Signal Attenuation Modelling in WLAN Positioning

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Abstract

Wireless Local Area Networks (WLAN), as the most widely used indoor positioning technology, can localise users by measuring the Received Signal Strength (RSS) from multiple Access Points (AP). The challenges of this approach are that measuring RSS can be easily affected by several parameters, including how the users hold the device, e.g. device orientation, and that accurate maps of RSS are required. This paper (A) introduces a bell-curve model of signal attenuation from orientation, allowing more accurate RSS measurement, and (B) identifies collinearity issues with a path-loss model used to automatically create RSS maps, suggesting a simpler and more robust alternative.

1 Introduction

WLAN has provided Signals of Opportunity (SoO) for indoor positioning purposes due to its wide-availability and the global adoption of WLAN-enabled devices, such as smartphones, providing a relatively low-cost ability to use the existing infrastructure of APs and devices. The primary approach for WLAN-based positioning is to measure RSS across multiple APs and compare to the previously produced RSS maps [9]. However, RSS measurements (and hence positioning accuracy) have systematic noise relating to measurement methodology, such as device orientation, and the surrounding environment, such as existing walls and furniture. This paper presents a model of signal attenuation due to device orientation, allowing the effect on RSS to be calculated and mitigated. Additionally, producing RSS maps through fingerprinting requires a large effort of on-site measurement, thus path-loss models are an alternative to reduce effort. This work investigates the Wall Attenuation Factor (WAF) model, a relatively well-known path-loss model first introduced in RADAR [2].

This paper is structured as follows: section 2 models the effects of device orientation on the received signal. In section 3, it is shown that the typical WAF model formulation has a problematic collinearity and proposes a simplified version with similar accuracy and a more straight-forward physical interpretation. Section 4 presents the conclusion and discussion.

2 Orientation

Heterogeneous and non-isotropic antenna gain (considering user and device holistically as an antenna) leads to variation in RSS. It has been shown in [10] that different smartphones affect RSS by up to 12dBm, and in [8] that device and user orientation lead to RSS variation of 4-8 dBm and 5dBm respectively, in addition to 12dBm of variation if user handgrip covers the antenna. Methods based on measurement combinations, such as SSD (Signal Strength Difference) [4] and Hyperbolic Location Fingerprint [5], have been proposed to remove the isotropic component of antenna gain heterogeneity, however these are ineffective for the anisotropic component.

Characteristic smartphone antenna gain patterns may show a flattened oval or heart-shape e.g. Fig 1. It is noted that this is equivalent to identifying attenuation as a bell-shaped function of orientation, with the top of the curve at the heading of maximum attenuation. Therefore, it is investigated whether attenuation from orientation fits a bell curve (similar to the effect of shadowing [6]). For a given scenario *i,* of AP and device position, it is proposed to fit the attenuation to a bell-curve:

$$RSSI_i(\theta) = k_i - \alpha e^{\frac{-(\theta-\delta_i-\beta)^2}{2\sigma^2}} \tag{1}$$

where k_i is a constant representing the sum effect of AP antenna gain, isotropic device antenna gain, and signal path-loss between AP and device; and the second term represents the attenuation bell-curve as a function of θ, user orientation with respect to a reference direction, and δ_i, the measured orientation of the AP from the device. The bell curve is parameterised by α, β, σ representing attenuation magnitude, directionality and width respectively.

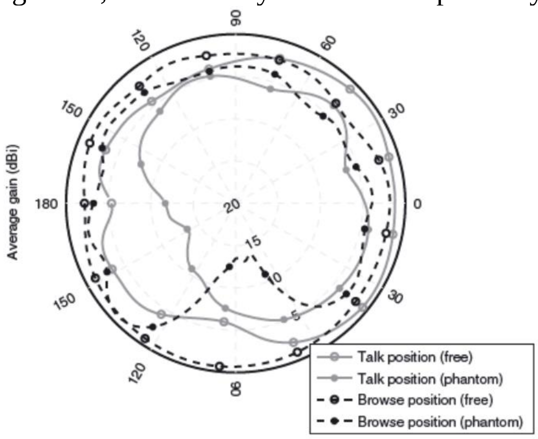

Fig 1: Pattern of smartphone antenna gain with and without a body (phantom) [3]

In order to model and test this, this paper conducts several experiments and measures RSS at 14 combinations of AP and device locations within a residential environment, including deliberately challenging conditions, as shown in Fig. 2.

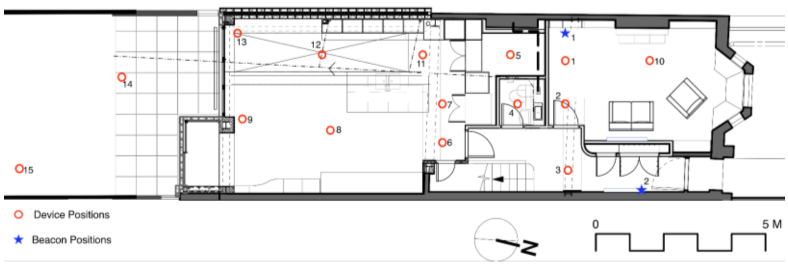

Fig. 2: Floor plan showing measurement locations

For each combination, repeated RSS measurements were taken at orientation intervals of 30º. The device was mounted on a tripod to avoid user interference. For 6 of the combinations a strong relationship held (see Fig. 3), with a model R^2 of 77% with respect to measured attenuation and RMSE of 1.9 dBm. For the remaining scenarios, attenuation patterns appeared to have either two peaks or no clear pattern, which relates to physical scenarios where there are either two signal paths of similar strength or no dominant multipath component. Analysis of the floor plan provided a reasonable ad-hoc justification for the multipath presence in all-but-one of the scenarios.

To make use of this result, we must identify when a dominant signal-path exists, which is not addressed by current path-loss models or fingerprinting methods, albeit ray-tracing could potentially provide this information. However, this result shows the ability to either directly remove the attenuation effect if orientation is known, or otherwise reduce error through using the correlations between different AP based on their relative heading. Both of these ideas rely on further work on how the bell-curve shape may vary by device and by position on the user.

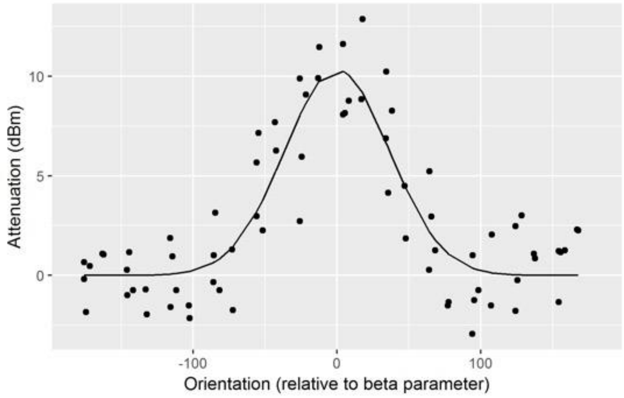

Fig. 3: Orientation model

3 Path-loss modelling

Path loss models have been developed for positioning to estimate RSS by extending the canonical free-space model [6]:

$$PL(d) = PL(1) - 10n \log_{10} d \tag{2}$$

where $PL(d)$ is the loss of signal strength, d is distance in metres, PL(1) is a constant reflecting RSS at the distance of one metre, and n, the path-loss exponent equals two. Basic extensions considered different path-loss exponents, however more accurate results have been produced by using floor plans to estimate the attenuating effect of objects in the path between beacon and device, e.g. the Wall Attenuation Factor model, first introduced in RADAR [2]:

$$PL(d) = PL(1) - 10n \log_{10} d - \sum WAF \tag{3}$$

where WAF is a wall-specific attenuation factor. This model is still used directly, e.g. [1] or as the basis for extended path loss models such as the WiCa Heuristic Indoor Propagation Prediction (WHIPP) model [7], however the problem of collinearity between walls passed and distance is not typically considered.

The sensitivity of the WAF model is investigated by linear regression on each parameter in turn, holding other parameters as per (2), before testing the original WAF model. The model is tested on a dataset of 29 combinations of AP and device location.

The results, shown in Table 1, identify that the greatest improvement in fit comes from introducing the wall attenuation parameter, with a restricted WAF model able to generate 85% R^2 and 3.8dBm RMSE on the test dataset. The improvements from allowing other parameters to vary, as typically used, has a relatively immaterial improvement in predictive power. Therefore it is suggested that a restricted WAF model is preferred to the original WAF model as it has a well-understood physical basis (which allows parameter tuning by reference to wall type) unlike fitting the PL(1) and n parameters.

Table 1: Path-loss model fitting results

#	Model	PL(1)	n	WAF	R^2	RMSE (dBm)
1	Free-space w. PL(1) est.	-34.2	2.0	-	8%	9.4
2	Free-space	-41.5	2.0	-	65%	5.8
3	Log-distance	-34.2	3.0	-	68%	5.5
4	restricted WAF	-34.2	2.0	5.3	85%	3.8
5	WAF	-33.8	2.4	4.1	88%	3.4

4 Conclusion and Discussion

This paper examined and modeled the effects of user orientation, and walls on the WLAN's RSS. The empirical results of the experiments conducted here, show that under certain conditions RSS attenuation due to the device orientation can be predicted. While further studies and experiments can measure the robustness of the results in other scenarios, this can potentially allow the device orientation correction co-efficient to be factored in WLAN-based positioning systems.

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