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Real-time smoothing of car-following data through sensor-fusion techniques

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Abstract

Observation of vehicles kinematics is an important task for many applications in ITS (Intelligent Transportation Systems). It is at the base of both theoretical analyses and application developments, especially in case of positioning and tracing/tracking of vehicles, car-following analyses and models, navigation and other ATIS (Advanced Traveller Information Systems), ACC (Adaptive Cruise Control) systems, CAS and CWS (Collision Avoidance Systems and Collision Warning Systems) and other ADAS (Advanced Driving Assistance Systems). Modern technologies supply low-cost devices able to collect time series of kinematic and positioning data with medium to very high frequency. Even more data can be (almost continually) collected if vehicle-to-vehicle (V2V) communications come true. However, some of the ITS applications (as well as car-following models, on which many ADAS and ACC are based) require highly accurate measures or, at least, smooth profiles of collected data. Unfortunately, even relatively high-cost devices can collect biased data because of many technical reasons and often this bias could lead to unrealistic kinematics, incorrect absolute positioning and/or inconsistencies between vehicles (e.g. negative spacing). As a consequence, data need filtering in most of the ITS applications. To this aim proper algorithms are required and several sensors and sources of data possibly integrated in order to obtain the maximum quality at the minimal cost. This work addresses the previous issues by developing a specific Kalman smoothing approach. The approach is developed in order to deal with car-following conditions but is conceived to take into account also navigation issues. The performances are analysed with respect to real-world car-following data, voluntarily biased for evaluation purposes. Assessment is carried out with reference to different mixtures of sensors and different sensors accuracies.

Selection and/or peer-review under responsibility of the Organizing Committee.

Keywords: Car-following; Vehicle control; Data fusion; Sensor funsion; Kalman filter; ACC; V2V

1. Introduction

This work is framed in a more general modelling effort aimed at obtaining high-quality measurement of the kinematics of vehicles, to be used for calibrating behavioural models in car-following contexts. The final goal is to develop fully-adaptive Advanced Cruise Control (ACC) systems, able to be calibrated in real-time and on-demand

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(Bifulco et al., 2008; Bifulco et al., accepted paper) by means of on board Electronic Control Unit (ECU) collecting data, possibly from multiple sensors, in order to learn about the driver's behaviour. The learnt behaviour is then applied by the ECU (running phase), aiming at automatically reproduce within an ACC application human-like reactions to stimuli received by the leading vehicle, once again captured by the on-board sensors.

In the previous context it is evident that measurements from sensors play a crucial role both in the learning-phase, where the calibration of the behavioural model should rely on high-quality data, and in the running phase, where the reaction of the ACC depends on the accuracy of the captured stimuli.

However, because of various technical reasons, data obtained by sensors are inherently affected by some degree of bias and even relatively high-cost sensors can often generate too much noisy time-series of data. One of the countermeasures generally applied in cases like that is to integrate complementary (or even redundant) measures from different sources. These techniques are often referred to as *multisensor data fusion*.

Data fusion techniques were originally developed (especially in USA) in the field of National Defense, then they have been progressively applied in other scientific and industrial fields, including transportation and traffic. A good introduction to fundamental issues and approaches in multisensor data fusion can be found in Hall and Llinas (1997). With reference to the specific application in ITS (Intelligent Transportation Systems), a recent review can be found in El Faouzi et al. (2011). Integration of sensor measurements in transportation has been applied to different fields, ranging from incident detection (Sethi et al., 1995) to identification of traffic patterns and performances of highways (Wang and Papageorgiou, 2005). However, in last years, two main tasks have attracted the scientists' attention: navigation and applications related to car-following.

In navigation the main topic is the accuracy of the positioning. Time-series of (estimated) vehicle positions can be obtained by two main kinds of sensors (Berdjag and Pomorski, 2004): absolute sensors collecting information from the exterior of the vehicle and producing absolute position estimates (like as GPS – Global Positioning Systems); and dead-reckoning sensors (e.g. gyroscopes, accelerometers, wheel speed sensors, ecc.) collecting information only from the vehicle itself and producing relative estimates. Dead-reckoning techniques rely on relative advancements and the position is sequentially estimated. In practice, a double integration of the accelerations (or a single integration of speeds, possibly estimated from wheels rotation) allows for computing linear displacement and a single integration of angular velocities allows for estimating angles of displacement. These integrations can induce a position error that grows over time as a result of successive small uncertainties. Dead-reckoning techniques are said to be accurate in the short term but inaccurate (with respect to position estimates) in the long term. On the contrary, GPS measurements are quite accurate in many conditions and this accuracy is stable in the long term, provided that each new measurement refreshes the estimated position independently from the previous. Thus, GPSs are said to be accurate in the long term. However, GPSs work well in open environments with no overhead obstructions, when the signal is not effected by multipath propagation phenomena and if a sufficient number of satellites is on the line of sight (say, at least five). If the previous conditions are not satisfied, the GPS measurements can be lost or are dramatically inaccurate. In other terms, the GPS is said to be possibly inaccurate in the short term. Thus, the fusion of different sources of measurements permits a reliable use of (even relatively low-cost) sensors and can be usefully pursued, also by taking into account that the exploitation of the GPS signal is naturally associated with increasingly-popular navigation applications and that at least some dead-reckoning data are easily available by the CAN (Controller Area Network) of the vehicle, for instance because of the presence of the ABS (Anti-lock Braking System).

In case of car-following, the absolute position of vehicles is not the main focus of measurements. The key variables are the velocity of the vehicle and the relative velocity and spacing with respect to the leading one. If the interest in car-following is motivated by off-line analyses, time-series of the key variables are measured by means of special equipment, not excluding the use of both dead-reckoning and GPS sensors on both the leading and the following vehicles. In case of on-line (e.g. ADAS – Advanced Driving Assistance Systems- applications, specifically ACC) the controlled vehicle is generally equipped by radar or lidar sensors directly measuring the relative speed and spacing, plus odometric and/or Wheel Speed Sensor (WSS) and/or Inertial Sensor (INS) in order to measure the velocity and/or the acceleration of the vehicle. Of course, the use of lidars/radars in case of off-line car-following studies can also be applied, as well as it could be useful to use GPS in case of on-line ADAS/ACC applications. The last can be done only for the controlled vehicle in order to obtain (apart positioning and position-increments) further estimates of velocity and/or acceleration (by applying derivatives on position time-series). It can be also done with respect to reciprocal positioning of the leading and following vehicles (say, the spacing) and this opportunity could quickly became a practice in future scenarios where v2v (vehicle-to-vehicle) communications will be developed.

In order to integrate different sensors for navigation applications, some approaches based on fuzzy methods or on artificial neural network have been proposed (e.g. Hiliuta et al., 2004 and El-Sheimy et al., 2006). However, the great part of the proposed approaches, for both navigation and car-following applications, are based on Kalman smoothing.

Kalman smoothing, in fact, allows for coupling model expectancies with real-world measurements, considering that both of them can be affected by some degree of inaccuracy. This can be used in our field in different ways. One way is to assume that different measures from one or more sensors (or some outputs of these measures) are the state variables of a dynamic system. A dynamic model of these measures can be built in order to relate current states to future ones; possibly, this dynamics can be represented by a simple random walking. Data from sensors represent the measurements of the measures. The result is a system of updated state variables which represents the updated measures. The previous approach can be defined as the *sensors-as-dynamic-system* one. An alternative approach is the one where the dynamics of the vehicle is explicitly considered. In this case the status variables are a set of entities (e.g. position, velocity, acceleration) that represent the true kinematic variables of the vehicles. These are assumed to be dynamically estimable by using a proper model; for instance, the vehicle could move with an uniformly accelerated low. Measures of the kinematic variables can be also directly obtained from sensors or computed by sensor measurements. These can be used to update the model expectancies. This approach can be defined as the *vehicle-as-dynamic-system* one; it is allowed for, in our case, by the fact that the measures actually coincide with the kinematics variables of the vehicle, viewed as a dynamic system.

The vehicle-as-dynamic-system approach can be used in order to correct time series from only one source, as done in Punzo et al. (2005) with reference to GPS data. The same approach, but extended to the smoothing of multiple sensor data, is applied by Ma and Andreasson (2007). It will be applied also in our work which, similarly to the ones by Punzo et al (2005) and Ma and Andreasson (2007), mainly refers to car-following-related issues, rather than to positioning. The sensors-as-a-system approach is applied by more navigation-oriented works, as the ones by Aono et al. (1998), Li and Leung (2003) and Spangenberg et al. (2007).

In Aono et al. (1998) the Kalman filter is adopted to fuse measurements from GPS and dead reckoning on-board devices, it is aimed at correcting the position of the vehicle assumed as isolated. The speed of the vehicle is consistently corrected too, but the proposed method is not extended to car-following conditions. Moreover, the effect of faults is mentioned but not explicitly analysed. In Li and Leung (2003) a Constrained Unscented Kalman (CUK) filter is adopted in order to fuse GPS and INS data and to constrain the vehicle dynamics by considering the road direction from digital maps. The non-linearity of the underlying model and the imposed constraints force toward the adoption of the CUK version of the approach. Spangenberg et al. (2007) adopt both an Extended Kalman Filter (EFK) and an Unscented Kalman Filter (UFK) in order to integrate WSS, INS and GPS under a non-linear problem. Comparison of EFK and UFK shows negligible differences, probably because the problem can be considered piecewise linear. On the contrary, relevant differences are shown in terms of accuracy in case of filtering or without filtering and use of only dead-reckoning data.

Berdjag and Pomorski (2004) adopt a sensors-as-dynamic-system approach, but they substitute the Kalman filter with an Information-Theoretic approach (see Manyika and Durrant-Whyte, 1994). This approach is mathematically equivalent to the Kalman filter but is more efficient in case of multiple (parallel) observations, provided that it leads to additive applications in decentralised frameworks. The information-theoretic approach is developed and tested against the traditional Kalman approach and the obtained results are not particularly encouraging; however, it should be mentioned that the problem at hand rarely can be viewed under a decentralised perspective.

Our approach is based on the application of a (linear) Kalman filter, the vehicle-as-dynamic-system approach is adopted and the analyses aim at understanding how the accuracy changes if the number and typology of integrated sensors changes. The main focus is toward ACC/ADAS real-time applications but also navigation and positioning issues are considered. As evident, in case of ADAS (including ACC) or ATIS (including navigation-oriented) applications, some peculiar requirements have to be satisfied, which are not common, for instance, to off-line behavioural studies and calibration of car-following models for traffic simulation purposes (e.g. Punzo et al., 2005). In particular, in our case, it is needed to rely on algorithms that should be:

- applicable in real-time;
- based on currently available on-board sensor (or on near-future likely technologies);

- as much low-cost as possible in terms of sensor requirements;
- robust with respect to possible faults of (a subset of) sensors.

2. The proposed smoothing approach

Our approach is to use a Kalman filter in order to smooth sensors-measured data. Smoothing of raw data toward useful time-series could be made (Gurushinghe et al., 2002) independently for time-series related to different variables at hand (speeds, spacing among vehicles, etc.). However, the use of the Kalman filter technique ensures the consistency among different measures related to the same physical phenomenon. This can be obtained thanks to the state space model underlined by the Kalman approach.

Here we assume that the kinematic variables of the leading vehicle and the follower obey to a physical phenomenon. In particular, we assume that the vehicles move from any discrete time *k-1* to the successive one *k* with uniform acceleration motion. In formal terms:

$$s_n(k+1) = s_n(k) + v_n(k)\,T + 0.5\,a_n(k)\,T^2 \tag{1}$$

$$v_n(k+1) = v_n(k) + a_n(k)\,T \tag{2}$$

where:

n, is the generic vehicle, in our car following context $n \in \{F, L\}$, where F identify the follower and L the leading vehicle;

s_n, is the total travelled distance by vehicle n starting from an arbitrary initial point (the same for all vehicles);

v_n, is the velocity in the direction of the motion;

a_n, is the acceleration in the direction of the motion;

T, is the (fixed) time step elapsed from k to k+1.

In order to prepare the coupling with GPS measurements, the position of the vehicle can be described by using North, East and Down directions (NED) with respect to the Earth-Centred Earth-Fixed (ECEF) coordinate system. Neglecting the elevation, the position can then be approximated by means of geographical Cartesian coordinates x and y. The position increments computed along the axis $\Delta x_n(k) = x_n(k+1) - x_n(k)$ and $\Delta y_n(k) = y_n(k+1) - y_n(k)$ can be obtained by projecting the advancement $\Delta s_n(k) = s_n(k+1) - s_n(k)$ in the direction of the motion according to the *direction* of the vehicle $\Psi_n(k)$:

$$\Delta x_n(k) = (s_n(k+1) - s_n(k))\cos(\Psi_n(k)) \tag{3}$$

$$\Delta y_n(k) = (s_n(k+1) - s_n(k))\sin(\Psi_n(k)) \tag{4}$$

Thus, by substituting equations 1 in equations 3 and 4:

$$x_n(k+1) = x_n(k) + (v_n(k)\,T + 0.5\,a_n(k)\,T^2)\cos(\Psi_n(k)) \tag{5}$$

$$y_n(k+1) = y_n(k) + (v_n(k)\,T + 0.5\,a_n(k)\,T^2)\sin(\Psi_n(k)) \tag{6}$$

In order to complete the dynamic model which is beside the Kalman approach, hypotheses are needed on the dynamics of accelerations of the leading vehicle and the follower; our approach is to assume a random walk model for both of them.

If the state space model is described by the vector $\mathbf{X}^T = [x_F, x_L, y_F, y_L, \Psi_F, \Psi_L, v_F, v_L, a_F, a_L]$, the resulting Kalman filter would be non-linear because of the presence of the sin() and cos() functions in equations 5 and 6. Because of this, we omit to identify the absolute position of the vehicles in x-y coordinates and we adopt the total travelled space (s). This assumption has some consequences that will be described later. Under the previous hypotheses the state vector of the dynamic system composed by the two vehicles in car-following conditions can be assumed as $\mathbf{X}^T = [s_F, s_L, v_F, v_L, a_F, a_L]$ and the state space model can then be written as:

$$\boldsymbol{X}(k+1) = \boldsymbol{A}\,\boldsymbol{X}(k) + \boldsymbol{\xi}(k) \tag{7}$$

Where no control input has been considered and where $\boldsymbol{A}$ is the state transition matrix and $\boldsymbol{\xi}$ the process error vector:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & T & 0 & 0.5\cdot\mathrm{T}^2 & 0 \\ 0 & 1 & 0 & \mathrm{T} & 0 & 0.5\cdot\mathrm{T}^2 \\ 0 & 0 & 1 & 0 & \mathrm{T} & 0 \\ 0 & 0 & 0 & 1 & 0 & \mathrm{T} \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad \boldsymbol{\xi}^{\mathrm{T}} = [\xi_{sF}, \xi_{sL}, \xi_{VF}, \xi_{VL}, \xi_{aF}, \xi_{aL}]$$

ξ_{sF}, ξ_{sL}, ξ_{VF} and ξ_{VL} are white noises; they take into account the approximations introduced on the positioning of the vehicles and on the velocities, including the ones deriving from the approximated uniformly accelerated motion hypothesis. ξ_{aF} and ξ_{aL} are the hypothesized random walking of accelerations (white noises too).

The elements of vector $\boldsymbol{\xi}$ are here considered as independently distributed Gauss variables with zero mean. The dispersion matrix (process noise covariance matrix) of $\boldsymbol{\xi}$ is $\boldsymbol{Q}$ and, because of independence, is diagonal. In section 3 it will be introduced how the values in matrix $\boldsymbol{Q}$ have been identified.

The kinematics of the vehicle is also instantaneously measurable by means of on-board sensors, for both the follower and the leading vehicle. The follower is assumed to be the controlled vehicle, on which the Kalman filter is applied by an on-board ECU (Electronic Control Unit) also responsible for the application of a more general ADAS/ACC system. The vehicle is assumed to be equipped at least by a radar, measuring relative spacing and velocity with respect to the leading vehicle. Likely, it is equipped by a WSS, measuring the velocity in the direction of the motion. Possibly, it is equipped with a INS able to measure the acceleration in the direction of the motion and/or with a GPS able to measure the absolute positioning. However, in equation 7 and matrix **A** the position is not identified by global positioning coordinates; rather, it is adopted the total travelled distance (from an arbitrary origin), which is not a straight measurement for GPSs. In fact, if x-y coordinates were used, a non-linear Kalman filter should be adopted, based on equations 5 and 6 instead of equation 1. As an alternative, x-y coordinates of GPS are transformed to estimates of the total traveled distance. This is fully compatible with the linear equation 7. It can be easily implemented in the laboratory environment described in next section 3, where we can imagine that outputs in terms of travelled distances have been computed from x-y absolute positions and that the error depends on both the GPS and the output computation. For practical use, the suitability of transforming GPS coordinates to total traveled distances should be carefully checked against real-time-computation requirements.

It can be considered that the WWS and/or the INS and/or the GPS are possibly also mounted on the leading vehicles and v2v communication is available. In this case the velocity, the acceleration and the position of the leading vehicle are also known by the ECU on the controlled vehicle.

Thus, the complete measurement vector is:

$$z^T = [\boldsymbol{zr}^T \mid vw_F, sg_F, ai_F, vw_L\ sg_L, ai_L] \qquad (8)$$

where

$$\boldsymbol{zr}^T = [\Delta s, \Delta v] \qquad (9)$$

and where Δs and Δv are the relative spacing and velocity measured by the radar and vw_n sg_n, ai_n are the velocities, the total travelled distance and the acceleration of vehicle n ($n \in \{F, L\}$) respectively measured by the WWS, the GPS and the INS.

The instantaneous measurement equation required by the Kalman filter can then be expressed by:

$$z(k) = \boldsymbol{H}\,\boldsymbol{X}(k) + \zeta(k) \qquad (10)$$

where $\mathbf{H}$ is the matrix that relates the measurement to the state variables and $\boldsymbol{\zeta}$ is the vector of measurement errors, here assumed to be distributed as a multivariate normal with zero mean and independent components.

$$\mathbf{H} = \begin{bmatrix} \mathbf{HR} \\ \hline \mathbf{HW}_\mathrm{F} \\ \hline \mathbf{HG}_\mathrm{F} \\ \hline \mathbf{HI}_\mathrm{F} \\ \hline \mathbf{HW}_\mathrm{L} \\ \hline \mathbf{HG}_\mathrm{L} \\ \hline \mathbf{HI}_\mathrm{L} \end{bmatrix} \quad \text{where} \quad \begin{aligned} \mathbf{HR} &= \begin{bmatrix} -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 \end{bmatrix} \\ \mathbf{HW}_\mathrm{F} &= [0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0] \\ \mathbf{HG}_\mathrm{F} &= [1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0] \\ \mathbf{HI}_\mathrm{F} &= [0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0] \\ \mathbf{HW}_\mathrm{L} &= [0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0] \\ \mathbf{HG}_\mathrm{L} &= [0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0] \\ \mathbf{HI}_\mathrm{L} &= [0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1] \end{aligned} \qquad (11)$$

The dispersion matrix associated to $\boldsymbol{\zeta}$ is denoted by $\boldsymbol{R}$. It is diagonal because of the hypothesis of independence and the values of the variances depends on the measurement accuracies that will be discussed in next session 3.

The vector of the measurements is complete if all sensors are available, as well as the v2v communication. Otherwise, only some components of the complete vector $\boldsymbol{z}$ have to be considered, as well as only the corresponding sub-matrices composing matrix $\boldsymbol{H}$.

3. Experiments with synthetic noise-controlled data

Our experiments are based on the real-world trajectories of two vehicles in car-following conditions, collected by using an equipped vehicle. The vehicle is a Fiat-Multipla with sensors and video-recording devices. It allows not only data collection for the vehicle itself but also for rear and/or front vehicles. The system is based on a laptop that manages the real-time acquisition by on board sensors. The PC mounts a PCMCIA-CAN (with 2 ports) and a PCMCIA-DAQ card (allowing for 8 analog outputs, 8 digital outputs, 2 counter/timers). The sensors are able to supply several data, including the vehicle speed, collected by means of a WSS, the angular position of the accelerator pedal, the brake and clutch position, the rotation angle of the steering and many other signals intercepted from the vehicle CAN (Controller Area Network). Moreover, it is possible to intercept data from the two on-board radars (TRW Autocruise AC10) and, in particular, the relative speed and relative spacing with respect to up to four vehicles ahead or behind. All data can be collected with high frequency; the one employed in our studies was 10Hz. This value is consistent with similar experiments described in literature (e.g. Wu et al., 2003) but higher values can be reached if needed. The video-capture system consists of three basic elements: the cameras (rear and front); the titling card; the digital video recorder. The images are captured by the cameras and sent to the titling card that makes the overlay of some information (absolute time, relative speed and relative spacing with respect to the vehicle ahead or below); finally, the recorder registers the titled videos. All real-time acquisitions are synchronized and managed by using a single software developed in LabWindows. Finally, the vehicle is equipped with a high-end GPS receiver and data recorder; it can be employed in order to collect standard, D-GPS and K-D-GPS data. The vehicle has allowed for obtaining very accurate data, provided the high quality of the sensors. However, some bias is unavoidable in real-world measurements. The following Figure 1 shows the speeds collected by both the WSS sensor and the GPS (the last computed by applying derivatives to the GPS positioning). As evident, noisy time-series have been collected; moreover, as widely known, inaccuracies have different characteristics, the WSS being on average more inaccurate but the GPS being occasionally drastically inaccurate.

Collected data have been filtered in order to obtain reference time-series to be considered as unbiased and to be used for generating laboratory-controlled noises and for comparison. To this aim a off-line procedure has been applied, allowing for mutually consistent and feasible reference values. The nature of the procedure is not essential, provided that once the reference time series has been obtained, it has been randomly perturbed (with known dispersion) in order to simulate measurement errors. Collected data consisted in traveled distances (from an arbitrary origin), velocities and accelerations, all of these referred to both the leading vehicle and the follower.

The reference time-series (to which a null measurement error is associated) has been also used in order to estimate the elements of the matrix $\boldsymbol{Q}$ (Noise Process Error); these are fixed at the smaller value allowing for accurate reproduction of the reference time-series in case of adoption of the Kalman procedure, null measurement errors ($\boldsymbol{R}$) and measurement inputs equals to the reference time-series itself.

Different assortments of sensors have been considered. In particular, a radar sensor has been in any case assumed. At each time step (with a 10 Hz frequency) the difference of the velocities and of the travelled spaces of the two vehicle were computed. In such a way the reference (assumed unbiased) relative speed and spacing were obtained from the reference trajectory. To these values a predefined random perturbation (zero-mean Gaussian) was applied in order to simulate the inaccuracy of the sensor. In a similar way it was simulated (by applying random perturbations twice, with two different levels of variance) the collecting of low-accuracy and high accuracy measurement of velocities (simulating WSS), vehicles' accelerations (simulating INS) and vehicles' total travelled spaces from an arbitrary origin (simulating estimated obtained by GPS). The designed laboratory experiments are synthesized in table 1.

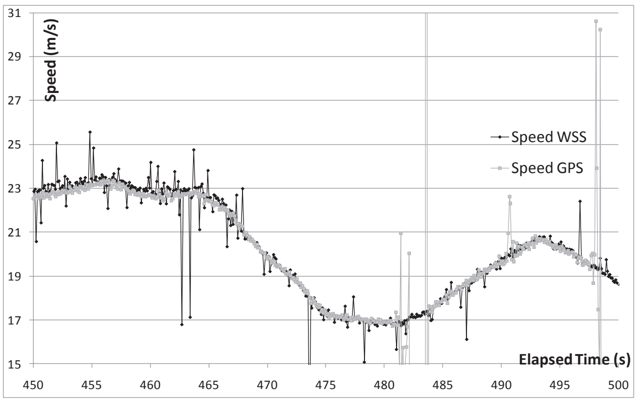

Figure 1 – Example of sensor data (odometer and GPS)

Table 1 – Full plan of the designed experiments

Vehicle	Sensor	Accuracy	Experiment																								
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Follower	Radar	One lev.	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	WSS	Low		X		X	X			X		X	X			X		X	X			X		X	X		
		High			X			X	X		X			X	X		X			X	X		X			X	X
	GPS	Low				X		X				X		X				X		X				X		X	
		High					X		X				X		X				X		X				X		X
	INS	One lev.								X	X	X	X	X	X							X	X	X	X	X	X
Leader	WSS	Low														X		X	X			X		X	X		
		High															X			X	X		X			X	X
	GPS	Low																X		X				X		X	
		High																	X		X				X		X
	INS	One lev.																				X	X	X	X	X	X

In section 4 results will be shown (for comparison purposes) also for only-GPS data (without Kalman filtering) and only-GPS data subjected to the Kalman procedure.

The presence of different sensors activates, according to previous table 1, the corresponding elements of the measurement vector z (equation 8) and the associated components of matrix $\boldsymbol{H}$ (equation 11). Moreover, the values of the variances in matrix $\boldsymbol{R}$ depend on the high or low levels of accuracy hypothesised for the sensors. In particular, the radar has been supposed to work with a standard deviation of the error of 0.70 m for the relative spacing and of 0.025 m/s for the relative velocity; the WWS is supposed to measures velocity with a standard error of 1.70 m/s in case of low accuracy and 0.42 m/s in case of high accuracy; the error for the positioning (expressed as total travel distance from an arbitrary origin) depends on the accuracy of the GPS (and on the environmental conditions in which it operates) as well as on the transformation of x-y coordinates in travelled distance, the resulting overall standard deviation of the error is considered to be 6.0 m in case of low accuracy and 0.20 m in case of high accuracy; finally, the standard deviation of the error of the INS is 0.0055 m/s^2.

All previous standard deviations have been employed in order to obtain data from the reference (considered unbiased) data time-series. Each time-series has been perturbed according to a (independent) normal variable with zero mean and standard deviation equals to the values in matrix $\boldsymbol{R}$. Of course different standard deviations have been employed in case of different sensor accuracies, according to previous Table 1. One of the most relevant aspects of this methodology, based on controlled noises, is that for each experimental case in Table 1 the measurements adopted as input of the smoothing procedure are drawn from random distributions perfectly consistent with matrix **R**. It is also worth mentioning that this synthetic experimental procedure allows us for having unbiased reference time-series to be employed for comparisons and for the assessment of the methodology.

4. Results of the experiments

For each of the experiments in Table 1 the reference time-series allows for the assessment of the obtained results. This allows the assessment of the proposed method, carried out for different mixtures of sensors and accuracies. For comparison we use the cumulated distribution of the discrepancies between the smoothed time-series and the reference (unbiased) one. Couples (x, F(x)) in following charts will denote the percentage F(x) of discrepancies that are equals or less than value x. Among all kinematic variables of car-following, the most challenging has been the spacing between the leading vehicle and the follower, we will show the results with reference to this output. Moreover, we will also show the output in terms of positioning of the following/controlled vehicle, expressed as total travelled distance; this is motivated by the attention to navigation issues and also by the fact that, even if not strictly needed for describing car-following phenomena, the absolute position of a vehicle is surely the most challenging output of any smoothing procedure.

Following Figure 2 shows the cumulate discrepancy distribution of the spacing for all the experiments, numbered according to Table 1. All sensors assortments with the Kalman filter technique show good results; the error in spacing with respect to real data is in all cases less than 5%. Assortments of sensors are reported in the legend of the chart in decreasing order of performance. The best assortments are these where Radar, WWS and INS are mounted but not GPS (experiments 8,9, 20 and 21), irrespective of the availability or not of v2v communication. A second group is composed by all other assortments with v2v communication (experiments 14, 16, 17, 18, 19, 22, 23, 24 and 25); this performs comparably (just negligibly better) with respect to the third group, composed by the experiments with only the GPS and experiments with heterogeneous assortment of sensors (1, 2, 4, 6, 10, 12), comprehensive of the only-radar one, which performs satisfactorily enough. The worst performing assortments are experiments 3, 7, 11, 13 and 15; they are characterised by high accuracy GPS together with high accuracy WWS or low accuracy WWS together with INS or, finally, by the high accuracy WWS with no other sensors (except the radar which is the default one). This worst-performing group is the one were to much dynamic measurements have to be accommodated and it is assumed a good confidence in them; in practice, this disrupts the relative amount of confidence given to the radar and introduces more bias than help.

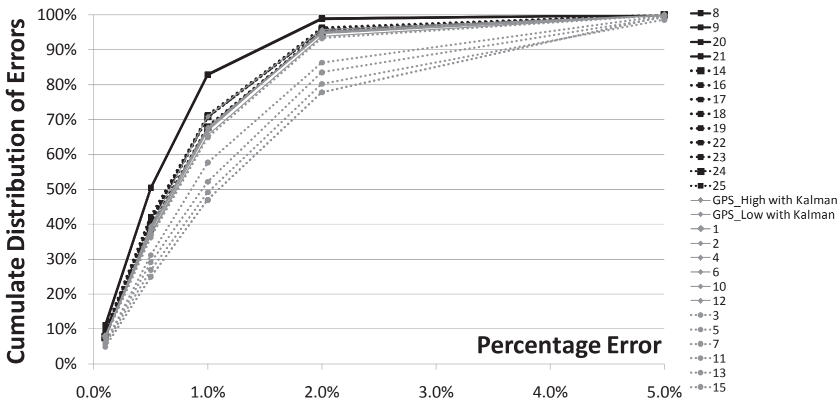

Figure 2 – Error in spacing between vehicles

For what concerns the accuracy in positioning the vehicle, different groups of sensor assortments can be clearly identified by looking at the following Figure 3. Group A (GPS_HighWithKalman, 5, 7, 11, 13, 17, 19, 23, 25), contains all mix of sensors with high-accuracy GPS, irrespective of the presence of v2v communication. Group B (GPS_LowWithKalman, 4, 6, 10, 12, 16, 18, 22, 24, 9), contains all mix of sensors with low-accuracy GPS (irrespective of the presence of v2v communication) plus the stand-alone vehicle equipped with high accuracy WSS and INS. Group C (2 and 3), contains the stand-alone vehicle with low or high-accuracy WSS and without INS. Group D (8, 14, 15, 21), contains vehicles with v2v communication and WSS, v2v communication with high accuracy WSS and INS, isolated vehicle with low-accuracy WSS and INS. Group E (1 and 20), contains the stand-alone vehicle with only radar and the vehicle with v2v communication with low quality WSS and INS.

As expected, the presence of v2v does not enhance, in this case, the performances. It will be seen later than v2v strongly influences the robustness of the system with respect to faults of the sensors. What plays here a preminent role is the availability of higly accurate positioning measures. The best option is the accurate GPS, even without using Kalman. Accurate GPS and Kalmann (group A) doesn't lead to better results, even if still highly satisfactory. The use of GPS with lower accuracy and without the Kalman filter leads to results that are relatively scarce (just a few better than group D), while coupling it with Kalman smoothing (and possibly with other sensors) allows for much better results (group B). Also Kalman smoothing and only WWS (group C) leads to better results with respect to the use of low accuracy GPS without Kalman. Group D is characterised by relatively poor performances; it contains assortments where GPS are not on board and too much confidence has been given (because of accurate if isolated) to sensors measuring velocity and acceleration. In these cases, the dead-reckoning approach becomes dominant, with all known consequent drawbacks. This phenomenon is exacerbated for experiments 20 and 1, as expected.

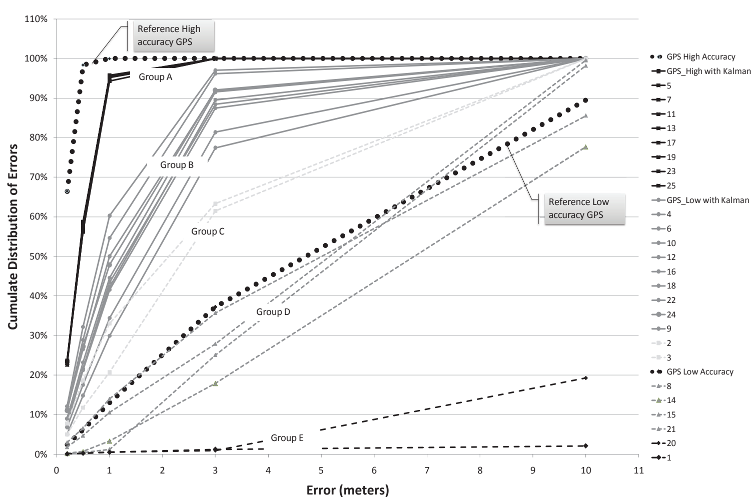

Figure 3 – Error in the positioning of the vehicle

5. Extension for dealing with sensors' faults

It is likely that sensors can fault for brief transients. In particular, the most likely sensors to temporarily fault are the radar and the GPS. For instance, the radar can fault because the leading vehicle is not in the line of sight and the GPS can fault because the vehicle enters a zone where the signal is not available (or too bad). It is worth noting that faults are different from inaccuracies. In case of fault measurements are missing or are so bad that the system assumes they are missing. We consider that the radar or the GPS or both can fail for a duration of 3, 5, 15 or 60 seconds. We evaluate the effect of fails by means of the *distance* of the simulated trajectory (with fails) with respect to the unbiased trajectory. An aggregate proxy of the distance, the RMSE (root mean square error) is adopted. The distance of the no-fault case with respect to the unbiased trajectory is also taken into account, to this aim a null (zero-length) fault duration is considered. Comparison is not directly based on RMSE; rather, it is applied an accuracy-index:

$$AI_i = 1 - (RMSEi - RMSE_{min}) / (RMSEi_{max} - RMSE_{min}) \qquad (12)$$

Where $RMSI_{min}$ and $RMSE_{max}$ are the minimum and maximum value of the RMSE computed over all the fault experiments for all assortments of sensors. It is evident that the value 1 for the accuracy-index is associated to the minimum possible discrepancy with respect to the unbiased trajectory, which holds for the zero-length fault. Similarly the value zero corresponds to the max discrepancy. The accuracy index allows for comparing different tests where the scale of the RMSE is different. In order to have an idea of the (large) range of errors, consider that $RMSI_{min}$ and $RMSE_{max}$ are 0.17 and 100.33 (meters) when the positioning of the vehicle is considered and 0.19 and 38.83 (meters) when the spacing of vehicles is considered.

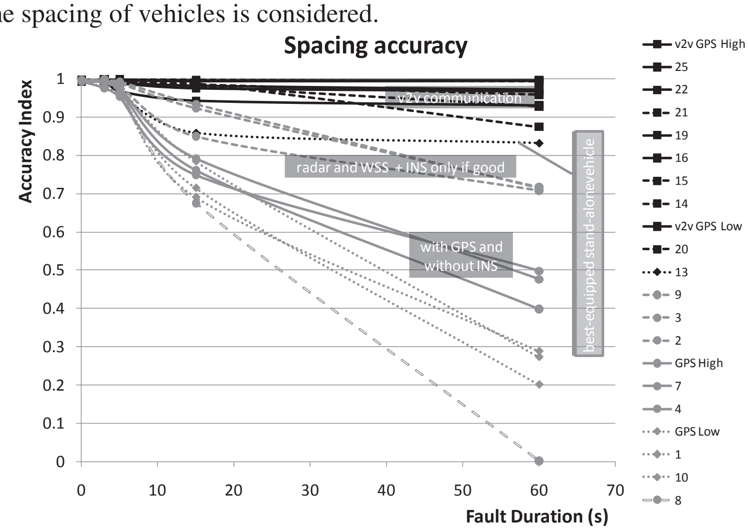

Figure 4 – Accuracy in reproducing spacing in case of radar fault

Figure 4 shows the accuracy index, in terms of spacing between the leading and the following vehicle, in case of the radar fault but when all other sensors still work. Faults with up to 3 or 5 seconds do not present significant problems; in this cases the proposed Kalman procedure is robust enough, whatever the sensor assortment. In case of faults with a 15 second duration or a 60 seconds duration, the assortment of the sensors is relevant with respect to the robustness of the procedure. Dark (both dashed and continuous lines) are related to scenarios with v2v communication. In case of continuous lines the leading vehicle and the follower are equipped with GPS, these are the most robust assortments in case of long (15 or 60 seconds) faults. In practice, the dynamics of both the vehicles is well estimated by means of the model and of the available measures and the inter-vehicle communication allows for a good estimate of the spacing. The dashed (dark) lines still relates to the presence of v2v communication, the dynamics of the vehicles is estimated without the GPS so that the positioning of both the vehicles is slightly less accurate than in the case of the presence of GPS. The best-equipped stand-alone vehicle (with greater assortment and high accuracy of all sensors) performs well enough. Intermediate results can be obtained by stand-alone vehicles with GPS but without INS, it seems in fact that adding too much information (if not all of them accurate enough) disrupts the performances of the system as well as having too few measures. Among the bad-performing assortment, in fact, it can be noted the one with only the (faulting) radar but also the one with all sensors (including GPS) but all of them with low accuracy (assortment 10). The worst performing assortment is the one with low accuracy devices and without GPS; likely, in this case, both the absolute dynamics of the controlled vehicle and the relative dynamics with respect to the leader are dramatically wrong.

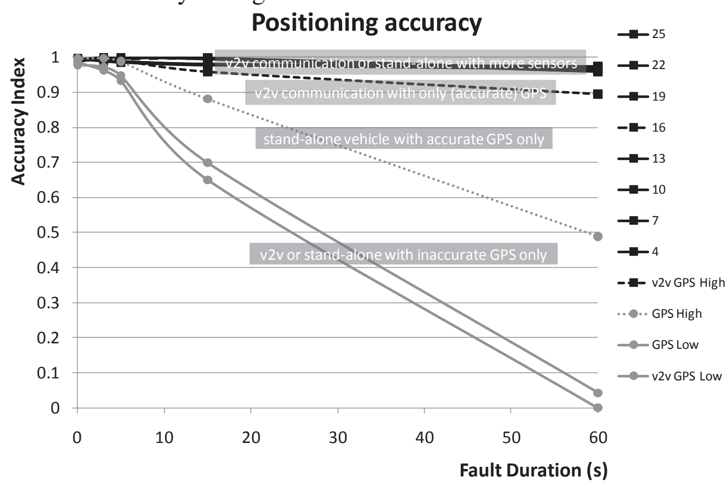

Figure 5 – Accuracy in reproducing positioning in case of both radar and GPS fault

Figure 5 shows the robustness of the method with respect to the positioning of the controlled vehicle in case of joint fault of radar and GPS. The considered assortments of sensors are those where a GPS device is included. When v2v communication is enabled or in case of stand-alone vehicles with high accuracy GPS and other sensors, the performances are good (thanks to the Kalman filter) also in case of 60 seconds of joint fault of radar and GPS. If other sensors, a part GPS, are on-board, then the system obtains good estimates of the positioning. Otherwise, if only the GPS is on-board, the estimates are poor in case of long-duration GPS faults (slightly better in case of v2v communication).

It is interesting also to assess the robustness of the method with respect to the inter-vehicle spacing in case of joint fault of radar and GPS. Results are shown in the following figure 6. They are not so different in terms of ranking of the assortments. What is evident is that (as expected) inter-vehicle communication strongly enhances the robustness of the system, especially in cases where multiple sensors ensure a better estimation of the positioning of both the leading vehicle and the follower.

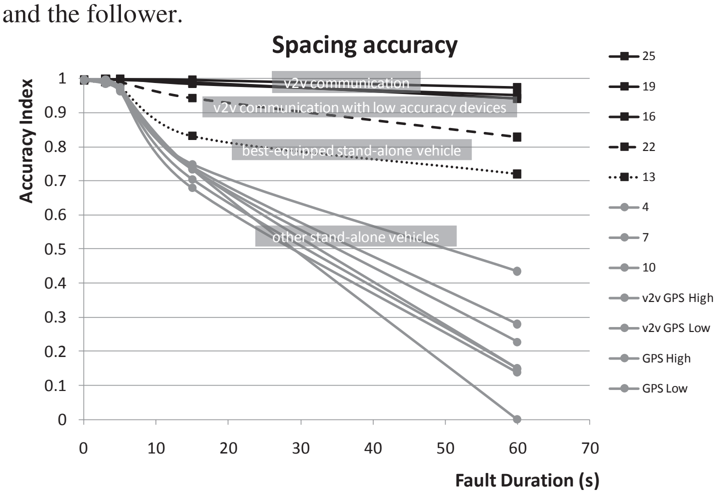

Figure 6 – Accuracy in reproducing spacing in case of both radar and GPS fault

6. Conclusions

The work has shown the impact of Kalman smoothing in order to improve and integrate measurements from different sensors. The analyses have been based on experiments based on synthetically-perturbed real-world data. The proposed approach seems to be successful and to suggest that good performances can be obtained in driving assistance and navigation also in case of low-cost sensors, if integrated with the proposed smoothing. Significant improvements in absolute positioning of vehicles can be obtained by using the Kalman filter and other sensors also in cases where high-end GPS are not available (or convenient). Good estimates of spacing (or more generally car-following data) can be obtained by integrating radar/lidar with other dead-reckoning sensors, even if the advantage with respect to only radar/lidar application of the Kalman smoothing is not drastic. Use of GPS for indirect improvement in inter-vehicle spacing or other relative kinematic variables introduce more bias than advantage (less evident in case of v2v communication). However, v2v communication, integration of different sensors (other than low-cost GPS) and Kalman smoothing seems to have a high effect on both navigation and driving assistance performances in case of long-duration faults of radar/lidar and of GPS.

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