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# Target tracking in the time-frequency domain for a driving aid application

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**Abstract**—Driving aid is an important emerging radar application. Among associated technological issues, detecting and tracking potential obstacles (cars, pedestrians, static objects . . . ) is of key interest. In this context, we propose an original tracking method, based on particle filtering, where the observation of the state vector is the cross-ambiguity function of the backscattered signal. Simulations for various waveforms demonstrate the improvement brought compared to the conventional approach, in which a detection step precedes the tracking.

**Index Terms**—radar; tracking; driving aid; ambiguity function; cross-ambiguity function; particle filtering.

## I. INTRODUCTION

About 80% of road accidents are due to human errors. European statistics show that in most cases, the root cause of the accidents is linked to a bad perception of the environment, followed by a wrong action of the driver. These factors make the development of perception and driving assistance an area of very active research. These systems aim at improving the perception of potential obstacles, even in cases of partial occlusions or bad weather conditions (fog for example). Detecting and tracking both static and moving, potential obstacles, is among the main challenges to be addressed.

A typical radar system relies on the emission of a waveform and on the analysis of the backscattered signal, with a view to extracting information on the position (related to the time delay), and the velocity (related to the Doppler shift) of the objects. The accuracy of measurement depends both on the selected waveform and the processing method.

For target tracking, the classical method involves two successive steps: first, the detection of the potential targets and the estimation of position and velocity parameters independently at each time, second, a filtering technique, typically a Kalman filter or another Bayesian filter [2].

In practice, particular structures of the waveforms under consideration are generally exploited. For instance, FMCW (Frequency Modulated Continuous-Wave) waveforms are a typical example [7]. Composed of two successive linear frequency-modulated pulses (Chirp) [1], with increasing and decreasing frequency respectively, these waveforms are used

for ACC (Automotive Cruise Control). The associated processing relies on the demodulation of the received signal by the emitted waveform, leading thus to harmonic signals with distinct frequencies during increasing and decreasing frequency periods. These frequencies are linear combinations of the Doppler and the delay of the target, such that the latter can be estimated using a Fourier transform. This approach is however waveform-specific. A more general purpose detection and estimation step consists in performing matched filtering at the outputs of a bank of Doppler demodulators, thus reconstructing cross-ambiguity function between emitted waveform and received signal. Detection threshold can account for ambiguity function side lobes level.

In this paper, we propose a general purpose method for target tracking. This is done by tracking the waveform ambiguity function displacement inside the time-frequency domain, by considering the observed cross-ambiguity function at each observation time. By using a state space model, we are able to perform the target parameters estimation and filtering at the same time. In classical techniques, the observation is restricted to an initial guess for target delay and Doppler, which amounts to focusing on the maximum of the cross-ambiguity function.

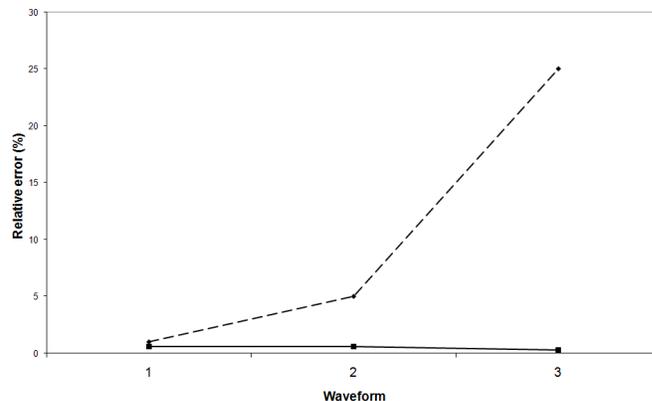


Fig. 1. Distance tracking performance of classical (dashed line) and new (solid line) method for three waveforms : 1. Chirp, 2. Barker codes, 3. Pulse train

In our approach, on the contrary, we fully exploit available data in the tracking procedure by considering the whole cross-ambiguity function. More precisely, the target contribution appears as a weighted and time-frequency shifted version of the ambiguity function in the cross-ambiguity function. By doing so, although the procedure is not waveform specific, specific time-frequency properties of the waveform under consideration are accounted for. Thus, we can expect higher parameter tracking performance with our approach than with the usual estimate then track approach.

Anticipating on the simulation part of the paper, Figure 1 shows how this approach can be fruitful. A comparison of the tracking performance for three standard waveforms (chirp, Barker codes and pulse train waveforms) demonstrates that a better precision is achieved in all cases with the proposed approach. In addition, accounting for the shape of the ambiguity function is a natural way to incorporate information about noisy signal amplitude statistics around the maximum of the cross-ambiguity. Clearly, this is not achieved in the classical approach. It may be point out that associating detection and tracking in a same processing step has already been considered in Track Before Detect (TBD) and Bayesian TBD techniques (see e.g. [3]). In TBD we are however more concerned with detection than with estimation. To our best knowledge, there is no study where joint tracking and estimation is considered and the ambiguity function spreading is large compared to radar image sampling steps.

The paper is organized as follows. In Section II, we recall the notion of ambiguity and cross-ambiguity function. In section III, we address the tracking problem and its general Bayesian solution. In Section IV, we describe the tracking method through our state space formulation of the target tracking problem. In section V, we evaluate the performances of our approach compared to the classical one.

## II. AMBIGUITY AND CROSS-AMBIGUITY FUNCTION

### A. Ambiguity function

The ambiguity function is a two-dimensional function of time delay and Doppler frequency  $\chi(\tau, f)$ . In a radar application, it is defined as the time response of an adapted filter to emitted signal, when this one is received shifted in time by a delay  $\tau$  and in frequency by a Doppler shift  $f$  relative to the nominal values (zeros) [1]. Formally, it is given by:

$$\chi_u(\tau, f) = \int_{-\infty}^{+\infty} u(t)u^*(t - \tau) \exp(i2\pi ft) dt \quad (1)$$

where  $u$  is the complex envelope of the signal. A target moving away from the radar implies a positive  $f$ . The ambiguity function fully characterizes a given waveform  $u$ .

The more localized the ambiguity function in the delay-Doppler space, the more accurate the estimation of the range-Doppler parameters. For a given signal energy, the total volume under the normalized ambiguity function (squared) is constant and independent on the signal waveform. Consequently, a trade-off has to be achieved between the peakness

of the ambiguity function and the level of the side-lobes. This results in the proposal of various waveforms.

### B. Cross-ambiguity function

The cross-ambiguity function is the time response to the backscattered signal  $r$  of an adapted filter to the delay-Doppler shifted emitted signal [1]:

$$\chi_{r,u}(\tau, f) = \int_{-\infty}^{+\infty} r(t)u^*(t - \tau) \exp(i2\pi ft) dt \quad (2)$$

The received signal is the sum of the contributions of the different targets, where each target backscatters the signal with specific delay and Doppler parameters corresponding to its position and speed, and an unknown scaling coefficient corresponding to the attenuation and the phase shift of the signal:

$$r(t) = \sum_n \alpha_n u(t - \tau_n) \exp(i2\pi f_n t)$$

The cross-ambiguity function is then the sum of translated ambiguity functions in the direction  $[\tau_n \ f_n]^T$  corresponding to the delay and Doppler shift of each target:

$$\chi_{r,u}(\tau, f) = \sum_n \alpha_n \chi_u(\tau - \tau_n, f - f_n) \quad (3)$$

## III. NONLINEAR BAYESIAN TRACKING

The tracking problem is largely explained in [2]. A target motion model is given by the evolution of its state vector sequence defined by the state equation  $X_k = f_k(X_{k-1}, V_{k-1})$ , where  $f_k$  is a possibly nonlinear function, and  $V_{k-1}$  a process noise sequence. Target tracking resorts to recursively estimate  $X_k$  from the observation modeled by the equation:  $Y_k = h_k(X_k, W_k)$ , where  $h_k$  is a possibly nonlinear function, and  $W_k$  a measurement noise sequence. Within a Bayesian setting, it amounts to stating the probability density function  $p(X_k|Y_{1...k})$ . It may be obtained recursively in a two-stage prediction-update scheme :

- Using the state equation, the prediction step determines the prior density function at time  $k$  via Chapman-Kolmogorov equation:

$$p(X_k|Y_{1...k-1}) = \int p(X_k|X_{k-1})p(X_{k-1}|Y_{1...k-1})dX_{k-1}, \quad (4)$$

- From the new observation, an update step of the estimate is carried out. It exploits the likelihood function defined by the observation model. The updated density function is then given by Bayes rule:

$$p(X_k|Y_{1...k}) = \frac{p(Y_k|X_k)p(X_k|Y_{1...k-1})}{\int p(Y_k|X_k)p(X_k|Y_{1...k-1})dX_k}. \quad (5)$$

These two steps modeled by the recurrence equations (4) and (5) form the optimal Bayesian solution for target tracking. It can be determined analytically only for particular cases such as the linear Gaussian problem (Kalman filter). Generally, the optimal Bayesian solution is approximated by linearization

(Extended Kalman filter), unscented transformation (unscented Kalman filter), or Monte Carlo simulation (particle filter) [4].

#### IV. TRACKING METHOD

##### A. State Model

We consider a single target moving along a one-dimensional axis corresponding to the direction of the radar. It is often the case in an automotive application as vehicles to be tracked move along the same direction as the vehicle equipped with the radar.

To model the dynamics of this target in the delay-Doppler space, the state vector of the target, at time step  $k$ ,  $k = 1, \dots, K$ , is given by:  $[\tau(k) \ f_d(k) \ a_{rel}(k)]^T$ , where  $\tau$  is the delay corresponding to the position of the target (distance between the radar and the target),  $f_d$  is the Doppler frequency corresponding to the velocity of the target relatively to the velocity of the tracker vehicle, and  $a_{rel}$  the relative acceleration of the target. From the formulation of a nearly uniform accelerated motion model, given in [6] among others, where we consider  $v_{rel} = v_{obj} - v_{ego}$ ,  $a_{rel} = a_{obj} - a_{ego}$ , and the linear equations  $\tau = 2d/c$ ,  $f_d = 2v_{rel}/\lambda_0$ , the state equation resorts to:

$$X_k = \begin{bmatrix} \tau(k) \\ f_d(k) \\ a_{rel}(k) \end{bmatrix} = F X_{k-1} + Q V_k \quad (6)$$

$$\text{where: } F = \begin{bmatrix} 1 & T & T^2 \\ 0 & 1 & 2T \\ 0 & 0 & 1 \end{bmatrix}, \quad Q = \begin{bmatrix} \frac{T^3}{3c} \\ \frac{T^2}{\lambda_0} \\ T \end{bmatrix}.$$

$T$  is the sampling period,  $c$  the celerity of light,  $f_0$  the carrier frequency and  $\lambda_0$  the corresponding wavelength.  $V_k$  denotes the noise model of relative accelerations.

The prior distribution  $p(X_k|X_{k-1})$  is issued from the state equation (6). Considering a white centered Gaussian noise  $V_k$ ,  $p(X_k|X_{k-1})$  will be a Gaussian distribution, with mean  $F\hat{X}_{k-1}$ , where  $\hat{X}_{k-1}$  is the state estimator at time step  $k-1$ , and a variance related to  $Q$ .

##### B. Observation Model

The observation that we consider consists of a discretized version of the cross ambiguity function :

$$\begin{aligned} Y_k(a, b) &= \chi_{r,u}(a, \delta\tau, b, \delta f) \\ &= \sum_n \alpha_n(k) \chi_{u,u}(a, \delta\tau - \tau_n(k), b, \delta f - f_n(k)) \quad (7) \\ &+ W_k(a, b) \end{aligned}$$

where  $W_k$  is the observation noise.  $a \leq A$ ,  $b \leq B$  are integers. The observation is then a matrix  $A \times B$ .

Given a state vector, the associated prediction of the discretized cross ambiguity function  $\chi_{r,u}$  can be compared to the real noisy observation  $Y_k$  up to the unknown scaling factor  $\alpha_n(k)$ . The likelihood model can be then be defined from a metric between the observation  $Y_k$  and the prediction  $Y_{X_k}$ .

Formally, it is stated as a Gibbs distribution, like in image processing tracking techniques [5] and is given by:

$$p(Y_k|X_k) \propto \exp(-\gamma \Delta(Y_k, Y_{X_k}))$$

where  $\Delta(Y_k, Y_{X_k})$  is the selected metric between the true observation  $Y_k$  and the predicted observation  $Y_{X_k}$ , and  $\gamma$  is a parameter that determines the shape of the distribution.

$\alpha_n(k)$  is an unknown propagation coefficient. It possibly changes at each time step. A solution to this problem could be to choose a power invariant metric as can be the mutual information [8]. Here, we estimate  $\alpha_n(k)$  in the mean square sense. Then, for a single target, our definition of  $\Delta$  reduces to

$$\Delta(Y_k, Y_{X_k}) = \min_{\alpha_n(k)} \|Y_k - Y_{X_k}\|^2$$

##### C. Tracking Algorithm

Given the non-linearity of the observation model, we apply a sampling importance resampling particle filter (SIRPF) [4], which will use the prior density  $p(X_k|X_{k-1})$  given by the state equation (6) as the importance density, and  $p(Y_k|X_k)$ , given by the equation of observation (7), as the likelihood distribution.

As explained in [9], every particle is a possible case of the state  $X_k$  of the target, that we will note by  $X_k^m$  where  $m = 1 \dots M$  is the particle index and  $M$  is the number of particles used. At time  $k-1$ , The state  $X_{k-1}$  is described by  $M$  particles  $X_{k-1}^m$  and  $M$  weights  $\omega_k^m$  ( $m = 1 \dots M$ ), each weight expresses the probability that have the correspondant particle to be the state  $X_{k-1}$ , given the observation. We independently propagate each particle to time step  $k$  using (6), which amounts to sampling from the prior distribution  $p(X_k|X_{k-1} = X_{k-1}^m)$ .

A predictor of the state  $X_k$ , before having the observation  $Y_k$ , could be given by:

$$\hat{X}_{k-} = \sum_{m=1}^M \omega_{k-1}^m X_{k-1}^m$$

While having the observation  $Y_k$ , we compute recursively the new weights using the likelihood probability function  $p(Y_k|X_k)$ :

$$\xi_k^m = \omega_{k-1}^m p(Y_k|X_k = X_{k-1}^m) \quad m = 1 \dots M \quad (8)$$

$$\omega_k^m = \frac{\xi_k^m}{\sum_{m=1}^M \xi_k^m} \quad (9)$$

The state estimator is given by:

$$\hat{X}_k = \sum_{m=1}^M \omega_k^m X_k^m$$

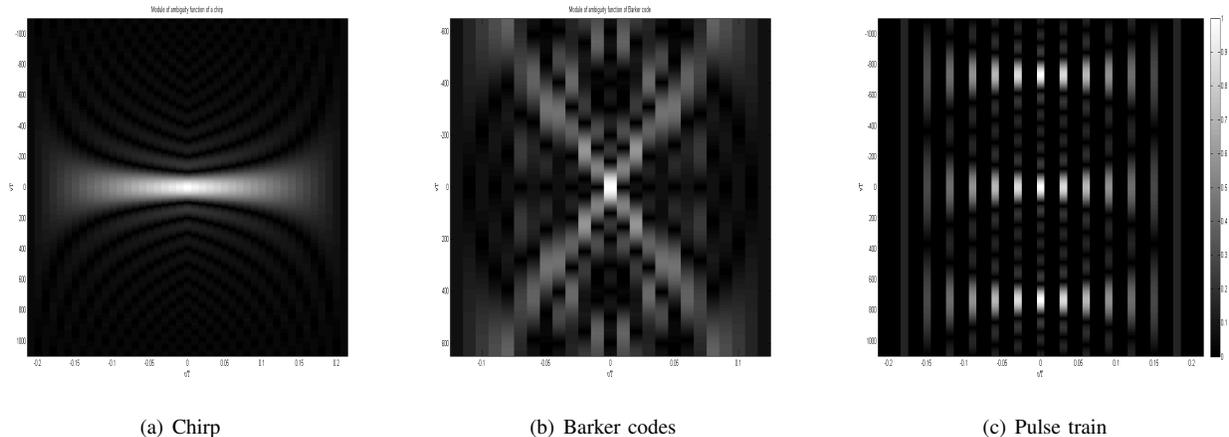


Fig. 2. Ambiguity function of the three simulated waveforms (modulus)

## V. SIMULATION RESULTS

Performance of the proposed approach is obtained on synthetic data. Simulated observation data correspond to a single target having a nearly uniformly accelerated motion relatively to the tracker vehicle. This results in dynamics in the time-frequency domain governed by state equation (6). The time step is set to  $T = 50ms$  and the simulation consists in a sequence of 100 time steps. The cross-ambiguity function is sampled on a  $201 \times 512$  delay-Doppler grid. The resolutions along the delay and Doppler axes are respectively of  $1m$  and  $1km/h$ . The targets can be detected up to a range of  $200m$  with a velocity comprised between  $-260km/h$  and  $260km/h$ . The state and observation noises are supposed gaussian with diagonal covariance matrices.

A comparison with the classical approach is carried out. For the classical approach, the detection step consists in the localization of the global maximum of cross-ambiguity function. Regarding the filtering step, a Kalman filter described in [4] is considered. For our approach, the particle filter exploits 300 particles. A quantitative evaluation is reported for three different waveforms: a chirp (linearly modulated pulse), a pulse train (6 pulses) and Barker codes waveform ([1 1 1 1 -1 -1 1 1 -1 1 -1 1]). Their ambiguity functions are given figure 2. We can see that for the Barker codes waveform and more clearly for the pulse train, the side-lobes are relatively high.

Can be observed on figure 3 the improvement of tracking performance with the new method for the three waveforms. For the pulse train one, we can especially observe a failure of the tracking with the classical method. This is probably due to the fact that the pulse train ambiguity function has high side lobes. The classical approach based on estimating then filtering can have for consequence to track the side lobe and not the principle. This problem does not appear in our approach because we consider the entire ambiguity function. Table I gives a quantitative evaluation of tracking performance for the two approaches and for the three waveforms.

TABLE I  
QUANTITATIVE COMPARISON OF TRACKING PERFORMANCES BETWEEN CLASSICAL AND OUR APPROACH

waveforms	Distance error (m)		Speed error (km/h)	
	Classical method	New method	Classical method	New method
Chirp	0.15	0.09	0.85	0.57
Barker Codes	0.83	0.09	2.88	0.87
Pulse train	4.93	0.06	9.21	0.47

## VI. CONCLUSION

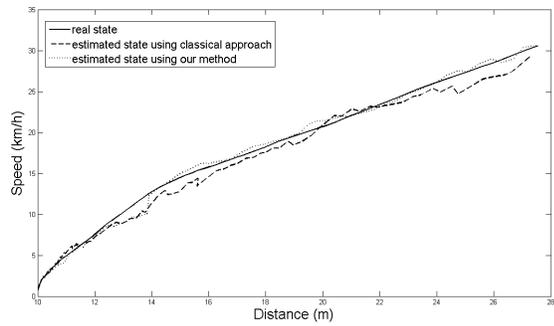
In this paper, we have developed a new solution for target tracking from cross-ambiguity observation. We have obtained significant performance improvement compared to the classical detection-tracking strategy and improved robustness with respect to waveform diversity.

In future work, we will adapt this approach for scan antennas that are considered in new ACC radars. In this context, target bearing will also be considered and antenna pattern will play a role in bearing estimation analog to that played by ambiguity function in delay-Doppler estimation.

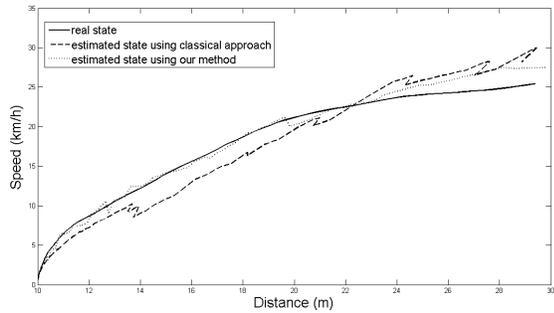
With a view to speeding up the algorithm, in future work, we will also refine cross ambiguity sampling strategy to make the amount of information to be handled as small as possible, while retaining high tracking accuracy. Using unscented Kalman filter or unscented particle filter is also a possible way to achieve reduced processing complexity. An extension to multiple target tracking will also be considered to comply with automotive environment.

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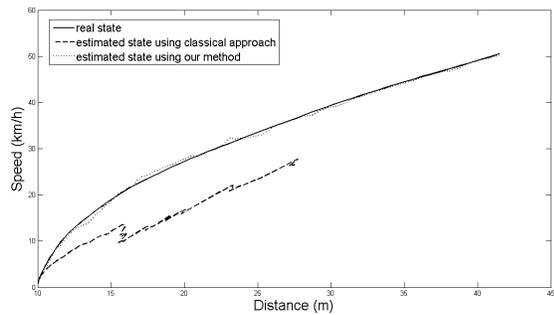
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(a) Chirp



(b) Barker codes



(c) Pulse train

Fig. 3. Tracking results with classical and new method for three waveforms

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