Multi-entity Device-Free WLAN Localization

Ibrahim Sabek
Computer Systems and Engineering Department
Alexandria University, Egypt
ibrahim.sabek@alexu.edu.eg

Moustafa Youssef
Wireless Research Center
Alexandria University and E-JUST, Egypt
moustafa.youssef@ejust.edu.eg

***Abstract*—We introduce *Spot* as an accurate and efficient system for multi-entity device-free (DF) detection and tracking. Current state-of-the-art systems focused on the tracking of a single entity because of the intractability of the multi-entity case that leads to exponential complexity. *Spot* provides a novel cross-calibration technique that reduces the overhead of multiple entities calibration from exponential to linear. *Spot* also captures the spatial relations between the entities' poses into a probabilistic energy minimization framework via a conditional random field model. The designed energy minimization function is solved by a binary graph-cut algorithm. We evaluate our system using a typical testbed and show that *Spot* can achieve a multi-entity median tracking error of less than 1.44m. This corresponds to 108.33% enhancement in median distance error over the state-of-the-art DF localization systems, which can only track a single entity. In addition, *Spot* can estimate the number of entities correctly to within one difference error with 92% accuracy. This highlights that *Spot* achieves its goals of having an accurate and efficient software-only DF tracking solution of multiple entities in indoor environments.**

***Index Terms*—Binary graph-cut, device-free localization, energy minimization, conditional random fields, multi-entity tracking and detection.**

I. Introduction

Device-free (DF) localization [1] makes use of the already installed wireless infrastructure, e.g. WLANs, to allow the detection and tracking of entities that do not carry any devices nor participate actively in the localization process. DF localization can be used in smart homes, intrusion detection [1], [2], border protection [3], and traffic estimation [4], [5]. Different approaches that require the installment of special hardware have been proposed to address the DF detection and tracking. These include, Radar-based systems, e.g. [6]–[8], computer vision systems, e.g. [9], [10], and radio tomographic imaging (RTI) [11]. On the other hand, [1], [2], [12]–[21] use the currently installed wireless networks only to provide scalable solutions in terms of cost and coverage area.

WLAN DF localization is based on the effect of human motion on the signal strength. A typical WLAN system consists of signal transmitters (e.g. standard APs); signal receivers or monitoring points (MPs), such as any WiFi enabled device (e.g. laptops and APs themselves); and an application server that collects the received signal strength (RSS) for the different streams (where a stream is a single (AP, MP) pair) readings and processes them to detect events.

DF tracking requires capturing the RSS behavior at different locations in the area of interest. Thus, typically, a fingerprint is constructed by recording the effect of a human standing at different locations in the area of interest on the RSS at the MPs. The complexity of fingerprint construction grows exponentially with increasing number of entities to be tracked due to the need for trying all combinations over all locations. This forced previous work to focus only on ***single entity*** tracking [1], [2], [12]–[21].

In this paper, we introduce *Spot* as an efficient multi-entities DF detection and tracking system in a WLAN environment. It provides a probabilistic energy minimization framework based on a conditional random field representation to capture spatial relations between moving entities. The potential function used for estimating the most probable active users' locations is designed to preserve *smooth* labels for active locations relative to their neighbors. The solution to this function is obtained by mapping the problem to a binary graph-cut problem. In addition, *Spot* reduces the calibration overhead of multiple entities by introducing a novel calibration technique. We evaluated *Spot* using a typical testbed. *Spot* shows superiority over current state-of-the-art techniques: It can achieve a median tracking error of less than 1.44m. This corresponds to 108.33% enhancement in median error over the state-of-the-art DF localization systems, while enabling the tracking of multiple entities. In addition, *Spot* can estimate the number of entities with 92% accuracy to within one difference error.

The rest of the paper is organized as follows: Section II presents the energy-minimization framework and our novel calibration technique. We evaluate *Spot* in a typical WiFi testbed and compare it to a state-of-the-art DF WLAN localization technique in Section III. We discuss different aspects and challenges of *Spot* in Section IV. Finally, we briefly present previous work related to *Spot* and conclude the paper in sections V and VI respectively.

II. Energy Minimization Framework

This section describes our probabilistic framework for multiple entities localization. This framework is designed to have an energy model that represents the spatial constraints on the human position by a Conditional Random Field (CRF) model favoring coherence between adjacent locations (Figure 1).

A. Notations and Model

Without loss of generality, let $\mathbb{X}$ be a 2-dimensional physical space with n locations. At each location $x \in \mathbb{X}$, we can get the signal strength from k streams. We denote the k-dimensional

978-1-4673-0921-9/12/$31.00 ©2012 IEEE

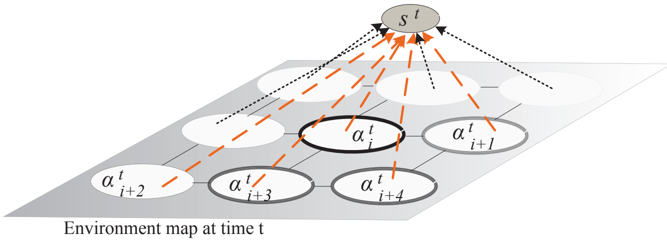

Fig. 1. Conditional Random Field model. This graphical model illustrates both the signal strength likelihood together with the spatial prior. Spatial dependencies are illustrated for a 4-neighborhood system. The entire environment map affects the RSS vector s^t.

signal strength space as $\mathbb{S}$. Each element in this space is a k-dimensional vector, $s = (s_1, ..., s_k)$, whose entries represent the signal strength readings from a different (AP, MP) pair. We further assume that the samples from *different* streams are independent. Given that m humans are standing in the area of interest, $m \geq 0$, these humans will affect the different streams. Therefore, the problem becomes to both estimate the number of humans $\hat{m}$ and, if $\hat{m} > 0$, the locations of these humans $\{x_i | 0 < i \leq \hat{m}, x_i \in \mathbb{X}\}$, such that the probability $P(x_1, x_2, ..., x_{\hat{m}}|s)$ is maximized. Let $\{\alpha_i^t, 0 < i < n\}$ be a set of bernoulli random variables, where α_i^t takes the value of 1 if a human is standing at location $i \in \mathbb{X}$ at time t, and 0 otherwise. Therefore, the problem can be equivalent to finding the assignment of α_i^t's that maximizes

$$P(\mathbb{M}^t|s) \tag{1}$$

where $\mathbb{M}^t = (\alpha_1^t, \alpha_2^t, ..., \alpha_n^t)$. We refer to $\mathbb{M}^t$ as the ***environment map*** at time t. In this case, $\hat{m} = \sum_{i=1}^{n} \alpha_i^t$ and the most probable locations of the $\hat{m}$ entities are the locations whose α_i^t's are assigned to one.

B. Framework Construction

Traditional work on probabilistic WLAN localization, both device-based and device-free, e.g. [22], use Bayesian inversion to estimate $P(\mathbb{M}^t|s)$. However, these systems typically assume only one entity in the area of interest. Moving to more than one entity makes this Bayesian inversion approach intractable as the complexity of estimating $P(s|\mathbb{M}^t)$ increases exponentially with the number of entities that need to be tracked (due to the need to try all combinations of humans' poses in the area of interest).

Based on CRF theory [23], [24], our model estimates the probability from Equation 1 as

$$P(\mathbb{M}^t|s^t) \propto \exp - \left\{E^i\right\} \tag{2}$$

where $E^i = E(s^t, \mathbb{M}^t)$ is an energy function that captures the required constraints on the DF tracking problem. That is, we want to estimate the current environment map given the current signal strength vector measured at the monitoring points. This is obtained by the joint maximization of the posterior in Equation 2, which is equivalent to the minimization of energy:

$$\hat{\mathbb{M}}^t = (\hat{\alpha}_1^t, \hat{\alpha}_2^t, ..., \hat{\alpha}_n^t) = \arg\min E^i \tag{3}$$

Energy Terms: For our DF tracking problem, each E^i is composed of two components:

$$\begin{aligned} E^i &= E(s^t, \mathbb{M}^t) \\ &= V^{\text{Sp}}(\mathbb{M}^t, s^t) + U^{\text{SS}}(\mathbb{M}^t, s^t) \end{aligned} \tag{4}$$

The term $V^{\text{Sp}}(\mathbb{M}^t, s^t)$ presents a spatial prior term which imposes a tendency to spatial continuity of the environment map, favoring coherent assignments.

The $U^{\text{SS}}(\mathbb{M}^t, s^t)$ term is a likelihood term that evaluates the evidence for location labels based on the RSS distributions in the case of human absence and presence.

Figure 1 shows the graphical representation of the model. Details of these factors are given in the next subsections.

1) Spatial prior term: This term should favor coherent environment maps, i.e. adjacent locations have similar labels. We adapt a variation of the Ising model commonly used for segmentation applications [25] where the spatial energy term can be represented as:

$$\begin{aligned} V^{\text{Sp}}(\mathbb{M}^t, s^t) &= \sum_{\{c_i, c_j\} \in \mathbb{N}} V^{\text{Sp}}_{\{c_i, c_j\}}(\alpha^t_{c_i}, \alpha^t_{c_j}, s^t) \\ = \gamma \sum_{\{c_i, c_j\} \in \mathbb{N}, \alpha^t_{c_i} \neq \alpha^t_{c_j}} &\left(\frac{1 + e^{-\left\| P(s^t|\alpha^t_{c_i}) - P(s^t|\alpha^t_{c_j}) \right\|^2}}{2} \right) \end{aligned} \tag{5}$$

where $\mathbb{N}$ is the set of pairs of neighboring locations. The term $P(s^t|\alpha^t_{c_i})$ represents the conditional probability of receiving the signal strength vector s^t when the human is present at location c_i ($\alpha^t_{c_i} = 1$) or not present ($\alpha^t_{c_i} = 0$). This can be estimated during the training phase as described in Section II-C. The constant γ is a strength parameter for the coherence prior that can be estimated based on the training data.

2) Likelihood for signal strength: The term $U^{\text{SS}}(\mathbb{M}^t, s^t)$ is the log likelihood of the received signal strength. The term is defined as :

$$U^{\text{SS}}(\mathbb{M}^t, s^t) = \delta \sum_{i=1}^{n} \left[-\log P(s^t \mid \alpha^t_i) \right] \tag{6}$$

where $\delta < 1$ is a discount factor to allow for multiple counting across non-independent locations whose optimal value is obtained discriminatively from the training data.

RSS likelihoods are learned during the offline training phase as described in the next section.

C. Fingerprint Construction

We need to estimate the RSS likelihood, $P(s^t \mid \alpha^t_i)$, during calibration. Based on the described signal strength terms in the energy function, i.e. the spatial prior and signal strength likelihood, the fingerprint of *Spot* is unique among all the previous device-based and device-free WLAN localization systems. In particular, we use a calibration technique where an entity standing at location x contributes to the active RSS likelihoods of x ($P(s^t \mid \alpha_x^t = 1)$) and the inactive RSS likelihoods of the all remaining $n-1$ FP locations ($P(s^t \mid \alpha_i^t = 0, \forall i \neq x)$). This has the advantage of converting the intractable exponential number of cases of building the fingerprint for traditional DF systems to a linear complexity problem, as only one human is needed for training, regardless of the number of humans to be tracked.

In summary, at each location, we have two histograms for the RSS corresponding to the active and inactive states respectively. The fingerprint is the collection of these two histograms over all locations $x \in \mathbb{X}$. We smooth the generated histograms by convolution with separable gaussian kernels to avoid the zero-probability problem of missing values in the training set.

D. Most Probable Map Estimation

Based on the results in [26], our DF energy minimization function can be solved using a graph-cut approach. An efficient binary graph-cut was proposed to solve the problem in a low order polynomial in n [27]. Although, the binary graph-cut algorithm requires $O(n^3)$ operations, where n is the number of fingerprint locations, [27] provides an iterative fast algorithm with $O(n)$ as average complexity. This has been confirmed in our experiments.

We construct a graph that has $n+2$ nodes, where n nodes are the original discrete environment map locations and two additional nodes are added to represent the source s and sink t nodes. There are two types of edges. Those between the original discrete environment map locations (n-edges) with weights based on $V^{\text{Sp}}(\mathbb{M}^t, s^t)$ and those between each node and the source and sink terminal nodes (t-edges) with weights based on $U^{\text{SS}}(\mathbb{M}^t, s^t)$. According to this assignment, we guarantee that the min-cut solution to this graph is equivalent to minimizing the energy function in Equation 3 [28].

III. Performance Evaluation

In this section, we analyze the performance of *Spot* and compare it to the state-of-the-art *Nuzzer* DF WLAN localization system [2], [15]. We start by describing the experimental setup and data collection. Then, we analyze the effect of different parameters on the system performance.

A. Testbeds and Data Collection

We evaluate our system in a typical testbed (Figure 2). The testbed covers a residential apartment with an area of $114m^2$ (about 1228 sq. ft. The testbed is covered by TP-link TL-WA500G APs and D-Link Airplus G+DWL-650 wireless NICs.

For data collection, we used a sampling rate of one hertz. We had six RSS data streams for both testbeds. A total of 25 fingerprint locations, uniformally distributed over the testbed, are sampled. An independent test set at 17 test locations was collected at different times and by different persons.

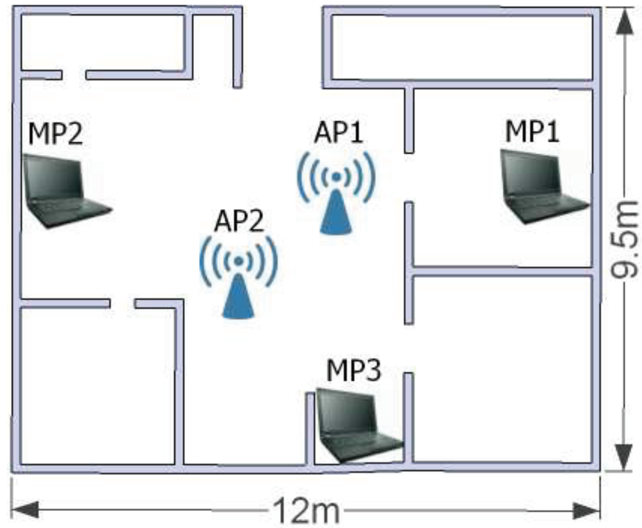

Fig. 2. Experimental testbed.

TABLE I
DEFAULT PARAMETERS VALUES.

Parameter	Default value	Meaning
k	6	Num. of used streams
n	25	Num. of FP locations

B. Parameters Effect

In this section, we study the effect of changing the system parameters on the performance of *Spot*. The median distance error is used as the main metric where the error is calculated as the difference between the estimated location and the closest ground truth location. We present **zone-based error** as the average error based on the centers of zones where estimated and actual locations belong to. To calculate the distance error for multiple entities, we use the Euclidean distance between the estimated zone of each entity and the closest fingerprint zone. Table I shows the default values of the different parameters.

1) Fingerprint density (n): Figure 3 shows that increasing the fingerprint density increases accuracy. As small as 20 locations, corresponding to a density of one FP location every $5.7m^2$, is enough to achieve the best accuracy. Increasing the density beyond this value does not significantly enhance the accuracy.

2) Number of streams (k): Figure 4 shows that increasing the number of streams increases the system accuracy, especially for a higher number of entities, to a certain limit after which the performance saturates. As few as four streams can achieve less than 3.5 meter overall accuracy.

C. Comparison with Other DF Systems

1) Accuracy: Figure 5 shows the CDF of distance error for the different techniques (note that current state-of-the-art supports only one entity). Table II summarizes the results. The results show that *Spot* has the best performance with an

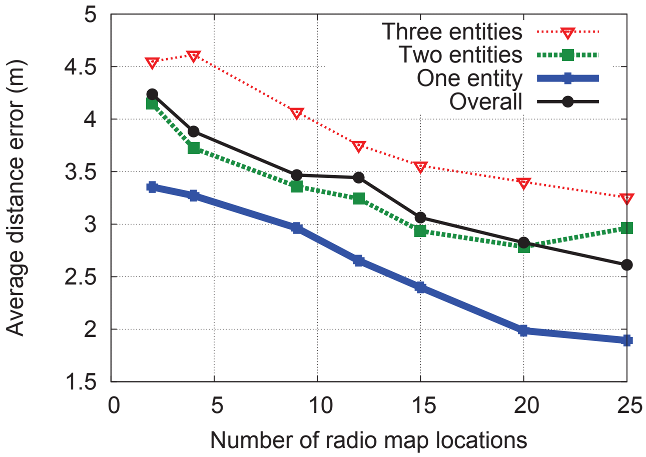

Fig. 3. Effect of changing the fingerprint density (n) on accuracy.

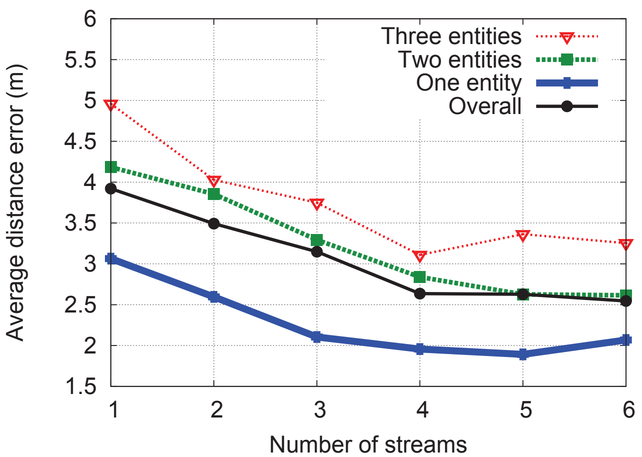

Fig. 4. Effect of changing the number of streams (k) on accuracy.

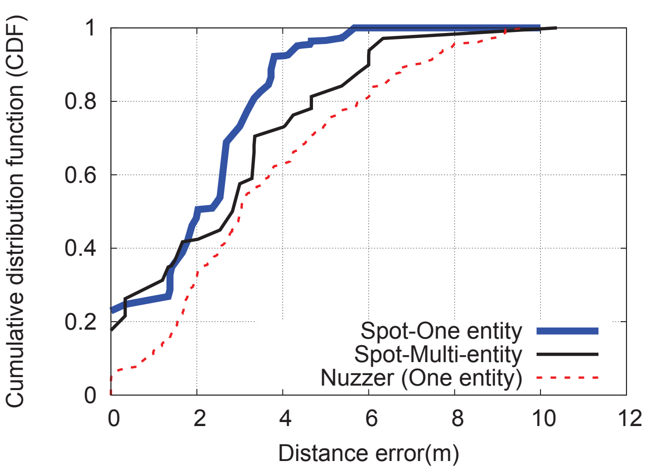

Fig. 5. CDF of distance error.

enhancement of 108.33% in median error over the state-of-the-art technique.

Figure 6 also shows that *Spot* can estimate the number of entities in the area of interest to within one difference error with more than 92% accuracy.

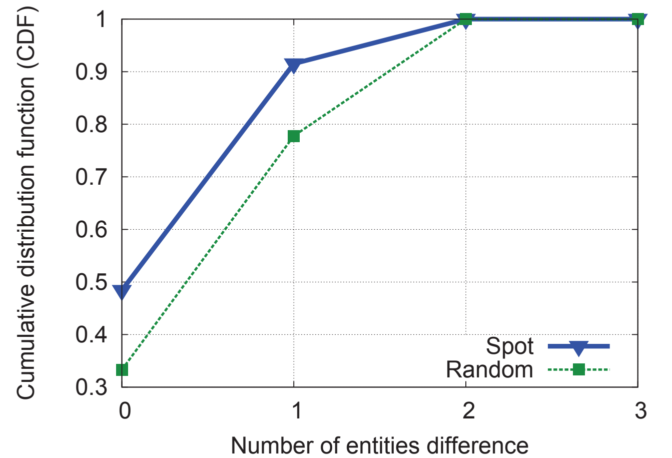

Fig. 6. CDF of num. of entities estimation error. A random estimator is a baseline that presents a lower bound on performance.

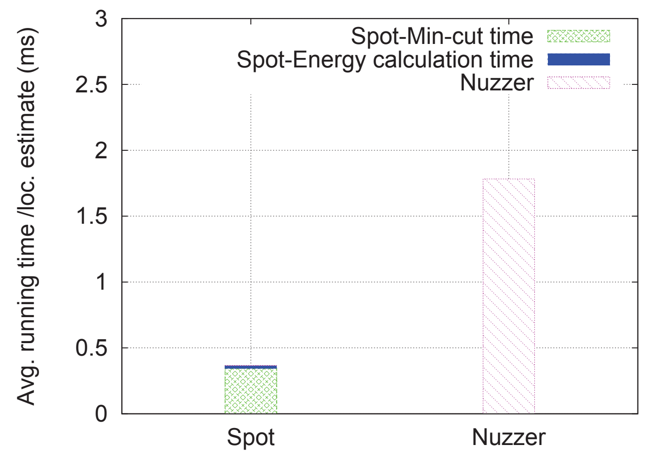

Fig. 7. Running time for the different components of the Spot system and a comparison with other systems running time.

2) Running Time: Figure 7 and Table II show the running time for *Nuzzer* and *Spot* components. The results show that the overall *Spot* operations take less $0.356ms$ per location estimate. The min-cut algorithm consumes the largest time, followed by calculating the probabilities. *Spot* significantly reduces the running time by 400% as compared to *Nuzzer*. This highlights the gains of *Spot* in terms of both accuracy and latency.

IV. Discussion

In this section, we discuss different aspects of *Spot*.

A. Path Training

Using the proposed framework, we could reduce the training complexity from $O(2^n)$ to $O(n)$. This is a significant reduction in the calibration overhead which turns the multi-entity tracking problem to a feasible problem. However, there

TABLE II
PERFORMANCE SUMMARY FOR THE DIFFERENT SYSTEMS. NUMBER BETWEEN PARENTHESIS REPRESENT PERCENTAGE OF SPOT-ONE ENTITY ADVANTAGE.

System	Median error	Average error	Running time
Spot-One ent.	1.44m	1.89m	0.356ms
Spot-Multi-ent.	2m (38.88%)	2.61m (38%)	0.435ms (22.19%)
Nuzzer [15]	3m (108.33%)	3.54m (87.3%)	1.78ms (400%)

is still some effort in calibrating the area of interest as the user has to stand at each location for a certain time. One possibility to reduce this overhead is to use path-based training, where a user continuously moves between two points and samples are collected along the path. This continuous calibration reduces the overhead, but provides less samples. Multiple passes around the area of interest can be used to increase the number of available samples along with density interpolation between adjacent locations. Further experiments need to be performed though to asses the tradeoffs of this technique.

B. Identification

Although we can track multiple entities in the area of interest, identifying these entities remains an open problem. This identification includes knowing the entities' physical identity (e.g. its name) or virtual identity, i.e. associating a unique ID to the detected entity. This entity labeling problem is well known in other fields, such as computer vision [29]. The entities movement history and trajectories can be used to detect these virtual identities.

C. Number of Entities History Model

Spot can correctly estimate the number of entities with high accuracy. This can be further enhanced based on adding constraints for the temporal smoothness of the number of entities. In other words, outliers in estimating the number of entities can be detected based on the history of the detected number of entities.

V. RELATED WORK

Over years, multiple technologies have been introduced to address the device-free tracking problem: radar-based, camera-based, sensors-based, and WLAN-based systems. Table III shows how *Spot* compares to the different systems.

Radar-based systems: The key idea is to transmit pulses of radio waves into the area of interest and track required objects via measuring the received reflections. Ultra-wideband (UWB) systems [6], doppler radar [7], and MIMO radar systems [8] are considered state-of-the-art radar-based technologies.

Camera-based systems: Inspired by computer vision, previous research work was proposed to exploit and analyse the captured images from cameras to estimate the trajectory of moving objects of interest. Device-free tracking is tackled from two perspectives: background subtraction and temporal correspondence [9], [10].

Sensor-based systems: these systems rely on installed sensor nodes to cover the area of interest. For example, [11] applies radio tomographic techniques to the readings of a dense array of sensors to obtain accurate DF tracking.

All the technologies above share the requirement of installing special hardware to be able to perform DF tracking, which reduces their scalability in terms of cost and coverage area. In contrast, WLAN DF tracking aims at exploiting the already installed WLAN. The DF localization in WLANs was first introduced in [1] along with feasibility experiments in a controlled environment. Several papers followed the initial vision to provide different techniques for detection and tracking [12]–[15]. However, all these techniques focus on the problem of a ***single entity***. Tracking multiple entities, to-date, has been considered an intractable problem due to the exponential increase in the number of training combination required.

Spot, on the contrary, is designed to provide accurate and efficient, i.e. linear training complexity, multi-entity DF localization for WLAN environments.

VI. CONCLUSION

We presented the design, analysis, and implementation of *Spot*: a system for accurate and efficient multi-entity device-free WLAN localization. *Spot* leverages probabilistic techniques to provide a smooth environment image. It uses a cross-calibration technique and an energy minimization framework to reduce the calibration overheard to linear in the number of locations, which turns the DF multi-entity tracking to a tractable problem. We showed an efficient solution to the proposed energy minimization framework by mapping the energy function to a binary graph-cut problem.

Implementation on standard WiFi hardware shows that *Spot* can achieve 1.44m median distance multi-entity tracking error, which is better than the stat-of-art techniques by 108.33%. In addition, it can estimate the number of entities correctly to within one entity difference 92% of the time. This highlights the promise of *Spot* for a wide range of multi-entity DF tracking applications.

Currently, we are expanding *Spot* in multiple directions including reducing calibration effort, entity identification, and tracking the history of the number of entities.

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*. New York, NY, USA, 2007, pp. 222–229.

[2] M. Siefeldin, A. Saeed, A. Kosba, A. El-keyi, and M. Youssef, "Nuzzer: A large-scale device-free passive localization system for wireless environments," in *ACM Transactions on Mobile Computing*, 2012.

[3] A. L. AlHusseiny, M. Youssef, and M. ELTowiessy, "WCPS-OSL: A wireless cyber-physical system form object sensing and localization," in *CyPhyCARD'11 in conjunction with CollaborateCom 2011*, 2011.

[4] N. Kassem, A. E. Kosba, and M. Youssef, "ReVISE: An RF-based vehicle detection and speed estimation," in *VTC Spring*, 2012.

TABLE III
COMPARISON OF DIFFERENT RF-BASED DF LOCALIZATION SYSTEMS.

	MIMO Radar-based Systems	**Radio Tomographic Imaging (RTI)**	**Nuzzer System**	**Spot System**
Special hardware required	Yes	Yes	No	No
Number of special nodes	Few	Many	None	None
Number of streams	N/A (echo based)	Large (756)	Small (6)	Small (6)
Coverage area	Limited (high freq.)	Limited	Yes	Yes
Computational Complexity	Low	High	Moderate	Low
Accuracy	Very High	High	Moderate	High
Muli-path effect	Limited	Yes	Limited (F.print)	Limited (F.print)
Multi-entity tracking	Yes	Yes	No	Yes
Multi-entity overhead	Low	Low	Intractable	Moderate (F.print)

[5] A. Lotfy and M. Youssef, "RF-based traffic detection and identification," in *VTC Fall*, 2012.

[6] Y. Yang and A. E. Fathy, "See-through-wall imaging using ultra-wideband short-pulse radar system," in *IEEE Antennas Propag. Soc. Int. Symp*, 2005.

[7] A. Lin and H. Ling, "Doppler and direction-of-arrival (DDOA) radar for multiple-mover sensing," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 43, no. 4, pp. 1496–1509, 2007.

[8] A. M. Haimovich, R. S. Blum, and L. J. Cimini., "MIMO Radar with Widely Separated Antennas," *IEEE Signal Processing Magazine*, pp. 116–129, 2008.

[9] T. B. Moeslund, A. Hilton, and V. Krger, "A survey of advances in vision-based human motion capture and analysis," *Computer Vision and Image Understanding*, vol. 104, no. 2-3, pp. 90–126, 2006.

[10] J. Krumm, S. Harris, B. Meyers, B. Brumitt, M. Hale, and S. Shafer, "Multi-Camera Multi-Person Tracking for Easyliving," in *Third IEEE International Workshop on Visual Surveillance*, 2000.

[11] J. Wilson and N. Patwari, "Radio Tomographic Imaging with Wireless Networks," in *tech. rep.* University of Utah, 2008.

[12] M. Moussa and M. Youssef, "Smart Devices for Smart Environments: Device-free Passive Detection in Real Environments," in *IEEE PerCom Workshops*, 2009.

[13] J. Yang, Y. Ge, H. Xiong, Y. Chen, and H. Liu, "Performing Joint Learning for Passive Intrusion Detection in Pervasive Wireless Environments," in *The 29th Conference on Computer Communications, INFOCOM*, 2010, pp. 1–9.

[14] A. E. Kosba, A. Saeed, and M. Youssef, "RASID: A Robust WLAN Device-free Passive Motion Detection System," in *PerCom*, 2012, pp. 180–189.

[15] M. Seifeldin and M. Youssef, "A Deterministic Large-scale Device-free Passive Localization System for Wireless Environments," in *PETRA '10: Proceedings of the 3rd International Conference on Pervasive Technologies Related to Assistive Environments*, 2010, pp. 1–8.

[16] K. El-Kafrawy, M. Youssef, and A. El-Keyi, "Impact of the human motion on the variance of the received signal strength of wireless links," in *PIMRC*, 2011, pp. 1208–1212.

[17] K. El-Kafrawy, M. Youssef, A. El-Keyi, and A. F. Naguib, "Propagation modeling for accurate indoor wlan rss-based localization," in *VTC Fall*, 2010, pp. 1–5.

[18] M. Youssef and A. Agrawala, "Small-Scale Compensation for WLAN Location Determination Systems," in *IEEE WCNC 2003*, March 2003.

[19] A. Eleryan, M. Elsabagh, and M. Youssef, "AROMA: Automatic Generation of Radio Maps for Localization Systems," *CoRR*, vol. abs/1002.1834, 2010.

[20] ——, "Synthetic generation of radio maps for device-free passive localization," *IEEE Globecom*, 2011.

[21] A. E. Kosba, A. Saeed, and M. Youssef, "Robust WLAN device-free passive motion detection," in *WCNC*, 2012.

[22] M. A. Youssef and A. Agrawala, "The Horus WLAN Location Determination System," in *ACM MobiSys*, 2005, pp. 205–218.

[23] S. Kumar and M. Hebert, "Discriminative random fields: A discriminative framework for contextual interaction in classification," in *Proceedings of the Ninth IEEE International Conference on Computer Vision - Volume 2*, ser. ICCV '03, 2003.

[24] J. D. Lafferty, A. McCallum, and F. C. N. Pereira, "Conditional random fields: Probabilistic models for segmenting and labeling sequence data," in *Proceedings of the Eighteenth International Conference on Machine Learning*, 2001.

[25] Y. Boykov and M. P. Jolly, "Interactive Graph Cuts for Optimal Boundary and Region Segmentation of Objects in N-D Images," in *ICCV*, 2001, pp. 105–112.

[26] V. Kolmogorov and R. Zabih, "What energy functions can be minimized via graph cuts?" in *Proceedings of the 7th European Conference on Computer Vision-Part III*, ser. ECCV '02, 2002.

[27] Y. Boykov, O. Veksler, and R. Zabih, "Fast approximate energy minimization via graph cuts," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, November 2001.

[28] I. Sabek and M. Youssef, "Spot: An Accurate and Efficient Multi-entity Device-Free WLAN Localization System," *CoRR*, vol. abs/1207.4265, 2012.

[29] J. Berclaz, F. Fleuret, E. Turetken, and P. Fua, "Multiple object tracking using k-shortest paths optimization," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2011.