# An Embedded Multi-Sensor Data Fusion Framework for Enhancing Vision-based Traffic Monitoring

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Abstract — In the present paper we introduce a novel threelayered multi-sensor data fusion framework. The design and implementation task is going to be performed for enhancing vision-based traffic monitoring. The aim of our fusion process is to achieve higher vehicle detection and classification rates, hence less false positives, more precise occupancy calculations and gain support for robust tracking. Finally, we want to show the feasibility of our approach in a real traffic monitoring environment using heterogeneous sensors (cameras, microphones and (IR) lasers). For reasons of network security we will appropriately set up a wired decentralized heterogeneous sensor network.

#### I. INTRODUCTION

Multi-Sensor Data Fusion is a widely used method to increase the robustness of sensor applications [1, 2, 3]. Especially in (time-)critical applications, e.g., traffic monitoring environments, where data has to be reliable, it is useful to combine data from different sensors to deduce more robust estimates. Most traffic monitoring applications are based on vision alone. This single sensor approach shows some limits concerning robustness and detection rates. Therefore we investigate an embedded decentralized multi-sensor approach. In a centralized fusion system all data to be combined is sent to a central fusion node that performs the complete fusion task. In the case of a decentralized fusion architecture, each node in the network is able to perform (partial) fusion locally. Local results are then sent to a distinguished fusion node that finally combines partial fused data to form a complete and consistent view of the universe of discourse.

We choose the decentralized approach to allow involved sensor nodes acting more autonomously especially regarding the fusion processing task. Furthermore, we decrease the risk of a total system breakdown by avoiding a single point of failure.

#### II. SENSOR NETWORK

Our sensor network consists of several sensor nodes (SNs), a single center node (CE) and a virtual SN (Fusion Backbone to Center, FBC) sending fused data to CE ("Figure 1"). FBC is called virtual because it is not an additional sensor node in the network. A FBC node is an

ordinary SN that has to be determined dynamically for final fusion processing ("decision making"). Each SN (CE and FBC, respectively) has a couple of attributes and methods defining state and functionality.

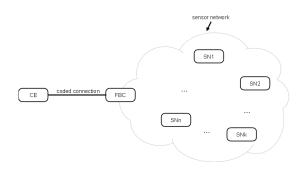


Figure 1: Overview - sensor network structure

It is important to note that the sensor network is hierarchically structured. Each cluster performs fusion on specific parts of the universe of discourse  $(1^{st}$  level cluster fusion) and is identified by the same cluster identification number (clusterID) of each SN within the cluster. The  $2^{nd}$  level fusion combines fusion results from all clusters forming a decision.

### **III. FUSION ARCHITECTURE**

Our proposed fusion architecture will consist of three layers as shown in "Figure 2". We choose a layered architecture to abstract and encapsulate the different processing steps within the whole fusion framework. Each layer has a specific structure and processing task contributing to the whole fusion process. In brief, layer 1 collects raw sensor data and performs normalization, layer 2 performs intra-cluster fusion and the final fusion is done within layer 3.

#### A. LAYER 1

The first layer is responsible for two things. Firstly, it acquires raw data from the involved sensors. Secondly, we have to normalize incoming heterogeneous data to have comparable measurements. Hence, the first layer has to deal with the underlying hardware (hardware layer).

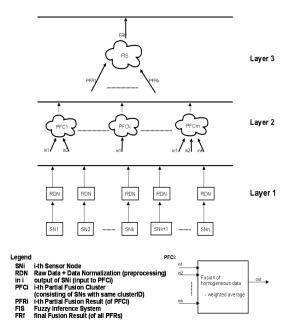


Figure 2: Three-layered fusion architecture

# B. LAYER 2

Layer 2 reflects the  $1^{st}$  fusion layer of the architecture performing competetive and complementary integration within the so-called Partial Fusion Cluster (PFC). Competetive integration only combines sensor data representing the same measurements reducing uncertainty and resolves possible conflicts. However, the complementary approach fuses incomplete sensor data to create a more complete model, i.e., enriching knowledge about environment [4]. All measurements that are to be combined in a PFC originate from sensors with the same clusterID. Since there is no partial fusion center within PFCs, a protocol has to be defined specifying where the distributed measurements are fused. Moreover, an appropriate algorithm has to be developed for intra-cluster fusion as well. If every involved sensor in the network has a different clusterID, each PFC consists only of a single sensor. Hence, layer 2 will simply be omitted, i.e., each sensor represents a PFC. The fused partial results are then forwarded to layer 3 to perform high-level fusion.

# C. LAYER 3

Layer 3  $(2^{nd}$  fusion layer) performs cooperative integration (e.g., using fuzzy inference system). Cooperative integration means combining independent measurements to gain additional information about the whole environment of interest, i.e., information that would not be available with a single sensor (e.g., using stereo vision to calculate disparity maps [3]). The number of inputs is directly dependent on the number of PFCs formed up in the previous layer. The outcome of the fusion process of layer 3 is a decision with high probability of being true (e.g., vehicle running the red light).

## **IV. PROSPECTIVE CONTRIBUTION**

We present a novel three-layered multi-sensor data fusion framework, where an architectural and algorithmic solution is introduced to perform multi-sensor data fusion in traffic monitoring environments. We choose a decentralized fusion processing approach on embedded platforms. Besides developing an appropriate architecture for networking and sensor connection to the platform, we want to find a new way of combining data from heterogeneous sensors considering spatio-temporal issues.

Presently, our scientific contribution will be in designing a novel fusion algorithm exploiting spatio-temporal relations in traffic monitoring environments. Besides, we want to develop a protocol for the flow of partially fused data through the network in an efficient way. Some questions herein are to be answered, e.g., Which SN is responsible for playing the FBC's part (and when)? Which data is sent when and where? How are the SNs organized throughout the whole sensor network? How many actual sensor instances are mounted on a SN?

To keep communication bandwidth as well as computation power requirements less demanding we decide from an information process model point of view - to perform fusion at the feature and decision level, respectively (higher level fusion). This allows for more system configuration flexibility in implementation. Furthermore, higher-level fusion is perfectly suitable for systems that should have physically distributed more independently working components [4]. This aspect harmonizes fine with our decentralized system approach.

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