Leakage Cancellation in Coded Automotive Radar

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Abstract—This paper concerns the study of automotive anticollision radar. It especially describes the leakage problem observed as undesired peaks in the correlation function. To resolve it, we propose a solution called Adaptive Leakage Cancellation (ALC) based on using of adaptive filter in order to identify the unknown echo path caused by the leakage. The output of this filter estimates the leakage signal that is subtracted from the received signal to let only the echos provided from targets. For comparison porposes we have considered three algorithms LMS (Least Mean Square), RLS (Recursive Least Square) and APA (Affine Projection Algorithm) to update the adaptive filter coefficient vector. The LMS algorithm is considered as an interesting algorithm due to its simplicity and the good leakage cancellation.

Keywords: coded radar, binary pseudo-random sequences, correlation, adaptive filtering

1 Introduction

Anti-collision automotive radar is the one of major sensor studied by many laboratories and industries in order to assure the safety in the automotive environment. It requires detection of distances to vehicles from a few meters to well over 150 meters regardless of weather conditions. The frequency range 76 GHz to 77 GHz has been recommended in Europe, USA and Japan for the anti-collision radar.

The main idea for the coded radar is to use an optimal receiver (correlation receiver) associated with a digital coding. The main coding technique uses Pseudo Random codes which are employed in Direct Sequence Code Division Multiple Access (DS-CDMA) [12] systems and allow multi-users detection due to their orthogonality. Thus, several vehicles are able to use, at the same time, the same detection system in the same environment. By this characteristics and in contrast of others radar techniques, the coded radar is robust to the interference caused by others users (i.e. radars).

In practice, the undesired peaks are observed in the correlation function due to some undesired leakage. These peaks cause false alarms because they are considered as targets whereas is not true. A digital signal processing approach is proposed for accurate cancellation of leakage power over a broad bandwidth [5]. The basic concept of digital leakage cancellation and some preliminary results for a single frequency have been reported in [6, 7]. Similar concepts have also been used for interference cancellation in wireless communications [1]. For the coded radar we propose a technique similar to the acoustic echo cancellation [3, 11].

This paper is organized as follows: In section 2, the leakage problem is described and its digital model is given in the coded radar system. An interesting solution is proposed in section 3. The different simulation results are presented in section 4, and finally the last section gives the conclusion of this work

2 Leakage problem

The coded anti-collision radar is based on the association of the pseudo random codes in transmission with the correlation in reception [2]. The using of the correlation receiver is therefore particularly adapted to the detection of signals submerged in a white Gaussian noise [4] because it maximizes the Signal to Noise Ratio (SNR) and the probability of detection. The BPRS (Binary Pseudo-Random Sequences) are used because they offer good detection performances, they are easy to generate and they allow multi-users detection [8]. The radar performances decrease with the leakage problem that can be defined as a set of undesirable echoes of the transmitted pseudo random signal $c(i)$. It's due principally to reflection from the ground and electromagnetic coupling between the transmitter and the receiver. We model digitally the radar system by the model described in the Figure 1. We represents the radar channel by an unknown filter $h(i)$. Since $c(i)$ is N periodic then, the radar channel is supposed a (Finite Impulse Response) FIR of length N. Then, the received signal is the sum of the convolution product $c(i) * h(i)$ and an additive Gaussian noise $n(i)$:

$$\mathrm{r(i)} = c(i) * h(i) + n(i) = \sum_{k=0}^{N-1} h(k)c(i-k) + n(i) \quad (1)$$

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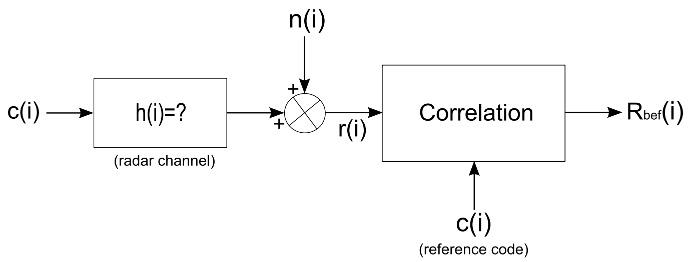

Figure 1: Digital model radar system.

We suppose that the impulse response of the radar channel can be represented by the sum of two impulse responses: $h(i) = h_l(i) + h_t(i)$ where $h_l(i)$ is the impulse response that represents the leakage echos and $h_t(i)$ is the impulse response that represents the echos returned by targets located in front of radar. We suppose that the length of the $h_l(i)$, $h_t(i)$ are L and N respectively.

When the leakage is absent and one target is considered, the impulse response of radar channel can be written as: one echo attenuated by a coefficient A and delayed by k samples:

$$h(i) = A.\delta(i - k) \tag{2}$$

Where $\delta(i)$ is the Dirac impulse.

The correlation $R_{bef}(i)$ between the reference code $c(i)$ and the received signal $r(i)$ will be maximum at instant $i = k$ and the target distance (in m) can be deduced by using the following expression:

$$D = k.\frac{c}{2f} \tag{3}$$

Where c is the velocity of light (in m/s) and f the code frequency (in Hz).

However, in practice the leakage is always present and the correlation has a form presented in the Figure 2. This phenomenon observed in [2, 8] causes the false alarm because they can considered as targets whereas is not true.

3 proposed solution

The principle of the proposed solution is to suppress from the received signal, $r(i) = h_f(i) * c(i) + h_t(i) * c(i) + n(i)$ the output signal of the added filter $w(i)$ as shown in Figure 4 ($z(i) = w(i) * c(i)$) . To have an error signal $e(i)$ contaning only the targets echos ($r_t(t) = h_t(i) * c(i)$), the filter $w(i)$ must identify the unknown filter $h_l(t)$ and the correlation will become, in case of one target, as shown the Figure 3.

The filter $h_l(i)$ can be estimated using the Wiener expression: $\underline{w}^o = R_c^{-1}.R_{rc}$, but the leakage filter can change in time and the characteristics of signals are unknown. Then, an adaptive filter is used and we call our proposed solution: Adaptive Leakage Cancellation. In contrast of the most application of the adaptive filtering, the error signal must converge to zeros, in our case the error signal not must converge to zeros but shall contains the useful part of the received signal. Then the length of $w(i)$ M must be inferior to N (this condition is verified in practice).

We note, for time instant i, $\underline{w}_i = [w_0, ..., w_{M-1}]^T$ the coefficients vector of the filter $w(i)$ of length M and $\underline{u}_i = [c(i), c(i-1), ..., c(i{-}\mathrm{M}+1)]$ the observation vector of the signal $c(i)$.

The filter coefficients vector, for $i \geq 0$, is updated by three most populars adaptive algorithms [10, 9]:

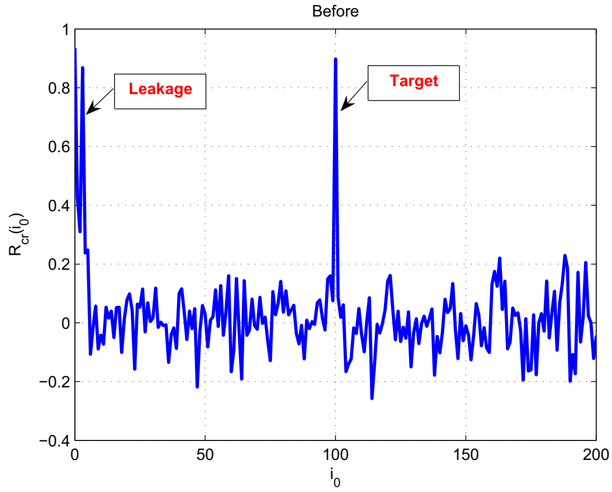

Figure 2: Correlation form in presence of the leakage peaks.

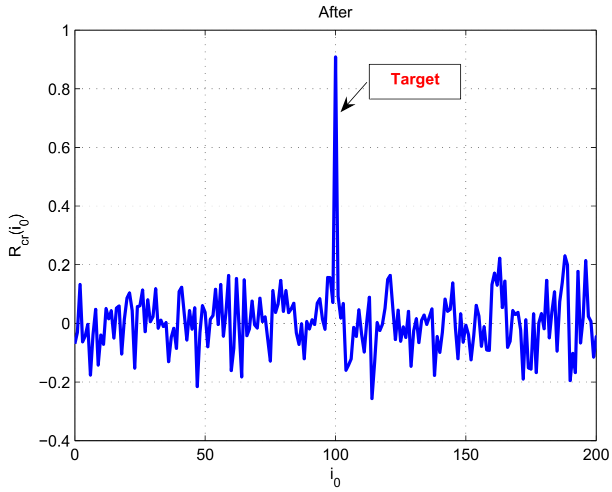

Figure 3: Correlation form in absence of the leakage peaks.

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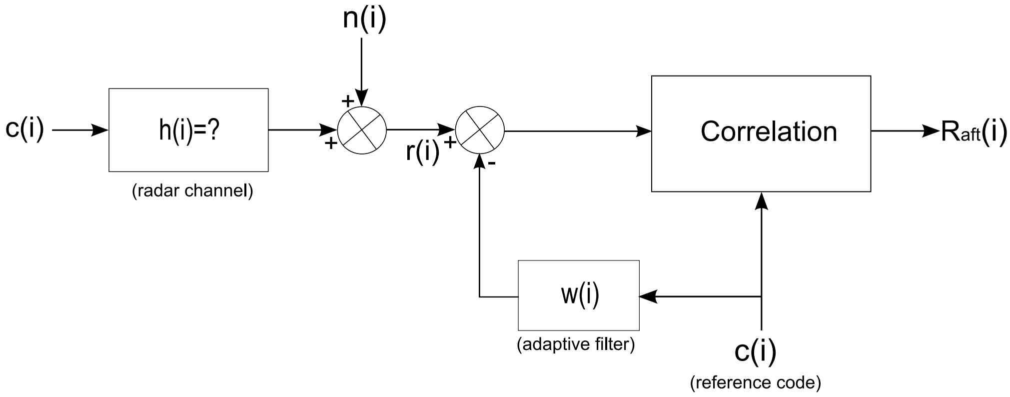

Figure 4: Principle of the Adaptive Leakage Cancellation.

- Least Mean Square (LMS) algorithm

$$\underline{w}_i = \underline{w}_{i-1} + \mu \underline{u}_i^* \left(r(i) - \underline{u}_i \underline{w}_{i-1} \right) \quad (4)$$

Where µ is a step size.

- Recursive Least Square (RLS) algorithm

$$\underline{w}_i = \underline{w}_{i-1} + P_i \underline{u}_i^* \left(r(i) - \underline{u}_i \underline{w}_{i-1} \right) \quad (5)$$

Where $P_i = \lambda^{-1}\left[P_{i-1} - \frac{\lambda^{-1}P_{i-1}\underline{u}_i^*\underline{u}_i P_{i-1}}{1+\lambda^{-1}\underline{u}_i P_{i-1}\underline{u}_i^*}\right]$ for $i \geq 0$ and $P_{-1} = \varepsilon^{-1} I$ and the parameter $\mu = 1 - \lambda$ is equivalent step-size μ of LMS.

- Affine Projection Algorithm (APA)

$$\underline{w}_i = \underline{w}_{i-1} + \mu U_i^* \left(\varepsilon I + U_i U_i^*\right)^{-1} \left(\underline{r}_i - U_i \underline{w}_{i-1}\right) \quad (6)$$

Where $U_i = \left[\underline{u}_i^T, \underline{u}_{i-1}^T ..., \underline{u}_{i-K+1}^T\right]^T$, $\underline{r}_i = \left[r(i), r(i-1)..., r(i-K+1)\right]^T$ and ε is a small number.

For all the algorithms, the initial vector is equals to zeros vector ($\underline{w}_{-1} = \underline{0}$).

4 Simulations tests

It's demonstrated in [8] that the output SNR is equals to the input SNR multiplied by the length of the used code:

$$SNR_{out} = N.SNR_{in} \quad (7)$$

Where $SNR_{in} = \frac{A^2}{\sigma_n^2}$ is the input Signal to Noise Ratio (SNR) of the correlator.

For this reason, it's required to use a code with the largest possible value for N. To have a low complexity of correlation computing and use the larger N, the value $N = 1023$ is considered as the interesting value for our application and we use it in our simulations. The motion of i^{th} iteration is used as the time needed of correlation computing between the i^{th} bloc of N samples of error signal and the reference code. For simulations, we define the target dynamic as the ratio between target peak and maximum noise after introducing ALC:

$$Dyn_t = 20log\left|\frac{R_{aft}\left(i=k\right)}{\left\{R_{aft}\left(i \neq k\right)\right\}_{max}}\right| \quad (8)$$

Before giving the simulation results, we presents the target dynamic as function of the input SNR in the case of one target without leakage and ALC. This dynamic is called reference dynamic and the results are presented in Figure 5.

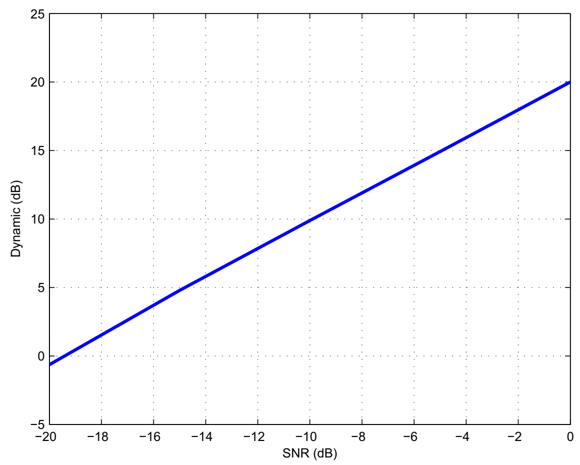

Figure 5: Reference dynamic in the case of one target.

4.1 Search of step-size µ

The simulations principle is to change the step size μ and compare the target dynamic with the reference dynamic. The leakage signal $r_l(i)$ is generated by filtering $c(i)$ by a filter $h_l = [1\,0.5\,0.2\,0.9\,0.2\,0.3]$ of length $L = 6$. The filter $h_t(i) = A\delta(i-k)$ is used to generate the target signal where $\delta(i)$ is the Dirac impulse. A is fixed at $A = 0.1$, one

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target is considered with $k = 100$, $\varepsilon = 10^{-9}$and $K = 5$. The noise $n(i)$ is added to have an $SNR = 10log(\frac{A^2}{\sigma_n^2}) = -10\,dB$.

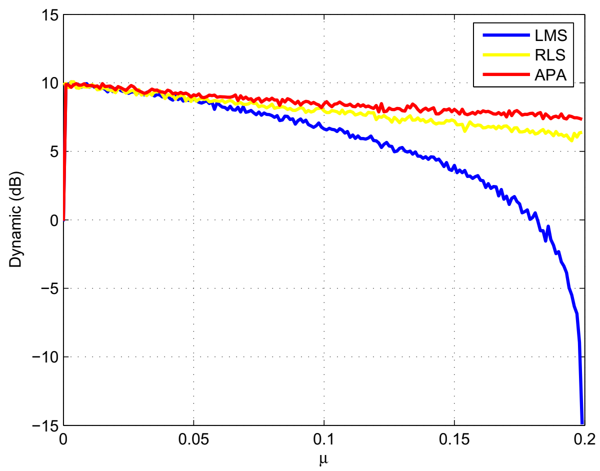

Figure 6: Target dynamic versus μ for an SNR=-10 dB.

The dynamics are computed at the 10^{th} iteration and length of adaptive filter is taken equal to $M = 10$. The results of these simulations are given in the Figure 6. The target dynamic achieves the reference dynamic in the following intervals:

1. $[3.10^{-4}\,10^{-2}]$ for LMS.
2. $[0\,10^{-2}]$ for RLS.
3. $[3.10^{-4}\,10^{-2}]$ for APA.

In these intervals, we have a good identification of $h_l(i)$ and the leakage peaks is completely concealed. We remark that the output noise is not reduced and doesn't depend to the used algorithm because we have for all algorithms the same value of target dynamic as reference dynamic. It's verified by another simulation, not presented in this paper, that these intervals do not change if we change M between 6 and 99 ($6 \leq M \leq 99$), A between 0 and 1 ($0 < A \leq 1$) and SNR between $-20\,dB$ and $0\,dB$ ($-20\,dB \leq SNR \leq 0\,dB$).

4.2 Convergence speed

To have an idea of the convergence speed of different algorithms, we trace the evolution of the dynamic for every iteration. The correlation result in the i^{th} iteration is the result of the i^{th} bloc of N samples of error signal with N samples of reference code. The leakage signal $r_l(i)$ is generated by filtering $c(i)$ by a filter $h_l = [1\,0.5\,0.2\,0.9\,0.2\,0.3]$ of length $L = 6$. The filter $h_t(i) = A\delta(i-k)$ is used to generate the target signal. A is fixed at $A = 0.1$, one target at $k = 100$, $M = 10$, $\mu = 10^{-3}$, $\varepsilon = 10^{-9}$and $K = 5$. The noise n(i) is added to have an $SNR = -10\,dB$. The target dynamic results as function of iterations is given in Figure 7.

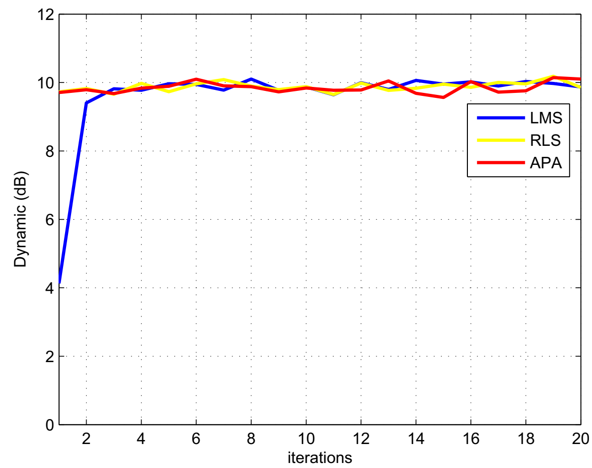

Figure 7: Target dynamic versus iterations for an SNR=-10 dB.

The good identification (i.e. good cancellation) is obtained in the first iteration for RLS and APA algorithms and in the second iteration for LMS algorithm. Other simulations are realized when the leakage filter changes after a given moment. So, we take the same parameters than the previous simulations and, for example, we change the leakage filter $h_l(i)$ at the 10^{th} iteration. After simulations, we obtain the results represented in the Figure 8. The good cancellation is obtained in the 1^{st} and the 11^{th} iterations for RLS and APA algorithms and in the 2^{ed} and the 12^{th} iteration for LMS algorithm. The LMS algorithm has nearly the same convergence speed than RLS and APA. LMS algorithm is preferred because it's simple and is able to reduce the leakage in the 1^{st} iteration (dynamic inferior to reference dynamic) and completely in next iterations (dynamic equals to reference dynamic).

4.3 Leakage power effect

To view the leakage power effect on the ALC performances, we take the case of one target and we trace the evolution of target dynamic by changing the leakage power. The leakage signal $r_l(i)$ is generated by filtering $c(i)$ by a filter $h_l = [1\,0.5\,0.2\,0.9\,0.2\,0.3]$ of length $L = 6$. The target filter $h_t(i) = A\delta(i-k)$ where $A = 1$ and $k = 100$. The noise n(i) is added to have a specified input SNR (called here $SNRtarget$). We change the power P_l of leakage signal $r_l(i) = h_l(i) * c(i)$ by multiplying it by some real to have a desired $SNRleakage = 20\,log(\frac{P_l}{\sigma_n^2})$. The parameters $\mu = 10^{-3}$, $\varepsilon = 10^{-9}$, $K = 3$ are used in these simulations. We trace, for three values of $SNRleakage$, the target dynamic as function of $SNRtarget$.

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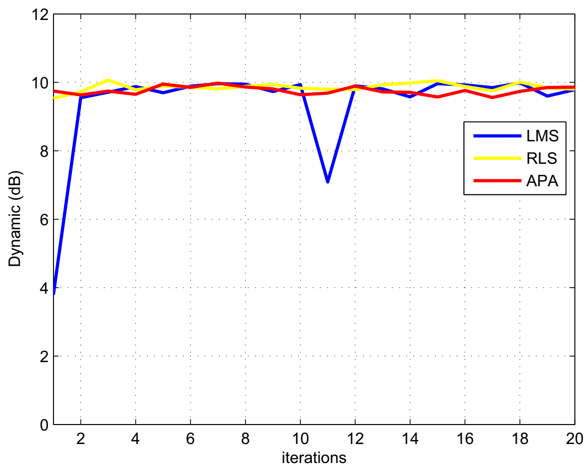

Figure 8: Target dynamic versus iterations for an SNR=-10 dB and leakage filter change.

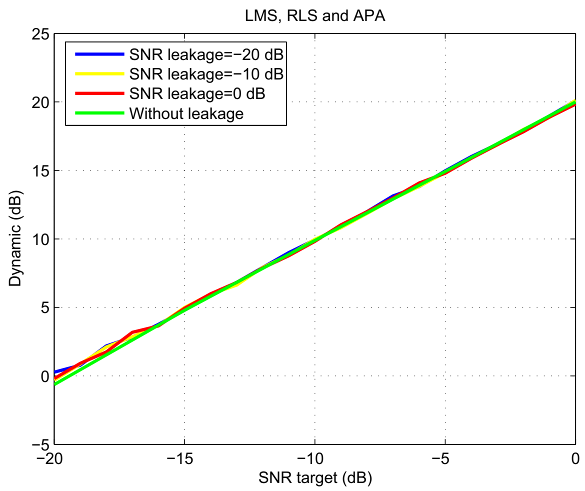

Figure 9: Target dynamic results for leakage power effect.

The simulation results are represented in the Figure 9 for the three adaptive algorithms. For all the algorithms, the target dynamic is equal to reference dynamic, i.e. the leakage is completely removed in the whole band $[-20\,dB, 0\,dB]$. Even if the power leakage signal is greater than the power target signal (for example $P_l = 10P_t$ with $SNRtarget = -10\,dB$ and $SNRleakage = 0\,dB$), the ALC cancels completely the leakage peaks.

5 Conclusion

In this paper we propose a solution called Adaptive Leakage Cancellation to reduce leakage peaks in the correlation function of coded radar. The simulation results confirm the good leakage cancellation and the LMS algorithm is more interesting than RLS and APA . The little disadvantage of ALC is the suppression of the targets echos with a delay inferior to the length of the adaptive filter minus one. All the presented simulations have been realised with one user (one radar), i.e. without interference due to other radars. Nevertheless, a situation can be studied, where the user can receive a set of signals returned from other users. This last situation will be discussed in future works and the ALC will be tested in the real conditions to determine the optimal length of the adaptive filter and the convergence step-size.

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