WiGEM: A Learning-Based Approach for Indoor Localization

Response to Reviewers' Comments

Reviewer 1:

1. Any localization solution needs to make some assumption to map signal properties to space. This is so fundamental that it should have been the first thing that the paper explains. Instead of that, the reader has to wait until page 6 to unravel the mystery. This is very frustrating.

   So, the secret of the approach is the use of the model that relates signal strength to distance from source. This is fine as an assumption since it is based on basic physics, it is simple to incorporate into the model, and since it gives good results it is great. You should describe that both in the abstract and the introduction

   - (modification in paper) As suggested, the abstract and introduction have been briefly updated.

2. A second rather "mystery" of the paper is the way that mobility works. The paper even claims that mobility helps! What exactly do you measure when a node moves around? Even the concept of location is not well defined now. Should we assume that mobility implies that a node travels to a new point, informs the central controller that it has moved location, performs the measurements, and then move to another location and perform the same cycle again. In other words, does the node informs the central location when changing location (at least from one x_i to another x_j)??

   - (modification in paper) Section 6.5 has been updated with new experiments which demonstrate the impact of mobility and how mobility during learning helps localization.

3. I can see that robustness comes from collecting many measurements and using a good method for estimation. However, I have also observed in wireless settings significant changes to RSSI values based on very random effects. For example, when measuring RSSI values in our environment the day measurements were consistent with each other, the night measurements also consistent, but the day and night measurements were inconsistent even for the same location. The reason was that during the day the doors were open and as a result we were observing stronger signals. Hence, it would seem natural that your system actually needs to be able to "forget" old measurements

   - (response) From our experiments we know that our algorithm converges pretty fast (# of samples), which means it attractive in an online setting whereby we can "forget" old measurements. There is not enough space to show these results.

4. The localization error (see e.g. Fig5 & 6) seems to be rather high for the size of the buildings. What is the reason for that?
   Also, it would be nice to examine the effect of changing the number of monitors on the localization error.

   - (response) Future work could be directed to evaluate if # of sniffers decreases the localization error. Currently the number of sniffers used is modest considering the building size. We can also study if finer grids help in reducing localization error. Future work can also explore the issue of using a subset of the sniffers.

   - (modification in paper) The above suggestion has been incorporated in the paper as 'Discussion / Future work'

5. I did not notice the running performance of the method, but I guess that it is rather efficient, right?

   - (modification in paper) Added Sec 6.6 on WiGEM running times

6. The same framework could also be used to do a more efficient training process. Basically, the model of Eq.(20) could maybe be substituted by a few carefully done measurements. The paper correctly identifies that such training works well for the device that performs the measurement but not for others. However, it seems that the inclusion of the power of the source in the model may increase the robustness of the method and make it work for various devices.

   - (response) This is actually a 'strengthening' comment.

   - (modification in paper) We have incorporated this note under 'Discussion / Future Work'

Reviewer 2:

1. The algorithm assumes that the number of locations is known. This may be difficult to estimate in practice because the signal strengths may vary considerably for locations that are close-by (because of walls, other obstacles, etc.)

   - (response) We can always superimpose a grid and find out the number of locations. This is the same approach we took in the paper.

2. There are typically constraints between the means of the Gaussians at the same location for different power levels. These constraints are enforced at initialization time when the means at a location for K power levels are initially set. But it is unclear how these constraints are enforced during the algorithm - so it seems possible that means for different transmit power levels at the same location may be quite far apart

   - (response) Our algorithm does not enforce constraints during run time

3. Overall, it seems like an innovative approach to determining location of devices, and the authors must be commended for seeing the connection between machine learning and device localization.

   - (response) Ok.

Reviewer 3:

1. The basic idea of the paper is interesting and I am a bit surprised that it works well without training.

   - (response) Ok.

2. The use of "learning data" in WiGEM as described in Section 6 needs to be clarified. Section 6.0 and 6.1 seems to suggest that WiGEM also uses half of the collected data for learning (just like RADAR?), so it is unclear how this reconciles with the paper's claims of completely obviating training. I think you mean that WiGEM only uses 100 samples from a single location as learning data in order to localize a device at that location; if so the description should be worded accordingly.

   - (modification in paper) Modified Section 1.0 to distinguish between 'training' and 'learning'

3. The evaluation is missing details of how test locations were chosen or how exactly the average error distance is defined. It is unclear if each experiment was conducted at a single location or across multiple/all locations, i.e., does the average error distance refer to the average across multiple tests at one location or the average across tests at different locations?

   - (response) We conduct our experiments across all locations (Section 5.3). Likewise the error distances reflect the aggregate metric across all locations.

   - (modification in paper) Section 6.0 has been modified to clarify this.

1. One simplifying assumption that makes the model more tractable is that the RSSIs observed at different sniffers are independent. Are they really? What is the impact of this assumption, and what would happen to the model if this weren't true? Is there any experiments you can do to validate this assumption on your testbeds ?

   - (response) This is a simplifying assumption. They could be correlated, but the correlation is not expected to be significant if the angle between the links is large

2. Another discussion missing is about the number and location of sniffers, and how it affects performance. Again, added discussion on what are the necessary conditions for good localization would we helpful. This also relates to the issue above, of the independence of the RSSIs at different sniffers, such that sniffers with independent RSSI strengths would be preferred?

   - (response) As above (reviewer 1), the suggestion about the number of sniffers has been incorporated in the paper as 'Discussion / Future work'

3. As the model uses unsupervised learning, a discussion of the nature of the errors and what could happen in degenerate situations would be welcome.

   - (modification in paper) We have incorporated this note under 'Discussion / Future Work'

4. In the graphs, please set the y axis to start at 0, unless there is a very good reason not to, as it creates the cognitive perception of better results and makes it harder for the reader to compare relative differences.

   - (modification in paper) The y-axis has been reset to 0 for Figs 5, 6, 7, 8, 9, 10, 11.

   - (modification in paper) Figs 5, 6, 7, 8, 9, 10 have been compacted to single column. This is done to add in new text in Sections 6.5, 6.6 and Sec 7.

   - (modification in paper) In Fig 6, the CSD testbed results have been added. It had been excluded earlier in Sec 6.1 for space constraints.

Reviewer 5:

1. The joint power/location idea is nice. After that the EM steps seem kind of standard. I was wondering how you were going to solve the idenifiability problem and was a little surprised when it involved initialising with a channel model, which hadn't been really advertised earlier. Still, the results are relatively convincing.

   - (response) Ok.

2. I was a little disappointed that you didn't try tracking mobility by doing learning and using the adjacency of the locations as information to track how motion could evolve. I guess this could reduce the error further? This seems to have been done with EM before : Adaptive localization techniques in WiFi environments",   Paolo Addesso, Luigi Bruno, Rocco Restaino, ISWPC'10. and might be nicely combined with your technique

   - (modification in paper) We have incorporated this suggestion under 'Discussion / Future Work'

3. I guess your system will work well with systems doing power control, because it will estimate the power of the transmission as you go (though it could break your assumption that x and z are independent)? Do you have any feeling for what would happen if you had a directional antenna on a device - for a regular dipole, I guess the directional gain is too small to make it worthwhile considering orientation? Will things work OK

if you have rate control on? In some cases RSSI estimates can depend on the transmission rate used, but again, maybe the variations are too small

- (response) In our experience most commodity wireless cards, like the ones we used in our experiment, do rate control by default. We did not set a fixed bit rate on any on the devices. Performance evaluation with directional antenna / fixed orientation of devices was not considered as a part of the experiments. Though this could certainly be done in the future

4. Could you feed other information to your estimator? For example, some people have proposed using delays (e.g. the "Distance tracking using WLAN time of flight" demo at Mobisys this year). Would it just depend on the distance errors being Gaussian.

- (response) This is possible and worth exploring.

5. I wasn't sure I'd understood the learning - is it just that you run a few EM steps without using (22) to estimate the location to get the parameters and then you no longer do EM steps when you generate estimates using (22)? In practice, I guess you could keep doing EM steps and generating location estimates as the device moves through the environment?

- (response) Correct. The above procedure was adopted so as to have a fixed test set for comparing other algorithms.
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- (modification in paper) Section 6.0 has been modified to clarify this.

6. In your measurements, could every AP successfully decode every transmission? Were devices free to do rate control?

- (response) Decoding the transmit ping packets was fairly robust. We used the tcpdump tool for this and no errors were observed.

- (response)Nothing specific for the experiments were done on the devices and they could do their default rate and power control, if any.

- (modification in paper) Section 5.3.1 has been modified to incorporate the above sentence.

7. page 6: You should say what U is for this problem

- (response) We do specify (Sec 4.4) that each component is the number of (location, power-level) pair

8. page 6: Do you need to assume that antenna gains at the monitors are the same? Otherwise generating the initial values might be tricky?

- (response) Yes. This is because we use the same hardware for all sniffers (Sec 5.1.1)

9. Fig 4: The square in the figures have different dimensions to those described in the text (2.75 vs 5.5 and 3.1 vs 3.3.

- (modification in paper) Section 5.3 modified to explain this better.

10. Fig5: I wonder if it would be worth including "K" (the symbol for number of power levels) in the description of the X axis here.

- (modification in paper) "K" added to the description of x-axis in Fig 5.

- (modification in paper) For improved readability in black / white, distinctive line and symbol styles added in Fig 5, Fig 6 and Fig 7. Cross hatching styles added in Fig 8, 9, 10, 11

11. Section 6.3: Why do you think there is such an improvement for the phones?

-   (response) This is possibly because the default settings for transmit power etc for phone-based devices are substantially different from laptops / netbooks. However we have not done any experiments to validate this in the present work.

12. Section 6.4.1: It seems it would have been nice if you could have trained on a laptop and a phone for both locations.

-   (response) Space constraints prohibit adding additional experiment results