Special Section on Multisensor Fusion and Integration for Intelligent Systems

THIS Special Section was inspired by the 2016 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI 2016), see `mfi2016.org`, which took place 19–21 September 2016 in Baden-Baden, Germany. The conference was sponsored by the IEEE Robotics and Automation Society (RAS) and the IEEE Industrial Electronics Society (IES). Several of the papers in this Special Section build upon papers presented at the conference. While a total of 106 papers were presented at MFI 2016, we invited only the authors of the highest-ranked papers to submit an extended version of their respective conference papers to this Special Section.

Besides contacting these selected authors, an open call for papers for this Special Session was published to broaden the scope and to allow for papers not presented at MFI 2106. For extended conference papers, an important constraint was to include substantially novel aspects, such as added theoretical work or new experimental results. Authors are required to cite their original conference papers and clearly specify the novel contribution of the journal paper with respect to the conference paper. All papers, those building upon previously presented MFI 2016 papers and additional papers submitted related to the open call for papers, underwent the same rigorous review process as regular submissions strictly according to the guidelines of the IEEE TRANSACTION OF INDUSTRIAL INFORMATICS (TII).

A total of 58 papers were submitted to this Special Section of the IEEE TII. After a careful review process, eight papers were finally selected for publication.

We have grouped the eight accepted papers into four sections. One theoretical approach and one practical implementation of Bayesian estimation for recursively fusing sensor measurements over time are described in Section I. In Section II, two approaches coping with the detection of objects in images and videos are introduced. Fusion of data for different types of sensors is considered in Section III, while Section IV comprises two approaches for integrating the information given by a network of sensors.

I. Recursive Estimation for Fusion

A practical solution to the simultaneous localization and navigation problem—which is extending the well-known SLAM problem with solving motion control in addition—for mobile robots is provided in the paper "Intelligent Range-Only Mapping and Navigation for Mobile Robots" by Miah *et al.* Instead of utilizing sophisticated hardware platforms or computationally complex estimation and control frameworks, the authors combine well-established methods and technologies toward a cost-efficient and easy-to-implement solution: from a network of radio sensors range and bearing measurements are extracted approximately, the robot is using differential-drive kinematics and the open-source ROS operating system, simultaneously localizing the robot and mapping the sensors is performed by EKF-SLAM, and motion control is achieved by combining a P-controller for calculating the steering angle with a fuzzy logic controller for calculating the driving speed. By means of a computational simulation and two real-world experiments for indoor environments, it is shown that this approach allows for a very satisfactory localization and navigation performance given the significant noise sources caused by the considered indoor environments.

The paper "Application of Discrete Recursive Bayesian Estimation on Intervals and the Unit Circle to Filtering on SE(2)" by Kurz *et al.* considers nonlinear estimation problems whose state is defined on the unit circle or intervals. Two different discretization approaches are investigated. The first approach is based on approximating the probability density with a piecewise constant function, whereas the second approach approximates the probability using Dirac delta components, i.e., point masses. Then, the Dirac-based approach is generalized to allow estimation on the group of rigid body motions in two dimensions SE(2) using a Rao-Blackwellization technique. The proposed approaches are evaluated in simulations and shown to significantly outperform the sequential importance resampling (SIR) particle filter.

II. Fusion for Computer Vision

The extraction of suitable features from an image is a fundamental task in computer vision. In this context, speed-up robust features (SURF) are widely used, e.g., for object detection, image registration, and localization. The paper "Real-Time FPGA-Based Detection of Speeded-Up Robust Features Using Separable Convolution" by Čížek and Faigl introduces a novel framework for an efficient calculation of SURF features using a field-programmable gate array (FPGA). In particular, the proposed framework allows for an accelerated salient point extraction. The most significant improvements are achieved with

1) a separable convolution,
2) a suitable implementation of the r-line buffer, and
3) a nonmaxima suppression method.

The article "Autonomous Flame Detection in Videos With a Dirichlet Process Gaussian Mixture Color Model" by Li *et al.* is about a flame detection approach that employs color, flickering, and dynamic features of flames. In the proposed framework, flame colors are modeled as Gaussian mixture distributions and a major contribution is that the number of components is estimated based on a Dirichlet process model. By this means, it can be avoided that an incorrectly chosen number of Gaussian components causes a poor detection performance. Dynamic and flickering properties are captured with a probabilistic saliency analysis in combination with a one-dimensional wavelet transform. Experimental results demonstrate an impressive performance of an accuracy of 95% per frame, which is significantly better than the state-of-the-art.

III. Multimodal Fusion

With the advent of initiatives like the industrial internet or Industry 4.0, predictive maintenance becomes an important method for achieving increased productivity and reduced maintenance cost in production lines. Effective predictive maintenance requires a sufficient exploitation of information provided by many different sensors. In "Deep-Coupling Autoencoder for Fault Diagnosis with Multimodal Sensory Data" by Ma *et al.* a fusion strategy for vibration and acoustic sensor signals is proposed for this purpose. The basic idea is to use individual deep autoencoders for both sensor types that are connected by means of an intermediate coupling layer. This layer ensures that the correlation between the multimodal signals are captured. To train the resulting deep network, a learning algorithm named DCAE is proposed, which optimizes a loss function reflecting both the deviation of the individual autoencoders from the desired output signals and the deviation between the both autoencoders. Experiments with a gear box and bearings indicate that the proposed fusion approach outperforms deep learning approaches where the sensor signals are merely processed in a combined feature vectors. This highlights the benefits of explicitly modeling the fusion of multimodel sensor signals by means of the coupling layer.

The paper "Multimodal Sensor System for Pressure Ulcer Wound Assessment and Care" by Chang *et al.* aims at developing a hand-held probe device for wound assessment to be used in hospitals or in households. Good assessments of wound is an important input for further treatment decisions and for detecting pressure ulcers, which can impose significant morbidity and mortality. To improve on the quality of the assessment, the authors combine various sensing modalities: color, depth, thermal, multispectral, and chemical. This information is used for tissue classification, three-dimensional wound size measuring, hot-spot detection, or infection detection. The validity of the approach is tested by means of a clinical study with labeled data. This study also reveals the need for improvements on increased robustness against varying illumination conditions.

IV. Sensor Network Fusion

Smart grids are causing a significant change in the energy market. Instead of merely relying on centralized large-scale energy sources, such as nuclear power plants or fossil fuel power stations, energy generation is getting more decentralized, where single households or neighborhoods become energy providers thanks to an increasing number of solar pannels being installed on rooftops or gardens. Controlling the stability and regulating the pricing of smart grids in real-time are open challenges. The latter is addressed in "Real-Time Pricing by Data Fusion on Networks" by Izumi and Azuma. The authors propose utilizing local power estimators in each energy source. In order to estimate the power consumption of the grid, a consensus protocol is used for communicating local power estimates to other estimators in the neighborhood. A centralized PI-controller is regulating the power price given the estimates of neighboring power estimators. The authors derive stability conditions under mild network topology assumptions that allow maintaining a reference total energy consumption without the need of communicating with all consumers. This approach scales well with an growing energy grid as the energy estimators merely require local information.

In "Covariance Intersection in Track-to-Track Fusion: Comparison of Fusion Configurations" by Ajgl and Straka, the problem of fusing the local estimates of various sensors is tackled. Instead of utilizing correlation information between the local estimates, the covariance intersection (CI) approach is employed, which requires no information about correlation. Thanks to upper bound approximations, CI avoids expensive communication between the sensors or to the fusion center. For the track-to-track fusion scenario, the authors consider different CI-based fusion configurations: fusion with full information feedback, partial feedback, and no feedback. Also the cases where the fusion center is either equipped with memory or has no memory are considered. By means of numerical examples, the different configurations are compared and conclusions are drawn under varying fusion parameters or under changing fusion rates.

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