

# SPOT Demo: Multi-entity Device-Free WLAN Localization

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## ABSTRACT

Device-free (DF) localization in WLANs has been introduced as a value-added service that allows tracking indoor entities that do not carry any devices. Previous work in DF WLAN localization focused on the tracking of a single entity due to the intractability of the multi-entity tracking problem whose complexity grows exponentially with the number of humans being tracked. We present a demonstration of *Spot* as an accurate and efficient system for multi-entity DF detection and tracking. *Spot* is based on a probabilistic energy minimization framework that combines a conditional random field with a Markov model to capture the temporal and spatial relations between the entities' poses. A novel cross-calibration technique is used to reduce the calibration overhead of multiple entities to linear, regardless of the number of humans being tracked. The demo presents the different components of the system in action.

## Categories and Subject Descriptors

C.2.4 [Computer-Communication Networks]: Distributed Systems—*Distributed applications*; H.3.4 [Information Systems Applications]: Miscellaneous

## Keywords

Binary graph-cut, conditional random fields, energy minimization, Markov models, multi-entity device-free tracking

## 1. INTRODUCTION

Device-free (DF) localization [1] is a concept that allows the detection and tracking of entities that do not carry any devices nor participate actively in the localization process. DF localization has a number of applications including intrusion detection, border protection, smart homes, and traffic estimation.

WLAN DF localization is based on the fact that the presence of an entity in an RF environment affects the signal strength generated by signal transmitters (e.g. standard APs) and received by monitoring points (MPs) such as any WiFi enabled device (e.g. laptops and APs themselves).

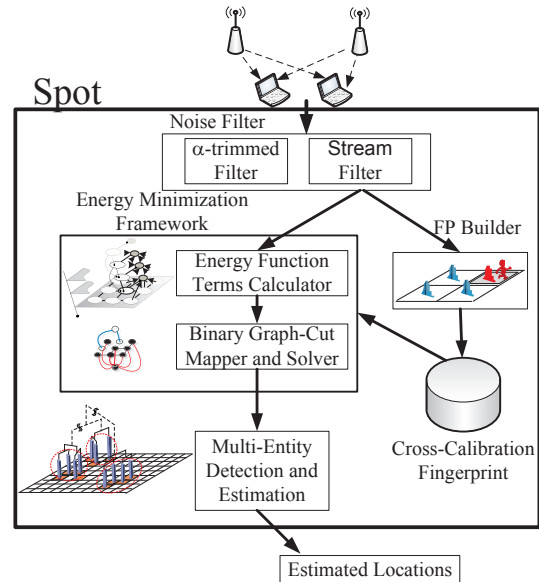


Figure 1: Spot system architecture.

In this work, we present a demonstration of *Spot* as a system for the accurate and efficient detection and tracking of **multiple DF entities** in a WLAN environment. *Spot* is based on a probabilistic energy minimization framework that combines a conditional random field with a Markov model. The problem of estimating the most probable active user locations is mapped to an energy minimization problem whose potential function is designed to preserve *smooth* and *consistent* labels for active locations relative to their neighbors and their movement history. *Spot* also introduces a novel cross-calibration technique to reduce the calibration overhead of multiple entities to **linear** in the number of locations, as compared to **exponential** for the current state-of-the-art. We further employ clustering on the estimated location candidates as a means for reducing outliers and obtaining more accurate tracking in the continuous space.

The demonstration enables users to interact with the system as well as change the different system parameters and see their effect in realtime on the system accuracy.

## 2. SPOT SYSTEM OVERVIEW

Figure 1 shows the system architecture. The system collects the signal strength readings from the monitoring points

(i.e. laptops) for processing. There are two phases of operation:

1) Offline training phase: to estimate the system parameters based on the collected signal strength readings and construct the device-free fingerprint. During this phase, a human stands at different locations in the area of interest and the RSS at each MP is recorded. Note that our formulation requires only one human for calibration in the offline phase, regardless of the number of humans during the system operation. This significantly reduces the calibration overhead as compared to the state-of-the-art DF systems.

2) Online tracking phase: to estimate the multi-entities' locations based on the received signal strength from each stream and the fingerprint prepared in the offline phase using the energy minimization framework.

The *Noise Filtering* module preprocesses collected RSS readings during the offline and online phases to reduce the noise effects and detect outliers. First, the measured RSS values are filtered using  $\alpha$ -trimmed Mean filter. In addition, since the readings of a single stream may have significantly changed between the offline and online phases, due to changes in the environment, we use the Analysis of Variance (ANOVA) to filter significantly changed streams.

The *Energy Minimization Framework* calculates the probabilities used in the energy minimization framework, constructs an equivalent graph, and estimates the most probable active locations (i.e. environment map) based on solving a binary graph-cut problem.

The *Fingerprint Builder* module estimates required likelihoods and priors for the energy function during the offline phase. We use a *cross-calibration* technique to build a fingerprint (FP) for  $n$  locations, where an entity standing at location  $x$  contributes to the *active* likelihoods of  $x$  and the *inactive* likelihoods of the all remaining  $n-1$  FP locations. Finally, the fingerprint is the collection of these active-inactive histograms over all locations. The generated histograms are smoothed by convolution with separable gaussian kernels to avoid the zero-probability problem of missing values in the training set.

The *Multi-Entity Detection and Estimation* module applies clustering to the output of the binary graph-cut algorithm, such that the number of output clusters determines the number of entities and the center of mass of each cluster gives the coordinates of the human corresponding to this cluster. A non-zero estimated number of entities is equivalent to a detection event in the area of interest.

### 3. DEMO GOALS AND DESCRIPTION

The demonstration applies and visualizes the system procedure to real data sets collected in real time. The demonstration enables the user to observe how *Spot* works by visualizing changes in the environment over time and the output of the location tracking module. Moreover, it enables the user to investigate the effect of different system parameters simultaneously. The demo can work in two modes of operation: online and offline.

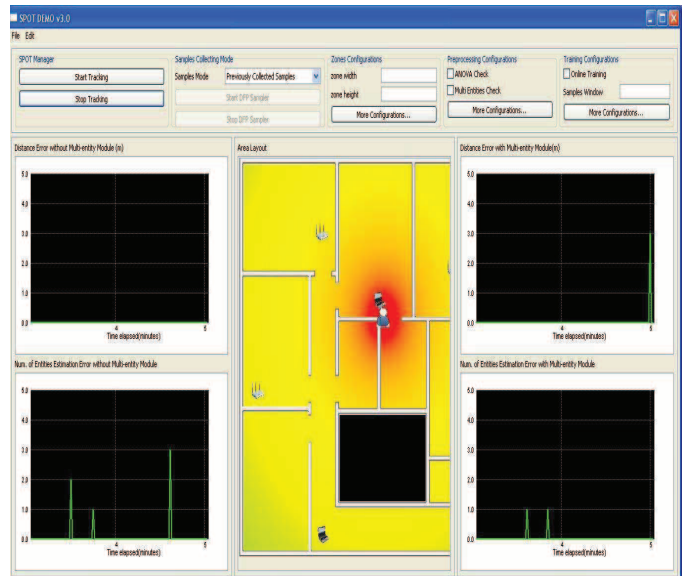


Figure 2: Spot localization interface during offline simulation.

### 3.1 Online Mode

In this mode, the operation has two phases:

1) Constructing a fingerprint from RSS values of locations in the area of interest via the RSS calibrator. The calibrator is initialized with required configurations for APs and MPs that will be used in the experiment. After that, it collects and samples RSS readings from all streams registered in it.

2) Performing localization using gathered RSS values and assigned configurations. Figure 2 shows the main interface for the demo. There are three main components: the output of tracking interface, configurations windows and illustrative curves about *Spot* behavior.

### 3.2 Offline Mode

This mode is effective to analyze different parameters for large-scale data sets. It is based on replaying data previously collected from actual environments. It visualizes the output of *Spot* localization and displays charts summarizing its sensitivity to various parameters. It needs no online calibration as it works on previously collected data sets in large-scale. These data sets include signal strength data collected in both silence and motion states. Figure 2 shows the interface while it simulates localization states.

## 4. ACKNOWLEDGMENT

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## 5. REFERENCES

- [1] M. Youssef, M. Mah, and A. Agrawala. Challenges: Device-Free Passive Localization for Wireless Environments. In *MobiCom '07: Proceedings of the 13th annual ACM international conference on Mobile computing and networking*, pages 222–229. New York, NY, USA, 2007.