Single-channel versus multi-channel scanning in device-free indoor radio localization

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***Abstract*—Indoor localization systems that involve Wireless Sensor Networks (WSNs) identify the target position by measuring the Received Signal Strength (RSS), the Time of Arrival (ToA), the Time Difference of Arrival (TDoA) or the Angle of Arrival (AoA). Of these, the most promising for low-cost applications are those based on RSS measures, which exploit approximate path loss models, or more reliably the relationship between the multi-path interference (shadowing) and the target position. These methods can work with WSNs based on Wi-Fi, Bluetooth and ZigBee wireless technologies.**

In this paper we concentrate on *device-free* RSS-based indoor localization methods. These methods, which have generated much research interest in the last few years, are now starting to hit the market.

Specifically, the purpose of this paper is to assess the performance improvements of a Variance-based Radio Tomographic Imaging technique, when scanning various radio channels with respect to using only one, the latter being the "minimum introduced interference" option.

In our setup, the data used for target localization are captured by wireless sensors deployed in the localization area, which are in line of sight among them. The localization error metrics include the mean square error and percentiles of the error distribution.

I. Introduction

Reliable, accurate and real-time indoor positioning services and protocols are required in the future generation of communication networks [1]. A positioning system enables a mobile device available for positioning-based services such as tracking, navigation or monitoring. Moreover, information of the users position could significantly improve the performance of wireless networks for network planning [2], load balance [3], etc.

Localization and tracking of objects can be achieved by means of a large number of different technologies, however only few of them are suitable for Ambient Assisted Living (AAL) applications, since they should be non-invasive on the users, they must be suited to the deployment in the user houses at a reasonable cost, and they should be accepted by the users themselves [4].

Considering these constraints, a promising technology is based on Wireless Sensor Networks (WSN), due to their low cost and easy deployment. Within WSNs, it is possible to estimate the location of a user by exploiting the Received Signal Strength (RSS), the Time of Arrival (ToA), the Time Difference of Arrival (TDoA) or the Angle of Arrival (AoA).

Of these, the most promising for low-cost applications are those based on RSS measures, which is a measure of the power of a received radio signal that can be obtained from almost all wireless communications devices we know of.

The RSS measured among fixed devices (whose position is known) and mobile devices (carried by the user) is leveraged by algorithms that estimate the coordinates of the user positions. In a smart environment, where the ambience is instrumented with sensors and wireless communication devices, the marginal cost of implementing an RSS-based localization system can be very low, as it can leverage the existing installed hardware.

In this paper, we consider one device-free RSS-based indoor localization method, that is, Variance-based Radio Tomography Imaging (VRTI) [5]. Here, "device-free" means that a person does not need to carry or wear any wireless sensor or device. These systems are based on a large set of small wireless devices spread over the area of interest in order to create a dense mesh, and exploit the RSS observed by each device on the radio links connecting it to other devices. A user moving within the area modifies the RSS pattern in a way that depends on his location; radio imaging therefore exploits the RSS measurements observed along the inter-device links to obtain a reconstruction of the object trajectory. Two working modes can be identified for these devices: either they dedicate some power and channel occupancy to sending ad hoc localization probing packets, or else they exploit data packets sent by other applications and measure their RSS for localization purposes. Using a single radio channel for scanning is friendlier to other devices in the environment, both in the case of dedicated localization devices and in the case of piggy-backing on different applications. In the former case, having a dedicated channel avoids interference and channel occupancy for other applications in the same environment. In the latter, since no ad hoc packets are generated, there is no additional channel occupancy and energy drain.

On the other hand, results for a similar method, that is Shadowing-based RTI, showed that sending probing packets on multiple channels gives an advantage in terms of local-

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ization accuracy with respect to using a single channel [6]. This means that at least in some device-free systems there is a trade-off between minimum disturbance and maximum accuracy when choosing between single- and multiple-channel localization. Here we use the same criterion applied to VRTI [7], in order to measure if any performance improvements are observed with this method.

The remainder of the paper is articulated as follows: Section 2 discusses the experimental setup; Section 3 describes the detail of the tomographic localization algorithm, while Section 4 presents some preliminary results; concluding remarks are given in Section 5.

II. Scenario

In this section we introduce the software, the hardware devices and the scenario used during our analysis. The RSS values are collected through a WSN composed by N nodes in the following named as *anchors*.

A. Software Tool

A modified version of token-passing protocol, named as Spin [8], is used to schedule node transmission, in order to prevent packet collisions and maintain high data collection rate. When an anchor is transmitting, all other anchors receive the packet and perform the RSS measurements. The payload of the transmitting packet is the set of RSS values between the transmitting node and the other sensors sampled during the previous cycle. This packet has been received also by the base station along with the node's unique ID. The base station collects the payload and forwards this data to a laptop for storage and later processing. The RSS values are acquired for a given channel c for all the nodes $n = 1 \ldots N$ in the network, i.e., when the last node of the network has transmitted by using the channel c, the first sensor node starts with a new cycle by using a new channel. The data collected from each sensor pair (a_i, a_j) in the following called *link*, are formatted as a string with the following fields: the identifier of the receiver (ID), the RSS values measured between the receiver and the others transmitting sensors, the timestamp at which the string was acquired, and finally the channel used for the acquisition. It is worth noting that in the literature taken into account for this paper the authors drop the assumption on the reciprocity of the links.

B. Hardware

The WSN used in this work is based on the IRIS Motes wireless sensor nodes, produced by Crossbow [9]. This hardware is based on the high performance RF transceiver, AT86RF230, operating at 2.4GHz compliant with the IEEE 802.15.4 and ZigBee standards. The hardware was programmed using the TinyOS operating system, specifically designed for low-power wireless devices. The AT86RF230 can return the instantaneous RSS and the average RSS values through two registers named *RSS_Val* and *ED register*, respectively. The first one is a 5-bits bit register, the second one is a 8-bit register.

C. Experimental Setup

The RSS values were collected in the presence of a human target (from now on named simply target) in a set of given positions. The localization area is about 6.8 x 5.6 meters where 20 sensors have been placed for the data acquisition. The measures are performed on a set of 1, 2 and 4 channels.

Each link is sampled with a frequency between 5 and 8 Hz, depending on the parameters used in the algorithm described in section III. The target movement was a sort of serpentine as shown in Figure 1 at a constant speed of about 0.2 m/s. The RSS data collected during each experiment consist of more than 5600 cycles, corresponding to more than 112000 RSS measures among anchors. Furthermore, no one other than the user to be localized is present in the area during the experiment.

The localization area of each scenario was marked to create a lattice, as shown in the figure 1, where the black squares are the WSN nodes. Through this lattice the position of the target has been evaluated, and comparing estimated position with the target's position in the lattice the localization error distribution is evaluated. From the error distribution the root mean square error (RMSE), the 75^{th} and 90^{th} percentile of the localization error are calculated.

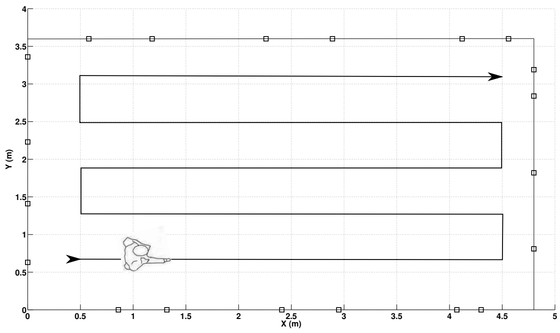

Fig. 1. Environment setup: N=20 anchors positioned near the room walls, at about 70 cm from the floor, and the path followed by the target.

III. Algorithm

The algorithm is an implementation of implemented a Variance-based Radio Tomographic Imaging (RTI) [10]. In the RTI algorithm the data used for the imaging are the RSS levels collected for each pair of wireless devices of the wireless sensor network deployed within the localization area.

The VRTI algorithm uses the path loss of the radio links between many pairs of nodes in a wireless network, in order to image the attenuation changes that occur within the localization area. In general, when an object moves into the localization area, the signal strength of the link involved in the target path will, on average, experience higher shadowing losses. VRTI is an inverse problem based on the path loss on the intersecting links, by which the image of the attenuation within the localization area is reconstructed to infer the location of the target. In the following we shortly describe how it works.

Consider the set of anchors $A = a_1, a_2, \ldots, a_n$ with known positions on the localization area; all the anchor pairs identify the L links of the wireless sensor network. In the localization area, a lattice with P pixels is introduced, and for each pixel its coordinates within the lattice are evaluated.

The first step for the evaluation of the attenuation image over the localization area consists in evaluating the matrix of the variance weighting, which links the RSS's variance of the link to the variance over the pixels, as shown in equation (1).

$$\mathbf{s} = \mathbf{W}\mathbf{x} + \mathbf{v} \tag{1}$$

In equation (1) $\mathbf{x}$ is the image vector that holds the values per pixel of the RSS's variance, $\mathbf{s}$ is the vector that holds the measured RSS's variance per link, $\mathbf{v}$ is the noise vector, and $\mathbf{W}$ is the matrix representing the variance weighting for each pixel and link.

The entries of the matrix $\mathbf{W}$ are calculated by assuming that the signal strength between nodes pair decays with the inverse square of the distance between two nodes, and that the movement of the target influences the set of pixels included in the ellipse shown in figure 2, whose foci are the nodes a_i and a_j, while λ, defined as $d_{lp}(1) + d_{lp}(2) - d_l$, controls the ellipse eccentricity. Equation (2) shows how to evaluate the entries of the matrix $\mathbf{W}$.

$$W_{lp} = \frac{1}{\sqrt{d_l}} \begin{cases} \Psi & d_{lp}(1) + d_{lp}(2) \leq d_l + \lambda \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

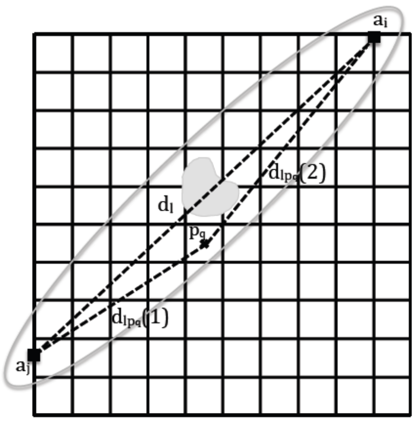

Fig. 2. Attenuation Area

In equation (2) d_l is the distance of the link l between node pair (a_i, a_j), $d_{lp}(1)$ and $d_{lp}(2)$ are the distances from the center of pixel p to the two respective nodes location on link l, and Ψ is a normalization parameter. For the scenarios analyzed in this paper some measurements have been performed to tune the parameters Ψ and λ, and the optimized values are $1\ [\mathrm{dB}]^2$ and $1\ \mathrm{m}$, respectively.

The output of the implemented VRTI algorithm is the vector image $\mathbf{x}$ of equation (1). The vector $\mathbf{x}$ can not be calculated through the equation (1) because it is an ill-posed inverse problem, hence, no unique solution to the least-squares formulation exists. The solution can be determined only through the resolution of a regularization problem; here, Tikhonov's least squares regularization problem was used [11], which can be formulated as in equation (3).

$$\hat{\mathbf{x}} = arg \min_{\mathbf{x}} \frac{1}{2} ||\mathbf{W}\mathbf{x} - \mathbf{s}||^2 + \alpha ||\mathbf{Q}\mathbf{x}||^2 \tag{3}$$

The equation of the regularization problem involves the matrix $\mathbf{Q}$ and the parameter α that are the Tikhonov matrix and the Tikhonov parameter, respectively. In many cases, this matrix $\mathbf{Q}$ is chosen as the identity matrix $\mathbf{Q} = \mathbf{I}$, giving preference to solutions with smaller norms. In other cases, low-pass operators (e.g., a difference operator or a weighted Fourier operator) may be used to enforce smoothness if the underlying vector is believed to be mostly continuous. This regularization improves the conditioning of the problem, thus enabling a numerical solution. The parameter α affects the convergence of the algorithm and can be evaluated by the numerical method described in [11].

In our case, the measured data $\mathbf{s}$ are subject to errors and these errors can be assumed to be independent with zero mean and standard deviation $\sigma_{\mathbf{v}}$. Moreover, the a priori uncertainties of the solution $\mathbf{x}$ can be taken into account through the covariance matrix $\mathbf{C}$. Then the solution for the regularization problem can be formulated as shown in equation (III), in terms of the a priori information $\mathbf{C}$ and the noise variance $\sigma^2_{\mathbf{v}}$ [11] [5].

$$\hat{\mathbf{x}} = \left(\mathbf{W}^T\mathbf{W} + \sigma^2_{\mathbf{v}}\mathbf{C}^{-1}\right)^{-1} \mathbf{W}^T\mathbf{s} \tag{4}$$
$$C_{p_r p_q} = \sigma^2 e^{-d_{p_r p_q}/\delta}$$

Precisely, the correlation between the attenuation over the pixel set can be calculated using an exponential spatial decay law. In this case, the variable $d_{p_r p_q}$ is the distance from center of pixel p_r to the center of pixel p_q, σ^2 is the variance of pixel attenuation, and δ is used to determine the desired amount of smoothness in the image. Hence equation (III) achieves the image reconstruction. For the scenarios analyzed in this paper the values of the parameters σ^2 and δ have been set to 0.3 and 3, respectively.

Then, the second step of the algorithm is to evaluate the solution of the regularization problem as described above.

The vector $\hat{\mathbf{x}}$ is used to estimate the target coordinates, selecting its maximum, and calculating the coordinate of the pixel with the maximum degree of attenuation. So, the final step of the algorithm is to show the image reconstruction $\hat{\mathbf{x}}$ through a color map, and the esteemed coordinate of the target position compared with the true position, depicted by a circle and a cross respectively, as shown in figure 3. The color degrees of the figure indicate the different levels of attenuation due to the target movement over the lattice pixels.

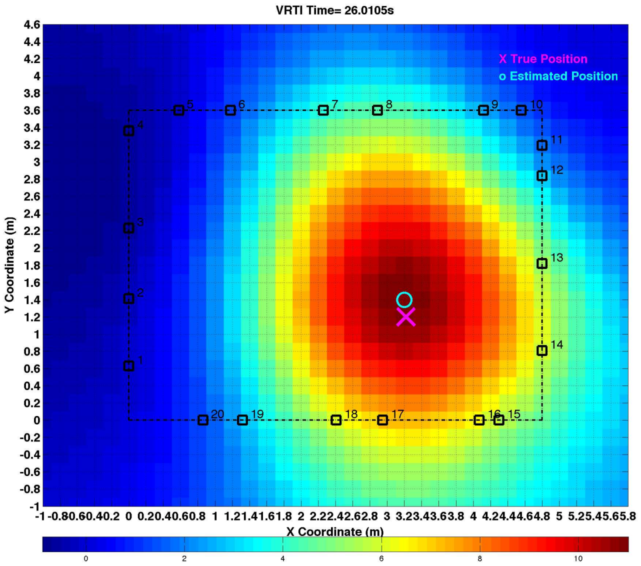

Fig. 3. VRTI Example

IV. Results

We used several criteria to try and compare the performance of single- versus multi-channel. They are detailed in the following four sub-sections.

A. Simple and bare comparison

Here we simply compare the performance of measurements done in single-channel mode on four different channels, with measurements done in bi-channel and quadri-channel mode, for a total of six cases.

The packet generation rate is around 55 pkt/s, which means one complete round of the 19 transmitting nodes in about 345 ms, or about three complete rounds per second. The window over which the RSS variance is measured is set at 3 s and 5 s, which means that the same measured data are used twice, and two sets of results are obtained. Note that the speed of the target is around 0.2 m/s meaning that, space-wise, the variance window is respectively 0.6 m and 1 m long for the two cases. In general, we expect to get a localization error not significantly smaller than the window size.

As shown in figures 4, we have found little difference between single-channel, bi-channel and quadri-channel measurements. The performance metrics we used are the RMSE (root mean square error) and two percentiles (75 and 90) of the localization error distribution. As an example, figures 5 show some typical error distribution for our experiments.

Note that the comparison in figure 4 is not rigorous, because it is based on six different measurements. This means that interference from radio sources may be different in the six measurements. Additionally, the actor's movement may be slightly different in the six measurements and people moving in nearby rooms may also have differently influenced the measurements. These issues are tackled in the next subsection.

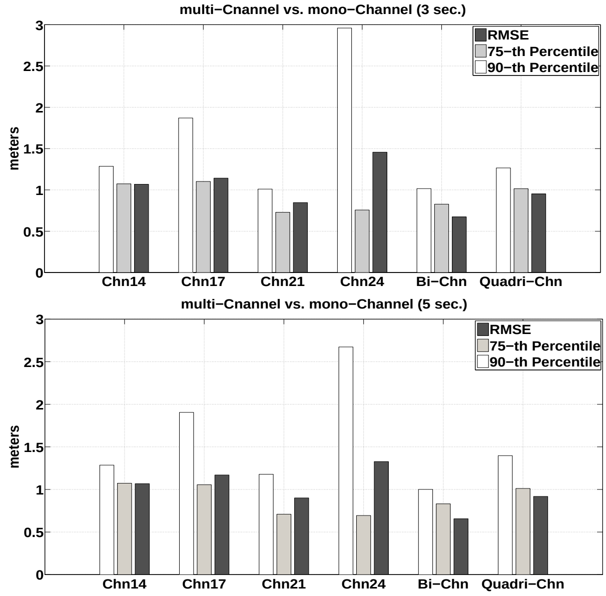

Fig. 4. Main comparison: single-channel performance for channels 14, 17, 21, 24 compared with bi-channel (17, 25) and quadri-channel (12, 16, 20, 24). 3 s and 5 s variance windows.

```
Measured:
      ABABABABABABABABABABABABABABABABABABABAB

Filtered:
Bi 1: A__BA__BA__BA__BA__BA__BA__BA__BA__BA__B
Bi 2:  BA__BA__BA__BA__BA__BA__BA__BA__BA__BA__
Si17: A_A_A_A_A_A_A_A_A_A_A_A_A_A_A_A_A_A_A_A_
Si25: _B_B_B_B_B_B_B_B_B_B_B_B_B_B_B_B_B_B_B_B
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Fig. 6. The original bi-channel measurement on channels 17(A) and 25(B) and three different ways of filtering it.

B. Filtering comparison

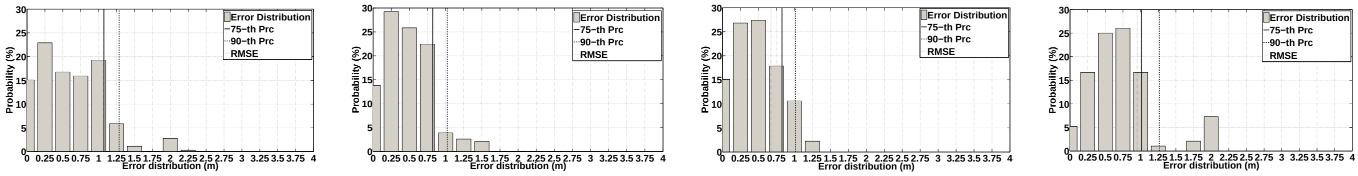
In order to remove the effect of possible differences between different measurements when comparing single- to multi-channel performance, we make a comparison that uses a single bi-channel measurement (the same as the one depicted in figure 4) and filter it in three different ways like shown in figure 6.

The purpose is to extract from a single measurement set a bi-channel trace and two single-channel traces, all of them with the same number of samples per second, so that a comparison among them is significant.

We used the same procedure starting from a quadri-channel measurements that we filtered in five different ways (see figure 7).

We should consider this filtering procedure as the most rigorous of the tests we made. Its main drawback is that the number of samples per second is reduced by two times in the bi-channel case and by four times in the quadri-channel case, which stretches the RTI algorithm ability to its limits. Figures 8 and 9 show the resulting comparison.

Again, we do not perceive any significant difference when comparing single- and multi-channel performance.



(a) Channel 14 (b) Channel 21 (c) Bi-channel (d) Quadri-channel

Fig. 5. Error distribution for some different experiments.

```
Measured:
     ABCDABCDABCDABCDABCDABCDABCDABCDABCDABCD

Filtered:
Qu 1: A____B____C____DA____B____C____DA____B__
Qu 2: B____C____DA____B____C____DA____B__A____
Qu 3: C____DA____B____C____DA____B__A____B____
Qu 4: DA____B____C____DA____B__A____B____C____
Si12: A___A___A___A___A___A___A___A___A___A___
Si16: _B___B___B___B___B___B___B___B___B___B__
Si20: __C___C___C___C___C___C___C___C___C___C_
Si24: ___D___D___D___D___D___D___D___D___D___D
```

Fig. 7. The original quadri-channel measurement on channels 12(A), 16(B), 20(C) and 24(D) and five different ways of filtering it.

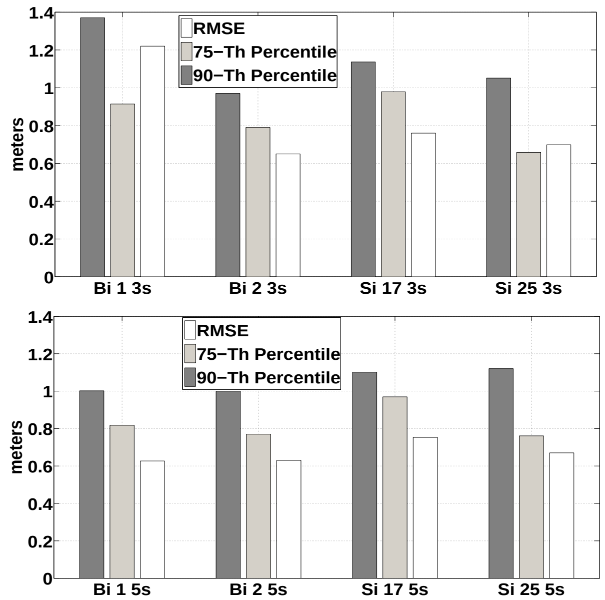


Fig. 8. Rigorous comparison: filtering bi-channel and single-channel from a bi-channel measurement. 3 s and 5 s variance windows.

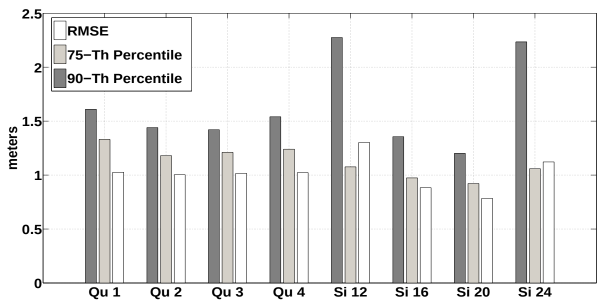


Fig. 9. Rigorous comparison: filtering quadri-channel and single-channel from a quadri-channel measurement. 10 s variance window.

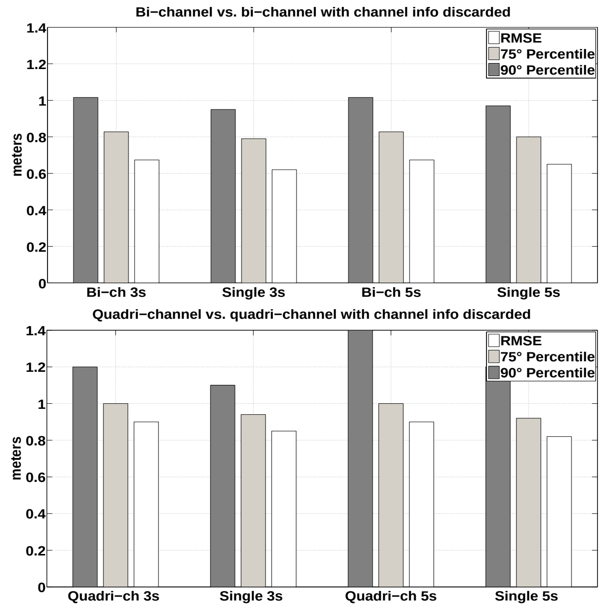


Fig. 10. Discarding channel information: treating multi-channel data as if they were single-channel do not significantly worsen the performance.

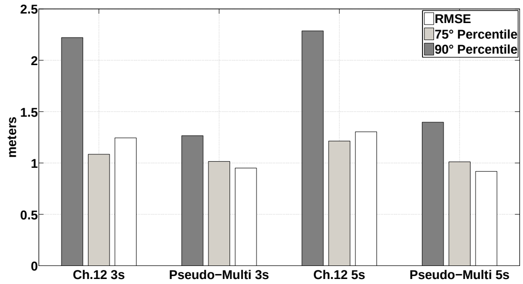
C. Removing multi-channel information

As one more criterion to check for the importance of measurements over different channels, we took a quadri-channel measurement and removed the channel information. In practice, we made the measurements on four different channels and run the algorithm on the complete data, including channel information, as well as on the data where the channel information has been removed (so all the samples appear to have been logged on the same channel).

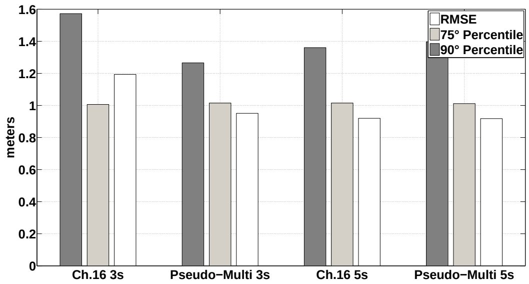
Before making the comparison, we cared about removing the mean value individually from each channel's data, in order to avoid spurious variance introduced by mixing different channel's data. The results are depicted in figure 10 and, again, do not indicate any significantly worse performance when the channel information is discarded.

D. Treating single-channel as multi-channel

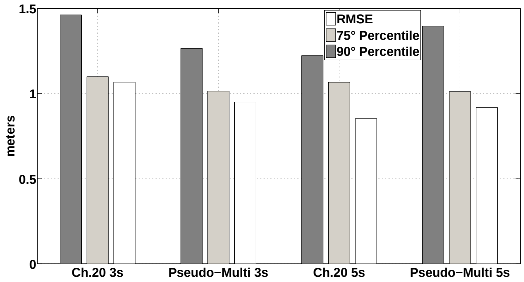
As a last test, we "invented" multi-channel information and added it to single-channel measurements. This test is a sort of security check that we did to verify that our implementation of the VRTI algorithm did not introduce any artifacts that advantage the single- or the multi-channel measurements.



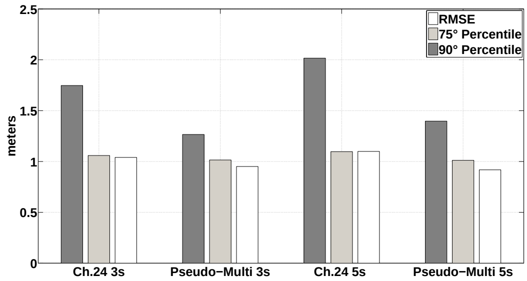
(a) Channel 14



(b) Channel 18



(c) Channel 22



(d) Channel 26

Fig. 11. Adding "invented" channel information: single-channel measurements are enriched with nonexistent multi-channel info.

In figure 11 we observe a small improvement when "inventing" channel information. We do not know the exact source of this improvement, but in practice we judge it as being too small to be significant.

V. Conclusion

In this paper, some preliminary measurement results relevant to an RTI-based localization technique have been presented and discussed. Main goal was at showing whether using multiple radio channels for collecting RSSI samples is advantageous with respect to using only one frequency channel, as far as variance-based RTI localization is concerned.

In general, using multiple channels may be more complex, especially if the packets are not explicitly generated for the purpose of measuring, but just for communication purposes. In the latter case, the channel is constrained by communication protocols because of interference criteria or more generally by spectrum sharing criteria. On the other hand, it may be useful to exploit multiple channels, if they can bring a benefit.

We used several criteria to compare the performance of single- versus multi-channel approach. Our preliminary conclusion is that we have no clear answer, that more experimentation in different conditions is needed, and that apparently there is not much difference in performance between single- and multi-channel when using variance-based RTI localization.

References

[1] C. Di Flora, M. Ficco, S. Russo, and V. Vecchio, "Indoor and outdoor location based services for portable wireless devices," in *Distributed Computing Systems Workshops, 2005. 25th IEEE International Conference on*, 2005, pp. 244–250.

[2] B. Rao and L. Minakakis, "Evolution of mobile location-based services," *Commun. ACM*, vol. 46, no. 12, pp. 61–65, Dec. 2003. [Online]. Available: http://doi.acm.org/10.1145/953460.953490

[3] E. Yanmaz and O. Tonguz, "Location dependent dynamic load balancing," in *Global Telecommunications Conference, 2005. GLOBECOM '05. IEEE*, vol. 1, 2005, pp. 5 pp.–.

[4] J. A. Álvarez-García, P. Barsocchi, S. Chessa, and D. Salvi, "Evaluation of localization and activity recognition systems for ambient assisted living: The experience of the 2012 evaal competition," *Journal of Ambient Intelligence and Smart Environments*, vol. 5, no. 1, pp. 119–132, 01 2013. [Online]. Available: http://dx.doi.org/10.3233/AIS-120192

[5] J. Wilson and N. Patwari, "Through-Wall Motion Tracking Using Variance-Based Radio Tomography Networks," *IEEE Transactions on Mobile Computing*, vol. 10, no. 5, pp. 612–621, May 2011.

[6] N. Patwari, M. Bocca, and O. Kaltiokallio, "Enhancing the accuracy of radio tomographic imaging using channel diversity," *2012 IEEE 9th International Conference on Mobile Ad-Hoc and Sensor Systems (MASS 2012)*, vol. 0, pp. 254–262, 2012.

[7] J. Wilson and N. Patwari, "Radio tomographic imaging with wireless networks," *Mobile Computing, IEEE Transactions on*, vol. 9, no. 5, pp. 621–632, 2010.

[8] ——, "Spin: A token ring protocol for RSS collection," http://span.ece.utah.edu/spin.

[9] C. Technology, "IRIS Datasheet," http://bullseye.xbow.com:81, 2013.

[10] J. Wilson and N. Patwari, "Radio Tomographic Imaging with Wireless Networks," *IEEE Transactions on Mobile Computing*, vol. 9, no. 5, pp. 621–632, May 2009.

[11] A. N. Tikhonov and A. V. Y., *Solution of Ill-posed Problems*. Washington: Winston & Sons, 1977.