WiFi Emission-Based vs Passive Radar Localization of Human Targets

Ileana Milani, Fabiola Colone, Carlo Bongioanni, Pierfrancesco Lombardo

Department of Information Engineering, Electronics and Telecommunications

Sapienza, University of Rome

Via Eudossiana 18, 00184 Rome, Italy

{ileana.milani; fabiola.colone; carlo.bongioanni; pierfrancesco.lombardo}@uniroma1.it

Abstract— **In this paper two approaches are considered for human targets localization based on the WiFi signals: the device emission-based localization and the passive radar. Localization performance and characteristics of the two localization techniques are analyzed and compared, aiming at their joint exploitation inside sensor fusion systems. The former combines the Angle of Arrival (AoA) and the Time Difference of Arrival (TDoA) measures of the device transmissions to achieve the target position, while the latter exploits the AoA and the bistatic range measures of the target echoes. The results obtained on experimental data show that the WiFi emission-based strategy is always effective for the positioning of human targets holding a WiFi device, but it has a poor localization accuracy and the number of measured positions largely depends on the device activity. In contrast, the passive radar is only effective for moving targets and has limited spatial resolution but it provides better accuracy performance, thanks to the possibility to integrate a higher number of received signals. These results also demonstrate a significant complementarity of these techniques, through a suitable experimental test, which opens the way to the development of appropriate sensor fusion techniques.**

Keywords—WiFi transmissions; passive radar; device-based localization; human targets localization.

I. INTRODUCTION

In the recent years, great effort has been devoted to the localization of human targets in local area environments, thanks to the possibility to exploit positioning information for many applications, such as surveillance, monitoring, services, etc.

In outdoor environments, this operation is obtained through the exploitation of satellite signals, using global navigation satellite systems as GPS, Glonass or Galileo. As well known, these signals cannot be used indoor. For this reason, an alternative solution is to employ other RF signals for localization purposes. Depending on the requirements of the specific application, several waveforms can be exploited as, for example, FM [1]-[2], DVB-T [3] and WiFi signals [4]-[8].

Different approaches can be considered to perform localization when exploiting these signals. In particular, two major classes can be discriminated based on whether an active device carried by the human target is required or not. Obviously, both classes of localization techniques have inherent advantages and drawbacks. A recent comprehensive review of such techniques is presented in [9], which compares the relative merits and issues.

In particular, the expansion of the WiFi networks in urban environments has led to the employment of WiFi signals in several applications, thanks to the coverage that they offer in both indoor and outdoor environments. It is clear that this characteristic makes them especially suitable for short range localization and surveillance applications. Therefore, this paper focuses on this type of signals to achieve human target localization.

The objective of this work is to compare the relative performance of two localization techniques, based on the IEEE 802.11 Standard, [10], and to verify their complementarity. In particular, we aim at analyzing and comparing the WiFi-based passive radar technique and the WiFi emission-based technique, whose concept is depicted in Fig.1. This is considered to be the first step for the development of appropriate sensor fusion techniques.

In the past, we have developed a WiFi-based passive radar [5]-[8], which performs the localization and tracking of moving targets, there including vehicles and human targets. In particular, as explained in [7], the localization can be performed using different set of measures, e.g. range/Doppler/Angle of Arrival (AoA). Due to the possibility to obtain the human target position without the necessity for the target to carry a device, this technique can be inserted into the group of the "Device-free localization" methodologies. It makes the WiFi-based passive radar attractive for local area surveillance and monitoring
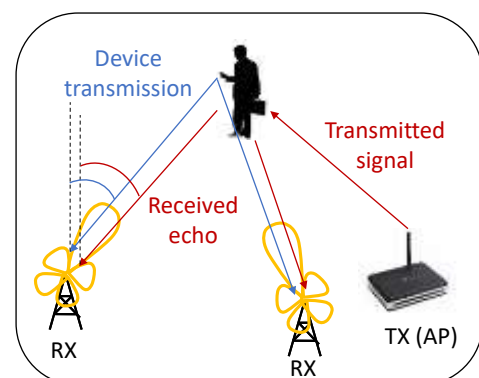

Fig. 1. Sketch of WiFi-based passive radar and WiFi emission-based approaches.

applications, especially where the targets cannot be assume to be cooperative, as in typical security applications. As well known, the passive radar does not allow the detection of stationary targets, due to the background echoes cancellation stage performed during the processing. Moreover, due to the frequency bandwidth of the WiFi waveforms, spanning from 11 to 20 MHz, the range resolution is not better than a few meters, which makes it difficult to discriminate closely spaced persons. In contrast, good localization performance can be achieved when the target is sufficiently separated either in range or in Doppler frequency from the other targets and it is not static. In this case, it is typical that a big number of echo packets can be integrated, so that a reasonable power can be collected from the target, which in turn provides an accurate position measurement.

The autonomous RF emissions of devices that attempt to connect to the WiFi network allow us a different way to localize the human targets. As mentioned also in [9], to reach this purpose, many techniques have been investigated and applied. Largely used are position solutions based on the estimation of AoA, Time of Arrival (ToA), and Time Difference of Arrival (TDoA). As apparent, this only allows localizing human targets carrying an active WiFi device. In addition, it could be potentially inaccurate for moving targets. On the other hand, it is an interesting solution for stationary targets localization and it allows the unambiguous association of the transmission to a specific target, based on the device code, so that even very closely spaced persons can be discriminated.

In this work, we show the result of controlled localization experiments that allow us to analyze and compare the performance of passive radar and device-based localization approach and investigate their complementarity. Clarifying both relative merits and characteristics makes them attractive for their fusion into a unified localization system that exploits the best of each approach and classifies types of targets. Therefore, to show the effective results, we start from the illustration of an experimental campaign, which gives us the data for both the passive radar and WiFi-emission based strategies analysis. Then, we analyze the results obtained by the individual approaches, before comparing them and presenting our discussion.

The paper is organized as follows. In Section II, we describe the experimental setup and the test that we carried out to perform our analysis. The WiFi emission-based localization is presented in Section III, where we define the necessary equations and the related results. Similarly, the results obtained with the WiFi-based passive radar are shown in Section IV. In Section V, we compare the previous techniques. Finally, we draw our conclusions in Section VI.

II. EXPERIMENTAL CAMPAIGN

The tests were performed in an outdoor environment (a parking area in Cisterna di Latina, Italy).

The illuminator of opportunity of the passive radar system was a commercial wireless Access Point (AP, D-Link DAP 1160), which was connected to a transmitting directive antenna.

Its transmissions were also used to establish the communication between AP and mobile devices. The AP was configured to transmit in channel 4 of the WiFi band (carrier frequency equal to 2.427 GHz). The beacon interval was set to 3 milliseconds, that defines the Pulse Repetition Time (PRT) of the passive radar.

The USRP 2955 by National Instrument was used to acquire the data. It is a four-channel receiving system for Signals Intelligence and Spectrum Monitoring Applications, which offers phase alignment through local oscillator sharing, enabling the creation of multi-antenna phased arrays and direction finding solutions. In addition, it gives the possibility to separately control the output gain of each receiving channel (from 0 to 95 dB).

For this experimental campaign, the acquisition system was characterized by three receiving channels, connected to three surveillance antennas (D-Link ANT24-1200). These antennas are characterized by a Horizontal Half Power Beam Width of about 80°, a Vertical Half Power Beam Width of about 23°, and a peak gain of 12dBi. In addition, we set an additional gain for each USRP receiving channel in order to have a comparable signal level. The gains are set to compensate the attenuations due to the employment of different length cables. In fact, as displayed in Fig. 2, two receiving antennas were located one beside the other, near the receiving system, whereas the third one was placed 25 m far from them, close to the transmitting antenna.

The acquired signal was sampled with a sampling frequency of 22 MHz, then it was stored and processed off-line. The first processing operation is the classification of the acquired packets, based on the possible transmitting source, to perform the association between packet and target (or AP).

During the acquisition measurements, we built a grid on the ground, whose 9 points have been used for the calibration stage and for comparing the estimated positions with the ground truth. For the calibration stage, we put the AP on each different point of the grid and we recorded few seconds of transmission. The
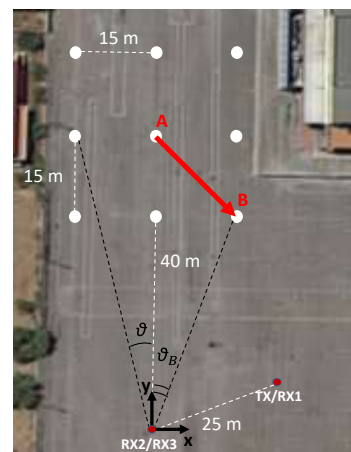

Fig. 2. Target localization and tracking experiment

AoA and the TDoA have been evaluated for each point and then they have been compared with the ground truth. The Minimum

Mean Square Error (MMSE) approach has been used to estimate the errors to be compensated for. As it is apparent, the correction of the angle error can be applied to both the techniques, while the TDoA offset is related to the length of the used cables.

After that, we carried out a test that could be interesting for both the techniques described before and could show the analogies and the complementarity between them. In this test, as shown in Fig. 2, a target with an active mobile device moves from the central point of the grid, namely the point A in the figure, and arrives to the point B. The acquisition duration is about 28s. The target takes 20s to reach point B, and then he stops there for about 8s.

During the whole 28 seconds, the user attempts connecting to the WiFi router used as illuminator multiple times, but there is not an ongoing continuous data upload. While a continuous upload would increase the emissions from the device, this condition appears to be largely more representative of a typical practical case, where a specific device is not strongly loading the network and the router is able to accept many connections.

III. WiFi EMISSION-BASED LOCALIZATION

Based on the receiver configuration presented in Section II, the WiFi emission-based localization can be obtained by measuring the AoA and the TDoA of the WiFi signals transmitted by the mobile device and received by the multiple receiving antennas. In practice, three receiving antennas are used to measure the device AoA and TDoA. In particular, the phase difference, $\widehat{\Delta\varphi}$, between the signals collected from each of the two closest antennas (RX2 and RX3 in Fig. 2) is used to estimate the angle of arrival, $\hat{\theta}$, of the target, as

$$\hat{\theta} = arcsin\left(\frac{\lambda \cdot \widehat{\Delta\varphi}}{2\pi d}\right) \qquad (1)$$

where λ is the wavelength related to the selected WiFi channel, and d is the distance between RX2 and RX3. To obtain a reliable estimate of the phase difference, $\widehat{\Delta\varphi}$, a Maximum Likelihood estimation technique is used, which leads to the following expression

$$\widehat{\Delta\varphi} = \angle s_2^H s_3 \qquad (2)$$

where s_2 and s_3 are the vectors containing the samples of the packets received by antennas RX2 and RX3, respectively.

The displaced antenna (RX1), which is located close to the TX in our experiment, is necessary to measure the TDoA. This is obtained by searching the peak of the cross-correlation between the signals received by RX1 and RX2:

$$\widehat{\Delta\tau} = \underset{\Delta\tau}{\operatorname{argmax}} \{R_{s1s2}\} \qquad (3)$$

From these two measures, we can perform the XY-localization through the intersection of a line (AoA) and a hyperbola (TDoA). In particular, we found:

- $$\widehat{x_t} = \begin{cases} \dfrac{(x_1^2+y_1^2)-(\widehat{\Delta\tau}\cdot c)^2}{2(x_1+\hat{m}y_1+\widehat{\Delta\tau}\cdot c\sqrt{\hat{m}^2+1})}, & if\ \hat{m} > 0 \\[4mm] \dfrac{(x_1^2+y_1^2)-(\widehat{\Delta\tau}\cdot c)^2}{2(x_1+\hat{m}y_1-\widehat{\Delta\tau}\cdot c\sqrt{\hat{m}^2+1})}, & if\ \hat{m} < 0 \end{cases} \qquad (4)$$

- $$\widehat{y_t} = \hat{m}\ \widehat{x_t}$$

where $\widehat{x_t}$ and $\widehat{y_t}$ are the estimated coordinates of the target in the Cartesian reference system centred in RX2/RX3, x_1 and y_1 are the coordinates of RX1 in the same system, c is the speed of light, and $\hat{m} = \hat{m}(\hat{\theta})$ is the estimated slope of the line defined by the AoA.

The above device-based target localization technique has been applied to the experimental data and the resulting performance is presented in Fig. 3. The resulting AoA and the TDoA estimates for the target-device transmissions are shown in Fig. 3(a) and Fig. 3(b), respectively (red crosses). Each point is the results of the coherent time integration of packets, and it depends on the number of device transmissions occurred in that particular time interval. The integration time was set to 0.5s.

For comparison, also the ground truth is reported in the same plots (solid blue lines).
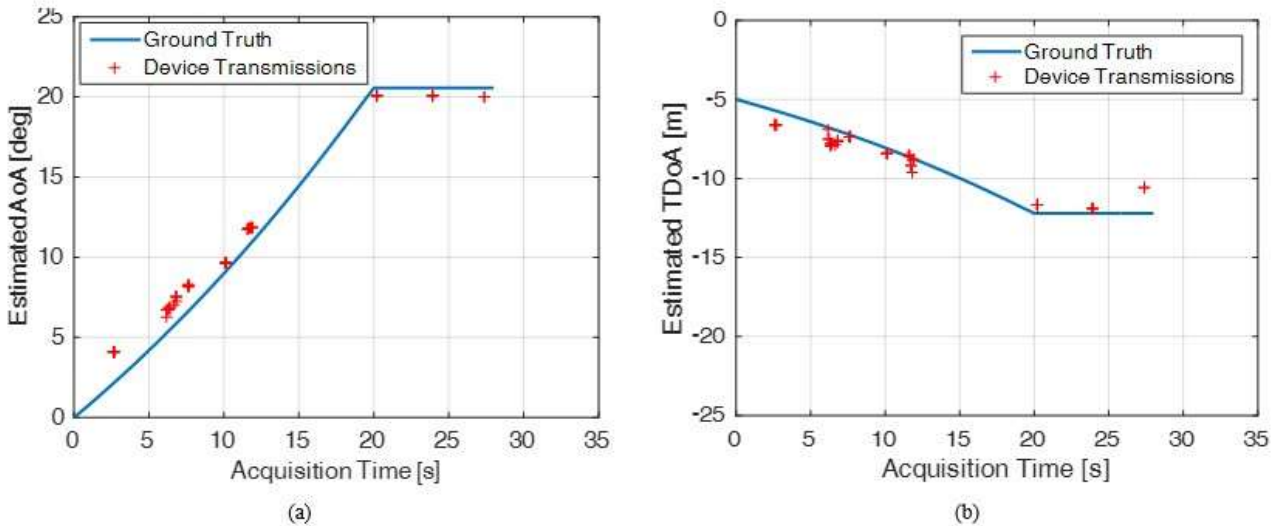

Fig. 3. Performance evaluation of device transmissions: (a) AoA estimation, (b) TDoA estimation
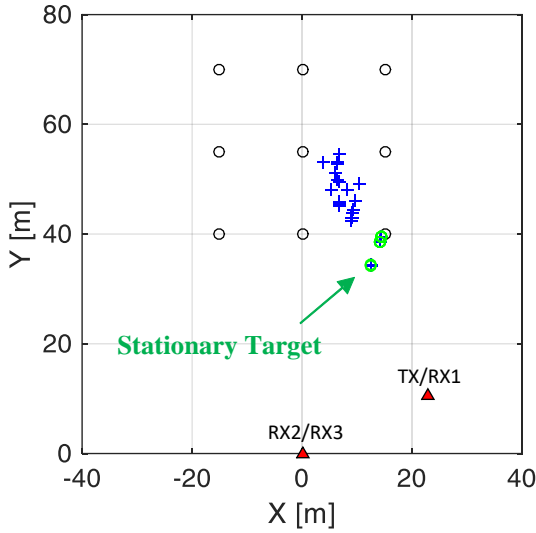
Fig. 4. XY-localization of the human target with device transmissions-based technique

The results show that the main problem of this technique is the limited number of device transmissions available for the estimation that allows us to reach a poor Signal-to-Noise Ratio (SNR) after the integration in the 0.5s. This is quite apparent by considering the interval between 13 and 20s in Fig. 3, where there are no transmitted packets by the device under examination, so that both AoA and TDoA measurements are missing.

Fig. 4 shows the results obtained when the AoA and the TDoA values are combined to get the estimates in the XY-plane. In this figure, the black circles indicate the nine points of the grid created on the ground, whereas the red triangles represent the positions of the receiving antennas. The position estimates are shown using blue crosses during the first 20s. The blue crosses are changed to green circles for the final 8s, to represent the estimates of the target position that is known to be stationary in this last part of the experiment. It can be noticed that the path of the target is correctly identified, but the estimates are quite variable when compared to the theoretical behavior (see red line in Fig. 2). This makes this technique effective but not very accurate. As explained before, this depends principally on the small number of packets available for the device, during the common connection activity.

IV. WiFi PASSIVE RADAR LOCALIZATION

The passive radar localization experiment was carried out at the same time of the device-based one, so that the same antennas configuration and the same target motion are present. Therefore, it is possible to evaluate the position, for example, through the measure of the bistatic range and the AoA of the received target echoes, as explained in [8]. This time, we have used the two closest antennas (RX2 and RX3) for the measure of both the bistatic range and the AoA, whereas the third antenna (RX1) has been exploited to acquire a copy of the reference signal. In fact, the processing is based on the evaluation of the bi-dimensional Cross-Correlation Functions (2D-CCF), obtained by cross-

correlating the surveillance signals received at RX2 and RX3 with the reference signal (received at RX1) on a pulse by pulse basis. Thereafter, the obtained results are coherently integrated over a set of consecutive pulses. This requires to be repeated for all Doppler frequencies of interest, thus providing the 2D output as a function of both bistatic range and bistatic Doppler frequency. To simplify the comparison of the results, as for the WiFi emission-based localization technique, the coherent integration time is set to 0.5s.

The processing scheme includes the range and Doppler sidelobes control, and the clutter/multipath cancellation stage for the disturbance removal. These processing schemes are applied to both the surveillance signals received at RX2 and RX3. After that, the range/Doppler maps are evaluated and the CFAR threshold is applied; target detection is declared only for the targets that exceed the threshold on both the receiving channels. Thereafter, the tracking of the detected targets is performed and both the angle of arrival and bistatic range are estimated. This allows to obtain the position of the target on the XY-plane, by intersecting a bistatic ellipse (range) and a line (AoA), which provides the following solution:

- $$\widehat{x_t} = \begin{cases} \dfrac{(x_{TX}^2+y_{TX}^2)-(\hat{R}_{bis})^2}{2(x_{TX}+\hat{m}y_{TX}-\hat{R}_{bis}\sqrt{\hat{m}^2+1})}, & if\ \hat{m} > 0 \\[4mm] \dfrac{(x_{TX}^2+y_{TX}^2)-(\hat{R}_{bis})^2}{2(x_{TX}+\hat{m}y_{TX}+\hat{R}_{bis}\sqrt{\hat{m}^2+1})}, & if\ \hat{m} < 0 \end{cases}$$ (5)

- $$\widehat{y_t} = \hat{m}\,\widehat{x_t}$$

where $\widehat{x_t}$, $\widehat{y_t}$ and $\hat{m} = \hat{m}(\hat{\theta})$ are defined as in (4), whereas (x_{TX}, y_{TX}) are the coordinates of the transmitter and $\hat{R}_{bis}$ is the estimated bistatic range.

In detail, the AoA is obtained using the same approach of the WiFi emission-based technique, namely through the estimation of the phase difference between the signals received at RX2 and RX3. In this case, the specific locations of the 2D-CCF, where the target has been detected, provide the estimate of the bistatic target range. Moreover, the phase difference is estimated as the phase difference of specific locations of the 2D-CCFs available for the two surveillance antennas, where the target has been detected.
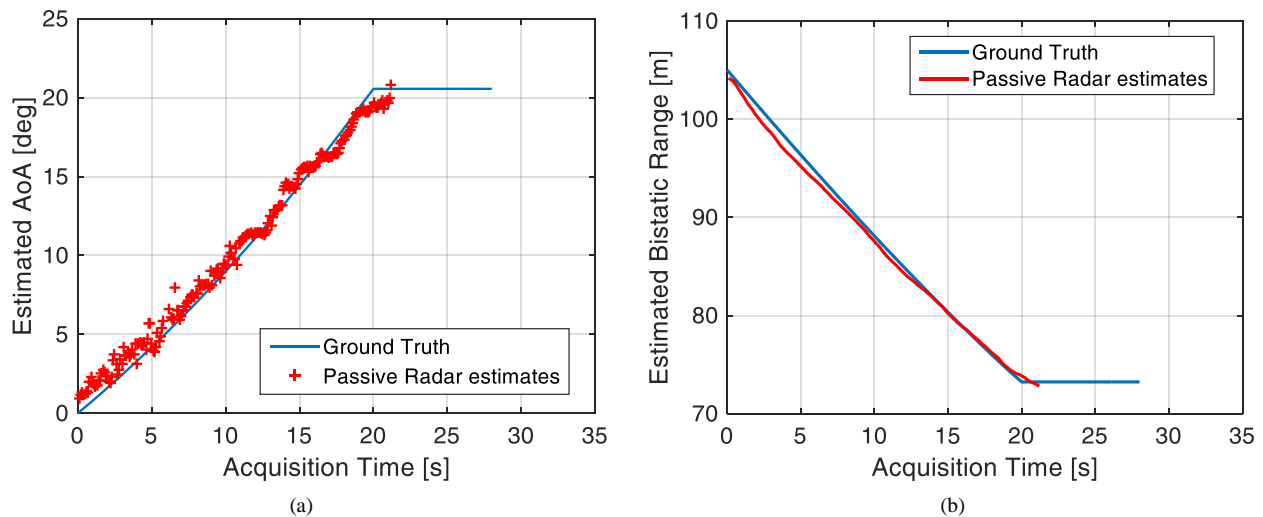
Fig. 5. Performance evaluation of passive radar technique: (a) AoA estimation, (b) bistatic range estimation
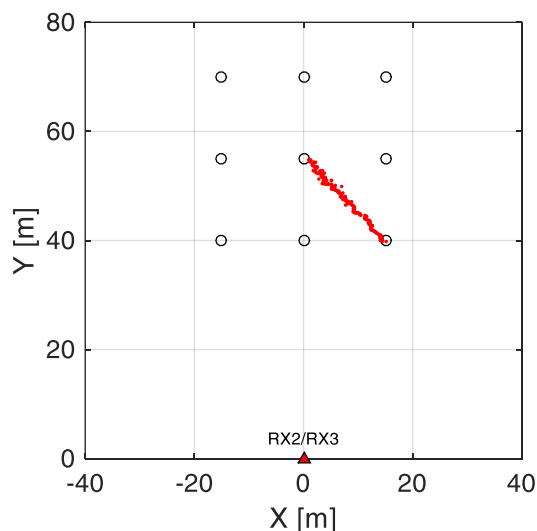

Fig. 6. XY-localization of the human target with passive radar technique

As mentioned above, the calibration for the angle estimation is the same for the WiFi-based passive radar and for the WiFi emission-based technique. The results obtained for the AoA (red crosses) and the bistatic range (solid red line) estimation, and their comparison with the ground truth (solid blue line), are shown in Fig. 5(a) and Fig. 5(b), respectively. For the bistatic range, a conventional Kalman tracking algorithm has been applied, which provides filtered range values [8]. It is interesting to see that both the estimates of AoA and bistatic range follow the theoretical behavior for all the time that the target is moving, namely until it arrives at point B (from seconds 0 to 20 of the acquisition). After that time, it is impossible to detect the target and in consequence measure angles and ranges. This is due to the cancellation stage employed by the passive radar processing chain that cancels all the echoes from static objects in the field of view, and therefore also the echoes of a static human target.

In consequence, during the last 8 seconds the target disappears from the passive radar results.

By combining the two measures of AoA and bistatic range, during the first 20s, the position estimation is easily obtained in the XY-plane and displayed in Fig. 6. It is apparent that the passive radar technique provides a fairly accurate estimate of the human target's position.

V. TECHNIQUES COMPARISON AND COMPLEMENTARITY

It is interesting to compare these two methodologies to understand relative merits and the relationship between them.

Firstly, we compare the AoA measurements, since they are available for both sensors and are quite homogeneous quantities. As shown in Fig. 7, during the first 20 seconds of the acquisition, the two strategies lead to comparable results. However, it is apparent that the passive radar has a higher number of angle estimates, which provides an almost continuous set of measurements. In contrast, the WiFi emission-based approach provides a reliable estimate only when bursts of packets are emitted. In our case, this provides a rather discontinuous set of measurements that is not quite desirable when the target is moving, since its AoA changes with time. As expected and discussed above, the WiFi emission-based localization technique has a key role when the target is stationary (from 20 to 28 seconds) since the passive radar system cannot detect it.

In Fig. 8, we present the comparison of the results obtained for the positions in the XY-plane. As apparent from the dispersion of the measurements, we can assert that the WiFi-based passive radar localization (red dots) provides better performance with respect to the device-based technique (blue crosses). This is due to the possibility to exploit a higher number of packets for the estimation of the measures of interest. In fact, we have to remind that the temporal distance between consecutive beacons is equal to 3 milliseconds, whereas the device transmits only when a communication with the AP
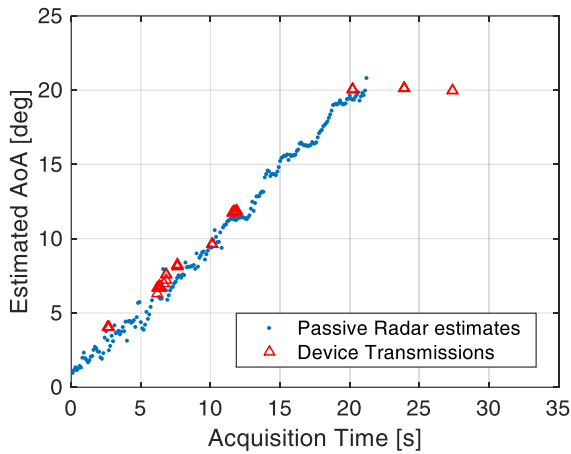
Fig. 7. Comparison between the AoA estimation with the passive radar technique and the WiFi emission-based technique
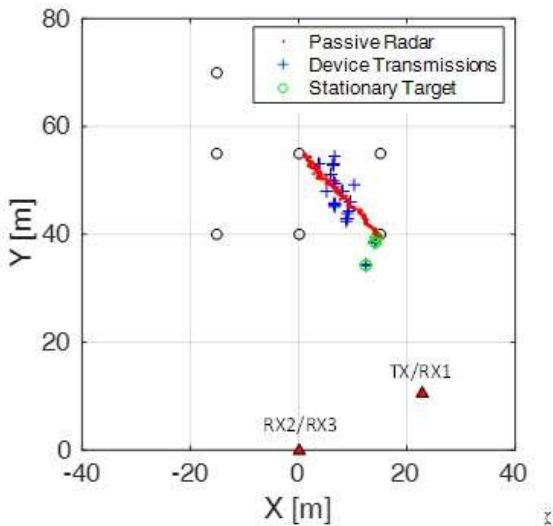

Fig. 8. Comparison of the WiFi emission-based and the passive radar localization on the XY-plane

occurs. In this particular experimental test, the device sends packets only to establish the connection with the AP.

The following additional considerations apply:

(i) the range resolution of the passive radar is limited due to the limited frequency bandwidth of the WiFi signals. This makes it difficult to discriminate closely positioned targets;

(ii) the device-based technique can exploit the device code to discriminate between multiple closely spaced targets; in fact the acquired device signals can be associated to the related target, thanks to the classification stage, based on the reading of the MAC Address written in the packets, which is performed before the localization operations.

(iii) the better performance of the passive radar is paid in terms of a higher computational cost with respect to the emission-based technique.

Summarizing the previous considerations, it is evident that these techniques present complementary aspects, which makes them suitable for a possible joint use of them. Firstly, the passive radar can help when the target has no active devices, so that the emission-based localization cannot be used. On the other hand, only the device-based technique can estimate the position when the target is stationary.

In addition, the passive radar can exploit a considerable number of data for the estimation of the measures of interest, thanks to the high transmission rate of the AP, whereas the emission-based technique uses only the signals transmitted by the mobile device during the connection with the AP.

Under different conditions, the relative performance of the two can be somewhat different. In particular, if the target increases its device transmissions, for example in upload activities, the number of AP emissions (especially in terms of emitted beacons) decreases. In this case, the WiFi emission-based localization would provide much more position estimates, whereas the signals available for the passive radar measurements would be reduced. Due to the impossibility to have simultaneous transmissions of AP and devices, it is clear that the joint use of both the techniques might compensate for the lack of data for one of them in a real scenario.

The considerations above provide a sound technical basis for a sensor fusion technique, which is under development. This is expected to exploit at the best both the signals emitted by the AP and those emitted by the devices to provide a continuous tracking of the human targets carrying an active WiFi device, while only resorting to the passive radar for human targets that do not carry any device.

VI. CONCLUSION

In this paper, we have investigated the relative merits of device-based and device-free passive radar techniques, together with their complementarity. The former exploits the signal emitted by the devices, so that provides measurements only when packets are transmitted by the device, but have the capability to identify and discriminate even very closely spaced targets and measure their position also when they are stationary

The passive radar (device-free) technique exploit the signals emitted by the AP, which tends to be more continuous due to the periodic environment scanning provided by the transmission of the beacon signals, and provides quite accurate measurements. Its quality tend to reduce when a significant activity is performed by the devices, which reduces the number of emitted beacon signals. In addition, it has poor spatial target resolution capability and cannot detect or track stationary targets.

The considerations above provide a sound technical basis for a sensor fusion technique, which allows to benefit of the good spatial discrimination and identification capability of the device-based technique, together with its capability to position static targets, as well as of the capability of passive radar to detect and position human targets that do not carry an active device. Such technique, which is presently under development, exploits at the best all both the signals emitted by the AP and those emitted by

the devices to provide a continuous tracking of the human targets carrying an active WiFi device.

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