

Towards Counting via Passive Radar using OFDM Waveforms

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Abstract—The capability of counting targets (people or things) in a monitored area is important for emerging wireless applications. To this aim, passive systems that rely on signals of opportunity and device-free targets are preferred to active systems that rely on dedicated or personal devices for preserving privacy and reducing implementation costs. This paper develops a framework for design and analysis of device-free counting systems via OFDM signals of opportunity. In particular, counting techniques based on model order selection are proposed. Preliminary results show the effectiveness of the proposed techniques in simple use cases.

Index Terms—Counting, signals of opportunity, model order selection, OFDM, passive radar.

I. INTRODUCTION

Counting targets, such as people or things, in a monitored area enables new important applications for business analytics, smart buildings, intelligent transportation, and public safety. [1]–[3]. Depending on the application and the operating environment, current solutions include image-based, device-based, and device-free approaches, in which data are collected from multiple sensors and processed to infer the number of targets in the monitored area.

In image-based approaches, the counting is performed by processing the foreground images collected by one or multiple cameras, after the removal of the background images [4]–[7]. In device-based approaches, the counting is performed by relying on personal or dedicated devices, such as personal smartphone or tags for radio-frequency identification [8]–[11]. Recently, device-free approaches have been investigated, where the counting is performed by sensing the wireless environment and inferring the number of targets from reflected signals [1], [10], [12]. Such device-free approaches preserve the privacy of the targets, as data are not related to the target identity, and they reduce the implementation cost with respect to device-based solutions.

Passive radars that rely on the exploitation of illuminators of opportunity represent good candidates for device-free counting as they have been employed in the literature for stealth and low-cost tracking [13]. In such a configuration, a network of receiving-only radars receives both the direct signal from the illuminator of opportunity and the signal backscattered

by the target. Previous works on passive radar investigated VHF/UHF radio and television stations, as well as WiFi base stations as illuminators of opportunity [14]–[16]. Digital signals are excellent candidates for passive radars, thanks to their wide availability and low error-rate signal reconstruction. In particular, orthogonal frequency division multiplexing (OFDM) signals recently gained interest since they can be efficiently exploited to detect and locate targets based on Fourier analysis across subsequent blocks, which significantly reduce the computational complexity [17]–[19].

Several signal processing techniques have been proposed in the literature to detect the presence and estimate the position of a target based on the received waveforms. For example, time difference-of-arrival (TDOA), frequency difference-of-arrival (FDOA) and angle-of-arrival (AOA) measurements are often adopted in this scenarios where synchronization is not guaranteed between receivers and transmitters [20]–[23]. In general, the transmitted signal of opportunity is unknown and therefore a reference receiver is deployed to receive only the direct signal from the illuminator of opportunity, which is decoded to provide a reference signal to the receivers.

Current solutions for multi-target detection and tracking systems rely on likelihood calculation and data association for each detected target [13], [24]–[26]. Data association is a computationally complex operation (growing exponentially with the number of targets) required for tracking while not necessary for counting systems that aim at estimating only the number of targets disregarding their position.

In this paper, we propose the use of passive radar systems that rely on OFDM waveforms for counting device-free targets. We develop a framework for design of device-free counting systems based on model order selection. This enables an understanding on how the main system parameters affect the estimation of the number of targets. The key contributions can be summarized as follows: (i) we provide a likelihood function for passive radar via OFDM signals; and (ii) we derive the model selection problem for device-free counting based on the likelihood function. The proposed framework is validated through sample-level simulations that take into account the main impairments affecting the counting performance, such as residual clutter and symbol reconstruction error.

The remainder of the paper is organized as follows. Sec. II describes the system model. Sec. III introduces the signal processing techniques. Sec. IV presents a case study and

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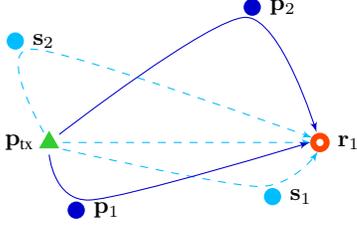


Fig. 1. Example of an operating environment with one transmitter of opportunity (green triangle), one receiver (red circle), two targets (blue circles) and two background scatterers (cyan circle).

numerical results. Finally, in Sec. V our final remark is given.

II. SYSTEM MODEL

Consider a network of receiving-only radars with index set \mathcal{R} , each radar in position \mathbf{r}_h with $h \in \mathcal{R}$ monitoring an area illuminated by an OFDM transmitter at \mathbf{p}_{tx} that emits a broadcast signal at center frequency f_c with equivalent low-pass version

$$s(t) = \sum_{i=-\infty}^{+\infty} s_i(t - iT') \quad (1)$$

where

$$s_i(t) = \sum_{n=-N/2}^{N/2-1} a_i[n] e^{j2\pi n \Delta_f t} \mathbb{1}_{(-T_{\text{cp}}, T)}\{t\} \quad (2)$$

$a_i[n]$ is the data symbol of time i on the n th subcarrier, Δ_f is the frequency spacing between two adjacent subcarriers, $T' = T + T_{\text{cp}}$, and T_{cp} is the cyclic prefix time. The transmitted signal $s(t)$ is decoded and reconstructed as $\hat{s}(t)$, for example based on the signal collected at a reference receiver (i.e. the reference signal). We consider a non ideal signal reconstruction, with probability of error per symbol P_{es} .

Each radar receives the signal after backscattering by all the objects that are present in the operating environment, also referred to as scatterers. The dynamic scatterers (velocity and Doppler shift different than zero) are named targets; the static scatterers (velocity and Doppler shift equal to zero) that are present also in the absence of the targets are named clutter. Fig. 1 shows an example of the operating environment with one transmitter of opportunity, one receiver, two target scatterers and two clutter scatterers.

Therefore, the signal collected by the h th radar after multipath propagation is [13], [24]

$$r^{(h)}(t) = r_b^{(h)}(t) + r_t^{(h)}(t) + n(t) \quad (3)$$

where: $r_b^{(h)}(t)$ is the signal component related to the background environment due to clutter and direct signal (the same component would be received in the absence of targets, when the area is empty); $r_t^{(h)}(t)$ is the signal component related to the targets; and $n(t)$ is the noise component. The background

estimate can be removed from the received waveform leading to $\check{r}^{(h)}(t) = r^{(h)}(t) - \hat{r}_b^{(h)}(t)$, which is the received signal after background removal.

The residual of the background component after background removal depends on the clutter mitigation algorithm, whose analysis is beyond the scope of this paper. However, we consider a simple model to take into account the effects of residual clutter on the counting performance. Also, experimental results show that the use of techniques that mitigate the effect of the direct signal and clutter, such as null steering, can attenuate the background component up to 100dB and reduce the corresponding dynamic range [17], [27]. To this aim, the clutter residual is modelled considering a *reduction factor* ξ for all the components. After clutter mitigation the signal becomes

$$\check{r}^{(h)}(t) = \frac{1}{\xi} \left(\sum_{k \in \mathcal{K}_c^{(h)}} \alpha_k^{(h)} \check{s}(t - \tau_k^{(h)}) \right) + \sum_{k \in \mathcal{K}_t^{(h)}} \alpha_k^{(h)} e^{jv_k \psi_k^{(h)}} \check{s}(t - \tau_k^{(h)}) + n(t) \quad (4)$$

where: $\mathcal{K}^{(h)} = \mathcal{K}_c^{(h)} \cup \mathcal{K}_t^{(h)}$ is the index set of multipath components due to all the scatterers, in which $\mathcal{K}_c^{(h)}$ denotes the multipath components related to clutter (i.e., static scatterers) and $\mathcal{K}_t^{(h)}$ denotes the target components (i.e., dynamic scatterers); $\tau_k^{(h)}$ is the arrival time for the k th path component and $\alpha_k^{(h)}$ is the amplitude for the k th path component. In particular, $\tau_k^{(h)} = (\|\mathbf{p}_{\text{tx}} - \mathbf{p}_t^{(k)}\| + \|\mathbf{r}_h - \mathbf{p}_t^{(k)}\|)/c$ is the arrival time of the component (backscattered by the k th target at $\mathbf{p}_t^{(k)}$) that propagates between the transmitter- k th target link and the k th target- h th receiver link.¹ As for the target scatterers, $\psi_k^{(h)} = 2\pi\beta_k^{(h)} f_c t$ where $\beta_k^{(h)} = f_k^{(h)}/(v f_c) = (\cos \omega_{t,k} + \cos \omega_{r,k})/c$ where $f_k^{(h)}$ is the Doppler shift, which is assumed to be constant over a block of duration T' , $\omega_{t,k}$ is the angle describing the relative direction between the transmitter and the target, and $\omega_{r,k}$ is the angle describing the relative direction between the target and the k th receiver.²

III. SIGNAL PROCESSING FOR COUNTING

The aim of a counting system is to estimate the number of target scatterers $n_t = |\mathcal{K}_t^{(h)}|$ by processing the received signals $\check{r}^{(h)}(t) \forall h \in \mathcal{R}$. The vector

$$\check{\mathbf{r}} = [\check{\mathbf{r}}^{(1)}, \check{\mathbf{r}}^{(2)}, \dots, \check{\mathbf{r}}^{(n_p)}] \quad (5)$$

represents the concatenation of the vectors of received signal samples for each receiver. The length of the vector is $n_m = |\mathcal{R}| n_s$, where n_s is the number of received signal samples

¹The c denotes the speed-of-light and $\|\cdot\|$ denotes the l_2 norm.

²The geometry-based single-bounce model is employed, where the number of multipath components is equal to the number of scatterers. This is a widely adopted assumption for two reasons: (1) the power related to a double or multiple bounce path is proportional to the product of the radar cross section of two or multiple targets; and (2) this is equivalent to consider a lower spatial resolution, which is a common assumption due to bandwidth limitations which are intrinsic to the hardware that is involved [28].

$\check{r}^{(h)}(nT_s)$ with $n = 0, 1, \dots, n_s - 1$, which depends on the sampling time T_s and the observation interval $T_{\text{obs}} = n_s T_s$. The vector

$$\mathbf{p}_t = [\mathbf{p}_t^{(1)}, \mathbf{p}_t^{(2)}, \dots, \mathbf{p}_t^{(n_t)}] \quad (6)$$

is the concatenation of the target position vectors. The estimation of n_t relies on the dependence of \check{r} on \mathbf{p}_t through the component $r_t^{(h)}(t)$ in (3).

Let \mathcal{H}_n denote the hypothesis that the number of target scatterers is $n_t = n$, and let n_{max} denote a supremum for n_t , i.e. $n_t \in \mathcal{N}_t = \{1, 2, \dots, n_{\text{max}}\}$. The aim of the system is to estimate n_t from \check{r} in (5), which is the vector of available data with size n_m , as

$$\hat{n}_t = \arg \max_{n_t \in \mathcal{N}_t} f(\check{r} | \mathcal{H}_{n_t}). \quad (7)$$

From (3) and (4), if the background is perfectly removed,³ that is $\hat{r}_b^{(h)}(t) = r_b^{(h)}(t)$ it follows that $\check{r}^{(h)}$ is a random vector that depends on a parameter vector $\boldsymbol{\theta}^{(h)} = [\mathbf{p}_t, \boldsymbol{\alpha}^{(h)}, \boldsymbol{\tau}^{(h)}, \mathbf{v}]$, where⁴

$$\begin{aligned} \mathbf{v} &= [v_1, v_2, \dots, v_{n_t}] \\ \boldsymbol{\tau}^{(h)} &= [\tau_1^{(h)}, \tau_2^{(h)}, \dots, \tau_{n_t}^{(h)}] \\ \boldsymbol{\alpha}^{(h)} &= [\alpha_1^{(h)}, \alpha_2^{(h)}, \dots, \alpha_{n_t}^{(h)}]. \end{aligned} \quad (8)$$

The parameters $\boldsymbol{\tau}^{(h)}$ and $\boldsymbol{\alpha}^{(h)}$, i.e. the arrival time and amplitude of the multipath components, are random variables (RVs) that depend on the channel instantiation. We are interested in estimating the dimension of \mathbf{p}_t and \mathbf{v} that is $n_p = d n_t$ for $\mathbf{p}_t^{(k)} \in \mathbb{R}^d$.

The counting problem can be seen as a model order selection problem for the estimation of a integer-valued parameter related to the dimension of the parameter vector given a data model [29], [30]. Consider the likelihood function of \check{r} given \mathbf{p}_t . Since the received waveforms from different transmitter-receiver pairs are independent, the marginal likelihood is

$$f(\check{r}, \mathbf{p}_t, \mathbf{v}) \propto \prod_{h \in \mathcal{R}} f(\check{r}^{(h)} | \mathbf{p}_t, \mathbf{v}). \quad (9)$$

where the probability distribution function (PDF) $f(\check{r}^{(h)} | \mathbf{p}_t, \mathbf{v})$ can be obtained as marginal distribution

$$f(\check{r}^{(h)} | \mathbf{p}_t, \mathbf{v}) = \mathbb{E}_{\boldsymbol{\tau}^{(h)}, \boldsymbol{\alpha}^{(h)}} \left\{ f(\check{r}^{(h)} | \boldsymbol{\theta}^{(h)}) \right\} \quad (10)$$

where the marginalization has been made with respect to $\boldsymbol{\tau}^{(h)}$

³We will evaluate the effects of imperfect background removal in the case study. An alternative solution is to extend derivations of the likelihood by including the positions of the unknown background objects in the parameter vector and considering the signal before clutter removal.

⁴We consider zero-mean Gaussian distributed noise samples $n_j^{(h)} = n^{(h)}(t_j) \sim \mathcal{N}(0, \sigma_n^2)$ and the variance σ_n^2 is considered known to simplify the notation.

and $\boldsymbol{\alpha}^{(h)}$, and

$$\begin{aligned} f(\check{r}^{(h)} | \boldsymbol{\theta}^{(h)}) &\propto \exp \left\{ 2 \sum_{k \in \mathcal{N}} \int_0^{T_{\text{obs}}} \check{r}^{(h)}(t) \left(\alpha_k^{(h)} e^{j v_k \psi_k^{(h)}} \right. \right. \\ &\quad \left. \left. \times s(t - \tau_k^{(h)}) \right)^* dt - \int_0^{T_{\text{obs}}} \left| \sum_{k \in \mathcal{K}_t^{(h)}} \alpha_k^{(h)} e^{j v_k \psi_k^{(h)}} s(t - \tau_k^{(h)}) \right|^2 dt \right\} \end{aligned} \quad (11)$$

is the PDF for a given channel instantiation, where T_{obs} is the observation time. By considering $T_{\text{obs}} = T_i$ and the OFDM structure of the signal we have [17]

$$\begin{aligned} f(\check{r}^{(h)} | \boldsymbol{\theta}^{(h)}) &\propto \exp \left\{ 2 \sum_{i=0}^{T_i/T'} \sum_{k \in \mathcal{K}_t^{(h)}} \sum_{n=-\frac{N}{2}}^{\frac{N}{2}} e^{j 2\pi n \Delta_f t} \left(\alpha_k^{(h)} a_i[n] \right)^* \right. \\ &\quad \left. \times H_{h,n}^{(h)} - \int_0^{T_{\text{obs}}} \left| \sum_{k \in \mathcal{K}_t^{(h)}} \alpha_k^{(h)} s(t - \tau_k^{(h)}) \right|^2 dt \right\} \end{aligned} \quad (12)$$

where

$$H_{h,n}^{(h)} = \int_0^T e^{-j 2\pi (n \Delta_f t + \psi_k^{(h)} t)} \check{r}^{(h)}(t - hT) dt. \quad (13)$$

The excess arrival delays of multipath components within each cluster depend on the environment, the specific target, and the orientation, that are unknown for realistic applications. Therefore, the marginalization with respect to the channel parameter may be impossible or lead to intractable problems. This hinders the use of tractable models [23]. In particular, we consider a single-bounce deterministic channel, where each scatterer introduces one resolvable multipath component with amplitude averaged over small-scale fading [13], [31], [32]

$$\bar{\alpha}_k^{(h)} = \mathbb{E}_s \left\{ \alpha_k^{(h)} \right\}. \quad (14)$$

The hypothesis \mathcal{H}_n , i.e. $n_t = n$ is true for any set of target positions such that the length of the vector $\mathbf{p}_t \in \mathbb{R}^d$ is $d n$. The density function $f(\check{r}^{(h)} | \mathcal{H}_n)$ is unknown in general, while $f(\check{r}^{(h)}, \mathbf{p}_t)$ is known. However, it is known that the order-selection rule that maximizes the likelihood function $f(\check{r}, \mathbf{p}_t)$ over any possible n is not the optimal rule [29]. This is true for nested models, because the maximum likelihood (ML) will always choose the maximum possible order n owing to the fact that the likelihood monotonically increases with n . One of the possible choices is to use a Bayesian approach, where the density function $f(\check{r}^{(h)} | \mathbf{p}_t)$ is marginalized over the space $\mathcal{P}_n = \{\mathbf{p}_t : n_t = n\}$, that is

$$f(\check{r}^{(h)} | \mathcal{H}_n) = \int_{\mathcal{P}_n} f(\check{r}^{(h)}, \mathbf{p}_t) d\mathbf{p}_t. \quad (15)$$

Such density function can be asymptotically approximated with respect to n , leading to the model order selection via Bayesian information criterion (BIC) as [29]

$$\hat{n}_t = \arg \max_{n \in \mathcal{N}_t} \ln f(\check{r}, \hat{\mathbf{p}}_{t,n}) - \frac{d n}{2} n_m \quad (16)$$

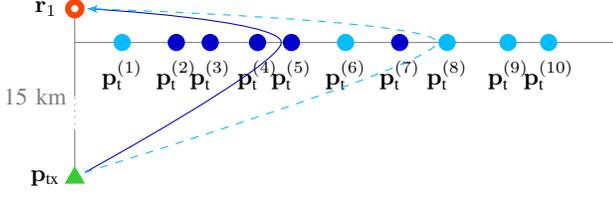


Fig. 2. Example scenario for the case study for the case $n_t = |\mathcal{K}_t^{(1)}| = 5$, $n_c = |\mathcal{K}_c^{(1)}| = 5$, $\mathcal{K}_t^{(1)} = \{2, 3, 4, 5, 7\}$, and $\mathcal{K}_c^{(1)} = \{1, 6, 8, 9, 10\}$.

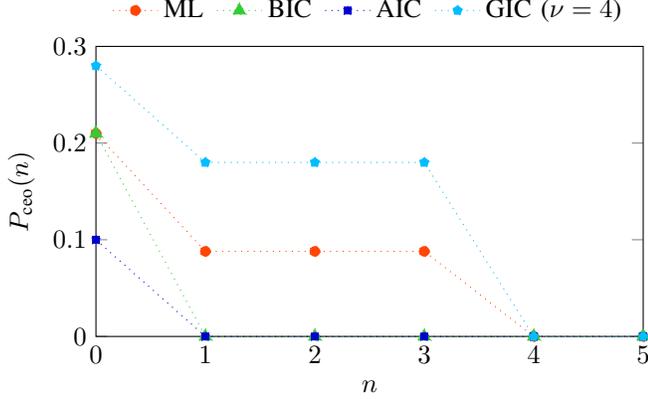


Fig. 3. Counting error outage P_{ceo} for three different information criteria.

where

$$\hat{\mathbf{p}}_{t,n} = \underset{\mathbf{p}_t \in \mathcal{P}_n}{\operatorname{argmax}} f(\check{\mathbf{r}}, \mathbf{p}_t) \quad (17)$$

is the ML estimate of \mathbf{p}_t for $n_t = n$.

Alternatively, \hat{n}_t can be obtained by minimizing the Kullback-Leibler divergence between the true PDF of the observed data and the one of the model, which results in [29]

$$\hat{n}_t = \underset{n \in \mathcal{N}_t}{\operatorname{argmin}} -\mathbb{E}_{\check{\mathbf{r}}}\{\ln f(\check{\mathbf{r}}, \mathbf{p}_t | \mathcal{H}_n)\}. \quad (18)$$

However, the true PDF of the observed data is unknown and therefore the expectation over $\check{\mathbf{r}}$ cannot be taken. To overcome this challenge, the unavailable log-PDF of the model is approximated by a second-order Taylor series expansion around the ML estimate. This leads to the Akaike information criterion (AIC) [29]

$$\hat{n}_t = \underset{n \in \mathcal{N}_t}{\operatorname{argmax}} 2 \ln f(\check{\mathbf{r}}, \hat{\mathbf{p}}_{t,n}) - \nu dn \quad (19)$$

with $\nu = 2$. It is demonstrated that a generalized information criteria (GIC) outperforms the Akaike information criterion (AIC) when $\nu > 2$, especially when approximated descriptions of the PDF are employed, as in the case of this paper (see eq. (14)).

IV. CASE STUDY

Consider a simple scenario as in Fig. 2 with one DVB-T transmitter at \mathbf{p}_{tx} and one receiver at \mathbf{r} , where the targets are distributed on a line of length 800 m and the distance between

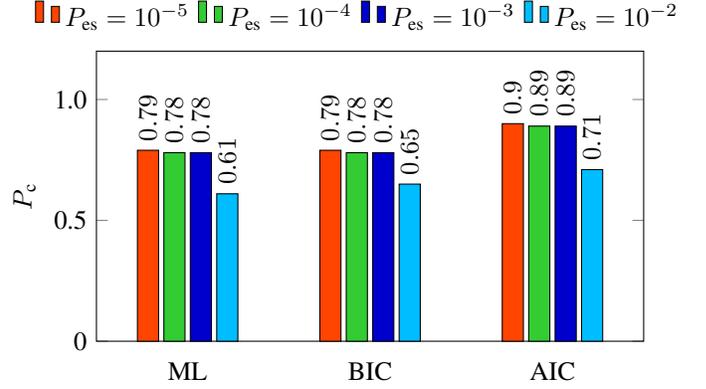


Fig. 4. Probability of correct counting P_c for different values of probability of error per symbol P_{es} and information criteria.

the transmitter and the receiver is 15 km. The minimum distance between the receiver and the target is 200 m. The maximum number of targets is $n_{\text{max}} = 5$ and results are obtained by averaging over $n_t = \{0, 1, 2, \dots, n_{\text{max}}\}$. The single radar receives a 2k-mode DVB-T signal from the transmitter of opportunity, whose symbols are reconstructed with error probability P_{es} . The transmitted signal of opportunity has bandwidth $B = 8$ MHz, QPSK modulation, number of carriers $K = 1705$, carrier spacing is $\Delta_f = 1/T_u$ with $T_u = 224 \mu\text{s}$ being the symbol duration, according to the ETSI standard [32].

Counting is performed with model order selection based on the ML, BIC, AIC, and GIC as in (19) with $\nu = 0, 1, 2$ and 4, respectively (see [29], eq. 93 and 94). The performance is evaluated in terms of correct counting probability P_c , i.e. the probability that the estimated number of targets is correct, and in terms of counting error outage $P_{\text{ceo}}(n)$, i.e. the probability that the counting error $|\hat{n}_t - n_t|$ is above n . The effect of imperfect signal reconstruction is evaluated by varying the probability of error per symbol P_{es} . The effect of clutter residual is evaluated by considering the presence of $n_c = |\mathcal{K}_c^{(h)}|$ static scatterers and different values of clutter mitigation factor ξ as defined in (4).

Fig. 3 shows the counting error outage $P_{\text{ceo}}(n)$ as a function of n , for different information criteria in the absence of clutter and with perfect signal reconstruction. It can be observed that the classic maximum likelihood estimation is outperformed by both the BIC and AIC. This underlines the importance of model order selection for the counting problem. In particular, the probability that the counting error is above 1 is 0.09 for the ML and 0.001 for the BIC and AIC. Furthermore, the AIC results to be the best choice because the probability of correct counting is $P_c = 1 - P_{\text{ceo}}(0) = 0.9$ with AIC while it is $P_c = 1 - P_{\text{ceo}}(0) = 0.78$ with the BIC.

Fig. 4 shows the probability of correct counting P_c for different values of probability of error per symbol P_{es} and varying the information criteria. It can be observed that the AIC outperforms the other criteria for all the values of P_{es} considered. For example, for the same value of $P_{\text{es}} = 10^{-2}$,

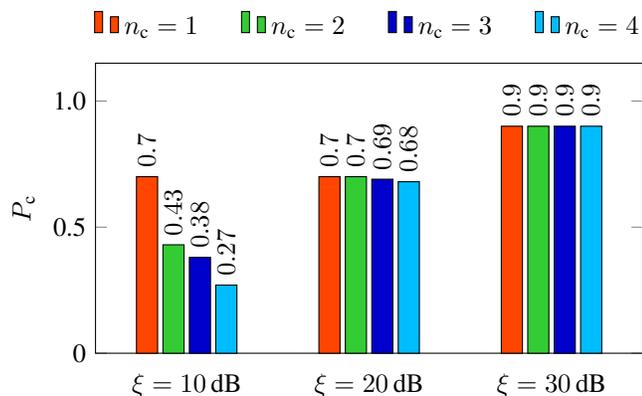


Fig. 5. Probability of correct counting P_c by varying the number of static scatterers and clutter mitigation factor with the AIC.

the probability of correct counting is $P_c = 0.61$ with ML, $P_c = 0.65$ with BIC, and $P_c = 0.71$ with AIC. Furthermore, the probability of correct counting does not have an important impact on the counting performance when $P_{es} \leq 10^{-3}$. For example, similar performance is obtained when $P_{es} = 10^{-5}$ and $P_{es} = 10^{-3}$. In fact, $P_c = 0.79$ for both ML and BIC and $P_c = 0.9$ for AIC when $P_{es} = 10^{-5}$ (same performance as with perfect reconstruction in Fig. 3). Similarly, $P_c = 0.78$ for both ML and BIC and $P_c = 0.89$ for AIC when $P_{es} = 10^{-3}$.

Fig. 5 shows the probability of correct counting P_c for different values of clutter mitigation factor ξ and number of clutter scatterers n_c . Results are obtained with the AIC. It can be observed that the probability of correct counting improves significantly with ξ . In particular $P_c = 0.9$ for $n_c = 4$ and $\xi = 30$ dB, which is comparable to the probability in the absence of clutter. The effect of the number of scatterers decreases with ξ . In fact, for $\xi = 10$ dB we have $P_c = 0.7$ with $n_c = 1$ and $P_c = 0.27$ with $n_c = 4$. Whereas for $\xi = 20$ dB we have $P_c = 0.7$ with $n_c = 1$ and $P_c = 0.68$ with $n_c = 4$. This can be due, in part, to the fact that we considered a constant mitigation factor for all the scatterers.

V. FINAL REMARK

A device-free counting system that relies on OFDM signals of opportunity is presented. The proposed counting system relies on model order selection through a likelihood function, which is derived for passive radar using OFDM waveforms. The counting system performance is evaluated in a simple case study varying the number of targets and clutter scatterers. Results show that the use of the proposed model order selection instead of a classical maximum likelihood approach significantly improves the system performance. Results also quantify the effects of the residual clutter and of the symbol reconstruction errors.

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