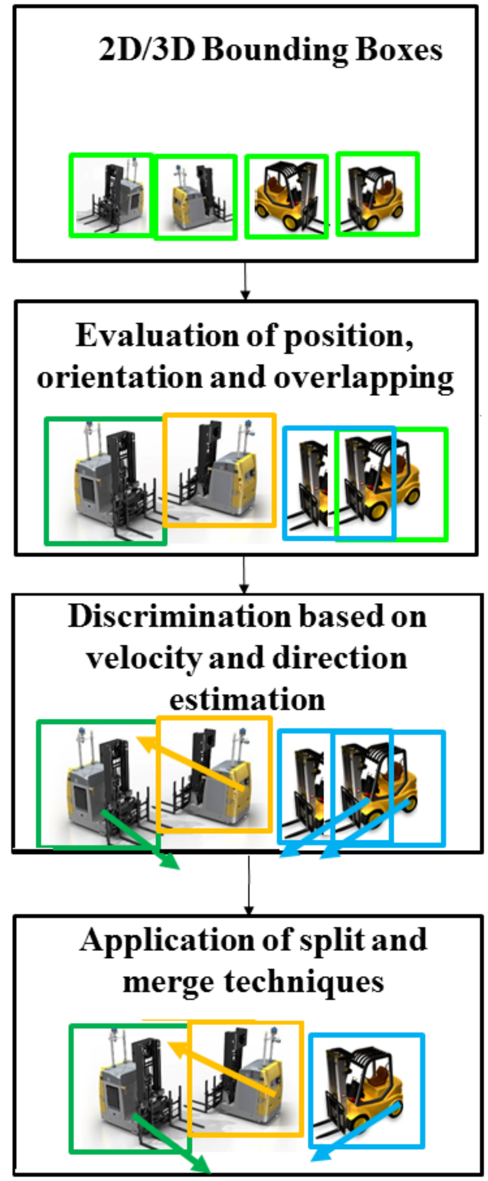

Fig. 2. Principal steps of the heuristic for the global live view implementation.

B. High level

The choice of the data fusion strategies for the implementation of the global live view can be considered, from an high level point of view, as a classifier combination problem. According to this problem formulation, the semi-autonomous plant exploration system, the on-board multi-sensor systems and the laser infrastructure-based perception systems represent a set of classifiers that, given an input pattern, provide an output score for each possible class of the system (human, manual forklift, AGV, other dynamic object, static object). This value represents a confidence measure for the class to be the correct class for the input pattern. Therefore, according to the type of classifiers' outputs, methods for classifier combinations at measurement level (or type III [33]) are investigated.

As discussed in [34] we can distinguish two categories of combination methods: score combination functions and combination decisions. In the first approach, a function is used to combine in a predetermined manner the classifiers' scores, while in the second method the classifiers' outputs are used as inputs to a secondary classifier, trained to determine the combination function.

Simple aggregation scheme at measurement level as sum-rule, product-rule, average-rule and max rule are all examples of score combination functions: despite their simplicity, these elementary combination rules compete with the more sophisticated combination methods, as highlighted in [35]. Although they demonstrated high recognition rates, the simple aggregation schemes do not allow to determine a priori which is the best rule for a particular data set.

Alternatively, to deal with the high level data fusion in the global live view it is possible to employ complex combination decisions methodologies as Neural Networks [36], Naive Bayes [33], Dempster-Shafer theory [37] and classifier ensembles, as Bagging [38] or Boosting [39]. In general, a drawback of these techniques concerns the complexity of the training scheme: in the architecture described for the implementation of the global live view we expect that the perception source systems provide accurate data as input for the data fusion, thus, training session may be a more complex solution than necessary. Moreover, when an obstacle does not appear in the field of view of a perception system, no classification hypothesis are provided by that system: in the data fusion process a missing response of a classifier does not mean unreliability. Furthermore, in our system architecture it is not suitable employing classifiers' combination strategies that require training session where different weights are assigned to each single classifier according to its recognition capabilities: similar and general purpose classifiers are used by the semi-autonomous plant exploration system, by the on-board multi-sensor systems and by the laser infrastructure-based perception systems, thus, a possible classification error is not related to lack of classification capabilities in a single perception source, but it can be mainly caused by occluded or partially visible obstacles from certain points of view.

For these reasons simple aggregation rules may be a better solution for the implementation of the high level data fusion in the global live view.

IV. Conclusions

We have seen how data fusion strategies for obstacle detection can be employed in an automated system for logistics in modern factories. According to the system architecture and requirements, it is fundamental to implement a module responsible for providing a global updated map representing the plant, the locations of all fixed warehouse components (racks, shelves, etc.) as well as dynamic data such as the positions, velocities, and driving directions of all AGVs and of all other stationary and non-stationary objects detected by on-board or infrastructure perception systems. This module, called global live view, is expected to perform data fusion for obstacle detection: for its implementation the principal categories of multisensor data fusion algorithms have been evaluated. One of the most promising considered techniques consists in the implementation of a generic architecture based on occupancy grids. Generally, the use of occupancy grids involves high computational costs, especially during the initialization and updating of the grid locations: the employing of Octree allows to reduce the cost of search algorithms employed to initialize and update the states of the grid cells. Since grid based approaches require the employing of low level features and for the global live view implementation we assume to process only medium and high level information, an alternative, cost effective solution is the use of an approach based on the separation between features and decision level data fusion: in this case, a heuristic that employs split and merge techniques for medium level data fusion may be combined with an aggregation rule to deal with the decision data fusion. The described heuristic could be combined with a grid based method in order to facilitate the implementation of path planning and navigation tasks.

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References

[1] H. Boström, S. F. Andler, M. Brohede, R. Johansson, A. Karlsson, J. van Laere, L. Niklasson, M. Nilsson, A. Persson, and T. Ziemke, "On the definition of information fusion as a field of research," University of Skvde, School of Humanities and Informatics, Tech. Rep. HS- IKI - TR-07-006, 2007.

[2] F. E. White, *Data Fusion Lexicon*. San Diego, USA: Joint Directors of Laboratories, Technical Panel for C3, Data Fusion Sub-Panel, Naval Ocean Systems Center, 1986.

[3] N. Bellotto and H. Hu, "Vision and laser data fusion for tracking people with a mobile robot," in *Proc. of the IEEE Int. Conf. on Robotics and Biomimetics (ROBIO 2006)*, Kunming, China, December 2006, pp. 7–12.

[4] W. Haijun and C. Yimin, "Sensor data fusion using rough set for mobile robots system," in *Mechatronic and Embedded Systems and Applications, Proceedings of the 2nd IEEE/ASME International Conference on*, Aug 2006, pp. 1–5.

[5] E. Bossé, P. Valin, A. Boury-Brisset, and D. Grenier, "Exploitation of a priori knowledge for information fusion," *Information Fusion*, vol. 7, no. 2, pp. 161 – 175, 2006.

[6] B. Bracio, W. Horn, and D. Moller, "Sensor fusion in biomedical systems," in *Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE*, vol. 3, Oct 1997, pp. 1387–1390.

[7] S. Tulyakov and V. Govindaraju, "Classifier combination types for biometric applications," *2012 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, vol. 0, p. 58, 2006.

[8] B. Krishnamachari, D. Estrin, and S. B. Wicker, "The impact of data aggregation in wireless sensor networks," in *Proceedings of the 22Nd International Conference on Distributed Computing Systems*, ser. ICDCSW '02. Washington, DC, USA: IEEE Computer Society, 2002, pp. 575–578.

[9] S. Joo and R. Chellappa, "A multiple-hypothesis approach for multiobject visual tracking," *Image Processing, IEEE Transactions on*, vol. 16, pp. 2849 – 2854, 2007.

[10] B. Khalegh, A. Khamis, F. O. Karray, and S. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Information Fusion*, vol. 14, no. 1, pp. 28 – 44, 2013.

[11] F. Castanedo, "A review of data fusion techniques," *The Scientific World Journal*, vol. 2013, Oct. 2013.

[12] R. Luo, C.-C. Yih, and K.-L. Su, "Multisensor fusion and integration: approaches, applications, and future research directions," *Sensors Journal, IEEE*, vol. 2, no. 2, pp. 107–119, Apr 2002.

[13] H. F. Durrant-Whyte, "Sensor models and multisensor integration," *Int. J. Rob. Res.*, vol. 7, no. 6, pp. 97–113, Dec. 1988.

[14] "Eurostat," http://ec.europa.eu/eurostat.

[15] L. Sabattini, V. Digani, C. Secchi, G. Cotena, D. Ronzoni, M. Foppoli, and F. Oleari, "Technological roadmap to boost the introduction of agvs in industrial applications," in *Intelligent Computer Communication and Processing (ICCP), 2013 IEEE International Conference on*. IEEE, 2013, pp. 203–208.

[16] C. Dima, N. Vandapel, and M. Hebert, "Sensor and classifier fusion for outdoor obstacle detection: an application of data fusion to autonomous off-road navigation," in *The 32nd Applied Imagery Recognition Workshop (AIPR2003)*. IEEE Computer Society, October 2003, pp. 255 – 262.

[17] M. Kalandros, L. Trailovic, L. Y. Pao, and Y. Bar-Shalom, "Tutorial on multisensor management and fusion algorithms for target tracking," in *American Control Conference, 2004. Proceedings of the 2004*, vol. 5, June 2004, pp. 4734–4748 vol.5.

[18] H. Jung, Y. Lee, P. Yoon, I. Hwang, and J. Kim, "Sensor fusion based obstacle detection/classification for active pedestrian protection system," in *Advances in Visual Computing*, ser. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2006, vol. 4292, pp. 294–305.

[19] K. Schueler, T. Weiherer, E. Bouzouraa, and U. Hofmann, "360 degree multi sensor fusion for static and dynamic obstacles," in *Intelligent Vehicles Symposium (IV), 2012 IEEE*, June 2012, pp. 692–697.

[20] A. Elfes, "Using occupancy grids for mobile robot perception and navigation," *Computer*, vol. 22, no. 6, pp. 46–57, June 1989.

[21] H. Moravec, "Sensor fusion in certainty grids for mobile robots," *AI Mag.*, vol. 9, no. 2, pp. 61–74, Jul. 1988.

[22] C. Braillon, K. Usher, C. Pradalier, J. Crowley, and C. Laugier, "Fusion of stereo and optical flow data using occupancy grids," in *Intelligent Transportation Systems Conference, 2006. ITSC '06. IEEE*, Sept 2006, pp. 1240–1245.

[23] P. Stepan, M. Kulich, and L. Preucil, "Robust data fusion with occupancy grid," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, vol. 35, no. 1, pp. 106–115, Feb 2005.

[24] J. Leonard and H. Durrant-Whyte, "Simultaneous map building and localization for an autonomous mobile robot," in *Intelligent Robots and Systems '91. 'Intelligence for Mechanical Systems, Proceedings IROS '91. IEEE/RSJ International Workshop on*, Nov 1991, pp. 1442–1447 vol.3.

[25] S. Pietzsch, T. D. Vu, J. Burlet, O. Aycard, T. Hackbarth, N. Appenrodt, J. Dickmann, and B. Radig, "Results of a precrash application based on laser scanner and short-range radars," *Trans. Intell. Transport. Sys.*, vol. 10, no. 4, pp. 584–593, Dec. 2009. [Online]. Available: http://dx.doi.org/10.1109/TITS.2009.2032300

[26] S. Thrun, "Learning occupancy grids with forward models," in *Intelligent Robots and Systems, 2001. Proceedings. 2001 IEEE/RSJ International Conference on*, vol. 3, 2001, pp. 1676–1681 vol.3.

[27] A. Hornung, K. Wurm, M. Bennewitz, C. Stachniss, and W. Burgard, "Octomap: an efficient probabilistic 3d mapping framework based on octrees," *Autonomous Robots*, vol. 34, no. 3, pp. 189–206, 2013.

[28] Z. Sun, G. Bebis, and R. Miller, "On-road vehicle detection using evolutionary gabor filter optimization," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 6, no. 2, pp. 125–137, June 2005.

[29] Y. Bar-Shalom and L. Campo, "The effect of the common process noise on the two-sensor fused-track covariance," *Aerospace and Electronic Systems, IEEE Transactions on*, vol. AES-22, no. 6, pp. 803–805, Nov 1986.

[30] Y. Bar-Shalom, "On the track-to-track correlation problem," *Automatic Control, IEEE Transactions on*, vol. 26, no. 2, pp. 571–572, Apr 1981.

[31] W. Khawsuk and L. Y. Pao, "Decorrelated state estimation for distributed tracking of interacting targets in cluttered environments," in *American Control Conference, 2002. Proceedings of the 2002*, vol. 2, 2002, pp. 899–904 vol.2.

[32] B. Parvin and G. Medioni, "Segmentation of range images into planar surfaces by split and merge," *Proc. of International Conference on Computer Vision and Pattern Recognition (CVPR86)*, pp. 415–417, 1986.

[33] L. Xu, A. Krzyzak, and C. Suen, "Methods of combining multiple classifiers and their applications to handwriting recognition," *Systems, Man and Cybernetics, IEEE Transactions on*, vol. 22, no. 3, pp. 418–435, May 1992.

[34] S. Tulyakov, S. Jaeger, V. Govindaraju, and D. Doermann, "Review of classifier combination methods," in *Machine Learning in Document Analysis and Recognition*, ser. Studies in Computational Intelligence. Springer Berlin Heidelberg, 2008, vol. 90, pp. 361–386.

[35] L. I. Kuncheva, J. C. Bezdek, and R. P. Duin, "Decision templates for multiple classifier fusion: an experimental comparison," *Pattern Recognition*, vol. 34, no. 2, pp. 299 – 314, 2001.

[36] D.-S. Lee and S. Srihari, "A theory of classifier combination: the neural network approach," in *Document Analysis and Recognition, 1995., Proceedings of the Third International Conference on*, vol. 1, Aug 1995, pp. 42–45 vol.1.

[37] A. Dempster, "A generalization of bayesian inference," in *Classic Works of the Dempster-Shafer Theory of Belief Functions*, ser. Studies in Fuzziness and Soft Computing, R. Yager and L. Liu, Eds. Springer Berlin Heidelberg, 2008, vol. 219, pp. 73–104.

[38] L. Breiman, "Bagging predictors," *Machine Learning*, vol. 24, no. 2, pp. 123–140, 1996.

[39] R. E. Schapire, "A brief introduction to boosting," in *Proceedings of the 16th International Joint Conference on Artificial Intelligence - Volume 2*, ser. IJCAI'99, 1999, pp. 1401–1406.