Intelligent Vehicle Systems:Applications and New Trends

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Abstract. Most people usually do not consider the car sitting in their driveway to be on the leading edge of new technology. However, for most people, the personal automobile has now become their initial exposure to new intelligent computational technologies such as fuzzy logic, neural networks, adaptive computing, voice recognition and others. In this chapter we will discuss the various intelligent vehicle systems that are now being deployed into motor vehicles. These intelligent system applications impact every facet of the driver experience and improve both vehicle safety and performance. We will also describe recent developments in autonomous vehicle design and demonstrate that this type of technology is not that far away from deployment. Other applications of intelligent system design apply to adapting the vehicle to the driver's preferences and helping the driver stay aware. The automobile industry is very competitive and there are many other new advances in vehicle technology that cannot be discussed yet. However, this chapter provides an introduction into those technologies that have already been announced or deployed and shows how the automobile has evolved from a basic transportation device into an advanced vehicle with a host of on-board computational technologies.

Keywords. Computational intelligence, vehicle systems.

1 Introduction

Although the automotive industry has always been a leading force behind many engineering innovations, this trend has become especially apparent in recent years. The competitive pressure creates an unprecedented need for innovation to differentiate products and reduce cost in a highly saturated automotive market to satisfy the ever increasing demand of technology savvy customers for increased safety, fuel economy, performance, convenience, entertainment, and personalization. With innovation thriving in all aspects of the automotive industry, the most visible advancements are probably in the area of vehicle controls enabled by the proliferation of on-board electronics, computing power, wireless communication capabilities, and sensor and drive-by-wire technologies.

The increasing sophistication of modern vehicles is also accompanied by the growing complexity of required control models. Therefore, it is not surprising that numerous applications of methodologies generally known as "intelligent", "soft computing", "computational intelligence", and "artificial intelligence" have become increasingly popular in the implementation of vehicle systems. In this chapter, we focus on applications of computational intelligence methodologies such as Fuzzy Logic, Neural Networks, Machine Learning, Knowledge Representation, Probabilistic and Possibilistic Reasoning as building blocks for intelligent vehicle systems. These examples are drawn from published sources with credible evidence of successful vehicle implementation, or research sponsored by automotive enterprises. This chapter does not provide an exhaustive bibliographical review, but limits the number of references that are necessary to illustrate relevant examples of applications of intelligent technologies.

In this review we describe the introduction of different methods of computational intelligence for vehicle control in chronological order. In the next section we review one of the first applications of computational intelligence for vehicle control: fuzzy-neural controls. Section 3 describes automotive applications of speech recognition, while Sect. 4 discusses the varied uses of on-board vehicle diagnostics. In Sect. 5 we describe applications of intelligent vehicle technologies which also include a discussion on the technology needed for autonomous vehicles. Section 6 discusses the emerging field of application of driver-aware technologies that monitor and mitigate adversary driver conditions, such as fatigue, impairment, stress or anger. The final section summarizes the chapter and presents our conclusions.

2 Fuzzy-Neural Systems Control

Fuzzy logic and neural networks were the first computational intelligence techniques implemented in the vehicle as viable alternatives to the classical control methods that may be infeasible, inefficient or uneconomical. The first commercial applications of fuzzy logic for speed control and continuous variable transmission date back to 1988 [37] [38].

Fuzzy logic controllers take advantage of human knowledge of the control behavior. The control process is described inside a set of "IF-THEN" rules that also includes probabilistic fuzzy variables for control values. In a fuzzy logic controller, the crisp sensor inputs are converted to the fuzzy variables that are processed against the rule base. A combined result is then converted back into a specific crisp control value.

There are a number of reviews outlining the advantages and production implementations of fuzzy logic in control of different vehicle systems, including anti-lock breaking systems (ABS), engine control, automatic transmissions, anti-skid steering, and climate control [4] [43]. In recent years, the proliferation of hybrid vehicles (e.g. vehicles that combine combustion engines and electric motors) created the potential for a new application area of fuzzy logic control for vehicle subsystems [32]. These examples demonstrate that incorporating expert rules expressed through fuzzy logic simplifies complex control models.

In addition, fuzzy logic allows the modeling of such inherently ambiguous notions as driver behavior in an efficient and effective way. Exploring this feature of fuzzy logic, Takahashi [38] presents the concept of vehicle control, where the driver plays the role of the human sensor for the control system. In this case, the driving environment and driver intentions might be predicted by analyzing the operations executed by the driver, such as pedal inputs and steering maneuvers. Furthermore, this control system makes it possible to infer driver classification (for example "defensive", "medium", "sporty" [45]) and adjust the characteristics of the engine, transmission and other vehicle subsystems to the driver preferences.

While fuzzy logic allows for the representation of the knowledge of human experts in the form of rules, neural networks allow for the capture of expertise through training. Often both techniques are combined together. Hayashi et al. [14] describes a Neuro-Fuzzy Transmission Control system developed at Isuzu Motors. This system combines both a Fuzzy Logic module and Neural Nets. Fuzzy Logic is used to estimate the automobile load and driver intentions from both the input shaft speed and accelerator position displacement. The Neural Net module determines the optimal gear-shift position from the estimated load, driver intentions, vehicle speed and accelerator pedal displacement. The Neural Net is trained using a standard gear-shift scheduling map, uphill driving data, and knowledge from an experienced driver.

The efficient control of vehicle subsystems depends on the accuracy and completeness of the feedback data from the system parameters. However, in many cases, the direct measurement of such system parameters is impractical due to complexity, noise and the dynamic nature of the system. Marko et al. [20] demonstrates that neural networks could be trained to emulate "virtual", ideal sensors that enhance diagnostic information from existing sensors on production vehicles.

The most prominent application area of neural-network based sensors is the on-line diagnostics of engine combustion failures, featured in the Aston Martin DB9 engine control system [1]. The importance of this application is enhanced by the fact that engine misfires are the leading contributors to excessive vehicle emissions and fuel consumption. In general, the identification of engine misfires can be done through the observation of crankshaft dynamics. However, the complexity of these dynamics can easily lead to misinterpretation. Neural Networks, trained by artificially inducing a combustion failure, can classify a misfire with a high level of accuracy based on indirect data, such as engine speed, load, crankshaft acceleration, and phase of the cylinder firing sequence [21] [28].

3 Speech Recognition

Speech technology is another important type of an in-vehicle AI application. The importance of an in-vehicle speech interface is related to requirements for non-destructive hands-free control of the ever increasing number of auxiliary functions offered in vehicles, such as telephones, entertainment, navigation, and climate control systems.

One of the first vehicle speech dialog systems, called Linguatronic, was introduced by Mercedes-Benz in their S-class car line in 1996 [15]. The speech recognizer used in Liguatronic is speaker-independent and based on the Hidden Markov Model (HMM) combined with the Dynamic Time Warping (DTW) word recognizer for a user definable telephone directory [6].

Most of the systems available today are based on a single utterance command and control paradigm. Such systems typically require the memorization of all commands from the manual that are often expressed in an artificial (non-natural) language. To address these limitations, automotive companies and suppliers have been actively pursuing research and development of the next generation of in-vehicle intelligent dialog systems [22] [27]. For example, Pieraccini et al. [27] presents a multimodal conversational interface prototype that was implemented on the Ford Model U Concept Vehicle shown at the 2003 North American International Auto Show in Detroit, Michigan. This system adopts a conversational speech interface coupled with a touch screen display. The speech recognition engine makes use of dynamic semantic models that keep track of current and past contextual information and dynamically modify the language model in order to increase accuracy of the speech recognizer.

4 On-Board Diagnostics and Prognostics

While intelligent systems in service diagnostics have been in use since the 1980s, vehicle on-board diagnostics and prognostics define an emerging area of computational intelligence applications. Each new vehicle currently contains a large number of processors that control the operation of various automotive subsystems, such as the engine, lights, climate control, airbags, anti-lock braking systems, traction control, transmissions, stereo systems and others. Each of these processors runs software that deals with faults and abnormal behavior in the various subsystems. This software has three main goals:

- Detection of faults
- Ability to operate when a fault has been triggered
- Ability to provide diagnostic information that can be used to locate the fault by a service technician.

Vehicle fault information is aggregated in the On Board Diagnostic (OBD) system that is a standard component of every modern vehicle. The fault detection algorithms (predominantly model based) provide input to the OBD that is used to evaluate the health of individual vehicle subsystems for on-board monitoring and to support off-line diagnostic maintenance systems. There has also been considerable work done to apply model-based systems and qualitative reasoning to support on-board diagnostics [36]. This work includes the development of the Vehicle Model-Based Diagnosis (VMBD) project in Europe. This project involves running model-based diagnosis on demonstrator vehicles to analyze problems with emissions in a diesel engine. In this case, a model was developed that represented the turbocontrol subsystem in the engine and a solution to a problem was found using a consistency-based diagnosis system. The model of the system is not a single model of the entire system, but instead contains a library of component models. Qualitative models capture the interdependencies and physical effects of the airflow and pressure that is present in the engine. The concept of model based diagnostics is further refined and developed by combining it with a dynamic Bayesian network [33] [34] [35]. The network model is applied to approximate the fault dynamics, interpret the residuals generated by multiple models and to determine fault probabilities. This approach was piloted for on-board diagnosis of the Anti-lock Braking System (ABS) and Electronic Stability

Program (ESP) of a Daimler Chrysler pilot vehicle and demonstrated an effective way to detect faults from multiple model residuals.

Fault prognostics recently became an important feature of on board diagnostic systems. The goal of this technology is to continually evaluate the diagnostics information over time in order to identify any significant potential degradation of vehicle subsystems that may cause a fault, to predict the remaining useful life of the particular component or subsystem and to alert the driver before such a fault occurs. Most of the work in this direction is inspired by the recent progress in Condition Based and Predictive Maintenance [7] [9]. Presently available on selected military vehicles [13], a prognostic capability is envisioned as becoming a substantial extension of OBD systems and vehicle telematics [5].

Model based prognostics assume models that are used to calculate the residuals between the measured and model predicted features, estimate the measure of degradation, and to evaluate the remaining useful life of the component. Model based prognostics use the advantages of first principle models and provide an accurate representation of the particular vehicle subsystems [18] [19]. Alternatively, learning based prognostic techniques are data driven and employ black box type models, e.g. neural networks, Support Vector Machines, fuzzy models, statistical models, and other approximators to identify the trend of change in the features, and can consequently predict fault scenarios [12] [13].

An open scalable Integrated Diagnostic/Prognostic System (IDPS) architecture for real time diagnostics and prognostics was proposed in [41]. Diagnostics is performed by a fuzzy inference engine and static wavelet neural network that is capable of recognizing the occurrence of a fault mode and identifying the fault. Prognostic functionality includes a virtual sensor to provide fault dimensions and a prediction module employing a dynamic wavelet neural network for fault trending and estimation of remaining useful life of bearings.

As the complexity of vehicles increases, the need for intelligent diagnostics tools, such as the ones described above becomes more critical.

5 Intelligent Vehicle Technologies

Intelligent Vehicle Technology is a concept typically associated with the development of autonomous vehicle functionality. The key attributes of intelligent vehicles include the following:

- the ability to sense the vehicle's own status as well as its environment;
- the ability to communicate with the environment;
- the ability to plan and execute the most appropriate maneuvers [42].

Intelligent vehicle technologies are a rapidly growing field pursued by the automotive industry, academia and government agencies [42] [2]. The general interest in intelligent vehicle technologies is also fuelled by a number of competitions for unmanned ground vehicles (UGV) around the world: the annual Intelligent Ground Vehicle Competition (see http://www.igvc.org) sponsored by the International Association for Unmanned Vehicle Systems held since 1993; the Defense Advanced Research Projects Agency (DARPA) Grand challenge (see http://www.grandchallenge.org/) started in 2004; and the European Grand-Robot Trail (see http://www.elrob.org/) held its first annual contest in May 2006. Today, the DARPA Grand challenge is probably the most publicized event with its grand prize of $2 million in 2005. In 2005, the teams had to complete a 132 mile race through the Nevada Mojave desert in less than 10 hours. Interestingly, a number of teams in the 2005 DARPA Grand Challenge based their design on existing production vehicles. For instance, the winning team from Stanford in collaboration with Volkswagen used a specially modified "drive-by-wire" diesel "Toureg" R5. Furthermore, the team "Gray" that completed the race in fourth place used a standard 2005 Ford Escape Hybrid integrated with other off-the-shelf instrumentation and control technologies. Team "Gray" specifically mentioned in their technical paper [40] that the team approached the Grand Challenge from the standpoint of being integrators rather than developers of such technology. These examples clearly demonstrate how close existing automotive products are in regards to the implementation of intelligent vehicle functionality.

Although the autonomous vehicle is not currently a goal of the automotive companies, the elements of this technology are quickly finding their way into passenger vehicles to provide driver assistance in critical moments. The applications of intelligent vehicle technologies to the automotive sector are often seen as the next generation of vehicle safety systems. Specifically, for applications within the automotive industry, Richard Bishop [2] defines "Intelligent Vehicle systems" as systems that sense the driving environment and provide information or vehicle control to assist the driver in optimum vehicle operation.

Today different data about the driving environment can be obtained through any combination of sources such as on-board video cameras, radars, lidars (light detecting and ranging, the laser-based analog to radar), digital maps navigated by global positioning systems, communication from other vehicles or highway systems. The on-board system analyzes this data in real-time and provides a warning to the driver or even takes over control of the vehicle. Examples of intelligent vehicle technologies existing today include lane departure warning, adaptive cruise control, parallel parking assistants, crash warning and automated crash avoidance.

In general, intelligent vehicle systems do not necessarily employ the full scale of computational intelligence techniques. However, it is clear that intelligent systems when combined with the conventional systems and control techniques can play a significant role to facilitate or even enable the implementation of many of the intelligent vehicle functionalities. For instance, analysis of images from video cameras calls for the application of traditional AI techniques such as machine vision and pattern recognition. The fusion of the disjointed data from multiple sources benefits from the application of neural networks in a similar fashion to the virtual sensor development in engine control. The implementation of real-time response to the changes in driving conditions may take advantage of fuzzy logic. For example, Tascillo et al. [39] describes the prototype of a system that identifies and classifies objects in close proximity using a neural net approach to select the best course of action to avoid an accident. Nigro and Rombaut [25] proposes a rule-based system incorporating linguistic variables to recognize driving situations. Engstrom and Victor [8] developed real-time recognition of the driving context (e.g. city, highway, suburban driving) using neural networks. Miyahara et al. [23] presents a vision-based target tracking system based on the range window algorithm and pattern matching. Schlenoff et al. [31] discusses the use of ontology to enhance the capabilities and performance of autonomous vehicles, particularly in navigation planning. These are only few examples from the vast on-going research using computational intelligence techniques to address intelligent vehicle functionality.

The integration of vehicle control systems and fusion of a different type of information provides another new dimension for building intelligent vehicle systems. For example, algorithms that combine engine and navigation (GPS) data create the opportunity for the development of predictive models and control strategies that optimize fuel efficiency and vehicle performance. In [29] [30] an intelligent control method using fuzzy logic is applied to improve traditional Hybrid Electric Vehicle (HEV) control. A rule-base with a fuzzy reasoning mechanism is used as a lower level controller to calculate the operating point of the internal combustion engine based on the current speed, engine efficiency and emission characteristics and driver required torque. A second fuzzy controller works as a predictor for the future state of the vehicle using information about the speed and elevation of the sampled route that is provided by the navigation system. The role of the second (supervisory) fuzzy controller is to anticipate changes in the vehicle state and to implement predefined heuristics based on the battery charge/discharge rate and on the estimated changes in the road and traffic conditions (e.g. downhill/uphill, city/highway). Fuzzy logic is then used in conjunction with the conventional HEV control system to provide additional flexibility and information fusion that result in substantial fuel economy and emission reduction.

6 Driver-Aware Technologies

In the past decade there has been an increased interest in technologies that monitor and mitigate driver conditions, such as fatigue, impairment, stress or anger that adversely affects the driver's vigilance and reduces their ability to safely operate the vehicle.

There are two main approaches for real-time detection of driver conditions: by monitoring the deviations in driver's performance in the vehicle operation and by monitoring the driver's bio-physical parameters [16]. The first approach involves the analysis of steering wheel movements, acceleration, braking, gear changing, lane deviation and distance between vehicles. The second approach measures and analyses bio-physical parameters of the drivers such as features of the eyes (such as eye closure rating, called PERCLOS), face, head, heart, brain electrical activity, skin conductance and respiration, body posture, head nodding, voice pitch, etc. These measurements can be conducted by using video camera, optical sensors, voice/emotion recognition, and steering wheel sensors.

There has been substantial research addressing the issues of driver drowsiness and fatigue. Many of the proposed systems rely on a number of soft computing methods, such as sensor fusion, neural networks, and fuzzy logic. For example, Ward and Brookhuis [44] describes project SAVE (System of effective Assessment of the driver state and Vehicle control in Emergency situations) and a subsequent project AWAKE (effective Assessment of driver vigilance and warning to traffic risK Estimation) undertaken in Europe in the late 1990s with the aim of real-time detection of driver impairment and the engagement of emergency handling maneuvers. In SAVE the data from the vehicle sensors is first classified using neural networks and then the final diagnostics is performed using fuzzy logic.

Ford has been extensively studying the efficacy of different methods to identify and provide remedies for drowsy drivers using VIRtual Test Track Experiment (VIRTTEX). Kozak et al. [17] describes the analysis of different methods to provide lane departure warning for drowsy drivers including steering wheel torque and vibration, rumble strip sound, and heads up display.

The emerging area of affective computing [26] opened up a new opportunity to monitor and mitigate the adversary driver behaviors based on negative emotions such as stress and anger. In fact, Prof. Picard considers that the automotive industry will be the first to apply truly interactive affective computing to products for safety reasons [3]. "Sensors can decide the driver's emotional condition. A stressed driver might need to be spoken to in a subdued voice or not interrupted at all."

However, the attention to affective technologies in the automotive industry encompasses more than just safety issues. The success of humanoid robots leaves no doubt of the importance of emotional intelligence for building machines and systems that can appeal to people. The description of the modern vehicle as a highly computerized machine that continuously interacts with the driver seems to be a reasonable candidate for the massive realization of the concept of emotional intelligence. It is reasonable to expect that a vehicle that is implanted with emotional intelligence ability can be appealing to the customer and may stimulate the creation of an emotional bond between the vehicle and the driver.

Toyota's POD (Personalization on Demand) concept vehicle [24] that was developed in collaboration with Sony is an intelligent vehicle control system that is able to estimate the driver's emotion and also exhibits its own emotional behavior corresponding to the vehicle status. The POD vehicle is inspired by the idea of affective computing and represents the first vehicle spin-off of humanoid robot technology [11]. From a systems perspective it implements a cognitive model that is similar to the cognitive emotional engine of Sony's Aibo companion robot [10] but with vehicle specific sensors and actuators. Its main components include three AI modules that are derived from the architecture of Aibo robot – Perception Module, Cognitive Behavior Module, and Control Module.

POD's Perception Module detects variations in driving conditions; monitors the steering wheel, accelerator and brakes, the pulse, the face and the perspiration level of the driver. Soft sensors screen driver's preferences, including driving style, music and other favorites. The result is a set of features that describe the current status of the driver and vehicle. A nonlinear mapping with predefined thresholds maps the feature set into 10 different emotional states.

POD's Cognitive Behavior Module estimates the new state based on the current and the previous state and pulls the set of behaviors (reactions) that correspond to this new state. This is the reaction of the POD vehicle to current emotional state of the vehicle and the driver. POD's behaviors are event driven software agents that create actions based on the information from the sensors and the other behaviors. The agents exemplify different behaviors; some of those behaviors are blended in ten different emotions, including happiness, surprise, sadness, etc. The cognitive module functions as an evolving adaptive controller that continually monitors the vehicle systems and driver's status and generates actions that maximize safety and comfort objective functions. POD's cognition module learns from the driver's habits and actions and evolves the behavior agents accordingly. The result of this is that POD's emotions continually evolve and reflect the current status of the vehicle and the driver.

POD's Control Module implements the actions associated with the selected behaviors by activating specific actuators. Actuators include color changing LED panels on the front, servomotors that change the positions of the headlamps, grille, and side mirrors that communicate the current emotional status of the vehicle. The POD actuators display warnings, chose the right music, control the A/C. The emotional state of the vehicle is expressed and communicated by controlling the shutters, antenna, vehicle height, windshield color, and ornament line.

7 Conclusions

In this chapter we have reviewed the major areas of intelligent system applications that are utilized in motor vehicles. The goal of this chapter was to focus on the technologies that are actually deployed inside the customer vehicle and interact with the driver. The modern passenger car or truck is an extremely sophisticated and complex piece of machinery that plays a critical role in the lives of many consumers. It is also much more than a mechanical transportation device and is often the center of passionate debate among consumers. There are few other industries that are as competitive as the automobile industry and this often results in very fast implementation of new technologies.

We discussed many approaches to intelligent system design that impact the driver with the intention of improving the overall driving experience. It has been shown that not all new technologies are readily embraced by drivers and the auto manufacturers have learned that "talking cars" and other intrusive technologies are not always welcome. Therefore, the automobile manufacturers must balance the benefits of introducing new technologies with the possible consumer backlash if the technology application is rejected. All of the applications described in this chapter have been deployed or tested and they show the wide range of technologies that have been adapted into the cars and trucks that we drive.

It is quite clear that the AI and intelligent systems have become a valuable asset that has many important uses in the automotive industry. The use of intelligent systems and technologies results in applications that provide many benefits to both the auto manufacturers and their customers. We believe that this trend will increase into the future as we move toward the age of intelligent vehicles and transportation systems.

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