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Redundancy-orchestrated Information Fusion
Exploiting Sensor Redundancy for Improved Model Robustness

Christoph-Alexander Holst, inIT – Institut für industrielle Informationstechnik, Technische Hochschule Ostwestfalen-Lippe, Lemgo, Deutschland
christoph-alexander.holst@th-owl.de

Abstract

Sensor defects are a common occurrence in technical and industrial systems, manifesting as deviations in sensor measurements due to factors such as ageing, wear and tear, or environmental effects [1]. These defects introduce outliers, noise, offsets, or drift. Sensor defects significantly impact machine learning (ML) models, as data distributions increasingly deviate from the training data with the severity of the defect, making them out-of-distribution. Because ML models are limited to the knowledge obtained from their training data, out-of-distribution data causes a decline in the accuracy of their predictions or classifications [1, 2].

To counteract this, inherent redundancy in a multi-sensor system can be exploited with information fusion techniques based on the possibility theory [3]. In such approaches, information from redundant sensors is fused before input to an ML model. This reduces the impact of sensor defects and provides the ML model with a cleaned input. Two requirements must be met to ensure the correct functioning of the preceding information fusion. Firstly, a set of sensors must be correctly clustered into redundant subsets, building a topology of fusion nodes. It is crucial that these nodes contain actual redundant sensors. Secondly, the applied information fusion rules must be robust towards sensor defects themselves. Designing the topology and the fusion rules of an information fusion system is referred to as orchestration.

In the state of the art, fusion systems are mainly orchestrated based on semantic expert knowledge—either manually or with matching algorithms working on ontologies [4]. Automated approaches that learn from training data are missing, which is an issue particularly for large multi-sensor systems. Possibilistic fusion rules, such as adaptive [4] or progressive fusion [6], are often prone to defects. Their outputs may be altered significantly by faulty sensor measurements. Additionally, fusion rules are often non-associative [4], which makes them unsuitable for redundancy-orchestrated topologies.

This work addresses both open research topics of (1) data-based automated fusion topology orchestration and (2) robust possibilistic fusion rules. A possibilistic redundancy metric is introduced, which is more cautious when assessing redundancy than naive correlation or mutual information. Based on this newly introduced redundancy metric, sensors are clustered into fusion nodes. Furthermore, an updated version of the estimation fusion rule is presented, which can be applied in distributed redundancy-orchestrated fusion topologies and actively detects and discounts faulty sensor measurements. The active detection presumes redundancy and is only suited for redundancy-orchestrated topologies.

The proposed redundancy-orchestrated information fusion is evaluated on real-world datasets in which sensor measurements are artificially superimposed with different types of defects (drift, noise, outlier, offsets). This allows for a comparative analysis of fusion outcomes between the original and modified datasets. Fusion robustness is assessed by the degree of output similarity, with robust fusion expected to yield similar outcomes. Results demonstrate the enhanced robustness of redundancy-orchestrated fusion across all defect types, with improvements of up to 4%. Conversely, the robustness of state-of-the-art possibilistic fusion rules varies significantly between defect types. Therefore, this work contributes to creating the prerequisites for increased robustness of machine learning models in multi-sensor systems.

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