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Robust distributed sensing with heterogeneous devices

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Abstract: In the ISM band multiple wireless technologies compete for a limited amount of spectrum, leading to interference and performance degradation. Reliable information on the spectrum occupation enables more optimal usage and can improve co-existence in the ISM band. In this paper, we study the robustness of the information obtained about the propagation environment when sensing with multiple, heterogeneous devices, at multiple diverse locations. More specifically, we look into the impact on the path loss estimation depending on the type, number and the location of the sensing devices. The analysis in this paper is done based on indoor measurements in the ISM band. Based on the presented measurements and analysis we conclude that analysis based on only one device type or in specific locations can lead to suboptimal or even incorrect estimation results.

Keywords: distributed sensing, robust sensing, measurement, heterogeneous devices

1. Introduction

The reliable detection of the presence of different wireless technologies is one the key enabling functionalities to improve the co-existence in the ISM band. Spectrum sensing is one of the most popular technologies to obtain this information.

In this paper the robustness of information obtained about the propagation environment using multiple, heterogeneous devices for spectrum sensing in multiple locations is studied. We used 6 different hardware platforms to capture the received power level while transmitting a controlled, constant 20 MHz wide OFDM signal modelled according to a repeated Wi-Fi packet transmission on WiFi channel 8. We use least squares regression to estimate the path loss environment and evaluate our results for the different hardware platforms guided by three questions:

1. What is the influence of the number of measurement points used on the accuracy of the spectrum view?
2. Should measurements in different locations be given a different weight when using them as input for building a path-loss model for the considered environment?
3. How heterogeneous is the conclusion drawn with different hardware solutions and can different heterogeneous measurements be combined to create a more reliable view of the spectrum?

Our study is different from previous work since it compares a large number of different sensing platforms. Although there has been a lot of work experimentally investigating the accuracy of sensing solutions, none of these studies experimentally compare the results of different sensing solutions or the impact of selecting specific distributed indoor locations to build a view on the spectrum environment. This work is a continuation of our previous work presented in [1], where the scope was limited to single-location sensing and no combination of multiple sensing measurements was investigated.

In [2] measurement data obtained in various outdoor locations is compared with various known path loss models, to verify how accurately each of those models predicts the propagation environment. Similarly, in [3] they study how feasible it is to use a database that is computed off-line to predict the propagation environment. To that extent, a pre-computed database is compared with measurement results obtained using dedicated measurement equipment. In contrast, the goal of this study is not to compare various path loss models (in fact, we use a very simple one), but to compare different types of sensing hardware and to determine how grouping the different spectrum sensors based on their location impacts the spectrum observation quality. Also, it is studied how much measurements on different locations and from different devices are needed to get to a reliable interpretation of the environment.

The remainder of this paper is organized as follows: section 2 introduces the metrics and hardware that are used, the calibration step and the processing. Section 3 describes the measurement setup and measured results. In sections 4, 5 and 6 the impact of the type, number and location of the devices is investigated. Finally, section 7 concludes this paper and gives some recommendations for robust distributed sensing with heterogeneous devices.

2. Methodology

One of the main concerns of sensing based opportunistic spectrum access is the robustness of the sensing information against environmental influences (such as shadowing and fading) and the robustness for spatial extrapolation (use information gathered in one location to estimate the spectral environment in another location). In this paper we investigate the above concerns based on large-scale distributed spectrum sensing experiments. What is important in the setup of the experiment, is first to determine the metrics of interest that will be used to interpret the sensing data, the technical details of the different sensing solutions used, how to (pre-) calibrate the different sensing solutions and finally how to (post-) process the different data sets in order to be able to fairly compare their results. These aspects are discussed below.

2.1 – Metrics

We use our measurement data to estimate the path loss exponent α and offset β of the well-known path loss model:

$$PL(d)\ [dB] = 20\ \alpha \log 10\ (d) + \beta$$

where d is distance between Tx and Rx in meter and PL is the path loss in dB. From the measurements we have path loss estimates for known distances so we are looking for α and β that provide the best match to this dataset. We test a least squares regression and robust fit algorithm to determine α and β coefficients. The least squares regression will attribute an equal weight to each set of inputs and the outcome will be α and β which will result in the minimum mean squared error over the complete set of inputs. Since least squares can be biased and drawn towards outliers we additionally fit the model using robust regression. The robust regression will iteratively attribute weights in such a way to reduce the impact of outliers.

We use the mean squared error (MSE) of the measurement points as a metric to judge the performance of a specific solution. There are two scenarios we use for reference:

the homogenous device reference and the heterogeneous device reference. In the homogeneous reference scenario, we compute the MSE to the regression based on the measurements of only one device (devRef). For the heterogeneous reference we compute the MSE to the regression based on the measurements of all devices (allRef). The heterogeneous reference is thus treated as a ground truth.

The general approach for all evaluations is that we use regression to estimate the path loss exponent α and the offset β using only a subset of the measurement points. This comes down to estimating the global path loss model with a set of local measurements. To assess the goodness of fit of this estimation, we compare it to the two references (devRef and allRef) described above. The difference between the estimated path loss model and the references is measured by the MSE. The MSE is directly related to the quality of the estimated path loss model, which eventually can serve as an indication of how suitable the corresponding estimation is in terms of distributed sensing.

2.2 – Hardware used

A range of six heterogeneous devices were used in the experiment, from low-cost commercial-off-the-shelf devices, to more sophisticated custom implementations. The following is a list of the devices used:

- Metageek Wi-Spy 2.4x with Kismet Spec-tools for Linux OS [4]
- Crossbow/Memsic TelosB [5][6] with CC2420 transceiver [7] and TinyOS application [8]
- Fluke Airmagnet Spectrum XT [9]
- Ettus Research USRP 2.0 [10] with XCVR 2450 daughterboard and Iris [11]
- VESNA sensor node [12]
- Imec sensing engine [13][16]

Rohde & Schwarz lab equipment (SMIQ06 & AMIQ02 [17]) is used to generate the test signals.

2.3 – Calibration

To calibrate the devices, each device was connected to a signal generator via a cable and power splitters. We transmitted the test signal also used in the experiments at different power levels and used these measurements to compute the offset on measurement levels reported by the different devices. Apart from this “automatic” calibration we also did a manual calibration based on the real measurements (e.g. to account for the antenna effects). We detected a constant offset for the Airmagnet and one of the Telos devices, which were manually adjusted. Furthermore one of the measurement points of the WiSpy sensor was obviously a false measurement and, thus, removed.

2.4 – Processing

Although each device has its own proprietary output format a conversion step was done ensuring all results are stored using a common data format [15][14] that was created as part of the CREW project and is based on the IEEE 1900.6 standard [14]. The common data format contains the relevant parameters of the sensing device, time and location information and measurement results. This enables the usage of common scripts for data processing and reduces the risk of introducing errors.

Since not all devices did an equal amount of measurements we compute the average received signal strength for all available device and location combinations. By using the average we attribute an equal weight to each device, whereas when we would use all available results without averaging the device with the largest amount of measurements would contribute more to overall result.

3. Measurements

3.1 – Measurement Setup

The experimental setup is shown in Figure 1, where 23 measurement locations and one transmit location were chosen within an indoor cafeteria on the premises of imec, Leuven, Belgium. The transmitter was set up to transmit a constant 20 MHz wide OFDM signal modelled according to a repeated Wi-Fi packet transmission on WiFi channel 8 (2.447GHz), with a power of 3dBm. Each platform then performed spectrum measurements, a minimum of thirty seconds in length, at each location. Background ISM traffic devices were switched off throughout the duration of the experiment. Measurements were performed in an asynchronous manner, however due to the constant nature of the transmit signal and the statistical nature of the readings we assume the results to be the same as if all measurements had been synchronised. The set up includes a mixture of both line-of-sight (LOS) and non-line-of-sight (NLOS).

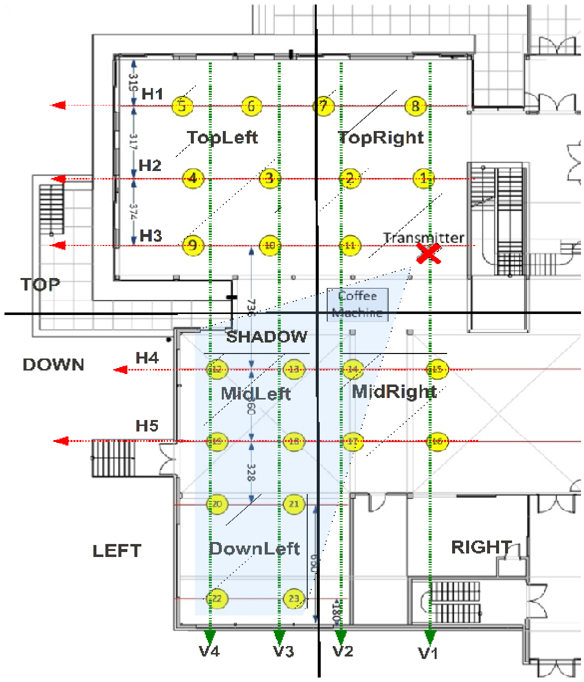

Figure 1: Experimental set-up and location group

3.2 – Measurement Results

As discussed in section 2.1 we test both a least squares and robust fit to estimate the path loss exponent α and offset β based on the results from the measurements described in section 3. This results in an α of 2.32 and 2.29 and β of 46.4 and 46.8 for the least squares and robust fit respectively. The value of the path loss exponent α is close to 2 for both methods, indicating that path loss behaviour close to free space propagation. Figure 2 shows the result of both fitting algorithms and the input points. We find that the impact of the type of regression, for these measurement results is very limited and hence we choose to select least squares fitted curve as the allRef, for the remainder of this paper.

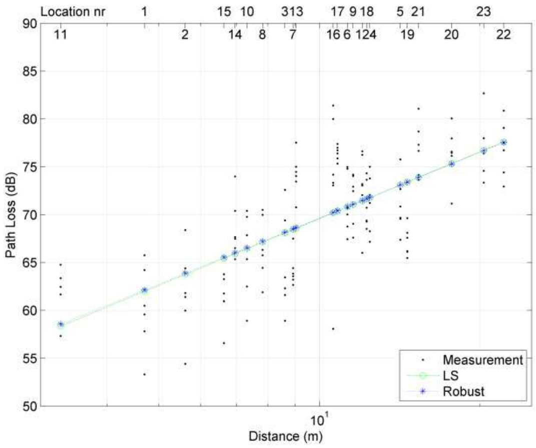

Figure 2: least squares and robust fit

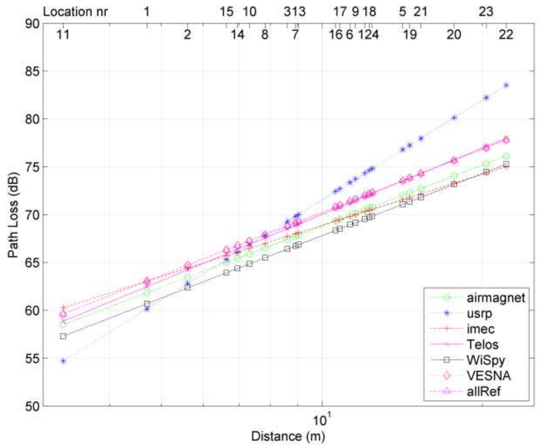

Figure 3: Least squares regression for individual devices

4. Heterogeneity of the devices

To compare different devices we start by computing a least squares fit solely based on the measurements from one device (devRef). These results are shown in Figure 3. As can be seen in the figure most devices display very similar behaviour, with the exception of the USRP. As the calibration, discussed in section 2.3, was done by connecting a cable directly to Rx and hence without the antenna, one possible reason for this deviant behaviour is different antenna properties. Further investigation is needed to fully clarify this observation.

We show the MSE between the estimated path loss curve and the average measurement result for all locations in Table 1 (first column). Additionally we also provide the MSE compared to the average measurements for all devices at all locations (allRef) in Table 1 (second column). This provides us with a metric to evaluate how close the estimation from one single device (on all locations) approximates our allRef. The results in Table 1 confirm what was already visible in Figure 3: the path loss estimation based solely on the USRP will lead to a significant error. The second observation is that the imec and VESNA devices produce the most consistent results, illustrated by low MSE compared to devREF.

Table 1: Mean Squared Error per device

Device Name	MSE	
	Compared to devRef	Compared to allRef
allRef		19.9883
Airmagnet	31.8376	20.7657
USRP	33.9482	28.8005
imec	14.8554	21.5957
Telos	28.5254	20.1824
WiSpy	25.9246	23.2951
VESNA	15.6993	20.4692

5. Number of devices

In this section we investigate how many sensing devices are needed in an area to have good estimate about the wireless environment in this area. To answer this question we estimate the path loss model with the least square error approach for each device based on a selected number of locations and calculate the MSE compared to devRef and allRef. In order to eliminate the influence of one specific location we have performed the analysis of all possible combinations for every number of selected locations and took mean over the MSE.

5.1 – Homogenous device analysis

The resulting MSE for each number of locations is shown in Figure 4. As expected, when 23 locations are used for fitting, the error is always 0 as this is what we defined as devRef. This analysis provides insights on the consistency of the individual device results, using of 3 or 4 locations form imec sensing agent or VESNA gives similar results as using 6 locations of USRP, Airmagnet or WiSpy. We can also see that there are not many differences if we take 9 devices or more.

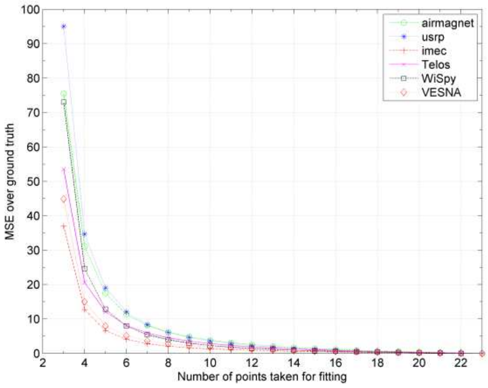

Figure 4: Homogenous device reference

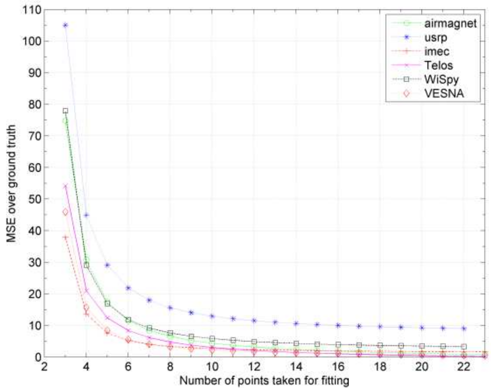

Figure 5: Heterogeneous device reference

5.2 – Heterogeneous device analysis

To compare different devices we amongst each other we conduct a similar analysis, only this time we calculate the MSE compared to the path loss estimation based on all devices, allRef instead of using devRef. In Figure 5 we see that imec sensing agent and VESNA node are able in this case to predict a path loss model close to allRef and the results are comparable to the previous analysis. For all devices we see a steep curve that flattens out fast when the number of devices increases, from this we can learn that, for this set up, using more than 9 devices will not help you to obtain a significantly better estimate of the path loss model. It is also very clear on Figure 5 that the USRP (and WiSpy to a lesser extent), even when using measurements from all locations, will not get close to allRef, which is consistent with the results from section 4. As a conclusion we can say that the MSE compared to both devRef and allRef reduces rapidly with increasing number of locations and that there is limit above which adding extra locations will not reduce the measurement error anymore.

6. Heterogeneity of locations

In this part we combine locations in different manners in order to discover the common characteristics and minimize the influence caused by the randomness of individual locations. We refer to a specific combination of locations as a location group. We used 2 ways to perform the division into location groups, illustrated in Figure 1:

- Clear line-of-sight to Tx (LOS group: all locations inTOP section + locations 15 and 16) or none line-of-sight to Tx (NLOS group: all locations in the DOWN section expect locations 15 and 16)

- Based on the mesh topology of the locations we group points on horizontal (H1-H5) and vertical (V1-V4) lines. We will further refer to this ‘line location’

. In each of the following 2 parts, the performance of every location group is presented, followed by comparison and explanation.

6.1 – LOS vs NLOS

The resulting path loss curves estimated based on LOS and NLOS locations are shown in Figure 6 and the estimated path loss exponent and path loss offset are listed in Table 2. We can see from Table 2 that compared to LOS model, NLOS has a smaller slope but higher offset. The high offset in NLOS estimation is typically caused by the shadow effect. For the same reason, around shadow, the increment of path loss caused by distance can be compensated by the decreasing amount of shadowing, hence the path loss exponent appears to be smaller than only LOS estimation.

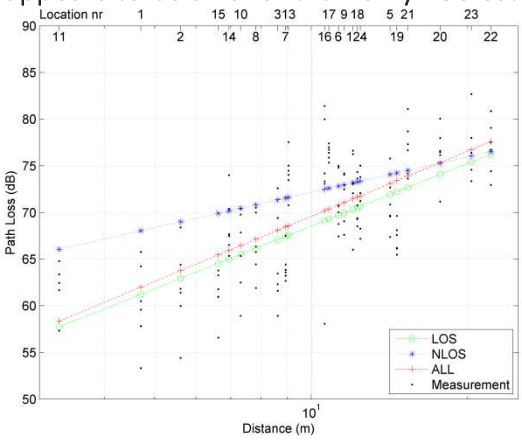

Figure 6: LOS vs NLOS pathloss estimation

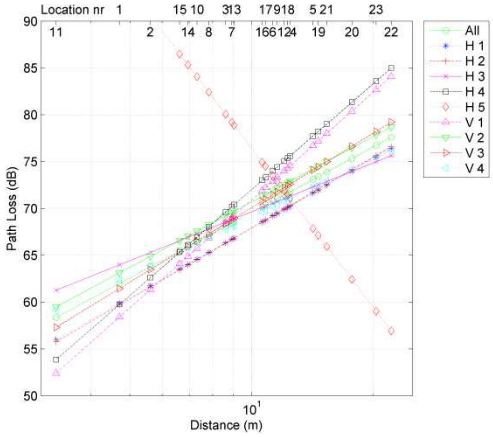

Figure 7: Line groups pathloss estimation

6.2 – Line location group

The estimation results for different line location groups are shown in Figure 7 and Table 2. There are 3 groups that have a path loss component significantly different from the other ones and our reference calculated in section 4, namely H4, H5 and V1. For H4 and H5 the reason is to be found in the simple path loss estimation model that is used. The H4 and H5 groups contain both LOS and NLOS locations which, in combination with the simple path loss model, leads to unrealistic estimations of the path loss exponent. The highest path loss exponent estimation comes from group V1, which might be caused by the fact the saturation effects for the locations closest to the transmitter (i.e. under estimating the received power level), but further investigation is required to validate this. In summary, shadowing effects can be very disturbing, the selection of locations should avoid the border of the shadow.

Table 2: Location heterogeneity overview

	PL exponent	PL offset	MSE
LOS vs NLOS			
LOS	2.229	46.25	1.14
NLOS	1.259	59.57	10.84
Line Location Group			
H1	2.458	43.35	2.91
H2	2.509	42.82	2.92

H3	1.731	53.56	1.33
H4	3.751	34.52	14.06
H5	-5.643	132.84	290.50
V1	3.82	32.71	10.59
V2	2.316	47.54	1.25
V3	2.639	43.71	0.65
V4	2.062	48.47	0.506

7. Conclusions

In this paper we present results from path loss measurements in the ISM band in an indoor environment with heterogeneous devices. Most devices give similar overall results in terms of estimation of path loss exponent and offset estimation. However not all devices display the same consistency for all locations. This behaviour is confirmed in section 5 where we see that the amount of devices needed to obtain a reliable estimate depends on the device type. Futhermore, some devices do not even achieve an estimation close to the overall reference when all available measurement points for that device are used. Finally we see that, when the device locations are not selected carefully, the path loss and offset estimation can be very far from overall result. In summary we conclude that analysis based on only one device type or in specific locations could lead to misleading conclusions.

In future work we are planning to perform similar analysis with heterogeneous devices mixed together and calibrate the devices including antenna in an anechoic chamber.

Acknowledgement

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