

# Optimizing the Design of a Multi-Sensor System for On-Line Driver State and Drowsiness Detection

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## Abstract

Driver assistance systems have become largely established in automotive applications, both for comfort and for safety functions. The monitoring of the driver state and intention, in particular, the detection of fatigue or drowsiness, is a relevant but not completely satisfying solved task both in consumer as well as commercial vehicles to improve both vehicle and road safety. Thus, in our research, a multi-sensor driver assistance system for this aim has been conceived in our DeCaDrive project [1]. Here, we have advanced the system realization towards higher flexibility, optimization as well as on-line drowsiness detection capability by moving it to the ORANGE multi-platform open-access environment [2] and employing Support-Vector-Machine classifier [3] on the DeCaDrive feature data. The employed methods, hierarchical SVM-based classification with automated finding of parameters as well as suitable features, gave comparable or even superior results with regard to previous investigations, as substantially smaller training sets for higher generalization capability were employed. Classification rates of 99.66 % could be achieved for five persons and one hour recorded driving data each.

**Keywords:** Automated intelligent system design, Impedance spectroscopy, Drowsiness detection, Depth perception, Multi-sensor fusion, Driver assistance systems

# 1 Introduction

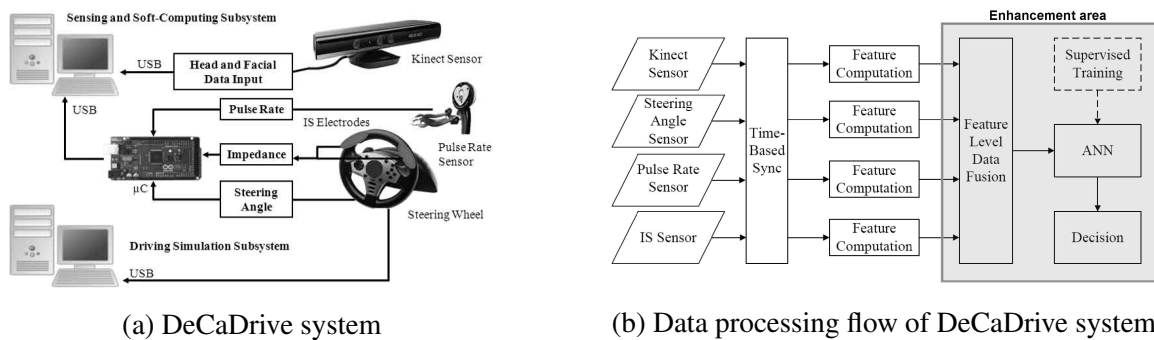
Nowadays the major trends of automotive applications such as electric vehicles, connectivity in particular vehicle-to-vehicle communications (referred to as V2X), (semi-)autonomous driving, etc. will lead to the future of automotive world with human centered safe and sustainable mobility through renewable energy and smart driving. Despite completely autonomous automated land vehicles are technically possible (e.g., Google driverless car [4]) human's active role will not diminish but refocus on cooperative interactions by means of re-defined/re-invented human-vehicle-interface. To realize this vision advanced driver assistance systems (ADAS) have paved the way to the mainstream automotive applications such as parking assist, 3D surround view, lane departure warning, traffic sign and pedestrian recognition, etc. ADAS systems with the feature of driver drowsiness/vigilance detection have been introduced by major automakers as active safety measures. *Driver Alert* from Ford Motor Company [5] and *Driver Alert Control and Lane Departure Warning* from Volvo [6] are camera based lane tracking system which can detect abnormal car movement associated with potential drowsy driving. *Attention Assist* from Daimler [7] is capable of monitoring steering behavior with the aid of high resolution steering sensor and issue visual or audible alarm if required. *Fatigue Detection System* from Volkswagen [8] and *Driver Monitoring System* from Toyota [9] are directly focusing on driver state in terms of head movement, facial features and ocular measures. The performance and robustness of the above mentioned ADAS systems are limited by sensing capability and application environment. In our previous work — DeCaDrive, an embedded multi-sensor driver assistance system, IR-depth, vision, vehicle data, e.g., steering wheel sensor information, as well as biomedical information of the driver, e.g., pulse or skin impedance, are collected and processed for drowsiness detection [1] [10]. Data has been extracted from five test subjects with 300 minute driving sequence in a driving simulator, which is part of the DeCaDrive set-up. Heuristic determination of the tiredness or drowsiness levels of the drivers in that acquisition time has been carried out for following supervised training. A solution based on feature selection and a first neural classifier was engineered and encouraging results have already

been achieved [2]. In this work, our DeCaDrive system will be optimized towards higher flexibility, robustness, as well as on-line recognition capability. The DeCaDrive system with embedded multi-sensor interface for driver state monitoring and drowsiness detection is presented in Section 2. The system design with optimized sensor data processing flow and hierarchical SVM based classification is addressed in Section 3. The enhanced system is validated and evaluated by presenting the new experimental results in Section 4. Finally, the current work is concluded with future perspectives in Section 5.

## **2 DeCaDrive: Multi-Sensor System for On-Line Driver State and Drowsiness Detection**

DeCaDrive system conceptually aims at both intelligent driver status monitoring and intention recognition. It has been realized based on a standard PC based driving simulation, sensing, and soft computing subsystems [1]. This comprises a IR-depth camera (Kinect sensor) for eye finding and feature extraction, which has been extended to an intelligent multi-sensor system incorporating sensor signal processing as well as diversified embedded sensor interfaces, e.g., pulse rate sensor, steering angle and related driving behavior sensors, and impedance spectroscopy. Context by tactile sensor and pressure sensors is considered in the next step, to avoid spurious readings of the skin resistance during absence of one or both hands from the steering wheel. As illustrated in Fig. 1a, data links of various embedded sensors on steering wheel are channelized to microcontroller based digital front-end so as to establish scalable adaptive multi-sensor interfaces. The IR-depth camera, as a key component of the sensing subsystem is connected to PC-based back-end directly. The sensing and soft-computing subsystem is logically independent from the driving simulation subsystem despite that two subsystems can be unified in embedded solution for future on-board device in vehicle. In the current information processing architecture, given in Fig. 1b, sensory data is collected from depth vision, steering angle, optionally brake and throttle information, driver pulse rate, and impedance spectrum from skin measurement, and fused on feature level. A Kinect sensor with active IR illumination is integrated in order to reliably provide visual cues of driver in-

cluding eye gaze estimation and blink detection. The multi-sensing interfaces enable A/D conversion, sensory data streaming, time-based synchronization for multiple sensors and can be adapted to different simulation scenarios such as for passenger cars, buses or trucks. Different driving scenes for highway, city streets, country roads, etc. can be simulated in PC-based driving simulation subsystem. Based on the outcome of feature computation the selected data sets are fused on the feature level to construct input vectors for pattern classification so as to detect driver drowsiness. The classifier being used in the previous work is built upon artificial neural network (ANN), here a multilayer perceptron (MLP), with supervised training procedure. A straightforward improvement is the use of renowned Support-Vector-Machine (SVM) classifiers instead on the ANN. The framework of presented intelligent multi-sensor system is reflected by its data processing flow as illustrated in Fig. 1b. Data sets of complementary sensors are synchronized on the same time base before being conveyed to feature computation components. In this paper, we extend the system architecture and processing to the structure depicted in Fig. 2, which includes hierarchical classification and automated design approach. The overall concept and architecture is not limited to cars but also targets on driver monitoring in utility vehicles, e.g., bussed, trucks, or agricultural machines, as well as airplane pilots.



**Figure 1:** The concept and the implementation of Lab on Spoon

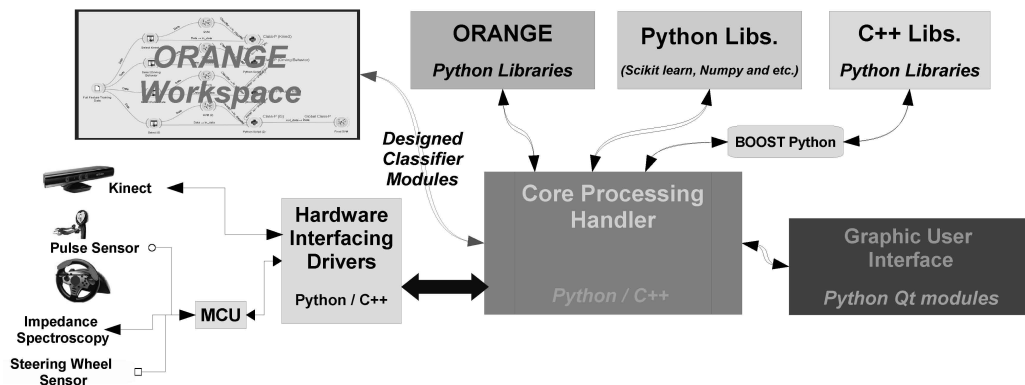
### 3 Enhancement of DeCaDrive-System Architecture

In this paper, we have advanced the system realization towards higher flexibility, optimization as well as on-line recognition capability by moving it to the ORANGE system [2] and employing Support-Vector-Machine classifier [3] on

the DeCaDrive data and feature level. In this approach, we aim to achieve an effective Automated Feature Selection as well as a robust on-line classification system.

### 3.1 Intelligent system design in ORANGE

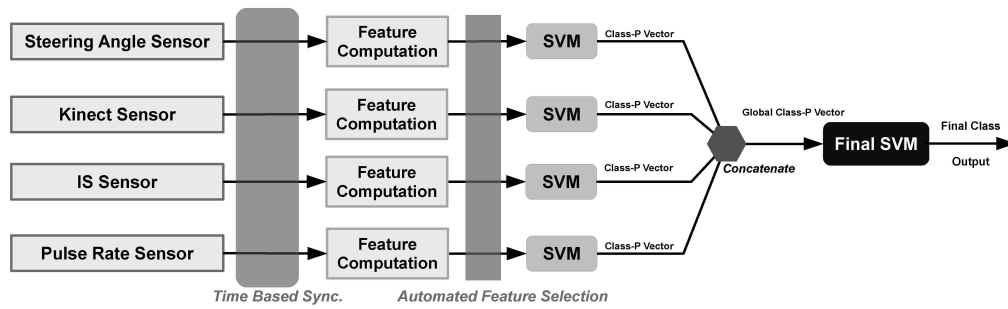
Our approach is based on a multi-platform flexible and open system, with an on-line classification capability, which is provided by the Python-based signal processing and computation intelligent libraries as well as , ORANGE, an open source python based machine learning software through visual programming. Initially, we have implemented a system that jointly operated of Python scripting and the heuristic DeCaDrive environment operators that have been achieved in our previous research [10]. We reuse our proprietary effective operators developed in C/C++ by using BOOST [11] for Python. The Serial Port Interface module communicates with the DeCaDrive acquisition device using serial port interface to control acquisition activity and import acquired data to store in ORANGE's data structure. The Feature Selector module allows user to manually filter data in term of sensory channels, e.g., pulse rate, steering wheel angle, Kinect features and impedance in the design process.



**Figure 2:** The proposed on-line DeCaDrive system

### 3.2 Pattern classification

The pattern classification tasks analyzes multi-sensory context from the DeCaDrive data acquisition system to on-line determine the driver status. In this work, the standard SVM classification technique first is employed to investigate a flat SVM classification approach based feature-level fusion together



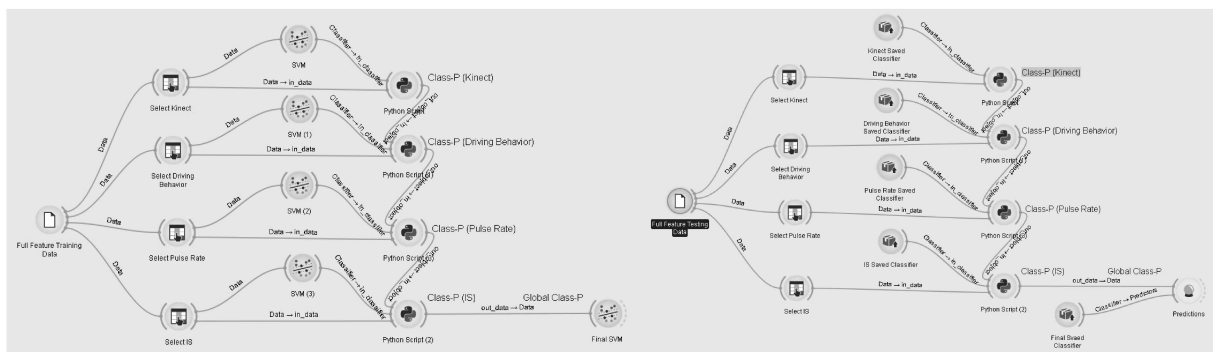
**Figure 3:** Overview of the extended DeCaDrive system with hierarchical processing

with the AFS option. In addition, our recent effective hierarchical approach in [12] is also applied to this work as a more powerful and robust classification technique as shown in Fig. 3. The hierarchical SVM (H-SVM) classification is constructed of multiple SVM classifiers with soft output in the first level processing stage, to produce class probability (class-P) vectors corresponding to the probabilistic patterns of different classes. Each SVM classifier in the first level stage locally and individually computes a particular sensor channel to generate a class-P vector. The final SVM classifier, in the top level, computes the global class-P vector, the concatenated of class-P vector from all sensor channels, to produce the final class output. To generate an optimum SVM model, two parameters,  $C$  which controls the error penalty of non-separable data points, and  $\gamma$  of the Radial Basis Function (RBF) kernel, are recommended to be appropriately defined with regard to the input data. The SVM optimum parameters searching procedure is generally taken place in the training step based only on the training data. In this work, the SVM automated parameters search option implemented in ORANGE with grid search and cross validation techniques is employed. SVM parameters are individually determined for each of the investigated feature channel SVMs and the top-level SVM.

## 4 Experiments and Results

The ORANGE project workspace of our approach with an integration of standard available ORANGE modules as well as our developed custom modules is shown in Fig.4 for the newly proposed hierarchical approach. The data sets are obtained from five test subjects each conducted by 60 minutes driving simulation on the DeCaDrive system. Each measurement is consisted of 31 features

(see Table 2) extracted from multiple sensor inputs including Kinect, driving behavior, pulse rate, and IS. The driver drowsiness states are distinguished in tree levels: alertness, drowsiness and deep drowsiness. The flat SVM classification approach was employed with 5 different data sets of: 8 SFS&IS, 8 SFS, without IS, Only IS, and Full feature obtained from our previous study [10]. The H-SVM classification approach was employed with the full data set as well as 8 SFS&IS. All data set were separated into training set and testing sets by using the hold out random sampling method with 80%:20% ratio for the flat SVM and more stringent 50%:50% ratio for the H-SVM as well as for a second reference run with flat SVM given in parentheses in Table 3. The parameter  $C$  and  $\gamma$  of all employed SVMs were optimized from the automated parameters search function with the searching range of 1-512 for  $C$  and 0-8.00 for  $\gamma$ . The obtained values are shown in Table. 1. The experiments conducted in this work confirmed the superiority of the SVM in both flat and hierarchical approach. To compare to the more lenient investigations of the previous work, first flat experiment was conducted with a larger training set. In the second, more extensive experiment, a substantially smaller training set was employed, which gives absolutely seen slightly smaller recognition rates of 99.66 %, but the system solution will have much higher general validity and the promise to perform better for newly acquired "life" data. AFS application compacted the solution for a more lean system, but it has to be revisited, as the full set of features gives slightly better performances, than the selection adopted from the prior work with only 99.58%. Fig. 5 shows the feature map plot of the full data and the hierarchical data (global class-P vector).



**Figure 4:** Hierarchical implementation of multi-sensor intelligent DeCaDrive system on Orange

**Table 1:** a: Flat SVM parameters generated from automated parameter search function

Parameter	Data set				
	8 SFS & IS (50%)	8 SFS	without IS	Only IS	Full
$C$	512 (32)	512	8	512	128
$\gamma$	8 (8)	8	8	8	2
no. of SVs	690 (674)	1124	1895	455	947

**b: H-SVM parameters generated from automated parameter search function**

Data set	Parameter	Sensor Channel				
		Kinect	Driving Behavior	Pulse Rate	IS	Final
Full	$C$	128	32	512	512	512
	$\gamma$	8	8	2	8	8
	no. of SV	700	1004	854	356	52
8SFS&IS	$C$	64	128	512	512	512
	$\gamma$	6	8	2	8	8
	no. of SV	560	848	854	356	50

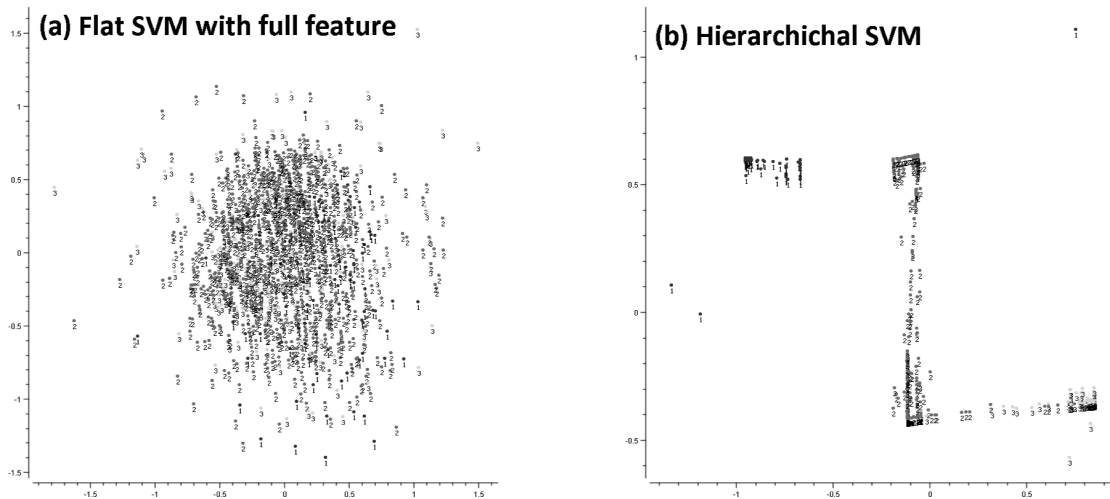
**Table 2:** Descriptions of the DeCaDrive data set including the selection of 8SFS data set

Feature	All	8SFS	Description
Kinect	1-3	1-3	Head pos. in x,y and z coordinates
	4-6	-	Head orientation in x,y and z coordinates
	7,8	-	Translat. and rot. head velocity
	9	9	Eyebrow position
	10,11	10	Eye lid closing freq. and duration
Driving behavior	12,13	-	Steering activity
	14	-	Standard deviation of steering activity
	15	15	Percentage of minimum steering activity
	16	-	Mean of magnitude
	17	-	Steering speed
	18	-	Center of FFT-band
Pulse Sensor	18,19	18,19	HF LF ratio of pulse freq. and Pulse freq.
IS	21,22	-	Mean and std. deviation
	23	-	Coefficient a (slope) after linear fitting
	24	-	Coefficient a after exponential fitting
	25-27	-	Coefficient a, b and c after polynomial fitting
	28	-	Coefficient a (slope) after linear fitting
	29-31	-	Coefficient a, b and c after polynomial fitting



**Table 3:** Classification Result

Feature	Levenberg-Marquardt algorithm	Flat SVM	H-SVM [Full feature, with 8 SFS & IS]
8 SFS & IS (50%:50%)	99.70	99.79 (97.21)	
8 SFS	89.38	78.28	
without IS	90.48	93.19	[99.66, 99.58]
Only IS	98.70	99.16	
Full	99.22	98.22	



**Figure 5:** Feature map plot of the full data (a) and the hierarchical data of the top-level (b). Clearly (a) shows, that the data possess a very high intrinsic dimensionality, which does not allow a mapping to 2-D with acceptable error.

## 5 Conclusion

In this paper, we enhanced the work on a multi-sensor system for driver state monitoring, denoted as DeCaDrive, by adding more powerful methods from computational intelligence, i.e., SVMs for decision making and automation capabilities for optimum parameter as well as feature determination. Further, the system was transferred to a new open-access multi platform environment. This ORANGE environment was substantially enhanced and the extended methods were implemented. The classification results of 99.66 % for the full data and 99.58% for the selected case appear to be a trifle worse than previously obtained results, but 30% less training data was used to achieve a more robust realization. One of the open issues in the DeCaDrive system modeling is the definition of ground truth of probands actual alertness or drowsiness, which still has been heuristically determined. In future work, we consider to use EEG-based meth-

ods as in sleep research to get a better, somehow invasive, determination of the ground truth using our emotiv kit. Another issue is a potential person dependency in the classification system due to the limited number and phenotypes of the probands, which will be overcome enlarging the database in the next steps. Further, we have extended the architecture to on-line classification and drowsiness estimation based on the established SVMs for freshly acquired data. The current system will be demonstrated on IAA Nutzfahrzeuge 2014 in Hannover.

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