Sensors Data Fusion for Smart Decisions Making Using Interpretative Machine Learning Models

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Sensor fusion is an important and crucial topic in many industrial applications. One of the challenging problems is to find an appropriate sensor combination for the dedicated application or to weight their information adequately. In our contribution, we focus on the application of the sensor fusion concept together with the reference to the distance-based learning for object classification purposes. The developed machine learning model has a bi-functional architecture, which learns on the one side the discrimination of the data regarding their classes and, on the other side, the importance of the single signals, i.e., the contribution of each sensor to the decision. We show that the resulting bi-functional model is interpretative, sparse, and simple to integrate in many standard artificial neural networks

Sensor fusion gains much interest during the last years. There are lot of advantages to combine the signals of several sensors: systems can get better reliability, stability and confidentiality or sensor failures can be compensated. Yet, the fusion of several sensor signals leads to challenges, too. Several questions must be answered for successful fusion: Which sensors should be applied to solve a specific problem? Which sensors are more robust? Are all sensors necessary and should all have the same influence on the decision?

Beside technical expertise for the task and sensors, artificial intelligence (AI) can go for answering these questions. In several publications the performance benefit applying different sensor fusion approaches using AI is analyzed [1,2,3]. From that, we notice that researchers' efforts are mainly dedicated to try different combination formats of sensing data. Yet, the importance of the single sensors for the performance are still hard to detect. Obviously, the influence is sensor and task depending and generally difficult or impossible to answer in general. However, for a given specific task AI may help to capture this information analyzing sensor behavior and comparing this to expected behavior.

In our contribution we present a neural network architecture taking a multi-sensor data input [4]. Thereby the network is built by two main blocks: the feature generation block and the bi-functional block including the classification and evaluation of the influence of multi sensor input (see illustration Fig.\ref{bi}). For the feature generation block, standard deep neural networks are chosen, which have been shown to be immensely powerful in many application areas, e.g., ResNet for image processing [7]. For the second block we use the prototype-based Generalized Learning Vector Quantization for the final classification task (GLVQ, [6]) integrated in a network structure [5]. This network architecture provides a competition layer, i.e., the data in the feature space were evaluated by calculating a distance to learned class-dependent prototypes and comparing them to find the best matching prototype. This is also known as Winter-Takes-All rule. Thus, the input is assigned to the class of this nearest prototype. The used distance measures can be also parameterized, in this sense that the influence of each sensor signal (feature) is weighted according to the importance for the discrimination [8,9]. We use this feature adapting property of GLVQ to learn the contribution of each sensor for our classification task additionally. Thus, our network response not only a classification model, but it also provides us the sensor importance.

We applied our network with the bi-functional block to detect humans using image of different sensor signals. Here three sensor signals are used, depth images and the aligned amplitude images of a time-of-flight camera and a radar image. It turns out, that the highest contribution has the amplitude image. Nevertheless, the depth and radar sensors are not unimportant.

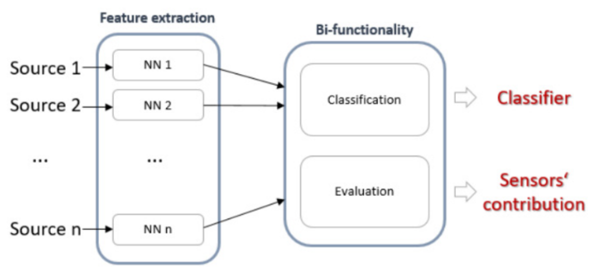

Figure 1 Illustration of a bi-functionality system for sample classification and sensors evaluation [4]

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