Design, Implementation and Testing of a Real Time System to Unambiguously Assign Detected Vehicles from Car-to-Car Communication and on-Board Camera

Simone Fontanesi[1,2], Luca Fanucci[1] and Frank Hofmann[2]
[1]*Information Engineering Department, University of Pisa, Via G. Caruso, Pisa, Italy*
[2]*Robert Bosch GmbH, Corporate Research, Robert-Bosch-Strasse 200, Hildesheim, Germany*

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Abstract: on-Board surround sensors, such as cameras and radars, are used in Advanced Driving Assistance Systems applications to improve the driver safety and comfort. In the meantime, Car-to-Car Communication systems are in the deployment phase and have been tested in huge test fields. In order to compensate the weaknesses and benefit from the strengths of both systems, their information can be fused. In this context, one major challenge is the unambiguous assignment of detected vehicles from different sensors, which is still an open research topic and the major target of this work. An innovative algorithm was first tested in Matlab using recorded data and then implemented on real hardware. The results obtained are promising and, from a spatial point of view, they show already a successful matching of vehicles. Compared with the solutions proposed in literature, the developed demonstrator is innovative, and represents the first step towards a real world application running in real time inside cars. Overall, this work is a useful contribution to active safety and autonomous driving applications based on sensor fusion and a good reference for further research on the topic.

1 INTRODUCTION

Advanced Driver Assistance Systems (ADAS) used to improve traffic safety and driving comfort currently rely on on-board surround sensors such as cameras and radars. These sensors provide reliable relative positions between the own vehicle and detected objects, but have a limited field of view and can suffer in situation with occlusion.

In parallel, Car-to-Car (C2C) and Car-to-Infrastructure (C2I) Communication systems (Baldessari et al., 2007; Fuchs et al., 2012) based on ad hoc networking are in transition to deployment and have already been tested in huge field tests (SimTD, 2008; Grace et al., 2012). These communication systems deliver information about the position and the movement state of cars and can extend the driver horizon with a higher range and non-line of sight capabilities. However, GPS position precision and communication channel congestion problems could affect the quality of the received data.

Therefore, the next logical step is the fusion of information from on-board surround sensors and C2C Communication, to benefit from the strengths of both systems and to compensate their weaknesses. In this regard, one major challenge is the unambiguous assignment of detected vehicles from different sources.

2 STATE OF THE ART

While many publications have addressed the problem of sensor fusion between on-board sensors, not much work has been done using also C2C Communication data. The most significant publications related to the topic of this paper are probably (Thomaidis et al., 2011; Obst et al., 2014). Indeed, (Thomaidis et al., 2011) addresses the problem of associating and fusing tracks coming from on-board long range radar with received vehicle positions from the vehicular network. In this paper the Unscented Kalman filter is used together with the constant turn rate and acceleration model to obtain vehicle tracks from Cooperative Awareness Messages (CAMs), the messages sent on a regular basis from the vehicles containing data regarding their position and their current dynamic state. The results of this work show that using the ITS G5 ad hoc network data the vehicle in front is tracked for 67% time frames more in comparison to radar sensor only, as the route consists in

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many curves and the target is often outside the radar field of view (FOV). Moreover, the authors affirm that only 1% of all track associations are wrong. Instead, in (Obst et al., 2014) C2C Communication and camera data are fused to check the correctness of CAM content. The cross-correlation between the data from CAMs and the MobilEye camera (Mobileye, 2015) is used to check the plausibility of received CAMs and to compute the existence probability of sending vehicles. In this way, the authors think that problems such as the malicious injection of a ghost-vehicle in the ITS G5 network could be avoided, providing a higher level of security to the users. The Kalman filter is used and the vehicle dynamics is described with constant velocity model. The fusion happens at track-level, hence there is a first measurement-to-track association step. Overall the results seem promising, but only one particular scenario is shown. A different approach is used in (Matthias Röckl and Thomas Strang and Matthias Kranz, 2008; Matthias Röckl and Jan Gacnik and Jan Schomerus, 2008), which considers C2C communications as a complementing sensor for future driver assistance systems. In these papers a particle filter is used to generate target tracks, so that both the system and the noise can be described with non-linear and non-Gaussian models. The results show good accuracy in the mean of the distribution, especially when the target is close and in the ego vehicle FOV. However, no real data are used to evaluate the algorithm performances. Indeed, all the evaluations happen within a simulation environment called CODAR (Matthias Röckl and Thomas Strang and Matthias Kranz, 2008).

In conclusion, the problem of data fusion between C2C Communication and on-board sensors still presents open challenges and room for improvement. In particular, no comprehensive solutions for unambiguous car detection and matching between detected vehicles from different systems have been presented yet. Of course, this makes the topic interesting and innovative, both from a research and practical application point of view.

3 METHODOLOGY

This section deals with the most important aspects of the study and describes the major parts of the research done, both from a theoretical and practical point of view. In particular, Section 3.1 presents the overall experimental setup and provides information regarding the hardware used to collect significant data. Then, Section 3.2 describes the challenges faced during the algorithm design, and the respective adopted solutions. Finally, Section 3.3 gives an overview of the algorithm main steps, while the actual real time implementation is described in Section 3.4.

3.1 Experimental Setup

All the data used to test the algorithm have been recorded as part of this work using a Volkswagen Passat B6 wagon and an Audi A6 Avant, both inside and outside the company premises. The Passat is equipped with both video and C2C Communication systems, while the Audi includes only the latter. For this reason in all the recordings the Audi is driving in front of the Passat, allowing the camera to detect the same vehicle that is sending CAMs. Figure 1 shows the described scenario.

Figure 1: Experimental setup.

The hardware used for the C2C Communication system corresponds to the ETSI ITS G5 standards and Figure 2 shows a prototype implementation. As for the video system, the camera used in this work is the second generation multi purpose camera MPC2 premium (Robert Bosch GmbH, 2015) developed by Bosch, which is able to recognize pedestrians, vehicles, road lanes and traffic signs. The detection range depends on the object size, and for vehicles it extends to more than 120 m (Robert Bosch GmbH, 2015).

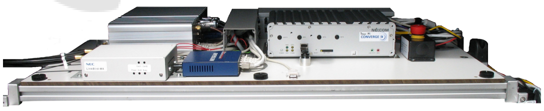


Figure 2: C2C Communication hardware.

3.2 Design Challenges

3.2.1 Sensor Fusion Mechanism

In multi-sensor problems involving target tracking two approaches are possible:

- Measurement-level fusion:raw data coming from sensors are preprocessed and directly combined to obtain the detected object tracks.
- Track-level fusion: for each sensor raw data are preprocessed and further elaborated to obtain tar-

get tracks. Then, considering the tracks belonging to the same target a unified information is produced.

The second approach has been used in this work because it allows to structure the problem in a modular way and has less strict requirements on temporal alignment and statistical knowledge of sensor behavior.

3.2.2 Geographic Coordinate Conversion

The spatial alignment between data coming from various sources is a necessary requirement in sensor fusion applications related to target detection and tracking. In our case the C2C Communication system provides the car positions in absolute coordinates, while the distances from the camera are referenced to the ego vehicle rear axle. Moreover, the C2C coordinates are expressed using the WGS84 format, which is not suitable for tracking applications and for this reason a first conversion into the *Universal Transverse Mercator* (UTM) format is needed. To convert from WGS84 to UTM, the formulas suggested in (Snyder, 1987) have been used.

As for the video system, the relative distance components from the video system are first projected onto the x and y UTM axes using a rotation matrix, then added to the ego vehicle position.

3.2.3 Time Synchronization

Concerning the C2C Communication system, all the CAMs include the time instant in which the message was generated, expressed in milliseconds and referenced to 2004-01-01T00:00:00.000Z (European Telecommunications Standards Institute, 2014). In particular, all ITS G5 network vehicles (including the ego vehicle) use the same time scale, hence it is quite easy to synchronize and align the data from different cars.

In order to align the camera data with the information from the CAMs and the ego vehicle, some modifications have been made to the existing system configuration: the application unit of the C2C Communication system is connected directly to the Private CAN bus of the Passat to access the camera data and to add a timestamp to them using the same reference. Even with this configuration some uncertainty is present, indeed data are timestamped when they are received on the CAN bus, and not when the frame is captured from the camera. In order to minimize the average error, a fixed offset value defined by a Matlab simulation is added to all the camera time instants. This does not completely remove the timing errors because both the frame processing time and the CAN sending time are not constant, but it is enough to proceed further with the study.

3.2.4 Target Track Generation

Tracking is the processing of measurements obtained from a target in order to maintain an estimate of its current state (Bar-Shalom and Li, 1995). Since the state observations are affected by noise and could be potentially wrong, usually a probabilistic algorithm involving an a priori model is used. Our implementation uses the Kalman filter (Bar-Shalom and Li, 1993) to update the vehicle tracks, both for C2C and video systems. (Robin Schubert and Christian Adam and Marcus Obst and Norman Mattern and Veit Leonhardt and Gerd Wanielik, 2011) concludes that in applications where only the position is needed, linear models perform quite well and the complications introduced by non-linear models are unjustified. For this reason, linear models and classic Kalman filter have been used in the project.

Concerning the C2C data, one vendor might simply connect a low-cost GPS receiver, while another one implements a sophisticated vehicle positioning algorithm (Obst et al., 2014). Nowadays some of the GPS errors can be corrected with mathematical models or advanced GPS techniques. However, measurements could still be inaccurate and imprecise. Moreover, the GPS receiver position is updated at low frequencies (approximately 1 Hz), which are not compatible with the requirements of automotive ADAS applications. Using the Kalman filter, it is possible to update the vehicle position more often, integrating GPS data with dead reckoning techniques. In the Kalman filter implementation the Constant Acceleration (CA) model has been used. In the reality, the acceleration is not constant and the vehicle dynamics is different from the CA model. In (Bar-Shalom and Li, 1993) two possibilities for modeling the acceleration error are presented. The continuous-time model has been used because, since the target moves continuously over time, it is more accurate than its discrete-time counterpart (X. Rong Li and Vesselin P. Jilkov, 2004). In figures 3 and 4 the improvements deriving from the Kalman filter are shown. Figure 3 presents a comparison between the GPS coordinates of the sending vehicle before and after the Kalman filtering. In particular, it is possible to appreciate that the position is updated more frequently after the filtering. Figure 4 instead shows how the filter behaves when an incorrect GPS position is received.

Also for the camera data it is convenient to use the Kalman filter to generate the target tracks. Indeed, it allows to have a smoother trajectory and to

(a) Unfiltered.

(b) Filtered.

Figure 3: Audi track from C2C Communication system.

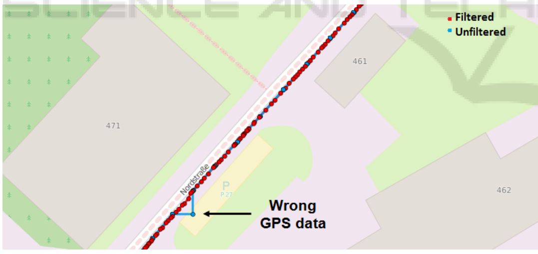


Figure 4: Kalman filter with wrong measurements.

give less importance to outliers or wrong data. Differently from CAM data, target vehicle speed and acceleration are not available from the video system. For this reason, to describe the vehicle dynamics the Constant Velocity (CV) model has been preferred over the CA model. Figure 5 shows a comparison of the target positions before and after Kalman filtering.

3.3 Algorithm Overview

The output of the algorithm is the association of vehicles from different sources. The inputs consist in the information included inside CAMs and in the data from the camera. In addition, ego vehicle information

(a) Unfiltered. (b) Filtered.

Figure 5: Audi track from video system.

such as GPS position, speed and acceleration is used.

The C2C Communication system algorithm uses the received CAMs to generate and maintain the sending vehicle tracks in UTM coordinates. First of all, from the vehicle type field it is possible to know if the message comes from an entity of interest. In particular, if the message comes from a different source it is ignored, otherwise it is considered for the following steps of the algorithm. Then, the vehicle ID field is used to determine whether the message has been sent from a new vehicle or if a track already exists for it. As in (Thomaidis et al., 2011), the vehicle pseudonym has been considered constant for simplicity. At this point two options are possible: if the sending vehicle is a new vehicle its track is initialized, otherwise its track is updated with the new measurement. In particular, the latitude and the longitude are converted into UTM coordinates. Then, the speed and the acceleration components in the UTM reference system are obtained from the respective absolute values and the vehicle heading. Indeed, using the notation presented in figures 6 and 7, the following equations can be written:

$$\begin{cases} v_x = v\sin(\theta_{UTM}) \\ v_y = v\cos(\theta_{UTM}) \end{cases} \tag{1}$$

$$\begin{cases} a_x = a_{long}\sin(\theta_{UTM}) - a_{lat}\cos(\theta_{UTM}) \\ a_y = a_{long}\cos(\theta_{UTM}) + a_{lat}\sin(\theta_{UTM}) \end{cases} \tag{2}$$

With this information the Kalman filter prediction and update steps are used to successfully update the vehicle track. These are:

State Prediction

$$\begin{cases} \hat{\mathbf{x}}_{k+1|k} = \mathbf{A}_k \hat{\mathbf{x}}_{k|k} \\ \mathbf{P}_{k+1|k} = \mathbf{A}_k \mathbf{P}_{k|k} \mathbf{A}_k^{\mathrm{T}} + \mathbf{Q}_k \end{cases} \tag{3}$$

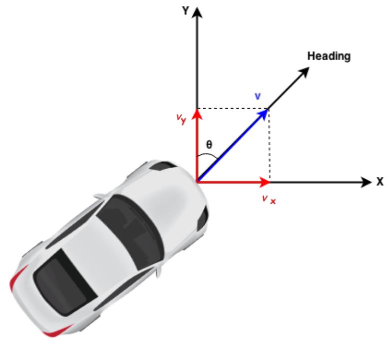
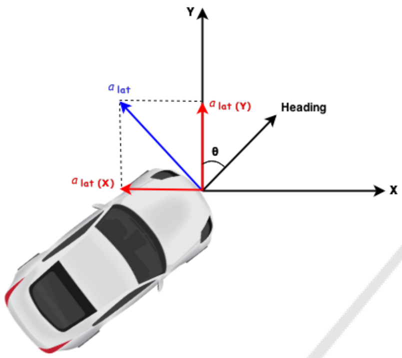
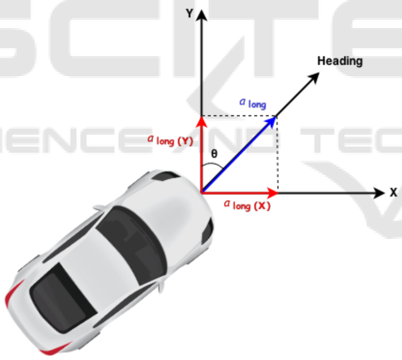


Figure 6: WGS84 to UTM conversion of vehicle speed.



(a) Lateral acceleration.



(b) Longitudinal acceleration.

Figure 7: WGS84 to UTM conversion of vehicle acceleration.

State Update

$$\begin{cases} \hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \mathbf{K}_{k+1}\left(\mathbf{y}_{k+1} - \mathbf{C}_{k+1}\hat{\mathbf{x}}_{k+1|k}\right) \\ \mathbf{P}_{k+1|k+1} = \left(\mathbf{I} - \mathbf{K}_{k+1}\mathbf{C}_{k+1}\right)\mathbf{P}_{k+1|k} \end{cases} \tag{4}$$

where:

- $\mathbf{x} \in \Re^n$ = state vector
- $\mathbf{y} \in \Re^m$ = observation vector
- $\mathbf{A} \in \Re^{n \times n}$ = state transition matrix
- $\mathbf{C} \in \Re^{m \times n}$ = observation matrix
- $\mathbf{P}$ = state estimate covariance matrix
- $\mathbf{Q}$ = state evolution noise covariance matrix
- $\mathbf{R}$ = measurement noise covariance matrix
- $\mathbf{K}_{k+1} = \mathbf{P}_{k+1|k}\mathbf{C}_{k+1}^{\mathrm{T}}\left(\mathbf{C}_{k+1}\mathbf{P}_{k+1|k}\mathbf{C}_{k+1}^{\mathrm{T}} + \mathbf{R}_{k+1}\right)^{-1}$

In particular, for the considerations made in Section 3.2.4, the matrices are:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & T_k & 0 & \frac{1}{2}T_k^2 & 0 \\ 0 & 1 & 0 & T_k & 0 & \frac{1}{2}T_k^2 \\ 0 & 0 & 1 & 0 & T_k & 0 \\ 0 & 0 & 0 & 1 & 0 & T_k \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

$$\mathbf{C} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

$$\mathbf{Q} = S_{\mathbf{v}} \begin{bmatrix} \frac{1}{20}T_k^5 & \frac{1}{8}T_k^4 & \frac{1}{6}T_k^3 \\ \frac{1}{8}T_k^4 & \frac{1}{3}T_k^3 & \frac{1}{2}T_k^2 \\ \frac{1}{6}T_k^3 & \frac{1}{2}T_k^2 & T_k \end{bmatrix} \tag{7}$$

where $S_{\mathbf{v}}$ is the power spectral density of the continuous-time white noise in the state evolution process and $T_k = t_{k+1} - t_k$ is the time interval between the instants t_{k+1} and t_k.

The camera algorithm uses the information regarding the objects detected by the video system to generate and maintain target tracks in UTM coordinates. First of all, the vehicle type field determines if the detected object should be considered or ignored. If the detected object is a car, a truck or a motorcycle, then the object ID is considered to distinguish between new vehicles and vehicles that have already been observed. In particular, a new track is generated only if the probability existence field of the new observation is high enough. This information is provided together with each detection and gives a probability estimate of its correctness. Every time a track is updated, it is necessary to convert the relative distance between the ego vehicle and the target into the UTM absolute position. In particular, the ego vehicle UTM coordinates are generated and filtered using the same procedure used for CAMs and then interpolated at the time instants in which the target was detected from the camera. Using the notation of Figure 8, the conversion is made applying the following equations:

$$\begin{cases} x_{UTM} = x_{ego} + \Delta x_{UTM} \\ y_{UTM} = y_{ego} + \Delta y_{UTM} \end{cases} \tag{8}$$

where Δx_{UTM} and Δy_{UTM} are calculated as:

$$\begin{cases} \Delta x_{UTM} = \Delta x \sin(\theta_{UTM}) - \Delta y \cos(\theta_{UTM}) \\ \Delta y_{UTM} = \Delta x \cos(\theta_{UTM}) + \Delta y \sin(\theta_{UTM}) \end{cases} \tag{9}$$

Once the target coordinates are available in the UTM format, the Kalman filter algorithm prediction and update steps are computed. In this case, the matrices are:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & T_k & 0 \\ 0 & 1 & 0 & T_k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{10}$$

$$\mathbf{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{11}$$

$$\mathbf{Q} = S_v \begin{bmatrix} \frac{1}{3}T_k^3 & \frac{1}{2}T_k^2 \\ \frac{1}{2}T_k^2 & T_k \end{bmatrix} \tag{12}$$

As shown is Section 3.2.4, the filtering enables to smooth the trajectory of the detected vehicles and to reduce the effect of outliers, improving the successive fusion results.

Finally, it is possible to fuse the data and perform the matching between the detected objects. Indeed, every time a new frame is processed from the video system, the algorithm checks the similarity between each camera track and the ones currently available from the CAMs. In particular, the Euclidean distance is used to calculate the difference in meters between corresponding positions. Two different methods have been utilized to compare the data in simulation:

- Considering only space.
- Considering both space and time.

The first method does not take into account the time instant in which a measurement was taken and for each position sample of the camera tracks the distance from the closest point in C2C Communication tracks is calculated. In practice this gives an estimate of how similar the tracks are, but only from a spatial point of view. On the other hand, the second method considers also the time and compares points taken at the same instant. In this case two tracks are similar only if both spatial and temporal alignment are correct and accurate. Depending on the application, different methods to compute the track similarity could be adopted. In this work three strategies have been used for evaluating the results:

- Considering whole tracks.
- Considering only the last sample of each track.
- Considering the samples included inside a moving time window.

When more than one sample is considered the mean value of the distances is computed to have an overall estimate of how similar the two tracks are. In order to have a more reliable measurement, outliers are removed before calculating the mean value.

3.4 Algorithm Implementation

The actual algorithm implementation consists of Java functions to collect and process in real time the data from the different systems. Indeed, the application unit of the C2C Communication system is programmed in Java using an OSGi framework, a set of specifications that enables a development model where applications are dynamically composed of many different reusable components (OSGi Alliance, 2015). The main advantage of using OSGi is the possibility to hide the implementation details of each component, and make them communicate through services using a publish-subscribe interface. The event publish-subscribe mechanism has been largely used in the implementation, to keep the data collection independent from the processing phase. Overall four bundles have been developed to collect, log and process the data coming from the different system. To access the data on the CAN bus a dedicated library in C has been developed and then imported in the Java code using the Java Native Interface (JNI).

As shown in Figure 13, the user interface (UI) displayed on an in-car monitor, consists mainly of two graphs, the bigger one displaying the vehicle tracks in UTM coordinates and the other showing the difference in meters between the Audi position from C2C Communication and video systems over time. On the right side of the main application window, there are some buttons and text fields that allow the user to visualize the data and to control the behaviour of the UI.

4 RESULTS

This section shows the results obtained using the algorithm developed within this research work. Two driving scenarios have been considered, analysing the data collected both inside and outside the company location. Inside the company grounds both cars drive slowly and the Audi often disappears from the FOV of the camera due to the numerous curves, while outside, in a normal traffic environment, the speed is higher and the target vehicle is continuously detected because of the topology of the street.

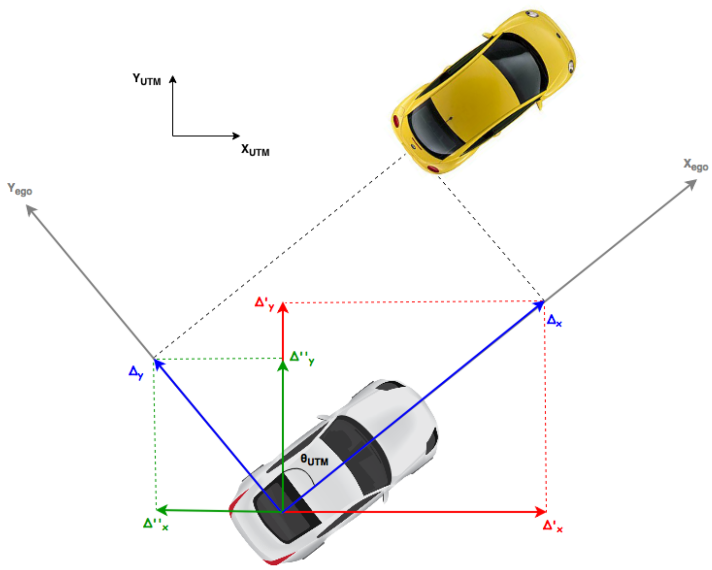


Figure 8: Coordinate conversion from relative to absolute.

4.1 Simulation Results

Before evaluating the results numerically, it is useful to visualize the situation to understand intuitively what happens. Figure 9 shows a comparison between the Audi track generated from the CAMs and the ones from the video system. In particular, the track obtained from the C2C Communication system is drawn in red, while the tracks from the camera have a different color every time a new ID is assigned to the car. This happens, for example, when the Audi disappears from the FOV of the camera, or when the camera detects other vehicles in a new frame and assigns them the ID previously belonging to the Audi. The tracks almost always overlap and overall the matching is good. Only the first camera track (on the left, starting at about X=150m,Y=200m) is wrong, but this does not depend on the algorithm as it is due to an intrinsic error in the GPS at the time in which the recording was taken. Besides this, some minor problems are present after the curves, when the car is detected again from the camera but the ego vehicle is still curving. This leads to a drift in the target vehicle track, which differs from the one obtained from the CAMs.

As with Figure 9, Figure 10 compares the tracks obtained from the two systems. This time the UTM coordinates are projected back into the WGS84 format using the formulas in (Beauducel, 2014), in order to display the car position on an OpenStreetMap map (OpenStreetMap, 2015).

Using the same data of the previous figures, Table 1 shows for each camera track the ID assigned to the vehicles, the time interval in which the object was tracked from the video system and the mean distance from the CAM track. In particular, the mean distance is calculated taking into account all the points of a track and using two different methods, which consider only the space and both the space and the time. In the first case for each element of a camera track the distance is calculated from the closest point in the CAM track, while in the latter points are compared considering the time in which the samples were taken.

When only the space is considered, the results show that on average the mean difference between camera and CAM tracks is small and the matching is almost perfect. Indeed, besides the first track that is affected by the GPS offset problem, in all the other cases the error is smaller than 2m and most of the time stays below 1 m. This shows that the spatial alignment between the two systems is good, and that from this point of view the sensor fusion is successful. However, when with the same data also the time is taken into account, the mean error drastically increases, being always higher than 3m and often more than 9 m. Three factors can be considered as the main reason for this behaviour. First of all, the time alignment between the data from the C2C Communications system and the camera is not perfect due to the reasons explained in Section 3.2.3. Moreover, the GPS receivers of both cars update the position just every second. Considering the information available from the ego vehicle CAN bus and CAMs, the Kalman filter is used to update the position more frequently. However, vehicles behave differently from

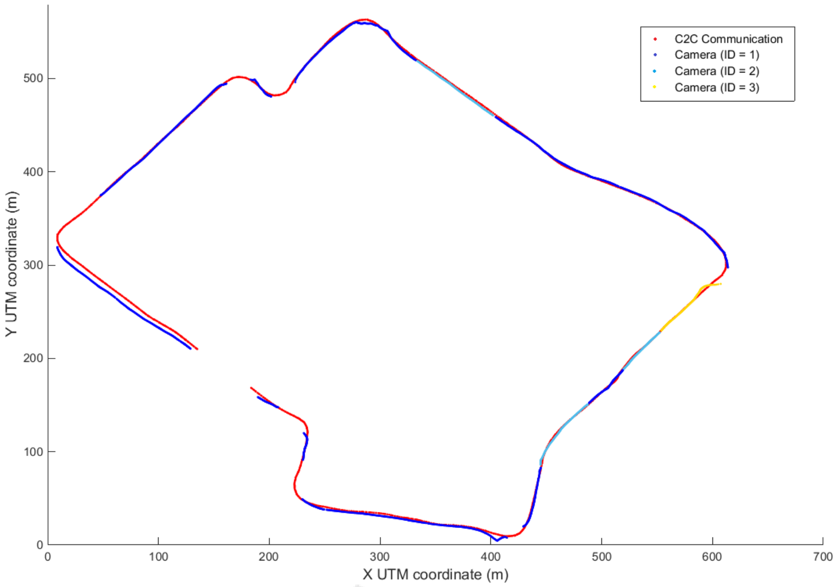


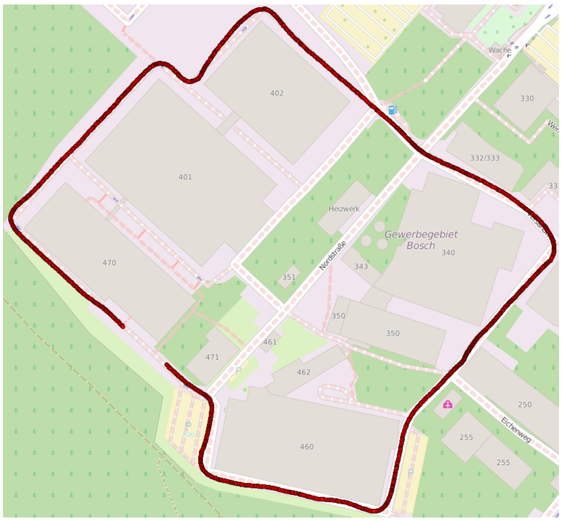
Figure 9: Audi tracks from C2C Communication and video systems.

Table 1: Sensor fusion algorithm results considering the whole tracks (inside company location).

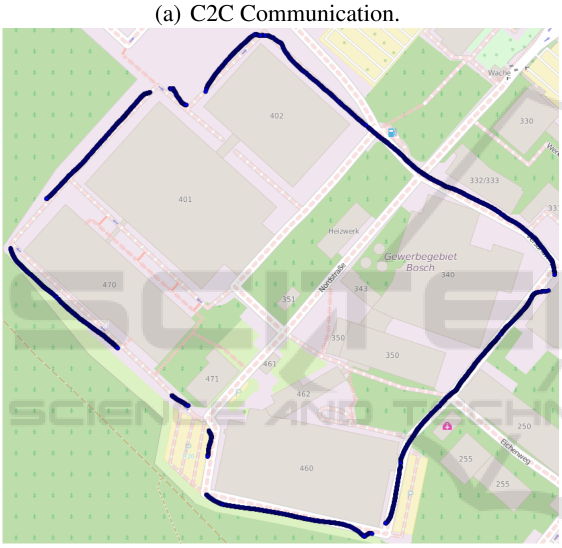
CAM ID	Camera ID	Start (s)	Stop (s)	Mean difference (only space) (m)	Mean difference (m)
444763658	1	0	25.25	5.19	11.46
444763658	1	36.23	91.80	0.89	11.90
444763658	2	91.97	102.95	1.60	11.72
444763658	1	103.17	144.11	0.79	9.44
444763658	3	147.80	158.68	0.61	7.80
444763658	2	158.88	169.90	0.65	5.18
444763658	1	170.07	181.05	0.63	3.36
444763658	2	181.17	192.19	0.78	7.95
444763658	1	192.36	229.60	1.32	9.68
444763658	1	237.02	251.43	0.84	9.34

the model, thus the predicted position can be different from the real one. In particular, the vehicle could be projected in front or behind its real position, which unfortunately is unknown. Since the problem is present in both vehicles, the error introduced can become relevant. Finally, the longitudinal distance accuracy of monocular cameras is typically worse than the lateral distance accuracy (William J. Fleming, 2008), and in particular the relative error can increase linearly with the distance from the target (Stein et al., 2003). When only the space is considered the longitudinal offset introduced does not affect the results, but when also the time is taken into account this error can become important.

Considering all the points of each track is useful to have a general idea regarding how good the algorithm performs. However, in real applications it would make more sense to consider just the new data, or the most recent data within a certain time interval in case the history of the system is of interest. In this way, the periods of time in which the tracks are similar are not influenced by the periods in which they are different, as for example immediately after a curve. Figures 11 and 12 show the distances between one camera track and the corresponding CAM track over time. In particular, in Figure 11 just the new samples are considered to compute the difference, while in Figure 12 the difference is calculated using a moving average over the last two seconds. In the reality, this value would vary depending on the application, since many factors such as the speed of the vehicle should be taken into account. In our case the value has been chosen to have an adequate number of samples to average and because the covered space was big enough (a car moving at $50\,\mathrm{km\,h^{-1}}$ makes about $30\,\mathrm{m}$ in $2\,\mathrm{s}$). The red line in the graphs represents



(a) C2C Communication.



(b) Camera.

Figure 10: Audi track on a map.

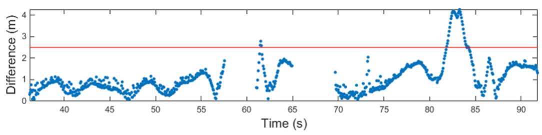


Figure 11: Difference between Audi tracks over time.

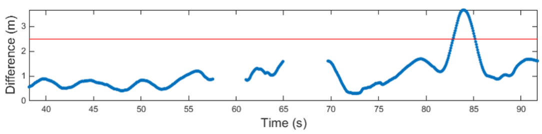


Figure 12: Difference between Audi tracks over time using moving average.

a hypothetical threshold value that decides when the matching between the tracks happens. In other words, values below the red line represent positive matching. The threshold has been adjusted to 2.5 m, considering the average car and street dimensions.

The same Matlab simulations have been performed also on the data recorded outside the company location. In this scenario the streets are mostly long and straight, and it is possible to drive faster than inside. As with the results presented in Table 1, the difference is small if only the space is considered. On the other hand, when also the time is taken into account, the same problems analysed for the first scenario arise and the results get worse of about a factor of ten.

4.2 Implementation Results

The results obtained with the real time implementation of the algorithm are perfectly aligned with the ones from the evaluation of the recorded data in Matlab. Concerning the software performance and the resource utilization, the real time demonstrator is able to run smoothly on the Java Virtual Machine (JVM) installed on the C2C Communication hardware and most of the resource usage derives from the data visualization.

Overall, the results obtained from the real time implementation of the algorithm can be considered positive and promising. Indeed, the demonstrator developed in this work represents the first step towards a real world application running in real time inside vehicles. This is something new and innovative compared to the state of the art works, which consist mainly in simulations based on fictitious or previously recorded data and do not allow the online visualization of the results.

Figure 13: Real time demonstrator.

4.3 Future Work

To obtain a better time alignment of the data, the video messages sent on the CAN bus should be timestamped directly from the camera using the ITS G5 network time reference. This could be easily done changing the current camera firmware or using a device that provides the functionality by default.

In order to obtain better track matching results when also the time is considered, the procedure used to update the position over time should be improved as well. First of all, it would be helpful to repeat the tests with the same algorithm but using a better GPS receiver to obtain more frequent and accurate position updates. Secondly, more sophisticated dynamics models could be used to predict the vehicle position. Other sensors, such as radar, lidar or stereo camera could replace the monocular camera or could be added to the current system. In particular, using these sensors it would be possible to improve the accuracy in the distance measurement and to achieve better results in the matching when also the time is taken into account. This would not require too much effort, given the modular approach used to design the algorithm.

Finally, another direction in which the future work should focus is the analysis of more scenarios. First of all, it would be extremely useful to use at least three vehicles sending and receiving CAMs, in order to have not only multiple targets from the camera, but also from the C2C Communication system. Moreover, different driving scenarios should be considered, for example with the target car arriving from an intersection, or during overtaking.

5 CONCLUSIONS

In this work a sensor fusion algorithm to unambiguously assign detected vehicles from C2C Communication and on-board sensors has been designed and implemented in real-time. All the main challenges faced during the design phase, i.e., the data collection procedure, the sensor fusion mechanism to be used, the spatial and the temporal alignment of data from the two systems and the track generation process, have been described and a solution to each problem has been proposed. Then, the sensor fusion algorithm has been developed and tested in Matlab using different metrics to evaluate the results and to understand the most critical parts that should be improved in the future work. Both simulated and recorded data from real driving scenarios have been used in this phase and, for this purpose, specific tools for data acquisition and storage have been deployed as well. Finally, the algorithm has been implemented inside an in-car system to demonstrate its capabilities in real time and to offer a convenient debugging environment for further research on the topic.

The overall results obtained using the developed algorithm are promising. In particular, the Matlab simulations show excellent results from a spatial point of view, with a successful and unambiguous detection and matching of target vehicles. Further research should be done to obtain likewise satisfying results when also the time is considered in the calculation of the difference between tracks. In this regard, concrete ideas and possible solutions for further research have been given. Concerning the results obtained with the real time implementation of the algorithm, they are perfectly aligned with the ones from the Matlab simulations and can be considered positive and encouraging as well. Compared with the solutions proposed so far in literature, the demonstrator that has been developed in this work is new and innovative, and represents the first step towards a real world application running in real time inside vehicles.

In order to obtain a reliable product that can be used in applications, further work on this topic should be done. Nevertheless, this work represents a good basis for the future research and an important contribution to the field of ADAS applications based on sensor fusion.

REFERENCES

Baldessari, R., Bödekker, B., Brakemeier, A., Deegener, M., Festag, A., Franz, W., Hiller, A., Kellum, C., Kosch, T., Kovacs, A., Lenardi, M., Lübke, A., Menig, C., Peichl, T., Roeckl, M., Seeberger, D., Strassberger, M., Stratil, H., Vögel, H.-J., and Zhang, B. W. W. (2007). CAR 2 CAR Communication Consortium Manifesto. Technical report, CAR 2 CAR Communication Consortium.

Bar-Shalom, Y. and Li, X.-R. (1993). *Estimation and Tracking: Principles, Techniques, and Software*. Artech House.

Bar-Shalom, Y. and Li, X.-R. (1995). *Multitarget-Multisensor Tracking: Principles and Techniques*. YBS Publing, 1st edition.

Beauducel, F. (2014). ll2utm. http://www.mathworks.com/matlabcentral/fileexchange/45699-ll2utm-and-utm2ll/content/Codes/matlab/ll2utm.m. [Online; accessed 07-April-2015].

European Telecommunications Standards Institute (2014). Etsi ts 102 894-2 v1.2.1: Intelligent Transport Systems (ITS); Users and applications requirements; Part 2: Applications and facilities layer common data dictionary. Technical Specification.

Fuchs, H., Hofmann, F., Löhr, H., Schaaf, G., and Kleine-Besten, T. (2012). Car-2-X. In Winner, H., Hakuli, S., and Wolf, G., editors, *Handbuch Fahrerassistenzsysteme: Grundlagen, Komponenten und Systeme für aktive Sicherheit und Komfort*.

Grace, N., Oxley, C., Sloan, S., Tallon, A., andTammy Black, P. T., Easton, A. V., program managers of the ITS Joint Program Office and the Federal Highway Administration, T., the Federal Motor Carrier Administration, the Federal Transit Administration, the National Highway Traffic Safety Administration, the Research, and Administration, I. T. (2012). Transforming Transportation through Connectivity: ITS Strategic Research Plan, 2010 - 2014 (Progress Update, 2012). Strategic Plan Report, U.S. Department of Transportation.

Matthias Röckl and Jan Gacnik and Jan Schomerus (2008). Integration of Car-2-Car Communication as a Virtual Sensor in Automotive Sensor Fusion for Advanced Driver Assistance Systems. In *FISITA 2008*.

Matthias Röckl and Thomas Strang and Matthias Kranz (2008). Demonstrator: V2V Communications in Automotive Multi-sensor Multi-target Tracking. In *2nd IEEE International Symposium on Wireless Vehicular Communications*.

Mobileye (2015). http://www.mobileye.com/ [Online; accessed 05-May-2015].

Obst, M., Hobert, L., and Reisdorf, P. (2014). Multi-Sensor Data Fusion for Checking Plausibility of V2V Communications by Vision-based Multiple-Object Tracking. In *2014 IEEE Vehicular Networking Conference (VNC)*.

OpenStreetMap (2015). https://www.openstreetmap.org/. [Online; accessed 06-May-2015].

OSGi Alliance (2015). http://www.osgi.org/Main/HomePage. [Online; accessed 01-June-2015].

Robert Bosch GmbH (2015). http://life.bosch.com.cn/ebrochures2015/automated/cc/da/mpc2/datenblatt_mpc2_en.pdf. [Online; accessed 07-July-2015].

Robin Schubert and Christian Adam and Marcus Obst and Norman Mattern and Veit Leonhardt and Gerd Wanielik (2011). Empirical Evaluation of Vehicular Models for Ego Motion Estimation. In *IEEE Intelligent Vehicles Symposium (IV)*.

SimTD (2008). http://www.simtd.de/index.dhtml/enEN/index.html. [Online; accessed 07-April-2015].

Snyder, J. P. (1987). Map Projections: A Working Manual. Technical report, U.S. Geological Survey.

Stein, G. P., Mano, O., and Shashua, A. (2003). Vision-based ACC with a Single Camera: Bounds on Range and Range Rate Accuracy. In *IEEE Intelligent Vehicles Symposium*.

Thomaidis, G., Vassilis, K., Lytrivis, P., Tsogas, M., Karaseitanidis, G., and Amditis, A. (2011). Target Tracking and Fusion in Vehicular Networks. In *2011 IEEE Intelligent Vehicles Symposium (IV)*.

William J. Fleming (2008). New Automotive Sensors - A Review. In *IEEE Sensors Journal, VOL. 8, NO. 11*.

X. Rong Li and Vesselin P. Jilkov (2004). Survey of Maneuvering Target Tracking. Part I: Dynamic Models. In *IEEE Transactions on Aerospace and Electronic Systems*.