2D Localization with WiFi Passive Radar and Device-Based Techniques: An Analysis of Target Measurements Accuracy

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Abstract: *The aim of the work is to investigate the performance of two localization techniques based on WiFi signals: the WiFi-based passive radar and a device-based technique that exploits the measurement of angle of arrival (AoA) and time difference of arrival. This paper focuses specifically on the accuracy of the AoA measurements. As expected, the results show that for both techniques the AoA accuracy depends on the signal-to-noise ratio also in terms of the number of exploited received signal samples. For the passive radar, very accurate estimates are obtained; however, loss of detections can appear only when the rate of the Access Point packets is strongly reduced. In contrast, device-based estimates accuracy is lower, since it suffers of the limited number of emitted packets when the device is not uploading data. However, it allows localization also of stationary targets, which is impossible for the passive radar. This suggests that the two techniques are complementary and their fusion could provide a sensibly increase performance with respect to the individual techniques.*

1. Introduction

In the last years, great attention has been focused on the localization of human targets and small objects. The interest on this topic is motivated by the huge amount of possible applications that require the knowledge of the target position. For example, in [1] the position estimation of persons is necessary for the coordination of rescue teams in emergency scenarios, as well as for monitoring and surveillance applications in critical areas, such as ports or airports, or even the provision of services to cooperative users in museums, hospitals and universities.
Since global navigation satellite systems, as GPS, Galileo and Glonass, have strong limitations indoor and require targets to cooperate in order for them to be detected and localized, the attention has focused on the use of the (opportunistic) RF signals already available for communication purpose. They have a wide coverage also in indoor areas and can be used to detect and localize non-cooperative targets. Passive radars have been widely used in long range applications based on FM, [2]-[3], and DVB-T signals, [4]-[5], whereas the WiFi transmissions are particularly suitable for short range positioning, [6] as well as for extracting target characteristics as cross-range profiles, [7].
The use of WiFi signals allows also exploiting the waveforms emitted directly by the device to localize them, [8]. Therefore, in this paper, we consider two different techniques: Firstly, the WiFi-based passive bistatic radar that exploits the Access Point (AP) as illuminator of opportunity is an interesting solution, especially for surveillance applications in local area environments, because it provides the position of non-cooperative targets, which do not carry an active device (the so called “device-free localization”), [9]. Secondly, the WiFi emission-

based localization, that in contrast uses the device transmissions to define the position of the target, is another possible strategy to reach the same goal, [8].
The performance of both systems are closely linked to the signal-to-noise ratio (SNR) of the data used for the estimation, and accordingly, to the signal energy and the number of samples available. As it is apparent, the higher the signal energy and the number of signal samples, the better the performance. In detail, the number of samples depends on i) the WiFi packet length, and ii) the number of packets occurred in a specific time interval, so that a time integration operation might be potentially performed. This means that the best possible situation is to have a big number of long packets for the estimation of the parameters of interest.
Nevertheless, these characteristics are related to the actual communication activity between AP and devices. In fact, as defined in the IEEE 802.11 Standard [10], the packets length changes according to the packet type (beacon, probe request, authentication, etc.), therefore it is possible to have available even very short signals. In addition, in a normal communication system, multiple users, e.g. APs and devices, could share the same channel. Therefore, they cannot transmit simultaneously, and the number of WiFi packets transmitted by each of them depends on the specific case. It is evident that when the device uploads data, the transmission rate of the AP decreases and the performance of the passive radar get worse, while the device-based technique performs better. In contrast, during download activities, the AP transmits more packets, thus the passive radar provides the best performance.
As it is clear from the previous considerations, the complementarity between the described approaches makes them suitable for a possible fusion in an integrated system, which provides the position estimation of targets during the whole observation time.
To reach this purpose, in this paper, we investigate the relationship between Angle of Arrival (AoA) estimation accuracy and energy features of the exploited signals. The analysis has been carried out on experimental data, acquired during appropriate measurement campaigns.

2. Experimental campaign

The analysis has been performed on experimental data, collected in an outdoor environment (a parking area in Cisterna di Latina). A commercial wireless AP (D-Link DAP 1160) was configured to operate in channel 4 of the WiFi band (carrier frequency of 2.427 GHz), with a beacon interval of 3 ms and a transmission rate of 1 Mbps (namely modulation and coding schemes are respectively DBPSK and 11-chip Barker sequence). The AP was connected to a directive transmit antenna (TX) that illuminates an area where human targets, equipped with a WiFi device, move along assigned paths to be used for measurement validation. As sketched in Fig. 1, a nine-points square-shaped grid was marked on the floor, to be used as reference for both sensor calibration and measurement accuracy evaluation.

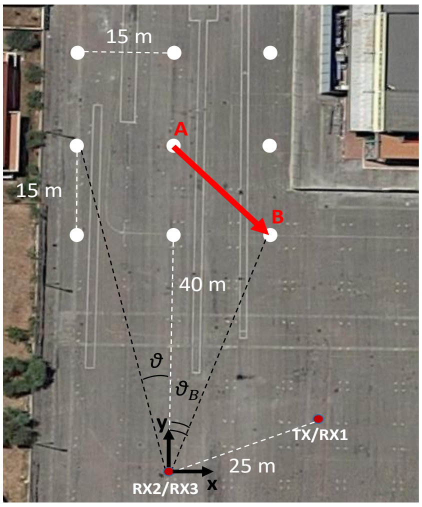

Fig. 1. Target localization and tracking experiment

Three receiving antennas were used to acquire the signals emitted by both AP and WiFi devices carried by the human targets. Two receiving antennas (RX2 and RX3) were positioned very close one another (with spacing of 12 cm between them) and 40 m from the side of the square grid. A Cartesian reference system is considered with origin in their midpoint and axes aligned with the sides of the grid. An additional antenna (RX1) is positioned close to the transmit antenna, 25 m away from them. The three receive antennas are characterized by a horizontal beam width of about 80° and a peak gain of 12dBi.
The USRP 2955 by National Instruments, providing with four receiving channels independently downconverted and digitized, was used to acquire the signals at the WiFi Channel #4. Each channel was connected to a receive antenna, whereas the fourth channel was used to digitize the signal emitted from the AP, which is spilled before the transmit antenna by a directional coupler. In this test, the gains were set in order to have comparable signal level in each receiving channel.

We carried out a test where a target with an active mobile device (Asus Zenfone 2) moves from point A in Fig. 1, i.e. the point of coordinates (0m, 55m) in the defined reference system, to the point B (15m, 40m). Then he stops in B for few seconds. During the whole observation time (around 28 seconds), the target device tries to connect to the WiFi router, but his transmissions only contain connection activities since a significant data exchange does not take place, therefore the device-emitted waveforms occupy the medium for a short time and only a few packets sent by the mobile device are collected by the three receive antennas.

Using the three receive antennas, the human targets (carrying the devices) can be located in 2D by exploiting the signals emitted by their devices. Specifically, the two closely spaced antennas (RX2 and RX3) can be used in interferometric mode to estimate the signal AoA, whereas the Time Difference of Arrival (TDoA) between the signals collected at antenna RX1 and RX2 provide the hyperbola that contains the target location. As apparent, using together the two measurements, two equation can be written in the two spatial unknowns (target x and y coordinates) so that the 2D target position can be obtained.

However, this setup also allows exploiting the signals emitted by the WiFi AP that are scattered by the human targets and reach the two closely spaced antennas (RX2 and RX3). In this case, the AP acts as the illuminator of opportunity of a WiFi-based passive radar; moreover the

human target localization does not depend on carrying a WiFi device, since they are not required to emit their own signals to be localized.
In detail, the passive radar can estimate the target position through the measure of the Angle of Arrival (AoA) and the bistatic range, both estimated by the closest antennas (RX2 and RX3 in Fig. 1). In this case, the fourth channel is used to collect a reference copy of the transmitted signal that allows measuring the bistatic range. Under these conditions, the 3 ms beacon rate provides a very high number of packets that can be exploited to locate the target.

With both the device-based system and the passive radar system, three receiving channels are exploited to obtain two measurements (resepctively AoA and TDoA, and AoA and bistatic range), which are finally used to solve the 2D localization system. The two types of received packets can be easily discriminated by decoding their bits, where we can find both source and destination addresses, so that they are exploited in the correct way.

Using this experimental setup, it is therefore possible to compare the localization performance of the two approaches and assess their relative merits.

3. Accuracy of device-based AoA measurements

Both device-based and passive radar target positioning techniques exploit the AoA measurement, obtained by the phase difference between the closely spaced antennas RX2 and RX3. The former extracts the AoA of the signals emitted by the WiFi devices, the latter the AoA of the AP signal scattered by the human targets towards the two closely spaced antennas.

Therefore, it is of high interest to compare the accuracy obtained by the two techniques. Unlike in the FM-passive radar case, it is not useful to attempt using multiple frequencies to increase the performance, [11]. In contrast, it is quite interesting to investigate the relationship between received signal energy and the AoA measurement accuracy. While a direct monotonic relationship is expected under ideal conditions (disturbance consisting of only constant level white Gaussian thermal noise), the practical accuracy also depends on packet distortion due to channel conflicts, interferences, etc … If the performance only depends on signal energy, it is quite essential to understand the relative number of packets available for the WiFi device-based technique and for the WiFi passive radar. Similarly, also the number of samples present inside the single packet is quite essential to obtain a global energy measure.

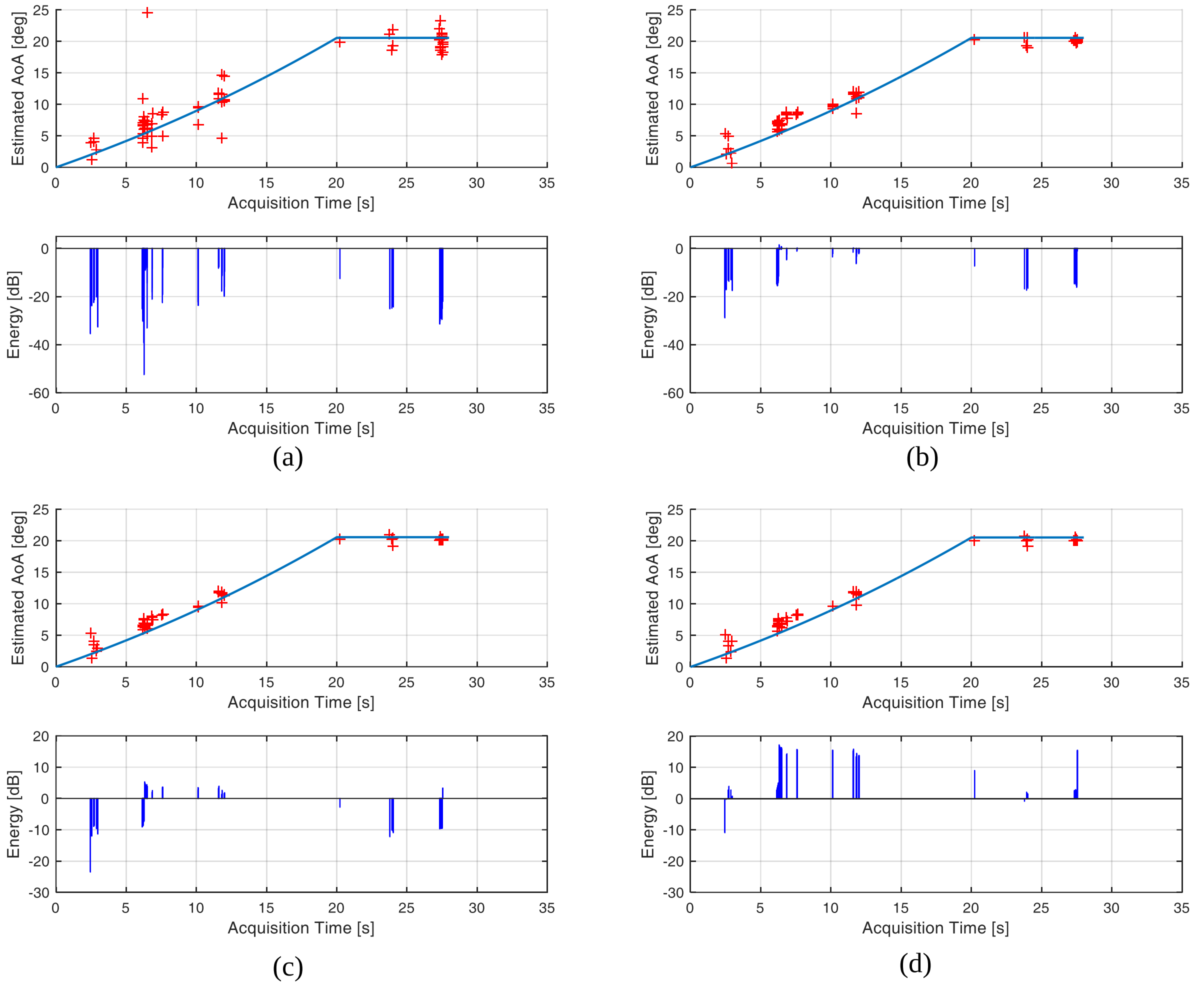

Fig. 2. Comparison between estimated AoA and the ground truth for: (a) 1, (b) 8, (c) 23 and (d) 375 samples, for the device-based technique.

We first analyze the estimate of the AoA obtained by the device-based technique. The estimates obtained using the individual packets are reported in Fig. 2 (red crosses), together with the ground truth (blue solid line). The latter is obtained by assuming that the target was moving with a uniform linear motion along the assigned path. To assess the relationship between accuracy and signal energy, subplots (a), (b), (c) and (d) are obtained by using only the first L samples of each received packet, being respectively L = 1, 8, 23 and 375.

In the lower subplot, also the corresponding energy level $E = \sum_{l=1}^{L} |s_l|^2$ is reported, for comparison, being s_l the l-th sample.

For direct comparison, Fig. 3 shows the AoA estimation error as a function of the time instant t_k, $e(t_k) = \hat{\theta}(t_k) - \theta(t_k)$, where $\hat{\theta}(t_k)$ is the estimated angle of arrival, whereas $\theta(t_k)$ represents the ground truth at the same time. As in Fig. 2, we report below the corresponding energy level for the single estimation.
We can see that, as expected, the accuracy increases when the number of samples, and consequently the energy level of the employed signal, increases. In addition, since we are in high SNR condition, the estimation provides good performance with just L=8 samples.

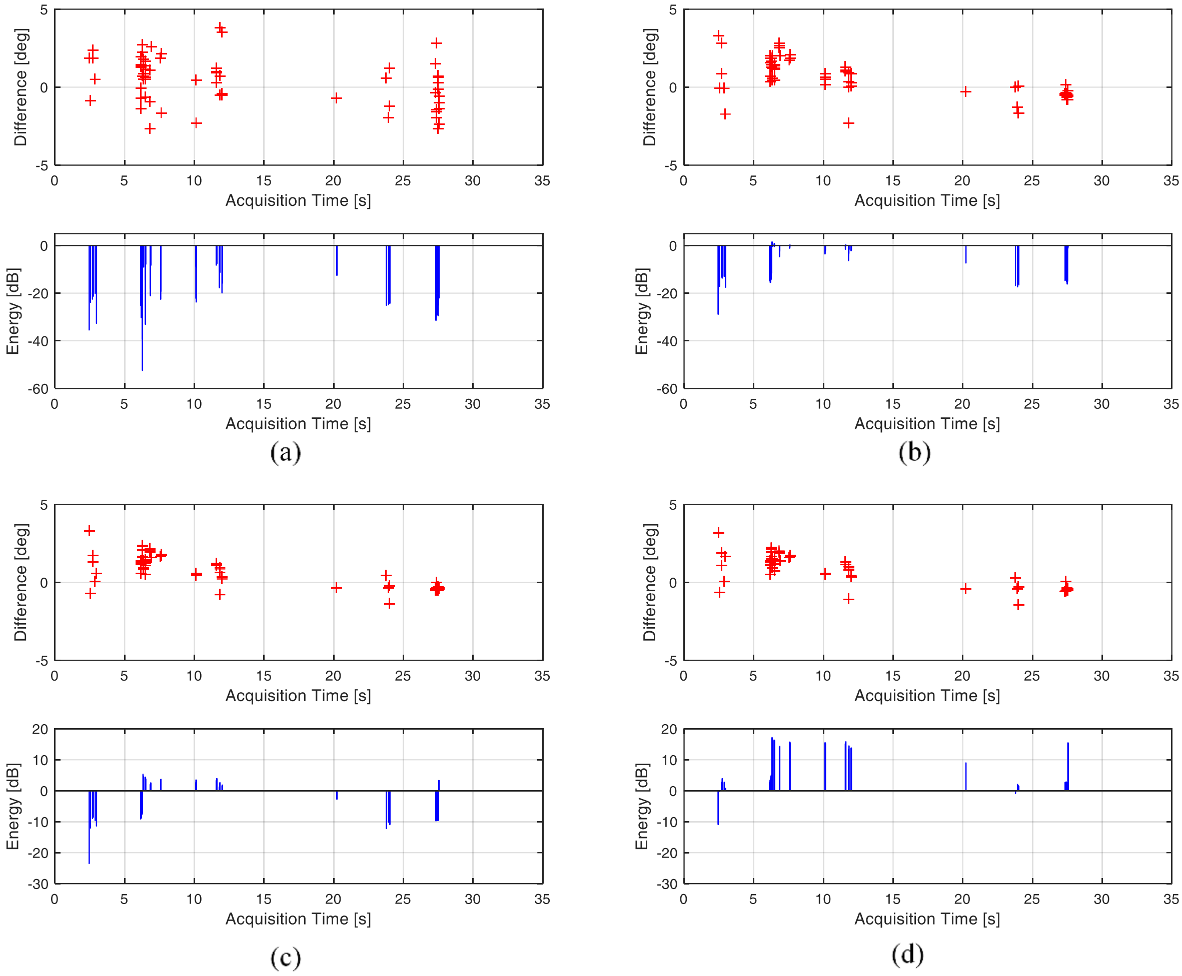

Fig. 3. Difference between the estimated AoA and the ground truth for: (a) 1, (b) 8, (c) 23 and (d) 375 samples, for the device-based technique.

From the figures above, it is clear that the signal energy is high and the estimation errors are limited even using a few samples per packet. It is interesting to analyze the impact of the degradation of the Signal to Noise Ratio (SNR) on the performance. To this purpose, we deliberately inject white Gaussian noise to degrade the SNR by 10 dB and 20 dB. In order to perform a quantitative comparison of the performance obtained in different case studies we report in Table 1 the root mean square error evaluated along the whole target path, $rmse = \frac{1}{N}\sqrt{\sum_{k=1}^{N}|e(t_k)|^2}$, based on all the available packets N. In this case also longer packet fragments are considered, with L=1, 2, 8, 23, 94, 375, 1500, 6000 and 9000 samples.

Table 1. Root mean square errors achieved without additive noise, with 10dBs of additive noise and with 20dBs of additive noise, for the device-based technique.

Number of samples	No noise	+10 dB noise	+20 dB noise
1	8.5947	13.8481	21.8472
2	5.2420	5.6495	15.5413
8	1.3111	1.4763	9.6439
23	1.1745	1.2457	6.4718
94	1.1802	1.1982	1.6206
375	1.1764	1.1784	1.3178
1500	1.1784	1.1811	1.2002
6000	7.7847	7.7676	7.7302
9000	6.8102	6.8099	6.8209

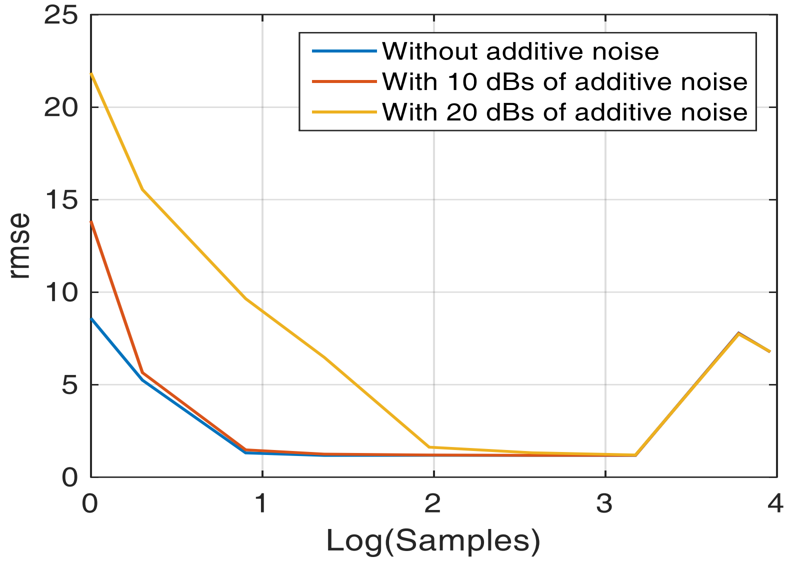

Fig. 4. Comparison between the rmse values achieved without additive noise, with 10dBs of additive noise and with 20dBs of additive noise.

Fig. 4 shows the values of Table 1, making it evident that the rmse decreases as the number of samples L increases up to the value of L=1500. After this value, a performance degradation is experienced, which has been verified to be caused by the possible presence of collisions between AP and device packets. In fact, notice that such rmse increase start at the same value of L, independently of the SNR condition. This analysis suggests to exploit only the first short portion of each emitted packet in order to limit the probability of collision. However, we also observe that, when operating against a noisier environment, a larger number of samples L is required to achieve the lowest rmse value, namely L=94 and L=1500 for SNR degraded respectively by 10 and 20 dB, instead of L=8 samples of the experiment conditions.

(a)

(b)

(c)

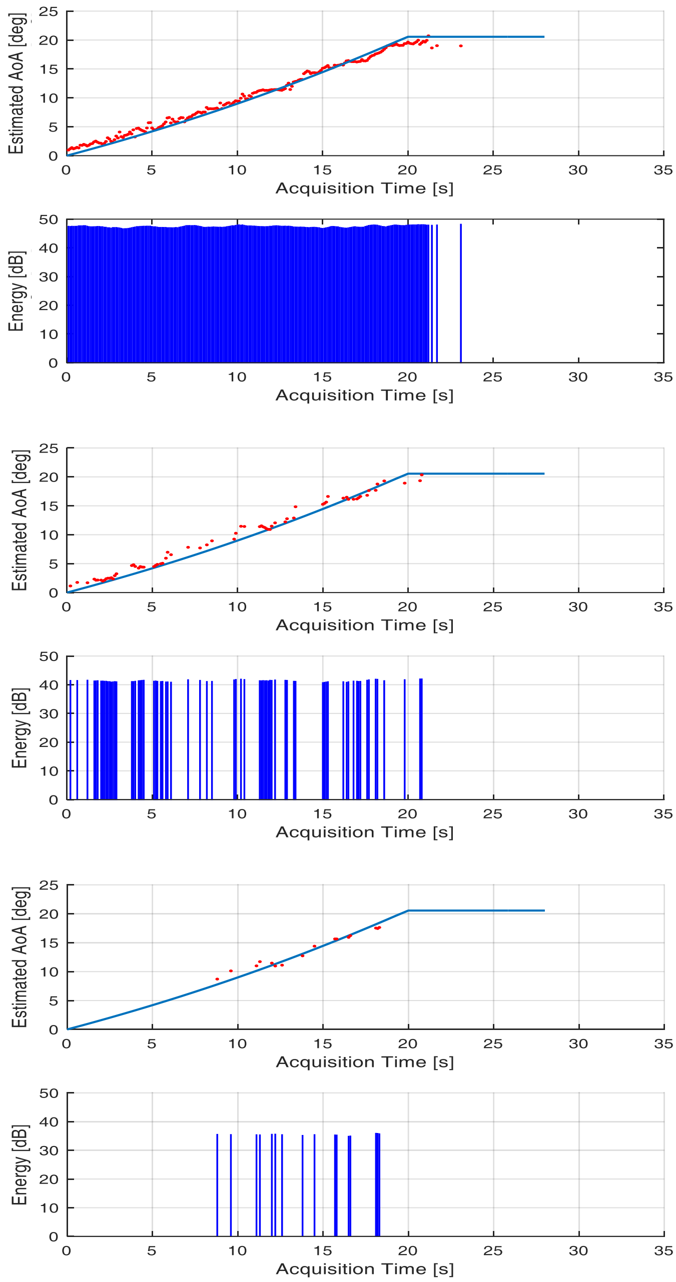

Fig. 5. Comparison between estimated AoA and the ground truth for: (a) PRT = 3ms, (b) PRT = 12ms and (c) PRT = 48ms, for the passive radar technique.

4. Accuracy of passive radar AoA measurements

A similar analysis is performed for the estimate of the AoA obtained by the passive radar technique. In this case, the AoA estimation is based on a train of coherently integrated packet echoes; therefore, the available signal energy depends both on the packet length and on the Packet Repetition Time (PRT). When exploiting all the available packets within a 0.5 s coherent integration time, we obtain the results shown in Fig. 5a.

Compared to the case of the device-based AoA approach, the measurements show a high continuity thanks to the high packet transmission rate of the WiFi AP. It has to be noted that in the passive radar case a much stronger signal attenuation is present due to the two-way propagation loss. Moreover, since the AP-emitted signals are scattered by all fixed object in the scene, appropriate cancellation filters are employed to remove all echoes from stationary objects. This allows an effective extraction and detection of the moving targets, while makes it impossible to detect and localize static persons, thus the track is lost when the target stops.

The long (0.5 s) coherent integration time clearly allows to gather enough energy to provide a remarkable estimation accuracy, as well as to separate the moving target echoes from those scattered by the stationary scene. By discarding packets in order to increase the average PRT to 12 ms and 48 ms, we obtain the results displayed respectively in Fig. 5b and 5c. As apparent, several measurements are lost in this process due to the corresponding SNR degradation, as well as to the reduction of the non-ambiguous Doppler region, that causes a partial overlap of moving target echoes with the echoes from the stationary scene that are removed.
The rmse reported in Table 2 shows a progressive decrease of angular accuracy up to PRT=24 ms. For higher values of PRT, the number of target detections is extremely reduced so that it does not allow a statistically significant result.

Table 2. Root mean square errors obtained for the passive radar technique and different PRT.

PRT [ms]	**3**	**6**	**12**	**24**	**48**
rmse	0.7493	0.7753	0.9561	1.4083	0.7514

An alternative way to degrade the available SNR is to limit the number of samples exploited for each packet within the coherent integration time of 0.5 s. The results are reported in Fig. 6 for 9000, 6000 and 375 samples. Table 3 compares the rmse for the entire packet to the rmse obtained using the first L= 9000, 6000, 1500 and 375 samples.
It is evident that with 375 samples the AoA estimation is less accurate than for longer packet fragments due to the reduced SNR. However, Table 3 shows that the estimation accuracy is sufficiently robust to a reduction of the packet length until the number of samples L falls below 6000 and even in this case it outperforms the device-based technique, except for static targets.

Table 3. Root mean square errors obtained for the passive radar technique and different number of samples.

Number of samples	**375**	**1500**	**6000**	**9000**	**Entire beacon**
rmse	0.9429	1.0011	0.7619	0.7591	0.7493

While this analysis has been performed using beacon transmissions by the AP, it shows that the passive radar technique can be effectively exploited against moving targets even in the presence of short data packets or using few collected samples to reduce processing hardware and costs.

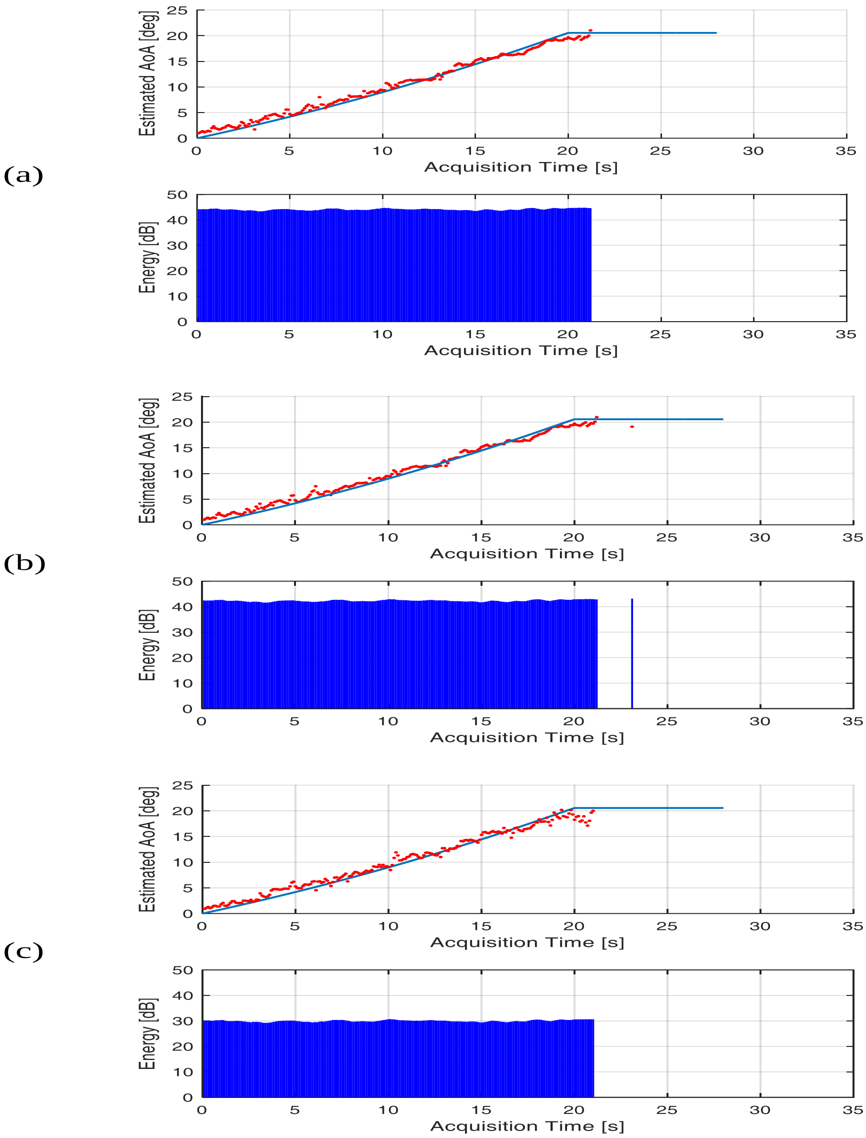

Fig. 6. Comparison between estimated AoA and the ground truth for: (a) 9000, (b) 6000 and (c) 375 samples, for the passive radar technique.

5. Conclusions

In this paper, the accuracy of the AoA measurements necessary for the 2D localization has been investigated. The analysis was performed on experimental data for two different techniques: the WiFi-based passive radar, which exploits the AP transmissions as signals of opportunity, and the WiFi emission-based technique, which uses the transmissions of an active mobile device.

These techniques are characterized by different transmission rates of the employed signals. In fact, while the passive radar can exploit the periodical beacon transmission of the AP (approximately each 3 milliseconds), the device-based approach has available only the signals sent during the device upload activities. In particular, in this work, we only analyzed connection activities between the AP and the mobile device, so that there is a very limited upload activity from the device, which affects the performance of device-based techniques.

For the device-based localization, the study has been performed through the estimation of the parameters of interest using different packet lengths. The basic idea is to emulate the decrease of the SNR, in order to observe its influence on the localization accuracy. As expected, the results for the AoA have shown that a lower number of samples lead to a poor SNR, which provides poor performance in terms of accuracy. In contrast, the probability that a collision occurs increases with the number of samples.
For the passive radar, in addition to the employment of less samples, as for the device-based localization, the effect of the reduction of the PRF has been investigated. This time the main problem is the loss of detections, which does not allow the target localization. This situation is typical of loaded networks, where the AP has to share the medium with other stations, which might also transmit with a high transmission rate. It is evident that, in these conditions, the device-based technique provides better performance with respect to the passive radar thanks to the possibility to exploit much more transmissions. Therefore, the complementarity of the techniques presented in this paper, makes attractive the possibility to integrate the described methodologies in a single system that could estimate continuously the target position in different network conditions. Similar results can be obtained for the time-difference of arrival.
In addition, the results of this paper suggest the possibility of using less samples with respect to the entire packet, without compromising the performance. This allows of reducing the computational cost of the whole processing, that is essential for localization applications.

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