Experimental System to Support Real-Time Driving Pattern Recognition

Vincenzo Di Lecce* and Marco Calabrese

Politecnico di Bari - DIASS
Viale del Turismo 8, 74100, Taranto, Italy
{v.dilecce, m.calabrese}@aeflab.net

Abstract. This work proposes an advanced driving information system that, using the acceleration signature provided by low cost sensors and a GPS receiver, infers information on the driving behaviour. The proposed system uses pattern matching to identify and classify driving styles. Sensor data are quantified in terms of fuzzy concepts on the driving style. The GPS positioning datum is used to recognize trajectory (rectilinear, curving) while the acceleration signature is bounded within the detected trajectory. Rules of inference are applied to the combination of the sensor outputs. The system is real-time and it is based on a low-cost embedded lightweight architecture which has been presented in a previous work.

Keywords: driving patterns, acceleration signature, fuzzy inference system.

1 Introduction

For many years there has been a widespread consensus on the benefits of Advanced Traveller Information Systems (ATIS) in enhancing personal mobility, safety and the productivity of transportation. The primary services of ATIS include pre-trip and/or en route traveler information concerning traffic conditions, route guidance, and "yellow page-type" information related to traveling as well as entertainment, dining and other services [9]. The basic ATIS architecture consists of a network of cameras connected to a processing center, thus giving the system user a real-time feedback on the whole traffic conditions and many other important pieces of information. This however does not solve all problems like safe driving which strictly depends on driver's behaviour along with his/her attitude to respect driving laws. Furthermore, the ATIS approach needs to be endowed with complex object recognition software to produce statistics on traffic flows or detect illegal driving behaviours. An alternative approach (that can be interesting for car insurance companies as well as public authorities interested in public safety) can be based on directly monitoring of driving behaviours using the vehicle as a probe. This can be accomplished by using low-cost devices that provide real-time driving information. This work presents such a system that, using a light-weight embedded low-cost architecture, is able to support real-time monitoring

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* Corresponding author.

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of driving behaviours. Up to the authors' knowledge this approach is quite novel in the context of driving information systems. The system is composed of a processing unit equipped with a GPS receiver and two biaxial accelerometers. Information coming from the two sources is fused within the processing unit, hereinafter technically referred as Device Server Unit (DSU), a hand-held device which requires very little space and no particular skills to be correctly mounted on board. The rest of the paper is divided as follows: Section II illustrates related work_on driving pattern recognition, Section III describes the proposed architecture, Section IV specifically accounts for pattern analysis and experiments. Finally, conclusions are drawn in Section V.

2 Related Work

Driving pattern recognition is an interdisciplinary topic that has been widely addressed under many points of view. One of them is represented by research about autonomous vehicle driving. In this field, three main approaches are commonly considered: neural network, explicit modeling and pattern matching [6]. Each of them handles different characteristics with respect to the way knowledge domain is structured and expressed. Neural networks and explicit modeling represent two supervised ways to teach a system how to follow a certain objective: in the first case an appropriate set of training samples is required, in the second case many parameters need to be tuned in order to get valid results. It is also possible to have a mixed approach. In [13] the overtaking task is considered and modeled in system theoretic terms; model results are then used to teach a neural network. An alternative approach is pattern matching. It basically consists in having a pre-built knowledge on some characteristics of road marks and therefore weighing the probability_that the real-time system state corresponds to one of those predefined road marks. Pattern matching encompasses the problem of defining an appropriate metric to estimate discordance between actual and recorded knowledge. However, in the case of driving behaviour, the cardinality of pattern set is quite small i.e. the alphabet of possible driving patterns is very limited.

As deeply investigated in the literature, the driving style can be affected by a number of different and independent reasons. Some researchers [11, 4] even identify driving behaviour signals as biometric information. They use force on brake and force on accelerator for this scope. These elements appear to be very sensitive to human subjectivity and they influence car-driving attitudes also in the presence of physical constraints like car following or maintaining lane. [5] for example refer to car-following behavior in Intelligent Driver Assistance Systems (ISAS). The authors assess the possibility that the current state between the lead and the following vehicle determines entirely the future state of the following vehicle, with no dependence on the past sequences of car motions that produced the current state. Other approaches [10] merge the two parameters of car-following and car-pedal use for enabling ISAS with customized assistance for drivers. Updated ISAS take also care of the ride comfort and there can be found some research about it, in particular [12]. Apart from car-following, other specific driving situations can be taken into account such as when approaching to intersection [12], when stopping or overtaking and so on. It is noteworthy however that, in many of these works, acceleration signature is taken in high consideration (see, for example [7]).

3 Used Architecture

The used architecture consists of a microprocessor based on DSU, equipped with both a 20-channel GPS receiver and a data acquisition (DAQ) device connected to the unit through an Ethernet connection. The ever-running data sensor acquisition threads continuously collect all data coming from the different sources and mark them with a timestamp for timing accuracy purposes. These data are periodically read by another ever-running task, which sends them to the application server by means of a GPRS connection. A block representation of the proposed architecture is shown in Figure 1. A wider description of this architecture has been presented in [3].

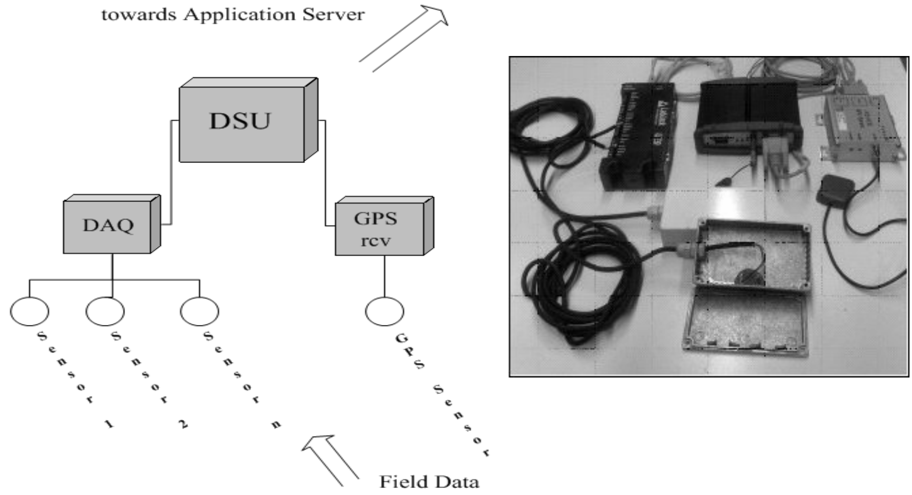

Fig. 1. Conceptual block architecture used to run experiments (left). Snapshot of real workbench (right) set up in accordance with the used architecture. The following elements have been captured: DSU Axis 89 (upper middle) with a USB Flash memory plugged (DSU front), A12 GPS receiver (right) connected through a RS232 serial cable and a PPS line to the DSU, DAQ Labjack UE9 (upper left), two biaxial accelerometers (forefront) connected to DAQ (one of them is visible in the ajar box).

The chosen DSU is an AXIS 89 Device Server containing 8 MB Flash memory and 16 MB SDRAM with a 300 MIPS 32-bit RISC CPU. DSU has 3 serial ports**,** 1 USB 1.1 and 2 Ethernet interface. The on-board installed operating system is Linux 2.6. The chosen DAQ is a LabJack UE9, having 14 analog inputs with a resolution of 12 bits at the maximum conversion speed (nearly 10 microseconds) and 16 bits at the lower speed of 2,4 ms. Analog input readings typically take 1.2+ ms depending on number of channels and communication configuration. Hardware timed input streaming has a maximum rate that varies with resolution from 250 samples/s at 16-bits to 50+ k samples/s at 12-bits. In our test a LabJack UE12 unit is used, the UE12 is also equipped with an internal 2MB buffer. The GPS receiver is WAAS/EGNOS enabled with a pulse per second (PPS) serial line (A12 model Thales Navigation in our tests).

The DSU represents the core system architecture, interposing between the sensor devices and the application server. By modelling the signal path from the sensors to the application server, it is clear that the DSU is the core unit. Two possible configurations can be implemented depending on both the system user's needs and performance requirements: stand-alone and client-server. In the stand-alone configuration DSU interfaces directly with the driver. In this case the system represents an add-on to commonly used GPS car navigation systems. In the client-server configuration sensor data is locally pre-processed and successively sent to a remote application server (i.e. for data mining purposes). Remotely monitoring real-time driving information can be in fact useful for a number of applications such as (to cite only a limited number) identifying safe truck driving conditions for hazardous material transportation, supervising correct liquid bulk tanks loading/unloading, monitoring ambulance fleets.

4 Pattern Analysis

This section presents how to use GPS positioning information in combination with the acceleration signature provided by biaxial accelerometer sensors to characterize driving patterns. In more details, GPS provides trajectory information, while accelerometers account for the way a driver, given a certain trajectory, uses brake/acceleration as driving inputs. The two data sources can be combined in a Fuzzy Inference System (FIS) to infer about driving styles. In this paper we focus on both the acceleration and GPS patterns, providing an overview of the whole framework comprising the fuzzy logic-based part.

4.1 Accelerometers

Biaxial accelerometers are inertial sensors for measuring acceleration along two orthogonal input axes. In our tests they have been mounted in a strap-down configuration with the two axes positioned one along the moving direction and the other on the left to it. Because they sense changes to inertia they respond positively to deceleration and negatively to accelerations along their input axes. They generally suffer from bias deviation from V_{cc} and, depending on their cost and manufacturing, they show a mean distance from the true value of 3-4% for very cheap ones.

From the above considerations, given the x-y plain representing the two input axes we can define seven fuzzy regions representing different acceleration conditions:

- ☐ **Uncertainty Area:** it can be assumed to be a circular region centered in the unbiased origin. It accounts for instrument inaccuracy or other undistinguishable states such as vehicle stopped or moving with a constant speed.
- ☐ **Acceleration Area:** it represents the region where acceleration along the moving direction is sensed. It can be essentially imputed to the driver push of the gas pedal, but it can be also related to a declining altitude
- ☐ **Deceleration Area:** it is the opposite of the previous one
- ☐ **Remaining areas of the four quadrants:** which account for curve entering or leaving

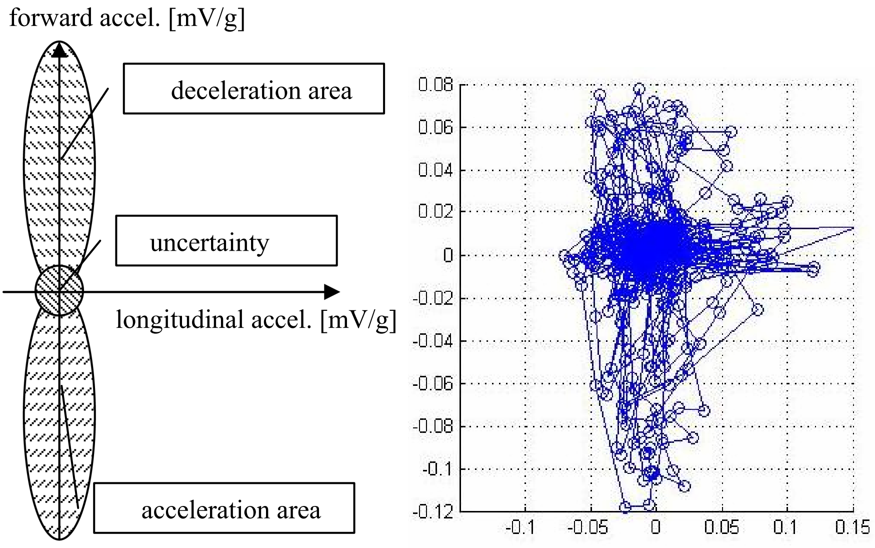

Fig. 2. (left) Pictorial representation of the areas defining different acceleration situtations and (right) plot of real data acquisition. The unit measure is [mV/g] because the sensor output is a voltage (1g = 312mV for the sensor used). Data have been detrended. The offset value was about 2.5 V.

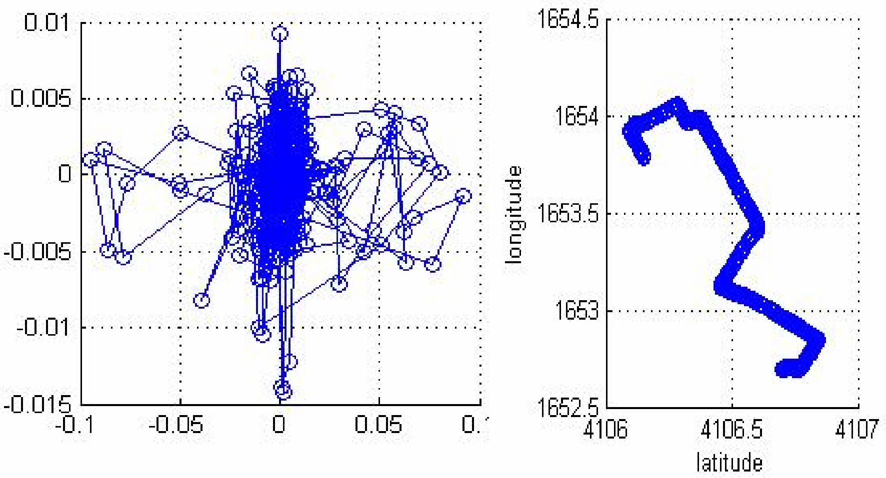

Fig. 3. Accelerometer and GPS data of the same test acquisition in comparison. Accelerometer signature (left side) shows more density patterns in entering/leaving left-handed curve. This assuption is confirmed by the nature of the actual trajectorey (right side). Vehicle starts in the lower-right part and progressively moves to the upper-left thus following (principally) a westward direction.

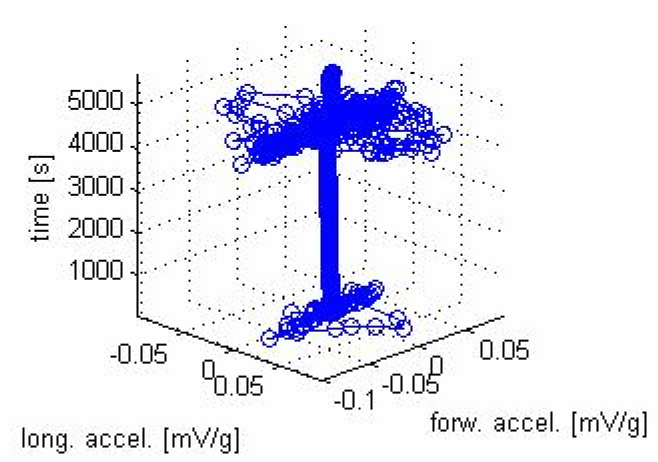

Fig. 4. 3D representation of the data presented in Figure 3. Z axis accounts for the time of the acquisition. From this perspective it is clear that the vehicle, after some short manoeuvres has stopped for nearly an hour before moving again.

The boundaries of the classified areas should be intended as fuzzy. This is the reason why a good way to handle them analytically is using a fuzzy approach. Fig. 2 depicts the comparison between the proposed classification and a real 10-minute acquisition. A plot of accelerometer data considering time passing is depicted in Fig. 4.

4.2 GPS

A GPS receiver provides information in terms of latitude, longitude and altitude at a given frequency (usually 1 second for most GPS receivers). Then, it is easy to reckon the mean speed as the vector difference between two consecutive GPS positioning acquisitions. Therefore, two differential variables can be extracted from the GPS receiver: the angular variation and the mean speed. Similarly to the accelerometer case, these values can be handled analytically using a fuzzy approach. It is noteworthy that data provided by GPS are strictly correlated to the accelerometer output. This means that GPS should "confirm" inferences deriving from accelerometer sensor only. To have an evidence of this, Figure 3 displays a test comparison.

4.3 Fuzzy Inference System

A FIS can be considered as an inference system that maps, by means of combination rules, input to output using fuzzy logic. A huge literature exists on this topic ([14], [2], [8] to cite only a few) and a wide variety of both academic and industrial applications is available today. Up to the authors' knowledge however, little contribution can be found about the topic discussed in this work.

Using the four inputs provided by the accelerometer sensor (forward and longitudinal acceleration) and the GPS receiver (angular variation and mean speed) a FIS can be

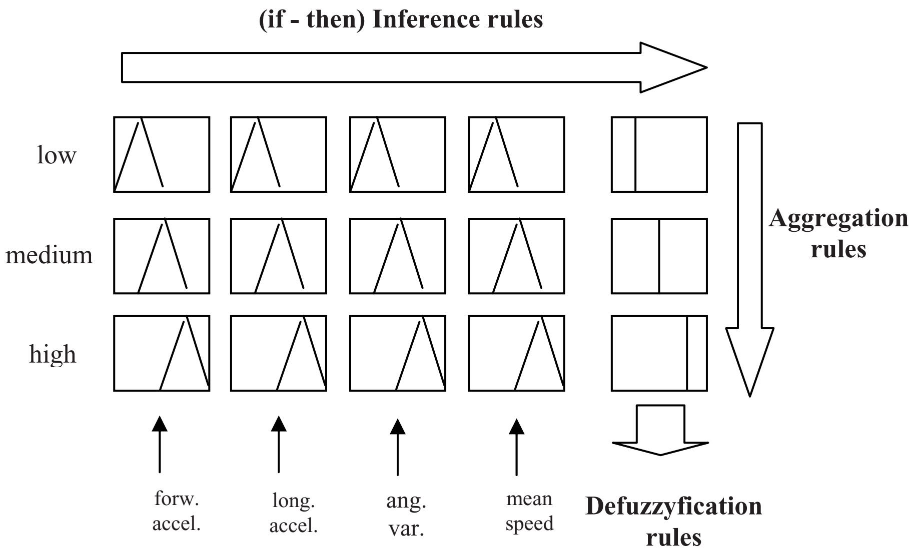

Fig. 5. Logical representation of a FIS for supporting driving information discovery

designed, according to the level of detail that one wishes to have. In a preliminary approach, three triangular membership functions representing "low", "medium" and "high" fuzzy concept values have been used in a Sugeno-like FIS architecture (Figure 5).

5 Conclusion

An experimental advanced driving information system that uses the acceleration signature provided by low cost sensors and a GPS receiver to infer on driving behaviour has been presented. Although this research is at an early stage, a prototypal architecture has been implemented for testing purposes. First results seem promising since they capture the "alphabet" of meaningful driving patterns in an efficient way. The architecture is robust and flexible enough to be adapted to various configurations depending on the user need and performance requirements. Further research will be primarily focused on better defining driving semantics, improving pattern detection algorithms and finally testing different inference rules with respect to the specific applications.

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