Bluetooth based Indoor Localization using Triplet Embeddings

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Summary

Motivation:

- Localize people within a building using low-cost IoT Bluetooth receivers, from RSSI information and location of the receivers.

In this work:

- We propose a model-free positioning algorithm based on Triplet Embeddings
- We leverage the missing information using RSSI information
- We do not use the RSSI values directly, but ordinal information in RSSI values

Setup

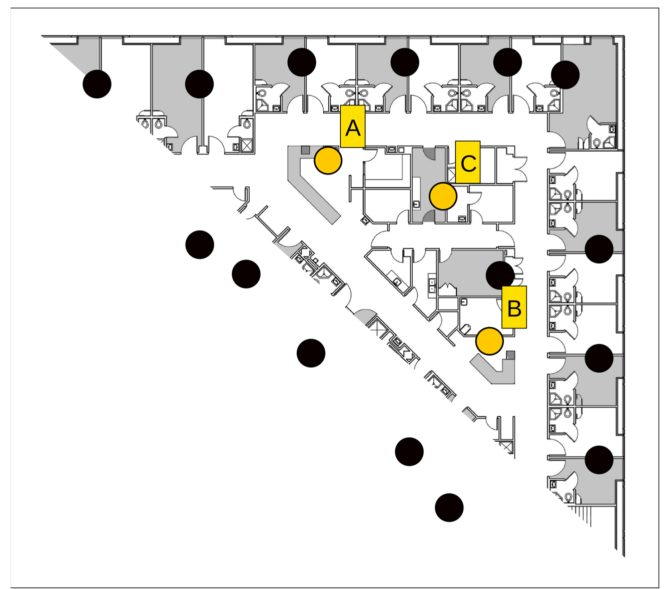

Figure 1: Owl installation for a nursing unit at USC's Keck hospital. The black circles show owl positions, placed in rooms shaded in light gray. The yellow circles show owls that we use as sender devices (one at a time) to validate our algorithm.

Assumptions

We assume that higher RSSIs imply smaller distances between source and receiver:

$$r_j > r_k \Rightarrow D_{sj} < D_{sk}, \quad \forall j \neq k, \tag{1}$$

where s is the sender device (source) and j, k are receivers.

Idea

- We know all the positions of the receivers, so we know:

$$D_{ij} \overset{?}{\gtrless} D_{ik} \tag{2}$$

- We know the receivers for which we have an RSSI greater than zero, so:

$$r_j > r_k \Rightarrow D_{sj} < D_{sk}, \quad \forall j \neq k, \tag{3}$$

where s is the sender device and j, k are receivers.

- From this information, we can create a list of *triplets*, and solve an optimization problem to find the location of the sender.

Triplets and loss function

We *observe* a set of unique triplets $S = (i, j, k) = t$, and variables $y_{(i,j,k)}$ that tell us if i is closer to j, or k [1]:

$$y_t = \begin{cases} -1 & \text{w.p } f(D_{ij} - D_{ik}) \\ +1 & \text{w.p } 1 - f(D_{ij} - D_{ik}). \end{cases} \tag{4}$$

We choose $f(x)$ to be the logistic function, such that:

$$f(D_{ik} - D_{ij}) = \frac{1}{1 + \exp(\sigma(D_{ik} - D_{ij}))}, \text{ with } \sigma = 1/\sqrt{2}. \tag{5}$$

We minimize the empirical risk:

$$\hat{R}_S(G) = \frac{1}{|S|}\sum_{t \in S} \ell(y_t \langle L_t, G \rangle) = \frac{1}{|S|}\sum_{t \in S} \ell(y_t(D_{ik} - D_{ij})), \tag{6}$$

We use the logistic loss, induced by our choice of f:

$$\ell(x) = \log(1 + \exp(-x)) \tag{7}$$

Algorithm

Algorithm 1: Estimate sender position from sensor positions and RSSIs
Input: $X \in \mathbb{R}^{d \times n}$: Known receiver positions
Input: $r \in \mathbb{N}^n$: RSSIs
Result: $\phi(\hat{x}_s)$: Estimated sender position

```
D = distances(X);
// Obtain triplets and compute the embedding
S, y = triplets(D, r, g);
Ẑ = embedding(S, y, f);
Ẑ = [X̂, x̂_s]
// Find the best affine transformation for the receiver
   positions.
φ = Procrustes(X, X̂);
// Apply affine transformation and return
if φ(x̂_s) ∈ conv(X) then
    return φ(x̂_s);
else
    return null;
```

Results

Table 1: Localization results for three different owls used as senders. Mean over approximately 3200 packets sent for each device.

Owl	Error [m] for $g_1(x)$		Error [m] for $g_2(x)$	
A	3.767	2.446	3.358	2.118
B	5.456	2.595	5.779	2.306
C	3.244	2.114	4.149	1.117

Results

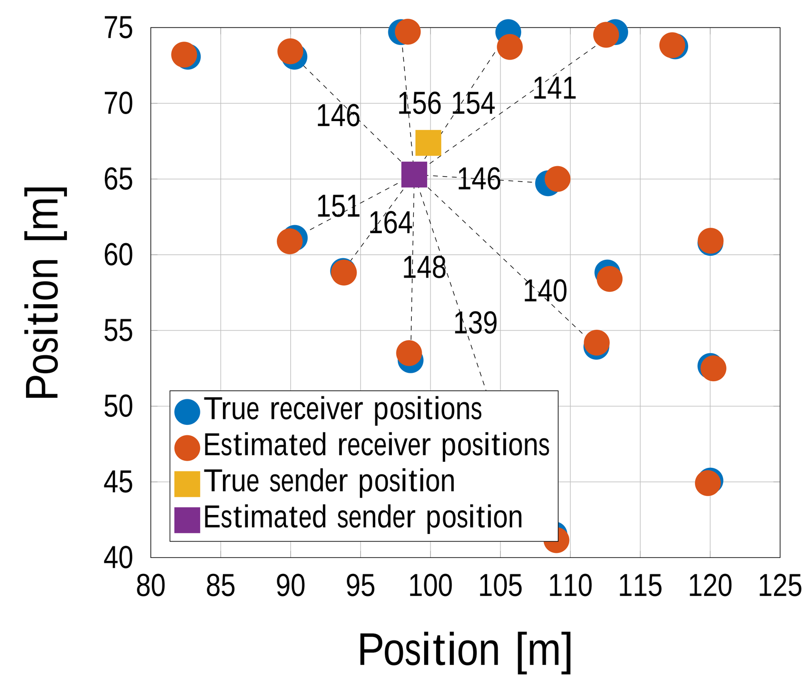

Figure 2: Positioning example using $g_1(x)$. Error is 2.320m from true location. Dotted lines show connectivity, numbers show RSSI values. Sender is A from Figure 1.

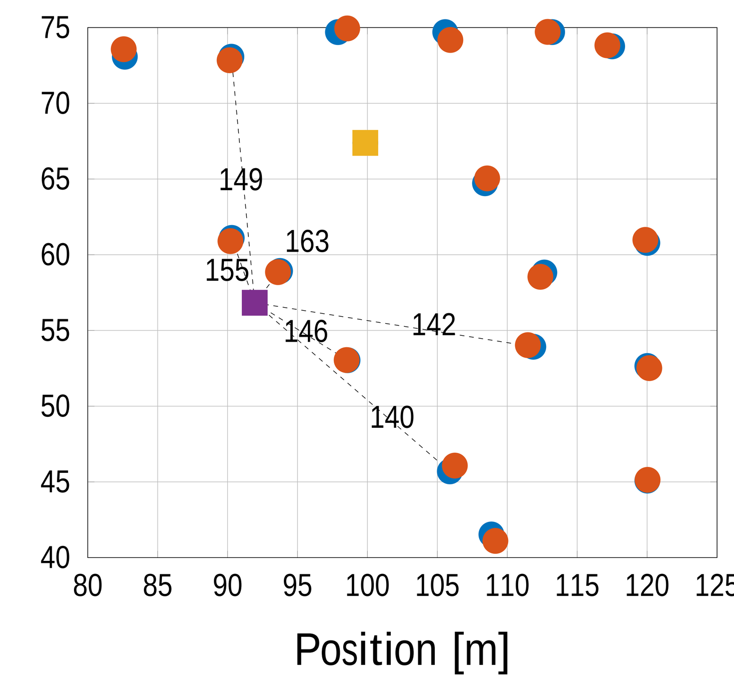

Figure 3: Positioning example using $g_1(x)$. Error is 13.191m from true location. Dotted lines show connectivity, numbers show RSSI values. Sender is A from Figure 1.

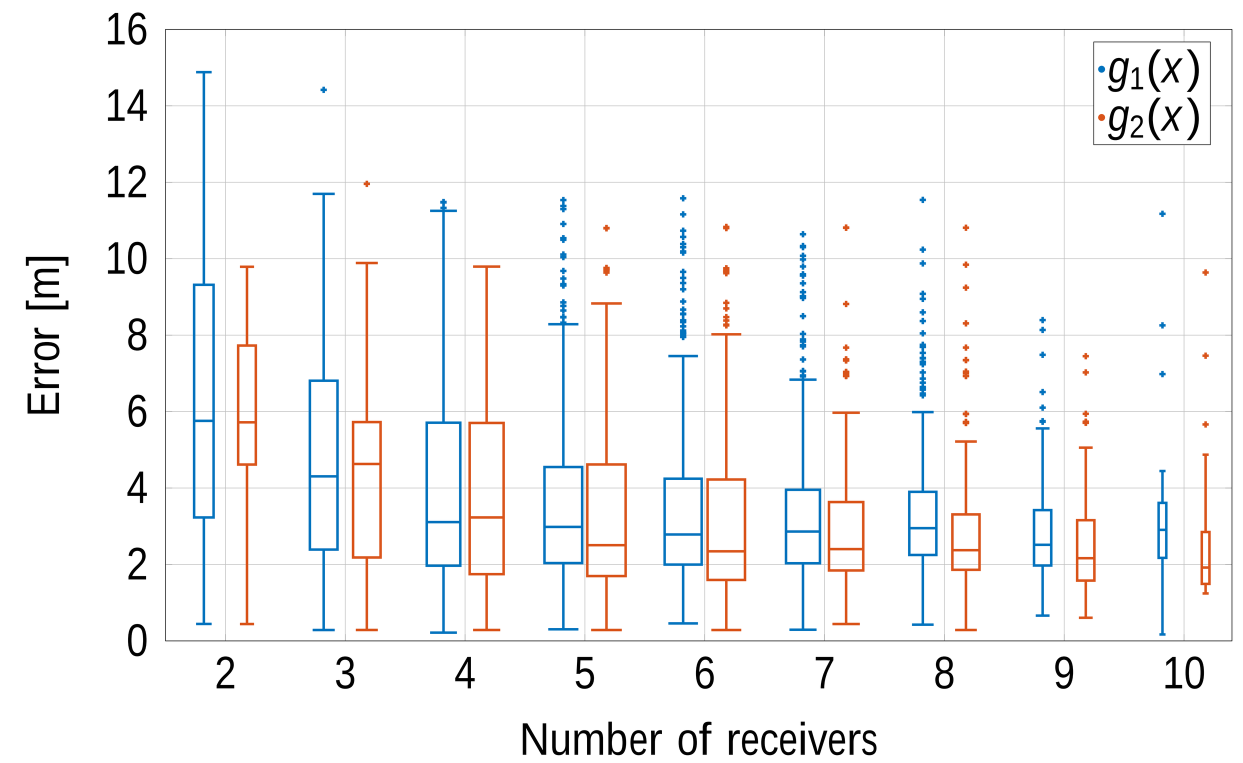

Figure 4: Box plot of the error as a function of number of receivers for a sent packet for two clipping function g_1 and g_2. The sender is device A from Figures 1.

Conclusions

- We propose a model-free algorithm for indoor localization that uses the ordinal information of the RSSI values
- We test an algorithm in a real-world setting: A heavy-traffic nursing unit within USC's Keck hospital
- We are able to localize different sources with an average error of 4m
- Code: `www.github.com/kmundnic/ICASSP2019`
- This research was funded by the IARPA MOSAIC program

References

[1] Lalit Jain, Kevin G Jamieson, and Rob Nowak. Finite sample prediction and recovery bounds for ordinal embedding. In *Advances In Neural Information Processing Systems*, pages 2711{2719, 2016.