Mitigation of WiFi Interference in Velocity Estimation for Staggered-PRT Weather Radar

Jorge Cogo
Universidad Nacional de Río Negro.
CITECCA
Instituto Balseiro. UNCuyo.
Bariloche, Argentina
jcogo@unrn.edu.ar

Juan Pablo Pascual
CONICET
Instituto Balseiro. UNCuyo.
Bariloche, Argentina
juanpablo.pascual@ib.edu.ar

Alejandro Javier Venere
CNEA
Instituto Balseiro. UNCuyo.
Universidad Nacional de Río Negro.
Bariloche, Argentina
alejandro.venere@ib.edu.ar

***Abstract*—In this paper we analyse the effect of interference from WiFi network transmissions on the Doppler velocity estimates of C-band weather radars using the Staggered Pulse Repetition Time (SPRT) mode, and we propose a method to mitigate this effect.**

Starting from a simplified signal model, we obtain closed form expressions of how interference affects two of the simplest and most widely used estimation methods, from which we derive our proposal. Through numerical simulations we analyze the performance of the different methods when using this simplified model and a more realistic and accepted signal model for the meteorological target. The proposed method achieves performance improvement for low Signal-to-Noise Ratios (SNR), both in conditions without interference and with moderate interference.

***Index Terms*—Weather Radar, WiFi Interference, Doppler Velocity Estimation, Staggered-PRT**

I. Introduction

A Weather Radar (WR) operates by transmitting short duration pulses modulated onto a high frequency carrier, and receiving the signals due to backscatter of each propagating pulse from present targets. The time interval between two successive pulses is called Pulse Repetition Time (PRT). In this interval, N complex samples of the received signal are taken at the output of the radar quadrature receiver followed by matched filter. Each sample is associated with the target's range, and the N samples corresponding to consecutive pulses can be arranged in consecutive columns of a data matrix [1].

Since in each scan the WR rotates in the azimuthal direction as it transmits pulses and receives the reflected signal, each row of the data matrix corresponds to observations made at the same range by different pulses. Because the WR motion is slow relative to the PRT and because the antenna beamwidth is narrow but not zero, a set of a few, say M, consecutive samples from each of these rows correspond to approximately the same region of space. This set defines the Coherent Processing Interval (CPI) [2].

One of the observables of interest in WR is the mean Doppler velocity, v_p, associated with the radial velocity of the scatterers (hydrometeors). The estimation of v_p, as well as other meteorological observables, is carried out by processing the samples corresponding to each CPI [2].

Two parameters of interest are the maximum radial velocity, v_a, and the maximum range R_a, that the radar can unambiguously observe. For the uniform-PRT mode of operation, i.e. when the radar transmits pulses every T_u seconds, R_a is proportional to T_u while v_a is inversely proportional to T_u. So, increasing v_a necessarily implies decreasing R_a [2].

An alternative to increase v_a without reducing R_a is to use the Staggered-PRT (SPRT) mode of operation, in which the radar varies the time interval between successive pulses. Although there are other proposals such as [3], a two-PRT configuration is normally used, in which the PRT alternates between T_1 and T_2. For this SPRT mode, R_a is proportional to the minimum between T_1 and T_2, while v_a is inversely proportional to the difference between T_1 and T_2. Generally, these values are chosen as $T_1 = n_1\, T_u$ and $T_2 = n_2\, T_u$, where n_1 and n_2 are two coprime integers.

Using the SPRT strategy implies that estimates of the autocorrelation in the lag T_u or the Doppler spectrum cannot be obtained directly. Therefore, the classical Doppler velocity estimation techniques based on Pulse-Pair Processing (PPP) or Spectral Processing (SP) summarized in [4] cannot be used. Instead, it is simple to obtain estimates of the autocorrelation in the lags T_1 and T_2. Two possible methods based on these estimates are the PPP extension for the staggered case (SPPP) presented in [5], and the Dealising Method (DA) presented in [6], the details of which we will delve into in Section II. SPPP performs poorly in terms of Root-Mean-Square Error (RMSE), while DA achieves much better performance by adding very little complexity.

One of the factors that affects the operation of WRs is the electromagnetic interference produced by other communication systems [7]. In particular, for C-band radars, such as those installed in Argentina [8], the main sources of interference are Wireless/Radio Local Area Networks (WLAN/RLAN) [9], [10], [11]. Most of these devices comply with the IEEE 802.11 standard and are commonly called WiFi transceivers [12].

When the WR antenna beam is pointed in the direction where there is any WiFi transceiver operating in the same band, the WiFi signal is picked up by the radar, and appears

This work was funded by UNRN PI 40-B-980 and UNCuyo C019-T1 Res. N°2118/22.

as additive interference that affects as many samples in the range dimension (consecutive elements of a column of the data matrix) as the duration of the WiFi frame [11]. There are different approaches to deal with this problem, from the identification and removal of the problematic sources, to alternatives of signal processing for the detection and mitigation of the effects on the observables [7].

In [10] the authors focus on analysing the effect of interference in estimation algorithms based on polarimetric observables. In [13] the authors carried out a study that quantifies the effect of interference in the estimation of polarimetric products, for a WR that operates in uniform-PRT mode. In [14] the authors present a more detailed analysis of the effect of the WiFi interference on the Doppler velocity estimation using PPP, also for the uniform-PRT mode of operation. Considering a simplified signal model that assumes a zero spectral width, [14] show that the interference can produce hops of v_a module in the velocity estimates, and derive the probability of this velocity hop, which depends on Interference-to-Signal power Ratio (ISR).

Regarding the detection and/or mitigation of the effect of interference on products, in [15] the authors study and measure WiFi signals looking for distinctive characteristics of those of WR, with the aim of improving and developing recognition techniques, while in [16] and [17] the authors present two separate identification methods based on fuzzy logic, and [17] also proposes a spatial filter to replace the contaminated pulses. In [18] the author proposes a 2D interference filtering algorithm, using the range/pulse domains, while in [9] and [19] the authors propose filtering techniques based on the wavelet transform and other discrete filters.

In this work we analyse the effect of interference on the estimation of velocity using SPPP and DA methods in a WR that operates in SPRT mode; and we propose a novel and simple method to mitigate this effect. The method, that we call Weighting DA (WDA), consists of combining the two DA estimates with the appropriate weights. The simplicity of the method is due to the fact that on the one hand it is based on simple estimators with low computational cost and on the other hand it does not require identifying or removing the interfered samples to perform the mitigation.

In Section II we present an overview of the radar received signal model and the formulation of the SPPP and DA velocity estimation methods. In section III, starting from a simple interference model, we mathematically analyze its effect on the estimates and derive our mitigation proposal. In Section IV we analyze the performance of the different methods, including our proposal, through numerical simulations. Finally, in Section V we draw the conclusions.

II. Problem Statement

The signal received by a WR in a particular CPI can be described by

$$z[m] = p[m] + i[m] + n[m], \tag{1}$$

where $p[m]$ is the meteorological target component, $i[m]$ is the interference component, and $n[m]$ is the noise component. In our analysis, we consider that there is no clutter in the CPI under test, and that $n[m]$ is Additive White Gaussian Noise (AWGN). These are common assumptions in velocity estimation methods.

To simplify the notation, we consider m to be the index of a fictitious uniformly-sampled at T_u signal, i.e. m is an integer ranging from 0 to $M-1$. Actually, we only have the samples corresponding to the staggered sampling instants, that is

$$m \in \{0, n_1, n_1+n_2, 2n_1+n_2, 2n_1+2n_2, \dots\, M-1\}\,. \tag{2}$$

We define K_1 as the number of pair of samples that are T_1 apart, and K_2 as the number of pair of samples that are T_2 apart. We consider $K_1 = K_2 = K$, then $M-1 = (n_1+n_2)K$.

A. Estimation Methods

The autocorrelation estimates in lags T_1 and T_2 are

$$\hat{R}_{zz}(T_1) = \frac{1}{K}\sum_{k=0}^{K-1} z[k\,n_T+n_1]\, z^*[k\,n_T] \tag{3}$$

$$\hat{R}_{zz}(T_2) = \frac{1}{K}\sum_{k=0}^{K-1} z[k\,n_T+n_1+n_2]\, z^*[k\,n_T+n_1], \tag{4}$$

where $n_T \triangleq n_1+n_2$.

In the SPPP method [5] the Doppler velocity estimator is

$$\hat{v}_p^{(\text{SPPP})} = \kappa \underline{/\hat{R}_{zz}(T_2)/\hat{R}_{zz}(T_1)} \tag{5}$$

where κ is a constant of proportionality and $\underline{/\cdot}$ denotes the argument, interpreted in the interval $(-\pi, \pi]$.

On the other hand, from $\hat{R}_z(T_1)$ and $\hat{R}_z(T_2)$ two ambiguous estimators of the velocity can be obtained as

$$\hat{v}_{p_1} = \kappa_1 \underline{/\hat{R}_{zz}(T_1)} \tag{6}$$

$$\hat{v}_{p_2} = \kappa_2 \underline{/\hat{R}_{zz}(T_2)} \tag{7}$$

where κ_1 and κ_2 are also constants of proportionality. DA [6] is based on that these two estimates could be aliased, but each of these aliases can take on values in a small (and different) finite set of possible values, so the aliasing term can be inferred and reversed based on both estimates. In this sense, $\hat{v}_{p_2}$ can be used as additional information to disambiguate $\hat{v}_{p_1}$, obtaining an unambiguous estimator

$$\hat{v}_p^{(\text{DA}1)} = \hat{v}_{p_1} + \text{daf}_1(\hat{v}_{p_1}, \hat{v}_{p_2}); \tag{8}$$

or $\hat{v}_{p_1}$ can be used as additional information to disambiguate $\hat{v}_{p_2}$ obtaining other unambiguous estimator

$$\hat{v}_p^{(\text{DA}2)} = \hat{v}_{p_2} + \text{daf}_2(\hat{v}_{p_1}, \hat{v}_{p_2}), \tag{9}$$

where $\text{daf}_1(\cdot)$ and $\text{daf}_2(\cdot)$ denote functions that choose the ambiguity factors to make the corrections.

III. Effect of interference and proposal for mitigation

For the analytical deduction of the effect of the interference on the velocity estimation we start from a *Simple Model* of the meteorological target component, given by

$$p[m] = Ae^{-j(\alpha v_p m+\phi)}, \tag{10}$$

where A is a constant associated with the power backscattered by the target, $\alpha \triangleq 4\pi T_u/\lambda$, being λ the wavelength, v_p is the radial velocity of the target, and $\phi = 4\pi r/\lambda$ is a constant phase term proportional to the distance r between radar and target.

Since the interference affects the signal in the range dimension, it affects a few samples in each CPI, and so we consider the model

$$i[m] = Be^{j\theta}\delta[m-m_\ell], \tag{11}$$

where B and θ are amplitude and phase factors, $\delta[\cdot]$ denotes the Kronecker delta and m_ℓ is an integer that takes values in the set (2) and that indicates the interfered pulse.

For simplicity in the deduction we firstly consider that the Signal-to-Noise Ratio (SNR) is high enough to neglect the noise component ($n[m] = 0$). Replacing (10) and (11) in (1) and then in (3) and (4) we obtain

$$\hat{R}_{zz}(T_1) = A^2 e^{-j\alpha n_1 v_p} + \frac{AB}{K}\, e^{\mp j(\alpha v_p(m_\ell \pm n_1)+\phi+\theta)} =$$

$$= A^2 e^{-j\alpha n_1 v_p}\left(1+\frac{\sqrt{\text{ISR}}}{K}e^{\mp j(\theta+\phi+\alpha v_p m_\ell)}\right) \tag{12}$$

$$\hat{R}_{zz}(T_2) = A^2 e^{-j\alpha n_2 v_p}\left(1+\frac{\sqrt{\text{ISR}}}{K}e^{\pm j(\theta+\phi+\alpha v_p m_\ell)}\right) \tag{13}$$

where $\text{ISR} = B^2/A^2$. The factor outside parentheses is what we would obtain in the case $z[m] = p[m]$ (ISR $= 0$), and the term that adds to one into parentheses appears due to interference (the only one of the cross products that survives in the sums when applying the delta property). In (12) the $\mp$ is "$-$" if $m_\ell = kn_T$ and "$+$" if $m_\ell = kn_T + n_1$. In (13) the $\pm$ is "$+$" if $m_\ell = kn_T$ and "$-$" if $m_\ell = kn_T + n_1$. Whatever the case, it can be seen that the terms into parentheses in (12) and (13) are complex conjugates. If we denote

$$D\, e^{j\beta} \triangleq 1 + \frac{\sqrt{\text{ISR}}}{K}\, e^{\mp j(\theta+\phi+\alpha v_p m_\ell)} \tag{14}$$

we arrive at

$$\hat{R}_{zz}(T_1) = A^2\, D\, e^{-j(\alpha n_1 v_p - \beta)} \tag{15}$$

$$\hat{R}_{zz}(T_2) = A^2\, D\, e^{-j(\alpha n_2 v_p + \beta)}. \tag{16}$$

Replacing (15) and (16) into (5) we obtain that the SPPP estimate results

$$\hat{v}_p^{(\text{SPPP})} = v_p + 2\beta/\alpha \tag{17}$$

while replacing (15) and (16) into (8) and (9), and assumming that β does not significantly affect the operation of $\text{daf}_1(\cdot)$ and $\text{daf}_2(\cdot)$, we obtain that the estimates result

$$\hat{v}_p^{(\text{DA}_1)} = v_p - \beta/(n_1\alpha) \tag{18}$$

$$\hat{v}_p^{(\text{DA}_2)} = v_p + \beta/(n_2\alpha). \tag{19}$$

In (17), (18) and (19) we can see that the effect of interference (throught β) is always to introduce an estimation error. We can also see that for a given value of β, this error is $2\,n_1$ times smaller in magnitude for DA_1 than for SPPP and $2\,n_2$ times smaller in magnitude for DA_2 than for SPPP.

It is important to remark that the derivation is valid for $m_\ell \neq 0$ and $m_\ell \neq M-1$. In case $m_\ell = M-1$ the term due to interference in (12) vanishes (does not appear in the sum). In the same way, in case that $m_\ell = 0$ the term due to interference in (13) vanishes. In the first case, the interference does not affect the DA_1 estimation. In the second case, the interference does not affect the DA_2 estimation. In either case, the magnitude of the error in SPPP estimation is halved.

A. Mitigation Proposal

From (18) and (19) we can see that a simple way to cancel the effect of interference is by combining both estimators with the appropriate weights. Thus, the estimator of our proposal, Weighting DA (WDA) is

$$\hat{v}_p^{(\text{WDA})} = \frac{n_1}{n_1+n_2}\hat{v}_p^{(\text{DA}_1)} + \frac{n_2}{n_1+n_2}\hat{v}_p^{(\text{DA}_2)}. \tag{20}$$

We can see that under the conditions in which the model is valid, replacing (18) and (19) into (20), the WDA estimate results $\hat{v}_p^{(\text{WDA})} = v_p$.

We can note that for the cases $m_\ell = 0$ or $m_\ell = M-1$ this error cancellation does not occur. However, in these cases the magnitude of the WDA error will be $2(n_1 + n_2)$ times less than the SPPP error, and therefore it is still the best alternative.

B. Realistic Considerations

First of all, although we did not incorporate the effect of noise in the derivation of the method, we will incorporate it to analyze performance.

Secondly, although the proposed model allows for mathematical development, it is unrealistic for modeling the behavior of the meteorological target. As an alternative, we will model $p[m]$ as a complex normal random process with Gaussian Power Spectral Density (PSD), given by [2]

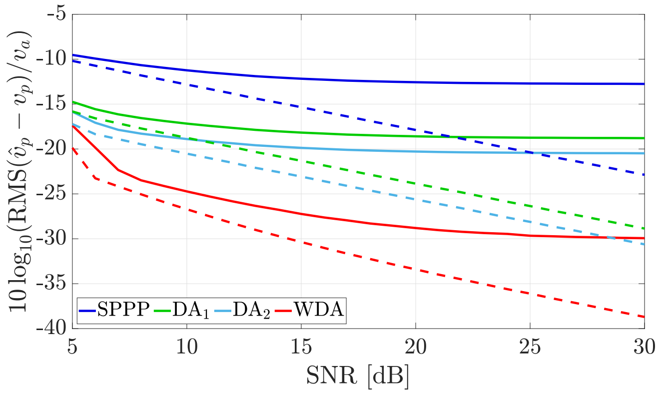
$$S_p(v) = S_0/(\sqrt{2\pi}\sigma_p)\, e^{-(v-v_p)^2/(2\sigma_p^2)} \tag{21}$$

where σ_p is the spectral width [m/s] of the phenomenon.

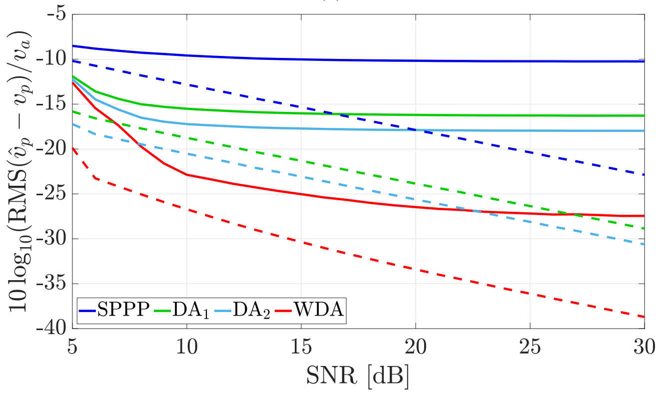
IV. Results

A. Simple Model

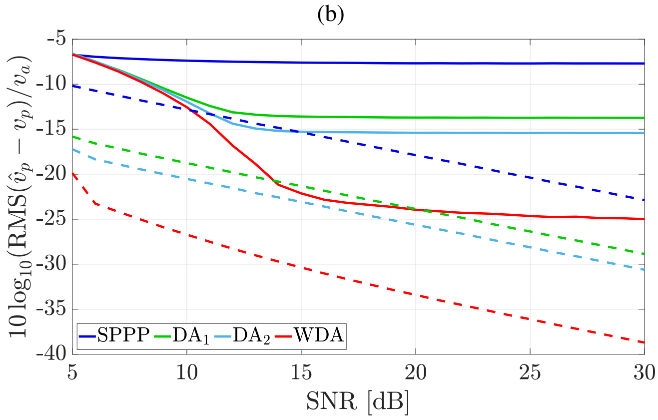
In order to analyse the performance of the method applied to the *Simple Model*, we conducted a total of $I = 1\times10^5$ Monte-Carlo simulations with the value $v_p = 0.4\,v_a$. We considered the case $n_1 = 2$, $n_2 = 3$ and $K = 15$, resulting in $M = 76$, which are typical values of use in practice.



(a)



(b)



(c)

Fig. 1: RMSE (in logarithmic scale) vs SNR for the four methods considering the simple model. The dotted line corresponds to the case without interference, while the solid line corresponds to the case with ISR = 5 dB (a), ISR = 10 dB (b) and ISR = 15 dB (c).

In each realization we took ϕ and θ as realizations of two independent random variables with continuous uniform distribution between 0 and 2π, and m_ℓ also random with discrete uniform distribution among the possible index values of (2) excluding extremes. We analysed four ISR situations: without interference, ISR $= 5$ dB, ISR $= 10$ dB and ISR $= 15$ dB; and values of SNR between 5 dB and 30 dB. We took RMSE as metric of performance.

Fig. 1 shows the RMSE over the estimates of the I realizations versus SNR. To better appreciate the details we plot the RMSE normalized to v_a on a logarithmic scale (we will refer to the unit of this scale as "dBe"). Each color refers to one of the four methods, as specified in legends. The dashed lines in the three sub-figures correspond to the case without interference, while solid lines correspond to the case ISR $= 5$ dB in Fig. 1(a), ISR $= 10$ dB in Fig. 1(b) and ISR $= 15$ dB in Fig. 1(c).

When the interference is not present we observe that the performance of the four methods enhance as the SNR increases, as is expected, and that the WDA method is consistently the best. For example, for SNR $= 20$ dB WDA is 15.5 dBe (≈ 35 times) better than SPPP and 7.8 dBe (≈ 6 times) better than the second best, DA$_2$. These differences remain practically the same for almost the entire range of SNRs, except for very low SNRs. This allows us to conclude that WDA filters noise in the way we expected it to filter out interference.

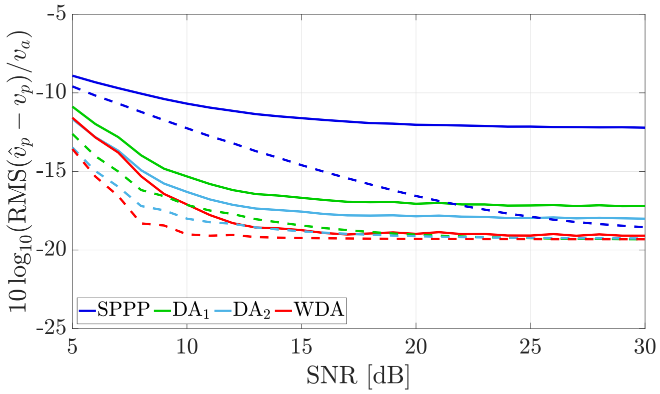
For the case with interference, comparing the same method, i.e. lines of the same color, with and without interference, we observe that the performance degrades, and that this degradation is worse as ISR increases. The performance of all methods is quite similar for low SNR, being the same for high ISR. This performance becomes better as SNR increases, being this enhancement more noticeable for WDA than for the others, and reaching a SNR value where the normalized RMSE becomes apparently constant. The point where this trend changes depends on the ISR. For SNR $= 20$ dB the enhancement of the methods against SPPP is quite similar to the enhancement for the case without interference: WDA is 16.3 dBe (≈ 43 times) better than SPPP and 8.6 dBe (≈ 7.2 times) better than the second best, DA$_2$. That is, WDA gets a little extra 0.8 dBe improvement over DA$_2$.

B. Gaussian PSD Model

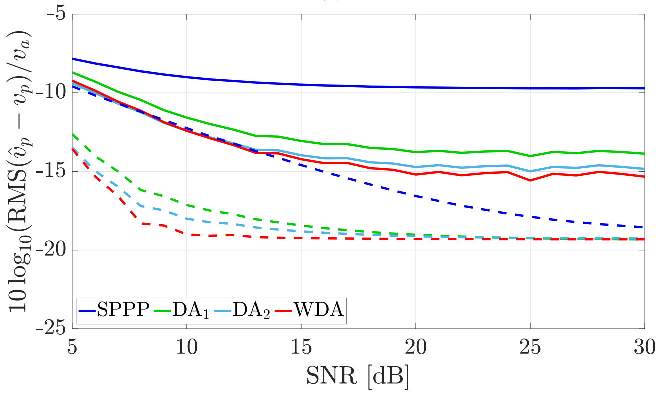
In order to analize the performance in this situation we conducted another set of $I = 1 \times 10^5$ Monte-Carlo simulations generating $p[m]$ as realizations of a random process with PSD given by (21) following the procedure of [20]. We test five spectral width cases, $\sigma_p = 0.5$ m/s, $\sigma_p = 1$ m/s, $\sigma_p = 1.5$ m/s, $\sigma_p = 2$ m/s, and $\sigma_p = 2.5$ m/s. We set the other parameters with the values used in the simulations of Section IV-A.

Fig. 2 shows the RMSE over the estimates of the I realizations versus SNR, for the case $\sigma_p = 1.5$ m/s. As previously, each color refers to one of the four methods, the dashed lines correspond to the case ISR $= 0$, and solid lines correspond to the case with ISR $= 5$ dB in Fig. 2(a), ISR $= 10$ dB in Fig. 2(b) and ISR $= 15$ dB in Fig. 2(c).

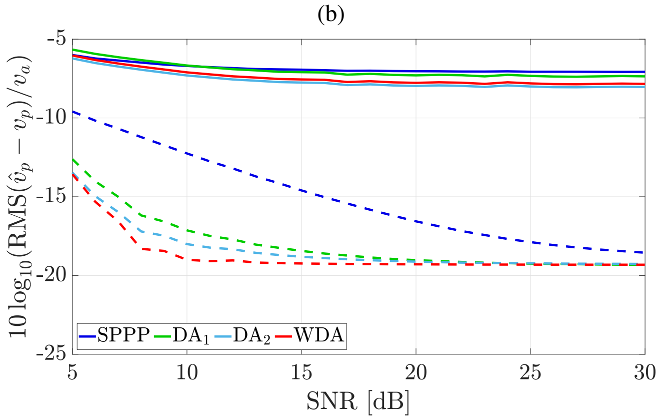
For the case without interference we observe that for the region of low SNR the performance of the four methods enhances as the SNR increases, but there is a value of SNR (around $20 \sim 25$ dB) beyond which the RMSE remains approximately constant. This is reasonable, and is due to the conjuction of the very randomness of the process that is trying to be observed and the limitations of the statistic used to observe it. Also, we can see that WDA performs better



(a)



(b)



(c)

Fig. 2: RMSE (in logarithmic scale) vs SNR for the four methods considering the gaussian PSD model with $\sigma_p = 1.5$ m/s. The dotted line corresponds to the case without interference, while the solid line corresponds to the case with ISR = 5 dB (a), ISR $= 10$ dB (b) and ISR $= 15$ dB (c).

than the other methods in the entire SNR range, although this improvement is more noticeable for low SNR values. Although due to space limitations the graphs are not shown, this behaviour is similar for the other analysed spectral widths. For example, for SNR $= 20$ dB and $\sigma_p = 0.5$ m/s, WDA is 5.5 dBe (3.5 times) better than SPPP, but only 0.6 dBe (1.15 times) better than the second best, DA$_2$. For SNR $= 20$ dB and $\sigma_p = 2.5$ m/s, WDA is 2.1 dBe (1.6 times) better than

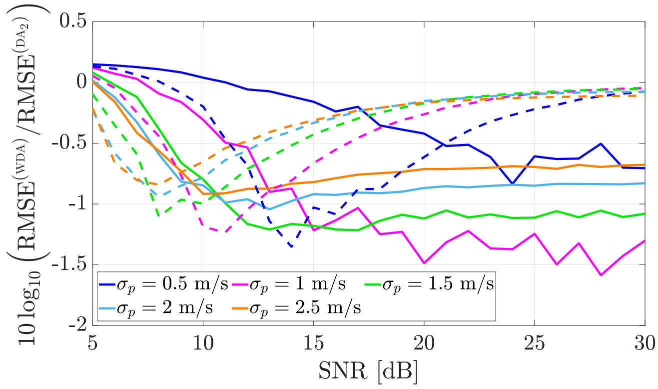


Fig. 3: RMSE enhancement of WDA over DA$_2$ (in logarithmic scale) vs SNR considering Gaussian PSD model with different σ_p values. The dotted line corresponds to the case without interference, while the solid line corresponds to the case with ISR $= 5$ dB.

SPPP, but only 0.2 dBe (1.05 times) better than the second best, DA$_2$. In any case, and considering that the model differs substantially from the one used in the deduction, we can conclude that in this situation WDA is the best of the methods.

For the case with interference we observe, that the performance almost always degrades and that this degradation is worse as ISR increases. We can see that for ISR $= 5$ dB (Fig. 2(a)) WDA mitigates the effect of interference, i.e. it reaches a performance similar to the case without interference, in the region of moderate to high SNR. We can also observe that for ISR $= 10$ dB (Fig. 2(b)) the improvement of WDA is not so appreciable (it achieves a slightly better performance than DA$_2$) while for ISR $= 15$ dB (Fig. 2(c)) it becomes slightly worse than DA$_2$ (although all the curves are very similar). This behaviour is similar for the other tested spectral widths. For example, for SNR $= 20$ dB, ISR $= 5$ dB and $\sigma_p = 0.5$ m/s, WDA is 5.4 dBe better than SPPP, but only 0.4 dBe better than the second best, DA$_2$. For SNR $= 20$ dB, ISR $= 5$ dB and $\sigma_p = 2.5$ m/s, WDA is 5.7 dBe better than SPPP, but only 0.8 dBe better than the second best, DA$_2$.

To complement this analysis Fig. 3 shows the differences in RSME of WDA method versus DA$_2$ method (the second best) as a function of SNR for the different tested spectral widths. In all cases we observe that there is an improvement of WDA over DA$_2$, and that this depends on σ_p. For the case ISR $= 0$ (dashed lines) the improvement is more noticeable for low to moderate SNR values, while for the case ISR $= 5$ dB (solid lines) it is more noticeable for moderate to high SNR values. With regard to interference mitigation, the behavior for $\sigma_p \geq 1$ m/s is as expected, as the width increases we move further away from the simplified model (zero width). However, the behavior for the width $\sigma_p \geq 0.5$ m/s is counter-intuitive in this sense, and should be studied in more detail.

V. Conclusions

In this work we addressed the study of the effect of WiFi interference on the Doppler velocity estimation in observations of weather radar that operates in SPRT mode. Based on a simplified model of the signal, which could be considered valid for a point target, and neglecting the effect of noise, we obtained closed form expressions of how the interference added to a sample in the CPI affects the estimates made by the SPPP and DA methods.

Based on the expressions of how the interference affects the two possible DA estimates, which we called DA_1 and DA_2, we obtained our mitigation proposal that consists of combining these estimates with the appropriate weights, and which we called Weighting DA (WDA). It is important to highlight that WDA does not require detecting and/or excluding interfered samples.

We tested by simulation the performance in terms of RMSE, considering this simple signal model and different ISRs, but adding AWGN noise with different SNRs. We observed that WDA performs better than all other methods in all situations, obtainig improvements of 7.8 and about 8.5 in logarithmic scale over the second best, DA_2, in situations without and with interference, respectively. In summary, WDA achieves a substantial improvement in reducing the effect of noise, but a slight improvement in reducing the effect of interference.

We also tested by simulation the performance in terms of RMSE, modelling the meteorological target signal term as a random process with Gaussian PSD, which is a more realistic and widely accepted model. We observed that WDA achieves a slight improvement in situations without interference and low to moderate SNRs, and in situations of moderate ISR and moderate to high SNRs, for all considered spectral widths.

The behavior observed considering both models seems to indicate that WDA is better at dealing with relatively low-intensity random signals that add up across all samples (such as noise) than with relatively high-intensity signals that add up in a single sample (such as interference). A possible cause could be the effect of the cross products of the noise and interference terms, which we did not include in the deduction, and which become considerable when the interference is high.

Another possible explanation, which should be studied in more detail, is that the interference may be causing DA_1 or DA_2 (or both) to fail in the disambiguation stage, an effect that cannot be later reversed by WDA. A further improvement may require improving the DA_1 and DA_2 methods (in wich WDA is based) with the consequent increase in complexity. Furthermore, in cases of high interference, it would be easier to detect and exclude the interfered samples.

It is important to note that although the more realistic model differs substantially from the simple model (and so far we have not been able to obtain closed expressions of the effect of interference in this model), WDA seems to be a low-cost alternative to improve RMSE in cases with moderate and without interference.

As future work we are interested in analysing the effect of interference in other more complex estimation methods, such as Magnitude Deconvolution [21] or Multi Pulse Pair Processing [22], and also include the effect of noise and/or a more realistic signal model in the mathematical formulation. We are also interested in analyzing other interference patterns such as those presented in [13].

References

[1] M. A. Richards, *Fundamentals of Radar Signal Processing*, 3rd ed. McGraw-Hill Education, 2022.

[2] R. J. Doviak and D. S. Zrnić, *Doppler Radar and Weather Observations, 2nd Ed.* Academic Press, 1993.

[3] M. Tahanout, A. Adane, and J. Parent du Châtelet, "An improved M-PRT technique for spectral analysis of weather radar observations," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 10, pp. 5572–5582, Oct. 2015.

[4] P. Mahapatra and D. Zrnić, "Practical algorithms for mean velocity estimation in pulse Doppler weather radars using a small number of samples," *IEEE Trans. Geosci. Remote Sens.*, vol. GE-21, no. 4, pp. 491–501, Oct. 1983.

[5] D. Zrnić and P. Mahapatra, "Two methods of ambiguity resolution in pulse Doppler weather radars," *IEEE Trans. Aerosp. Electron. Syst.*, vol. AES-21, no. 4, pp. 470–483, Jul. 1985.

[6] M. Sachidananda and D. S. Zrnić, "An improved clutter filtering and spectral moment estimation algorithm for staggered PRT sequences," *J. Atmos. Oceanic Technol.*, vol. 19, pp. 2009–2019, Dec. 2002.

[7] E. Saltikoff, J. Y. N. Cho, P. Tristant, A. Huuskonen, L. Allmon, R. Cook, E. Becker, and P. Joe, "The threat to weather radars by wireless technology," *Bulletin of the American Meteorological Society*, vol. 97, no. 7, pp. 1159 – 1167, 2016.

[8] RMA-C320 page https://www.invap.com.ar/en/divisions/defense-security-and-environment/c-band-weather-radar/.

[9] G. O. Petracca, "Estudio e implementación de métodos de eliminación de interferencias WLAN/RLAN en radares meteorológicos," Master's thesis, Universidad Nacional de Córdoba, 2017.

[10] M. Vaccarono, C. V. Chandrasekar, R. Bechini, and R. Cremonini, "Survey on electromagnetic interference in weather radars in northwestern italy," *Environments*, vol. 6, no. 12, 2019.

[11] G. W. E. Giovanardi, J. Cogo, and J. P. Pascual, "Medición de señales WLAN/RLAN que interfieren a los radares meteorológicos argentinos," in *ARGENCON 2022*.

[12] B. H. Walke, S. Mangold, and L. Berlemann, *IEEE 802 Wireless Systems: Protocols, Multi-Hop Mesh / Relaying, Performance and Spectrum Coexistence*. Wiley, 2007.

[13] E. Correa, J. Cogo, and J. P. Pascual, "Degradación de los observables de radar meteorológico debido a la interferencia Wi-Fi," in *ARGENCON 2022*.

[14] D. Benoit, J. Cogo, and J. P. Pascual, "Análisis del efecto de la interferencia WiFi sobre la velocidad Doppler en radar meteorológico," in *ARGENCON 2022*.

[15] R. Keränen, L. Rojas, and P. Nyberg, "Progress in mitigation of WLAN interferences at weather radar," in *36th Conf. on Radar Meteorology, Breckenridge, CO, Amer. Meteor. Soc., 336.*, 2013.

[16] L. Rojas, D. N. Moisseev, V. Chandrasekar, J. Selzler, and R. Keränen, "Dual-polarization spectral filter for radio frequency interference suppression," in *Seventh European Conference on Radar in Meteorology and Hydrology (ERAD 2012)*, 2012.

[17] Q. Cao and M. Knight, "Mitigation of radio frequency pulse interference on dual-pol weather radar," in *American Meteorological Society 99th annual meeting*, Jan. 2019, pp. 6–10.

[18] J. Y. N. Cho, "A new radio frequency interference filter for weather radars," in *Journal of Atmospheric and Oceanic Technology, Vol. 34*, Jul. 2017.

[19] R. J. González, "Eliminación de interferencias WLAN/RLAN en imágenes de radar meteorológico mediante la implementación de wavelets y otros filtros discretos," Trabajo Final Integrador, Universidad Nacional de Río Negro, 2020.

[20] D. Zrnić, "Simulation of weatherlike doppler spectra and signals," *Journal of Applied Meteorology and Climatology*, vol. 14, no. 4, 1975.

[21] M. Sachidananda and D. S. Zrnić, "Clutter filtering and spectral moment estimation for Doppler weather radars using staggered pulse repetition time," *J. Atmos. Oceanic Technol.*, vol. 17, pp. 323–331, Mar. 2000.

[22] J. P. Pascual, J. Cogo, A. C. Rosell, and J. Areta, "Multipulse processing algorithm for improving mean velocity estimation in weather radar," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, 2022.