On ML estimation for automatic RSS-based indoor localization

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In a nutshell: **RSS-based indoor localization via Maximum Likelihood**

- reference scenario: low-cost Wireless Sensor Networks (WSN)
- only fully automated methods
- channel and position estimation as coupled problems

Findings:

- channel estimation via simple linear regression combined with ML localization has the potential to achieve good accuracy while keeping a very low level of computational and implementation complexity if channel model is matched (simulation)

- in 3D localization the vertical error is considerably larger than the horizontal error
Motivations

Low-cost is key to commercial applicability, impacts on design:

I. fabrication → use only RSS signal, lightweight processing

II. deployment → rules out fingerprinting

III. operation → fully automatic “zero-configuration”

Time-variant indoor radio channel

small- and medium-scale fluctuations (fading, shadowing), mid-to-long term changes due to unstable environmental conditions

downward

the channel model parameters cannot be assumed known and must be automatically estimated
Towards a systematic study

- a systematic study must combine theoretical analysis, simulations and real-world experimentation
- discriminate the limitations of the estimation technique from the effects of channel model mismatching

\[ \Downarrow \]

*simulations in a virtual environment matching exactly the channel model*
target (blind) node with unknown position $\mathbf{p} = [x \ y \ z]^T$

- $N$ fixed anchor nodes (beacons) with known coordinates $\mathbf{p}_i = [x_i \ y_i \ z_i]^T$, $i = 1, \ldots, N$
Channel model

Average received power (Path-Loss Model)

\[ r_i \text{ [dB]} = P_0 - 10\alpha \log_{10} \frac{d_i}{d_0} + n_i \quad i = 1, \ldots, N \]

- \( \alpha \): path-loss exponent
- \( P_0 \): rx power at ref. distance \( d_0 \) (e.g. \( d_0 = 1 \text{ m} \))
- \( d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} = \|p - p_i\| \)
  distance between the target and anchor \( i \)
- \( n_i \): gaussian r.v. accounting for fading
ML estimation

No off-line calibration phase → two estimation problems:
- estimation of channel parameters
- estimation of target node location

We studied three solutions:

1. Joint ML channel and location estimation
2. Separate channel estimation and ML localization
3. Channel estimation and Lateration
(1) Joint ML channel and location estimation

It results from the optimization problem:

$$\hat{p} = \arg \max_{p, \alpha, P_0} \prod_{i=1}^{N} P_{\hat{\sigma}}(r_i | p, \alpha, P_0)$$

where $P_{\hat{\sigma}}(\cdot)$ is the pdf of RSS $r_i$ after maximizing over $\sigma$

- ☑ it is the optimal ML approach to the problem
- ☹ it must resort to an heavy numerical procedure
- 😞 the delivered solution is sub-optimal due to stop criterion
Three different solutions

(2) Separate channel estimation and ML localization

Uses anchor-anchor measurements for channel estimation

- the ML estimation turns to be a *simple linear regression*
- the accuracy improves quadratically with $N$

The localization problem turns into nonlinear Least Squares:

$$\hat{p} = \arg\min_p \| r - \hat{P}_0 + \hat{\alpha} f(p) \|^2$$

where $f_i(p) \overset{\text{def}}{=} 10 \log_{10} \left( \frac{\| p - p_i \|}{d_0^i} \right) \quad i = 1, \ldots, N$

It can be solved by a lightweight procedure, e.g. *gradient descent*:

$$p[k + 1] = p[k] - \gamma \frac{20\alpha}{\log 10} \sum_{i=1}^{N} \left[ r_i - P_0 + \alpha f_i(p[k]) \right] \frac{p[k] - p_i}{\| p[k] - p_i \|^2}$$
(3) Channel estimation and Lateration

Target localization by anchor-target measurements (two steps)

i) **ranging**: estimate the target-anchor distances

ii) **positioning**: find the position $p$ via *lateration*

It is a more heuristic approach:

- approximated version of the ML approach
- computationally simple
- no guarantee of optimality
- estimated distances are biased
- low accuracy, it tends to amplify the measurement noise
Localization error

- room $10 \times 10$ meters, height 3.5 meters, $\alpha = 1.6$ and $\sigma = 6$
- two deployments: planar (left) and “carousel” (right)

In the carousel setting (right):

- 😊 lateration performs dramatically better
- 😊 ML + Ch.Est. improves considerably
Error components

(Left)

- Vertical error is predominant in all scenarios
- Horizontal error remains contained
- Vertical error is reduced sensibly in “carousel” deployment

(Right)

- Horizontal error does not improve upon the “ideal” choice
- Local minima problem is mitigated but still present along z-axis
The “carousel” setting

Reasons for improvement:

- Lateration involves the inversion of a matrix that becomes ill-conditioned for near-coplanar anchors.

- Anchor coplanarity worsens the problem of local minima in ML estimation along the vertical axis.

- Linear regression in the channel estimation phase benefits from a higher degree of distance diversity between the anchors.

Despite the improvement, the achievable accuracy along the vertical axis remains poor as far as the vertical displacement between the anchors remains contained (“flat” rooms).

ML localization + channel estimation (2) yields slightly better performance than the joint ML estimation (1).
Warehouse scenario

Anchor selection

- warehouse of $60\text{m} \times 30\text{m}$, $\alpha = 1.9$ and $\sigma = 6$
- 24 anchors in “carousel” deployment, lower density than room scenario

Some authors have proposed to select only the subset of nearest anchors to estimate the target location (e.g., $M$ anchors with largest average received power)
Facts on anchor selection

- it does not have any clear impact on the vertical error.
  - this confirms that accurate vertical localization cannot be achieved in flat environments of limited height.

- it has a *negative* impact on the horizontal error.
  - the improvement reported by other works is more likely related to technological factors and/or different effects not accounted in the Path-Loss model.

- as far as the horizontal localization is concerned:
  - the “carousel” anchor deployment performs slightly better than the planar one.
Conclusions and remarks

- given the Path-Loss channel model, separate channel and location ML estimation (2) provides an excellent compromise between simplicity and performance.

- in flat environments (low height), a good level of accuracy can be achieved only on the horizontal plane.

- further research on RSS-based localization should focus more on robustness to channel model mismatching.