A Bayesian Multisensor Fusion Approach Integrating Correlated Data applied to a Real-time Pedestrian Detection System

Laurence NGAKO PANGOP, Roland CHAPUIS, Sebastien BONNET, Sebastien CORNOU and Frederic CHAUSSE

***Abstract*— The pedestrian detection is a challenging task in automotive research, which often suffers from the lack of reliability due to the occurrences of spurious detections. This paper presents a Bayesian approach, which fuse information from multiple sensors to improve the performances of a pedestrian detection system. The main contribution of this paper is the way to incorporate the information potentially correlated in the Bayesian formalism. We model the observations by an autoregressive (AR) model therefore the conditional likelihoods, required in the Bayes' rule, are derived from that AR model. In our implementation, the correlation is estimated empirically. Simulation results as well as the results of the experiments conducted on real data demonstrate the effectiveness of the proposed approach. Moreover, the proposed algorithm runs in real-time.**

I. INTRODUCTION

As many as 8000 vulnerable road users, pedestrians and cyclists, are killed every year in the European Union. The accident statistics indicate that despite the recent advances in safety due to the introduction of passive safety systems and tighter pedestrian legislations, the pedestrian accidents still represent the second largest causes of traffic-related injuries and fatalities; the first being accidents involving car passengers [1]. Nowadays, the emphasis in automotive research is on active safety systems. Active measures alleviate the conditions under which impact may take place, e.g., by reduction of impact speed. The challenges faced by such systems on moving vehicle are movement of the sensors; unpredictable road situations and background scenarios; variations in the size, appearance and pose of pedestrians. Moreover, the automotive constraints, limited computing resources and need for high reliability, are added to these perception issues. Therefore, the developed systems have to be efficient using the lowest processing resources.

Regarding the sensing part of such systems, the video camera seems to be the best sensor to perform the recognition task. Vision-based systems are widely used for pedestrian detection [2] and [3] because the cameras provide enough resolution for accurate classification. In addition, the relatively low cost of cameras and their potential use for other perception functions in the vehicle (e.g. traffic sign recognition or lane departure warning) give them a strong advantage over other sensors technologies. The disadvantage of image-only detection systems is the high computational cost associated with classifying a large number of regions of interest (ROI). Moreover, in outdoor environments the performance of vision-based systems may be negatively affected by weather conditions. Therefore, another sensor types have to be combined with cameras [4].

A study of sensor-based pedestrian detection, presented in [1], indicates that the laser scanner in cooperation with camera is a good solution to be developed. Each of these two sensor technologies, used separately, has demonstrated its capability to provide good performances for pedestrian detection systems [5], [6] and [7]. Therefore, when used together the problem is how to combine the diverse and sometimes conflicting amounts of information in the best manner, to outperform the best results expected from the use of a single sensor technology.

Many works have been done to solve the problem of data fusion for multiple applications. In the particular case of pedestrian classification, several approaches have been proposed. Some authors only make use of both sensors' complementarity [8]. The laser scanner segments the scene and then provides some ROI, which are confirmed to contain pedestrian by a vision-based classifier. Other authors have developed both the complementarity and redundancy of the information provided by both sensors [9] and [10]. The segmentation and tracking processes are performed only in the laser space whereas the object classification works in both sensor spaces. The main difference between these two solutions is in the data fusion techniques. In [9], a Bayesian-sum decision rule is used to combine the results of both sensor classifiers. The classification is done frame by frame classification. Whereas in [10], we proposed to used a Bayesian framework to fuse sensor information at feature-level. This solution is especially interesting because data can be asynchronously treated [11]. Moreover, the temporal coherence of observations is developed by the integration of past knowledge. That helps smooth the computed probability and then enhance the system reliability.

In this paper, we propose to introduce the correlation among data in the formalism developed in [10]. Our aim is to make our pedestrian detection system more robust to spurious detections and avoid the probability grows fast to one or zeros when all the measured data are highly correlated. Our motivation comes the fact that if a sequence of identical measures is used for the classification using our formalism, the probability will converge to zero or one after a certain time and remains constant, whereas one can expect to have a constant value of the probability in case of assuming that these measures are strong correlated. That means that non-informative measures have to be detected and take into account in our formalism to avoid changing the probability value. The Bayesian formalism offers the possibility to integrate correlated data in the formalism as soon as the conditional likelihoods between a current observation and the previous are modeled. The autoregressive (AR) model seems to be a good and elegant solution to solve this problem. An AR model is a time series where a given datum is a weighted sum of some previous data and noise term. However, this AR model gives raise to another question: how to compute practically the AR parameters. Theoretical solutions utilizing the autocorrelation function of the data are presented in [12]. In the particular cases of object classification from a moving vehicle, we assume that correlation is mainly due to either the observation of the object from the same point of view during a while or no change of the scale factor. Therefore, we estimate the correlation (AR parameters) by using the relative displacement of objects in the sensor space. Simulation results demonstrate the effectiveness of our approach. In addition, experiment results on real data confirm the simulation result and validate way to compute the correlation value. The proposed approach has been implemented in a vehicle demonstrator and runs in real-time.

The paper is organized as follows. An overview of the system is presented in the next section. Section III briefly describes the preprocessing steps. Section IV elaborates our Bayesian approach for the multisensor fusion of correlated observations for the purpose of object classification. In section V, simulation and experimental results are presented to demonstrate the effectiveness of the proposed approach. Finally, the conclusions are presented in section VI.

II. SYSTEM OVERVIEW

Architecture of the developed pedestrian detection system is shown in Fig.1. The object segmentation is performed in the laser scanner and image spaces. The segmented objects are sorted, in regard of their size, in two groups: pedestrian-like objects and "wide" objects. In the rest of the paper, only pedestrian-like objects are considered (classified) and we will refer to as segmented objects or simply objects. The two feature used for the classification are speed and score (output of an Adaboost classifier). The Bayesian classifier computes the probability of an object to be pedestrian regarding the observations of these two features.

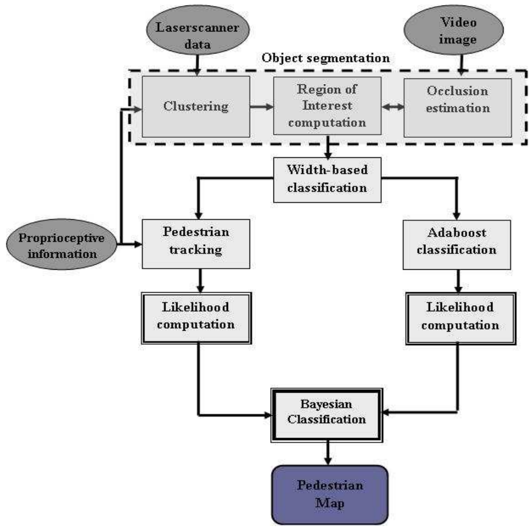

Fig. 1. Multi-module architecture using a lidar and vision information for pedestrian detection and classification

III. OBJECT SEGMENTATION AND FEATURES EXTRACTION

To speed up the system an attention area where all the relevant objects are located is defined. Due to the location of the sensors on our experimental platform (illustrated in Fig. 2) an object can be detectable in the lidar space and occluded into the image and vice versa. However, in our method only the first case is detected because even if both sensor images are used for the segmentation, it is the lidar that generates all the clusters. The segmentation algorithm is as follows

1) Lidar-based clusters located in the attention area are projected into the image.
2) If the bounding boxes of two pedestrian-like objects have an overlapping area greater than a set percentage of the smallest bounding box area (representing the further object). The further object is discarded.
3) If the bounding box of any pedestrian-like object overlaps with the bounding box of any wide object and the pedestrian-like object is further, then it is discarded.

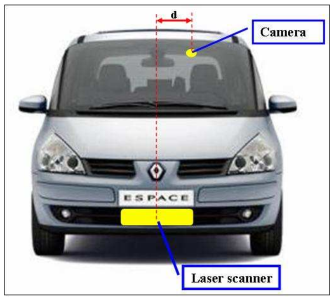

Fig. 2. The locations of the sensors in our experimental platform are highlighted.

The effectiveness of the proposed segmentation process was tested on many sequences. In most of the cases, it entails an average reduction of 70% of the pedestrian-like objects which are further classified. Fig.3 shows the results obtained in a sequence without any pedestrian.

The features extracted from the sensors and used for the classification are:

1) speed : estimated by the mean of the well-known Kalman filter with a constant velocity model;
2) score : the output of an Adaboost algorithm using the Haar-like features detailed in [6].

The feature extraction process is detailed in [10].

IV. BAYESIAN PEDESTRIAN CLASSIFICATION

For clarity, this section is divided into three parts. At first, the Bayesian algorithm in the case of one sensor provided correlated information over time is presented. Afterward, The

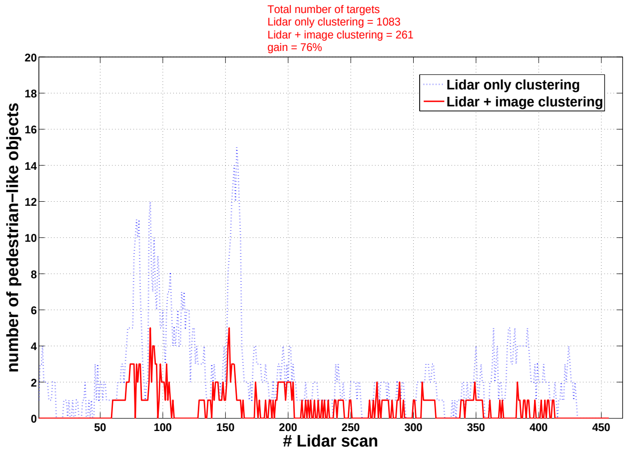

Fig. 3. Comparison between a segmentation based on the lidar only clustering and one using lidar clustering coupled to image treatment.

Bayesian algorithm for a multisensor system is presented. For simplicity, the time does not appear in this part. Finally, an example of the fusion of two sensors information with correlation consideration is developed.

A. Bayesian algorithm with correlated observations from a single sensor

From a Bayesian perspective, the classification problem is to recursively calculate some degree of belief in the object class H_k at time k, being a pedestrian class, given the observations $z_{1:k}$ up to time k. Thus, it is required to construct the posterior probability density function (pdf) $p(H_k|z_{1:k})$. It is assumed that the initial pdf $p(H_0|z_0) \equiv p(H_0)$ which is also known as the prior, is available (z_0 being the set of no observations). Then, in principle, the pdf $p(H_k|z_{1:k})$ may be obtained recursively, in two stages: prediction and update.

Suppose that the required pdf $p(H_{k-1}|z_{1:k-1})$ at time $k-1$ is available. The prediction stage involves using the system model to obtain the prior pdf of the state at time k via the Chapman-Kolmogorov equation

$$p(H_k|z_{1:k-1}) = \sum_{H_{k-1}} p(H_k|H_{k-1})p(H_{k-1}|z_{1:k-1}) \qquad (1)$$

Note that in (1), use has been made of the fact that $p(H_k|H_{k-1}, z_{1:k-1}) = p(H_k|H_{k-1})$ as the system model describes a Markov process of order one. In our system H_{k-1} can take only two values H_{k-1} and its complementary $\overline{H_{k-1}}$. The probabilistic model of the object class evolution $p(H_k|H_{k-1})$ is defined as follows

$$p(H_k|H_{k-1}) = 1 \qquad (2a)$$

$$p(H_k|\overline{H_{k-1}}) = 0 \qquad (2b)$$

Equation (2) means that the object class does not vary with time k. The equation (1) becomes

$$p(H_k|z_{1:k-1}) = p(H_{k-1}|z_{1:k-1}) \qquad (3)$$

At time step k, an observation z_k becomes available, and this may be used to update the prior (update stage) via Bayes' rule

$$\begin{aligned} p(H_k|z_{1:k}) &= \frac{p(z_{1:k}|H_k)p(H_k)}{p(z_{1:k})} \\ &= \frac{p(z_k, z_{1:k-1}|H_k)p(H_k)}{p(z_k, z_{1:k-1})} \\ &= \frac{p(z_{1:k-1}|H_k)p(z_k|z_{1:k-1}, H_k)P(H_k)}{p(z_{1:k-1})p(z_k|z_{1:k-1})} \\ &= \frac{p(H_k|z_{1:k-1})p(z_k|z_{1:k-1}, H_k)}{p(z_k|z_{1:k-1})} \qquad (4) \end{aligned}$$

where $p(z_k|z_{1:k-1})$ is a normalizing factor. The equation (4) depends on the likelihood function $p(z_k|z_{1:k-1}, H_k)$ which is the conditional likelihood integrating correlation among observations.

1) Autoregressive model:

The notation $AR(p)$ refers to the AR model of order p. If the set of observation $z_{1:k}$ is considered as a time series. Its $AR(p)$ model is written [13]

$$z_k = c + \sum_{k=1}^{p} \varphi_i z_{k-i} + \varepsilon_k; \qquad (5)$$

where $\varphi_1, \ldots, \varphi_p$ are the parameters of the model, c is a constant and ε_k is a white noise. The constant term is omitted by many authors for simplicity.

Some constraints are necessary on the values of the parameters of this model in order that the model remains stationary. For example, processes in the $AR(1)$ model with $\|\varphi_1\| \geq 1$ are not stationary.

We decide to limit our study to an $AR(1)$-process means that we assumed that the observation z_k describes a Markov process of order one. Its $AR(1)$-process is given by:

$$z_k = c + \varphi z_{k-1} + \varepsilon_k; \qquad (6)$$

where ε_k is a white noise process with zeros mean and variance σ_ε^2. (Note: the subscript on φ_1 has been dropped). The process is covariance-stationary if $\|\varphi\| < 1$. If $\|\varphi\| = 1$ then z_k exhibits a unit root and can be also considered as a random walk, which is not covariance-stationary. The link between the expectation of z_k, μ, and the constant (assuming covariance stationarity) is

$$\begin{aligned} E(z_k) &= E(c) + \varphi E(z_{k-1}) + E(\varepsilon_k) \\ \mu &= c + \varphi\mu + 0 \\ \mu &= \frac{c}{1-\varphi} \qquad (7) \end{aligned}$$

And the link between the series variance, σ^2 and the noise variance, σ_ε^2 is

$$\begin{aligned} Var(z_k) &= E(z_k^2) - \mu^2 \\ &= \frac{(c-\varphi\mu)^2 + \sigma_\varepsilon^2 - \mu^2}{1-\varphi^2} \\ \sigma^2 &= \frac{\sigma_\varepsilon^2}{1-\varphi^2} \qquad (8) \end{aligned}$$

Calculation of the AR parameters
The AR parameters may be calculated using least square regression or the Yule-Walker equations:

$$\gamma_m = \sum_{k=1}^{p} \varphi_k \gamma_{m-k} + \sigma_\varepsilon^2 \delta_m \quad (9)$$

where $m = 0,...,p$, yielding $p+1$ equations. γ_m is the autocorrelation function of z, σ_ε is the standard deviation of the input noise process, and δ_m is the Kronecker delta function. Other techniques to calculate these parameters are presented in [12].

In our application, we do not have the autocorrelation function. So, the AR parameter φ is empirically calculated. That is present in the experimental result section.

2) Conditional likelihood:

Once modeling the dependence between consecutive observations by an AR model, we can derive the sought conditional likelihood using equation (6)

$$\begin{aligned} p(z_k|z_{k-1},H_k) &= p(c+\varphi z_{k-1}+\varepsilon_k|z_{k-1},H_k) \quad (10)\\ &= p(c|z_{k-1},H_k) * p(\varphi z_{k-1}|z_{k-1},H_k)\\ &\quad * p(\varepsilon_k|z_{k-1},H_k)\\ &= \delta(z_k-c) * \delta(z_k-\varphi z_{k-1}) * \mathcal{N}(z_k;0,\sigma_\varepsilon^2)\\ &= \mathcal{N}(z_k;\varphi z_{k-1}+(1-\varphi)\mu,(1-\varphi^2)\sigma^2) \end{aligned}$$

where c was replaced by its expression obtained in equation (7); δ is the Dirac function and $\mathcal{N}(z;\mu,\sigma^2)$ is a Gaussian density with argument z, mean μ and variance σ^2. μ and σ^2 are different for the pedestrian and non-pedestrian classes.

B. Bayesian algorithm for a multisensor fusion

Let's consider a set of n features, the classification system determines if an object belongs to pedestrian class, H. From each observed feature Z_i, assuming that the likelihoods $p(Z_i|H)$ are available, the Bayesian classifier fuses them with any prior $p(H)$, to arrive at a global consensus posterior probability, $p(H|Z)$, where $Z = \cup_i\{Z_i\}$ $\forall i$. Bayes' rule is written as follows

$$p(H|Z) = \frac{p(Z|H)p(H)}{p(Z)} \quad (11)$$

where $p(H|Z)$ is the posterior probability of the object being a pedestrian H given the observations Z. $p(Z|H)$ is the probability of the particular set of observations Z knowing that the object is of class type H. This term is the likelihood of H to be correct given the set of observations Z. $p(H)$ is the prior probability of class type H. $p(Z)$ serves as a normalizing function, ensuring the posterior probabilities sum to one over the set $\{H,\overline{H}\}$.

For a multisensor system, it is reasonable to assume that the likelihoods from each informational source $p(Z_i|H)$, $i = 1,\ldots,n$, are independent since the only parameter they have in common is the state.

$$p(Z|H) = p(Z_1|H)p(Z_2|H)...p(Z_n|H) \quad (12)$$

Thus, equation 11 can be rewritten:

$$p(H|Z) \propto p(H)\prod_{i=1}^{n} p(Z_i|H) \quad (13)$$

$$\sum_H p(H|Z) = 1 \quad (14)$$

C. An example of the fusion of two sensors information with correlated observations

From a Bayesian perspective, the classification problem is to recursively calculate some degree of belief in the object class H_k at time k, being a pedestrian class, given the observations $y_{1:k'}$ and $z_{1:k}$ up to time k ($k' < k$). Thus, it is required to construct the posterior probability density function $p(H_k|y_{1:k'},z_{1:k})$. Suppose that the required pdf $p(H_{k-1}|y_{1:k'},z_{1:k-1})$ at time $k-1$ is available ($k' \le k-1$). At time step k, an observation z_k becomes available. It is used to update the prior via Bayes' rule

$$\begin{aligned} p(H_k|y_{1:k'},z_{1:k}) &= \frac{p(y_{1:k'},z_{1:k}|H_k)p(H_k)}{p(y_{1:k'},z_{1:k})}\\ &= \frac{p(y_{1:k'}|H_k)p(z_{1:k}|y_{1:k'},H_k)p(H_k)}{p(y_{1:k'})p(z_{1:k}|y_{1:k'})}\\ &= \frac{p(y_{1:k'}|H_k)p(z_{1:k}|H_k)p(H_k)}{p(y_{1:k'})p(z_{1:k})}\\ &= \frac{p(H_k|y_{1:k'})p(z_{1:k}|H_k)}{p(z_{1:k})}\\ &= \frac{p(H_k|y_{1:k'})p(z_k,z_{1:k-1}|H_k)}{p(z_k,z_{1:k-1})}\\ &= \frac{p(H_k|y_{1:k'})p(z_{1:k-1}|H_k)p(z_k|z_{1:k-1},H_k)}{p(z_{1:k-1})p(z_k|z_{1:k-1})}\\ &= \frac{p(H_k|y_{1:k'},z_{1:k-1})p(z_k|z_{1:k-1},H_k)}{p(z_k|z_{1:k-1})} \quad (15) \end{aligned}$$

Equation (15) can be easily generalized to more than one sensor. The main assumption is that observations from different sensors are conditionally independent whereas observations from the same sensor are correlated.

V. Experimental results

The objective of experiments conducted (in simulation and on real data) is to show how our Bayesian approach improves the classification performances of the pedestrian detection system. In our previous developments, the likelihoods of features used in the fusion were obtained from training processes. Fig. 4 illustrates the pdf $p(feature|pedestrian)$ and $p(feature|non-pedestrian)$ used for the speed and score. Correlation is not taking into account yet.

One specificity of our application is that only the scores are assumed to be potentially correlated. Indeed, we suppose that the speed information is always informative as it is a derivation of the position. However, in a static scene (everything is stopped) we assume that the different values of score do not give any new information. The correlation is derived from the relative displacement of the object in the sensor space (image). That means that low relative displacements

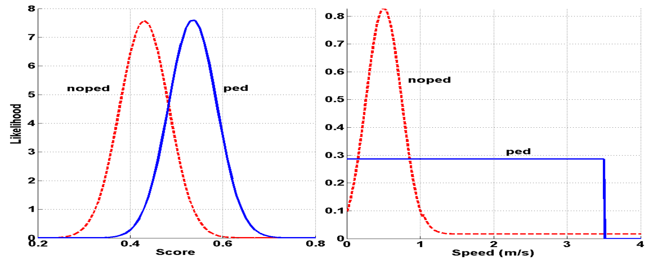

Fig. 4. Likelihood vs. feature considering each class (blue line for pedestrian class and red dashed line for non-pedestrian).

gives high correlation value. The calculation of the amount of correlation is performed in the sensor space because for the same relative displacement (in world coordinates) the effect is more perceptible if the object is closer to the vehicle than if it is further. The correlation is recalculated at each iteration because the relative displacement of objects is not constant from one frame to another.

A. Simulation results

We generated a sequence of 70 correlated scores,random values following the pedestrian distribution illustrated in Fig. 4. The correlation is set: $\varphi = 0.5$. Two different experiments were conducted. The objective of both is to demonstrate that the consideration of correlation in the Bayesian framework improves remarkably the classification results. It is noticeable in Fig.5 that the correlation consideration helps smooth the probability means that the effect of spurious observations is attenuated. On the contrary, when the correlation is not considered spurious observations affect instantaneously the probability. Sometimes in real experiments, some sudden

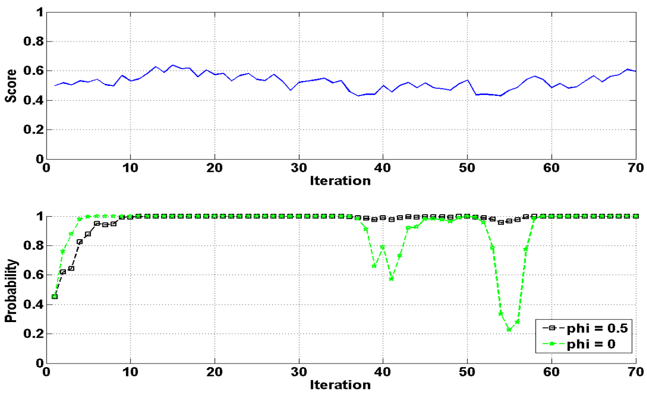

Fig. 5. Evolution of the probability when taking or not the correlation into account.

errors (different from the observation noise) occur. For instance, a bad estimation of the pedestrian position or speed leads to a bad projection of the ROI in the image therefore a wrong score is calculated. To simulate that we randomly added wrong values (low scores) to the correlated data previously generated. The effect of this kind of perturbation is evaluated and the results are shown in Fig. 6. Our observation model with correlation, even slightly erroneous in this case, performs better than the observation model without correlation consideration. The latter model fails completely when these errors are combined to noisy observations. .

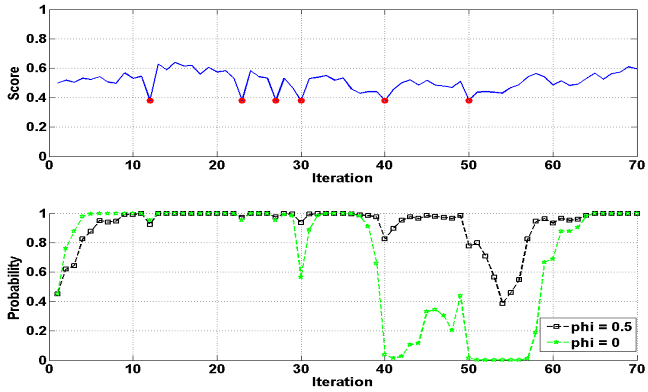

Fig. 6. Evolution of the probability when taking or not the correlation into account : the effect of the sporadic perturbations.

B. Experiments in urban areas

The experiments were conducted in Versailles (France). The testing platform is a Renault Espace equipped with a lidar, a camera and proprioceptive sensors. The lidar employed is the 4-layers IBEO lidar, named Alasca XT; running at $12.5Hz$ and measuring ranges up to $200m$ with an angular resolution of $0.125°$. It is mounted on the vehicle bumper at $0.45m$ above ground level, targeting the pedestrian leg height. The video camera is an automotive sensor, a VGA gray-level camera running at $30fps$. It is fixed behind the windshield. Fig. 2 illustrates the sensors configuration.

1) Probability computed using a real data sequence:

The objective of this experiment is to confirm the results demonstrated in simulation. On the contrary, of the simulation the correlation has to be estimated. Fig. 7 shows some snapshots of the scene for different positions of the pedestrian. As previously mentioned, the correlation value depends on the relative displacement between two consecutive iterations. In Fig. 8 it is noticeable that the correlation is high when the pedestrian moves slowly. However, the correlation value is not a linear function of the speed. It also depends on the object position. Given a constant relative displacement, the correlation is higher when the pedestrian is close from the vehicle than when he is further. It can be observed in Fig. 8 that ignoring correlation leads to a rapid convergence of the probability. Any new observation, once it follows the pedestrian likelihood model has no effect on the computed probability. On the contrary, when considering the correlation the probability raises gradually. Finally, the speed affects greatly the probability. Because even the score is coherent with the pedestrian distribution, one can observe that at low speed the pedestrian is simply classified as a non-pedestrian. Indeed, speed distributions in Fig. 4 suggest that low speed objects are more likely to be of the non-pedestrian class than the pedestrian class. Anyway, when the vehicle is in motion a security area is defined in front of it to set off a warning as soon as an object is located inside this area, regardless its class.

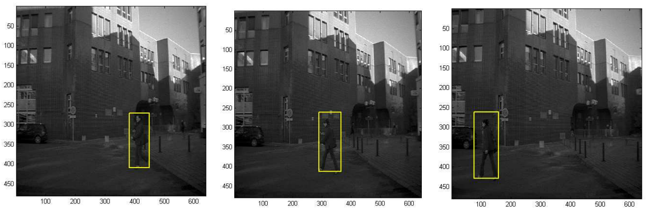

Fig. 7. Snapshots of the scene: the detected pedestrian is crossing the road.

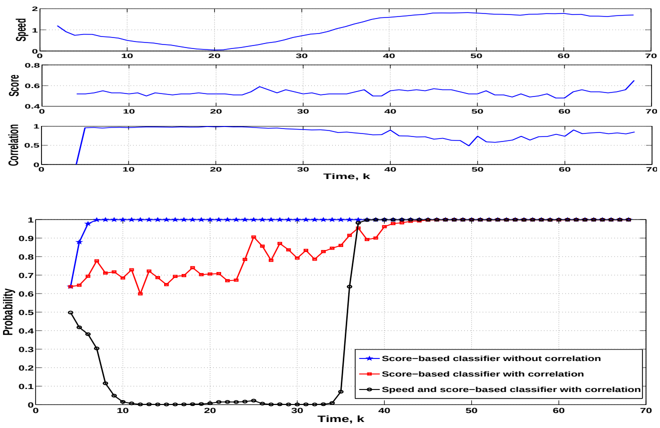

Fig. 8. Features extracted, correlation estimation and probabilities.

2) Processing time analysis:

An important constraint to fulfill when providing algorithmic solutions for the automotive applications is the limited computing resources available in the vehicle computer. As much as the reliability, the processing time is of prime importance. Our approach has been implemented in C++ and runs on a PC, equipped with a Pentium 4, 3GHz with the times indicated in table I. These times are the average of the times measured for a given sequence in a semi-cluttered area. Computation without the attention area consists in detecting the pedestrians in the whole sensor images (during these experiments, the lidar range was limited to 50*m*). Of course, it takes more time than when an attention area is defined. Moreover, the false positive rate is higher in that case because there are more objects to classify and sometimes there are further from the sensors. These computation times vary with clutter, especially vision-based time. However, even in a crowded scene is still low because the segmentation algorithm discards most of the irrelevant objects. Moreover, the features computation algorithms (Kalman filter and AdaBoost algorithm) are very fast.

VI. Conclusion

In this paper, we present a multisensor pedestrian detection system. The fusion algorithm is applied in a Bayesian framework. Our method consists in tracking objects position while computing a probability for each track to be a pedestrian. This probability is updated at the arrival of each new observation from any sensor. The proposed approach enables to integrate in an original manner correlated observations into the probability computation using the AR model. The results of experiments on simulated data as well as real data demonstrate the effectiveness of our approach. Moreover, the proposed method runs in real-time.

The next step is to test our system on more data sequences to be able to characterize it in term of false positive and good detection rates.

TABLE I

Comparison of the processing time with the attention area and without it

	With the attention area	Without the attention
Lidar processing time	41.5*ms*	50.5*ms*
Camera processing time	0.25*ms*	1.35*ms*

References

[1] D.M. Gavrila. ”Sensor-based Pedestrian Protection,” *IEEE Intelligent Systems*, vol. 16, NR.6, pp. 77-81, 2001.

[2] l. Zhao and C. Thorpe. ”Stereo- and neural network-based pedestrian detection,” *IEEE Transaction on Intelligent Transportation Systems*, 1(3), 2000.

[3] A. Broggi, M. Bertozzi, A. Fascoli, and M. Sechi. ”Shape-based pedestrian detection,” *In Proc. IEEE Intelligent Vehicle Symposium 2000*, pp. 215-220, Dearborn, USA, 2000.

[4] T. Gandhi and M. Trived. ”Pedestrian Collision Avoidance Systems: A Survey of Computer Vision Based Recent Studies,” *In Proc. of the IEEE Intelligent Transportation Systems Conference*, pp. 976-981, Toronto, Canada,2006.

[5] M. Bertozzi, A. Broggi, R. Chapuis, F. Chausse, A. Fascioli, and A. Tibaldi. ”Shape-based pedestrian detection and localization,” *In Procs. IEEE Intl. Conf. on Intelligent Transportation Systems 2003*, pp. 328-333, Shangai, China, October 2003.

[6] P. Viola and M. Jones. “Rapid object detection using a boosted cascade of simple features,” *In IEEE Conference on Computer Vision and Pattern Recognition*, 2001.

[7] KC Fuerstenberg and U. Lage. ”Pedestrian Detection and Classification by Laserscanners,” *9th EAEC International Congress*, Paris, France, June 2003.

[8] M. Szarvas, U. Sakai and J. Ogata. ”Real-time Pedestrian Detection Using Lidar and Convolutional Neural Networks,” *In IEEE Intelligent Vehicles Symposium 2006*, Tokyo, Japan,2006.

[9] G. Monteiro and C. Premebida and P. Peixoto and U. Numes, Tracking and Classification of Dynamic Obstacles Using Laser Range Finder and Vision. *In Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems 2006.*

[10] L. Ngako Pangop, F. Chausse, S. Cornou and R. Chapuis. ”Feature-based Multisensor Fusion Using Bayes Formula for Pedestrian Classification in Outdoor Environments,” *In IEEE Intelligent Vehicles Symposium*, Istanbul, Turkey, June 2007.

[11] L. Ngako Pangop, F. Chausse, R. Chapuis and S. Cornou. ”Asynchronous Bayesian Algorithm for Object Classification: Application to Pedestrian Detection in Urban Areas,” *In International Conference on Information Fusion*, Cologne, Germany, July 2008.

[12] J.P Burg. ”Maximum Entropy Spectral Analysis,” Ph.D. Thesis, Geophysics department, University of Standford, Standford, California, USA, 1975.

[13] George Box, Gwilym M. Jenkins, and Gregory C. Reinsel. ”Time Series Analysis: Forcasting and Control,” Third edition. Prentice-Hall, 1994.