Poster Abstract: Spray, Embracing Multimodality

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Abstract. We present *Spray*, a localization system that compensates for low accuracy of individual localization measurements by combining measurements from multiple localization modalities.

1 Introduction

Location plays an important role in numerous WSN applications [1], since it provides valuable context in interpreting sensed data, or is often the data that needs to be sensed. GPS devices cannot be used in all environments [2]. Hence, the localization process must rely on node to node measurements, or other types of local data [3]. These types of measurements are often associated with high uncertainty, and low accuracy [4–6]. The inherent uncertainty in localization stems from errors in signal parameter measurements, which arise from sources such as noise, multipath, blockages, interference, clock drifts, and environmental effects. There are, currently, no measurement methods that produce reliable results in all types of operational conditions, and especially not, when nodes are not in line-of-sight of each other.

The key benefit of *Spray* is that it can compensate for low accuracy of individual measurements by combining multiple localization modalities, and thereby produce improved position estimations. The types of available modalities depend on the particular deployment environment. It is, therefore, important that the parts of the system that represent the different modalities are made independent of each other, so that they can be excluded or included independently in order to tailor the system to a specific scenario. *Spray* accomplishes this by separating different modalities into individual *components*. A particle filter is then used to fuse together the results from the individual components.

2 System Architecture

The core of *Spray* consists of a particle filter based algorithm in which the particles represent possible node locations. Each particle has a weight that represents the confidence that the particle's location is the true node location. The estimation procedure is an iterative process, in which each node's position is estimated, one at a time, until all unknown nodes have been estimated. This is then repeated multiple times to refine the location estimations.

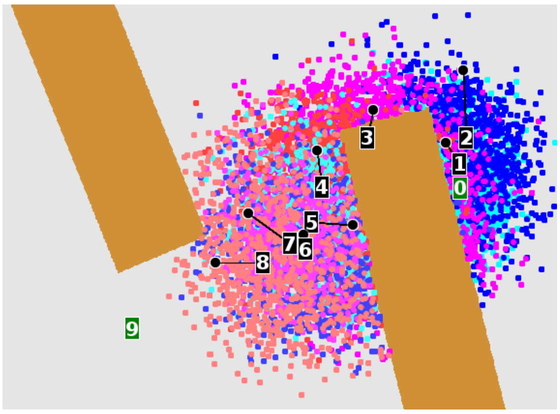

Fig. 1. A map over the outdoor environment. The brown rectangles represent buildings.

The components representing the individual modalities, implement *generators*, and *evaluators*, which are used to generate and evaluate particles based on the measurements of the associated modality. All evaluators operate on all particles, i.e., also the ones generated by other components, so that each component contribute in the weighting process of every particle.

The process of estimating the position for node i is as follows: (1) Each generator generates a number of particles. (2) Each evaluator e computes a weight $z_{e,k}$ for each particle k. The manner in which an evaluator computes these weights depend on the nature of the modality associated with that evaluator. (3) The geometric mean is then computed to estimate the total weight for each particle k according to Equation 1, where n is the number of evaluators.

$$w_i^k = \prod_{e=1}^{n} z_{e,k}^{\frac{1}{n}} \tag{1}$$

The reason for using the geometrical mean is that it is insensitive to difference in scale of the weighting functions of the different components. (4) Finally, the particles are resampled with replacement, such that N particles are selected to represent the node's location.

3 Evaluation

We evaluate *Spray* in the outdoor environment shown in Figure 3 using the following components:

1) *Map:* Uses information from predefined maps specifying possible node locations (Grey regions in Figure 2). 2) *Range:* Uses information from two-way time-of-flight RF range measurements. 3) *Non-proximity:* Assumes that nodes which are not within each other's radio range, are not likely to be close to each

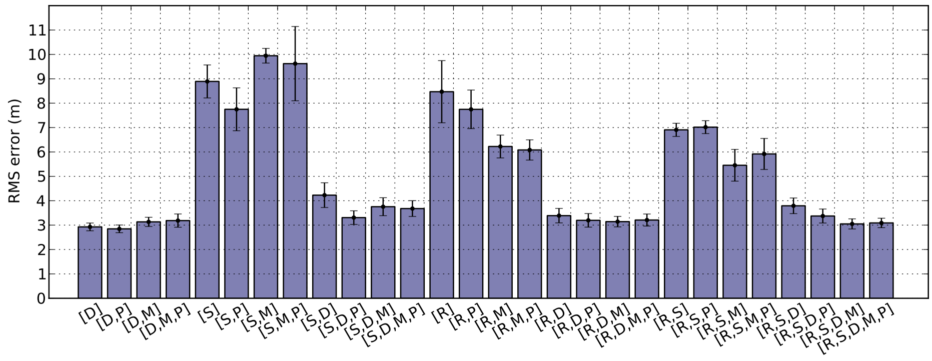

Fig. 2. Localization results: Combination of different components with 2 anchors.

other. 4) *Step count:* Uses the number of steps (measured using an accelerometer) walked between node locations by the operator, to estimate a maximum range between nodes. 5) *Dead Reckoning:* As step count, but with the additional information of the orientation of each step (measured using a compass).

We examine the individual contribution of the different component combinations. We base our results on the mean results for 100 runs for each combination. In each run, we iterate the algorithm 5 times, and compute the root-mean-square (RMS) error for all the non-anchor nodes after the last iteration. The final result for each component combination is then presented as the mean value of the 100 individual RMS values.

Figure 2 shows the result of each combination that contains at least one particle generator (the Map, and non-proximity components do not have generators). Node 0 and node 9 are anchor nodes with known locations. The respective bars corresponding to **D**ead reckoning, non-**P**roximity, **M**ap, **S**tep count, and **R**anging are labeled with the letters D, P, M, S, and R. The results show that blindly combining components does not necessarily improve the estimation accuracy. On the contrary, it can actually result in lower accuracy. One example of this is e.g., using the step component alone, in comparison to combining it with a map. Moreover, all combinations that include the dead reckoning component result in lower accuracy than using the dead reckoning component alone, although many are of the same magnitude as using dead reckoning alone. On the other hand, looking at the combinations that includes the ranging component (the last 16 bars), we see that adding any of the other components, resulting in combinations ([R P], [R M], [R D], or [R S]) increases the accuracy compared to using ranging alone. These combinations are also improvements over using the other components alone, except for dead reckoning as mentioned earlier. Adding a third component (resulting in the triples [R M P], [R D P], [R D M], [R S P], [R S M], and [R S D]) further improves the result in most cases. The only triples that significantly result in lower accuracy are: [R D P] over [D P], and [R S D] over [S D]. Another observation is that including the step count component decreases the performance for all combinations that do not include the ranging component. In combination with the ranging component, on the other hand, results are improved or are comparable, with the exception of [R D] and [R S D].

Although, it is possible to obtain better results by combining multiple modalities in some cases, the results show that we cannot combine components blindly, and expect to improve estimation accuracy. The reason, in our experiments, is that the dead reckoning component provides much more accurate localization data than the other components. In fact, for a component to actually improve on the estimation accuracy, it must provide some complementary information. For instance, step counting imposes an upper limit on the range between two nodes, and when used in combination with ranging it can improve accuracy in cases when the range measurements are over estimated. In the case of the dead reckoning component, on the other hand, the step count information is already available, and adding the step count component will only generate more particles in incorrect places, and moreover, weight these, and other particles within the step count range, with the same weight as for the particles generated by the dead reckoning component. Even though the particles generated by the dead reckoning component will typically obtain a higher total weight, a number of the other particles will still be resampled in the resampling step.

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References

1. Á. Lédeczi and M. Maróti. Wireless sensor node localization. *Philosophical Transactions of the Royal Society A*, 370(1958):85–99, 2012.
2. H. A. El-Natour, A. Escher, C. Macabiau, and M. Boucheret. Impact of multipath and cross-correlation on gps acquisition in indoor environments. In *National Technical Meeting of The Institute of Navigation*, San Diego, CA, January 2005.
3. L. Girod, M. Lukac, V. Trifa, and D. Estrin. The design and implementation of a self-calibrating distributed acoustic sensing platform. In *Proceedings of the 4th international conference on Embedded networked sensor systems*, SenSys '06, pages 71–84, New York, NY, USA, 2006. ACM.
4. C. D. Whitehouse. *Understanding the Prediction Gap in Multi-hop Localization.* PhD thesis, University of California, Berkeley, 2006.
5. B. Kusý. *Spatiotemporal coordination in wireless sensor networks.* PhD thesis, Vanderbilt University, 2007.
6. G. Zhou, T. He, S. Krishnamurthy, and J. A. Stankovic. Impact of radio irregularity on wireless sensor networks. In *Proceedings of the 2nd international conference on Mobile systems, applications, and services*, MobiSys '04, pages 125–138, New York, NY, USA, 2004. ACM.