Using Generalized Similarity Filter to Enhance Proximity Detection for Sparse Beacon Deployment

Li Zhu†, Rong Ran†, Pai Chet Ng‡, James She‡
†School of Electrical and Computer Engineering, Ajou University; Email: {julie0309, sunnyran}@ajou.ac.kr
‡Department of Electronic and Computer Engineering,
Hong Kong University of Science and Technology; Email: {pcng, eejames}@ust.hk

***Abstract*—Considering an incomplete signals acquisition due to a sparse beacon deployment, this paper proposes a generalized similarity filter to improve the performance of proximity detection and thus guarantee the quality of proximity-based service (PBS). In particular, this paper leverages Bluetooth Low Energy (BLE) Beacons to realize a PBS system which comprises a number of Proximities of Interest (PoIs). We define a PoI as an object or area which is associated with a beacon such that each PoI can announce their presence implicitly through the beacon's signal. However, under a sparse beacon network condition in which some beacons associated with some PoIs are malfunction or their batteries die before the scheduled maintenance, a receiver (e.g., smartphone) might fail to return the target PoI correctly. In view of the quality degradation in consequence to the sparse condition, we refine the performance of classical compressive sensing based algorithm with a generalized similarity filter. The effects of different similarity measures on proximity detection performance are also investigated. Simulation results indicate that the proposed algorithm improves the detection accuracy as compared to the conventional compressive sensing based algorithm. Specifically, Chordal-based similarity filter achieves substantial improvement in comparison with Mahalanobis and Euclidean-based similarity computation.**

I. Introduction

Recently, the increasing demand of context awareness services require, in particular, the developement of indoor localization techniques [1][2][3]. A majority of localization approaches, however, aim to address the issue of outdoor location finding, and are not available to provide accurate indoor geolocation due to the complicated indoor environment. Indoor location-based services (LBSs) vary significantly from outdoor positioning systems, which rely on users to deliver their location information functionality via mobile applications [2][3]. For example, a plenty of travelers at an airport are able to find out where to eat, drink, and get a message about flight delays to associate with mobile airport service. However, with focus on the influence of multipath in indoor environment, most indoor location techniques are being struggling to settle this problem to get a satisfactory level of accuracy. Clearly, the estimation up to sub-meter accuracy plays a key role for all these issues, besides that, the relevance of services is also beneficial for detecting where specific events happened, and tracking mobile target. Therefore, the proximity-based service (PBS), which is delivered when mobile devices are in close proximity regardless of their exact location information, has been employed as a substitution to LBS [4][5].

Due to the constraints of cost and power consumption, it is feasible to equip Bluetooth Low Energy (BLE) Beacons as nodes for PBSs to get the proximity information of a mobile device and deliver diverse services. In a beacon-based PBS system, it firstly defines a region along with a PBS, and the region is divided into several proximities of interest (PoIs) in term of the structure and area. Each PoIs is responsible for delivering a part of contents based on service. For example, in a museum of history, which provides a proximity-based exhibition explanation service, could be defined as a PBS region that consists of several PoIs, and each PoI contains a part of explanation of history [6]. For guaranteeing a certain level of quality-of-service (QoS), each PoI should be associated to at least one BLE beacon to broadcast their signal to announce their presence to the ambient object (or mobile device), which results in a dense beacon deployment when the PoIs are closely spaced. The broadcasted signals via beacons of all PoIs will be collected by an encountered mobile device for identifying the target PoI where the mobile device is located. After that, an intended service will be delivered via a server to the mobile device.

The fundamental requirement of achieving a PBS with high QoS is that the mobile device must have a complete and comprehensive knowledge of all signals broadcasted by beacons of all PoIs. However, it is not possible to always have such ideal conditions in terms of faulty circuit components or died batteries as time goes by. On the other hand, if too many beacons are exploited, the scanning duration may be long, which is practically prohibitive. Besides, some PoIs possibly need to compromise with no beacon association due to some physical deployment constraints.Therefore, it is necessary to consider a sparse beacon network scenario rather than a dense one. In [7], authors have studied a problem of PoI detection in a sparse beacon network and proposed a compressive sensing based algorithm to improve the detection accuracy rate for those PoIs where beacons are missed, compared to some conventional detection algorithms, e.g., MaxRSSI [8]. The simulation results show the proposed algorithm is effective. However, the algorithm, on one hand, was proposed for a relatively specific testbed at which four workable beacons were equipped at four corners of a PBS region, even though it has practical meaning but lack of generalization. On the other hand, we have noted that the performance of the proposed algorithm in [7] is sensitive to similarity computation in which Euclidean distance is used to compute the similarity between the instantaneous received signal strength (RSS) to the reference RSS stored in a fingerprinting database. However, Euclidean-based similarity filter does not take the correlation of two vectors into account. When the size of testbed is relatively small, the RSS measurement of adjacent PoIs might have strong correlations which may affect the performance of the proposed algorithm in [7].

Therefore, in this paper, considering the same sparse beacon deployment scenario described in [7], we propose a generalized similarity filter to further refine the performance achieved by the compressive sensing based algorithm. Before adopting a particular similarity filter, we study the effect of different type of similarity computation including Mahalanobis, Euclidean and Chordal. Simulation results show that the chordal-based similarity filter performs better than the rest. By integrating the chordal-based similarity filter into compressive sensing based algorithm, a substantial improvement in detection performance is observed, which further verifies the superiority of chordal-based similarity filter over both Mahalanobis and Euclidean-based similarity filter in proximity detection.

The rest of the paper is organized as follows. We introduce a sparse beacon network, and then overview the compressive sensing based algorithm with similarities filter in [7] in Section 2. Section 3 discusses the effects of different types of similarity computations. Simulation results and discussions are given in Section 4. Finally, Section 5 derives the conclusion.

II. Sparse Beacon Deployment and Compressive Sensing

This section describes a sparse beacon deployment and briefly overviews the algorithm proposed in [7].

A. A Sparse Beacon Deployment

A region might contain multiple PoIs following the grid fashion ($n \times n$). Moreover, the grid scenario has its practical meaning and widely used in our daily life. For example, in a restaurant, dining tables may be set up following the grid fashion and at each dinning table is associated with a beacon (i.e., each dining table represents a PoI). The PBS system intends to deliver their food menu to customers, and each PoI has its own meta attributes such as the table number, special offer, etc. Also, a similar application in campus life is an attendance based on desk setting in a classroom. Each PoI is associated with a beacon. In such a scenario, the conventional maxRSS algorithm can guarantee an acceptable detection accuracy rate. However, some beacons may be out of function due to some unexpected reasons resulting in a sparse beacon deployment scenario, which is illustrated in Fig.1. where the functioned beacons are highlighted in blue color.

B. Compressive Sensing based Algorithm

Given a sparse beacon system with $n \times n$ PoIs, illustrated in Fig.1, the proximity detection problem is to detect the index

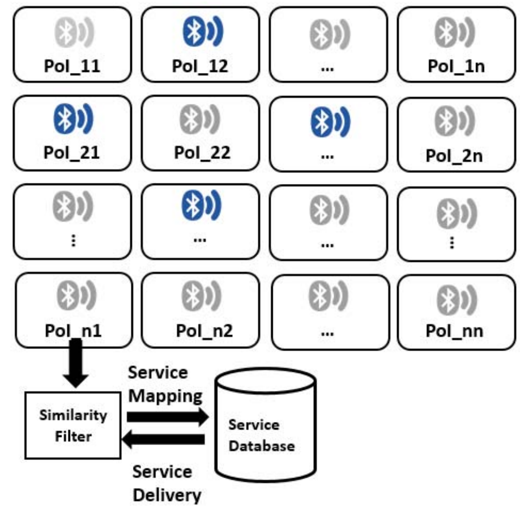

Fig. 1. A Sparse Beacon Deployment in a classroom

of PoI where the target mobile device is located, and has a sparse nature since the location information of the target mobile device can be represented as a vector given as

$$\mathbf{b} = [0, 0, \ldots, 1, 0, \ldots, 0]^T \tag{1}$$

where $\mathbf{b}$ is a $n \times 1$ column vector consisting of most zeros and a unique one, and the index of 1 in this vector is relevant to the index of PoI where the target mobile device is located. Note that the sparsity of $\mathbf{b}$ is always one since the mobile device is impossible to show up in multiple PoI areas simultaneously.

Suppose that $\mathbf{r}_{RSSI} = [r_{RSSI_1}, \ldots, r_{RSSI_m}]^T$ is the average online RSSI values respectively received from the $m(\leq n)$ working beacons by the mobile device. Then the relation between the received RSSI vector $\mathbf{r}_{RSSI}$ and the sparse vector $\mathbf{b}$ hidden the information of the mobile device's location can be described as the following linear equation,

$$\mathbf{r}_{RSSI} = \Psi \Phi \mathbf{b} + \mathbf{v} \tag{2}$$

where the average online RSSI vector $\mathbf{r}_{RSSI}$, considering a scanning duration T_n, is achieved via

$$r_{RSSI_i} = \frac{1}{N(t_k)} \sum_{t=t_1}^{t_k} RSSI_i(t) \tag{3}$$

where $RSSI_i(t)$ denotes the RSS measured at discrete time t for all $t_k \leq T_s$. Φ is a $n \times n$ sensing matrix which is achieved through an offline site surveying, the achieved matrix is constructed as follows,

$$\Phi = \begin{pmatrix} \phi_{1,1} & \phi_{1,2} & \cdots & \phi_{1,n} \\ \phi_{2,1} & \phi_{2,2} & \cdots & \phi_{2,n} \\ \vdots & \vdots & \ldots & \vdots \\ \phi_{n,1} & \phi_{n,2} & \cdots & \phi_{n,n} \end{pmatrix} \tag{4}$$

where $\phi_{i,j} = (\frac{1}{N(t_k)})\sum_{t=t_1}^{t_k} RSSI_{i,j}(t)$ is the average of RSSI reading in the jth PoI from the ith beacon over a time period T, and is also referred to a radio map in other references. Ψ is a $m \times n$ measurement matrix in which each row of Ψ contains zeros and unit one which indicates the index of PoI associated with a beacon and **v** represents the measurement noise.

Note that Eq.(2) is a underdetermined system ($m \leq n$) with a very sparse input vector **b**. Therefore, the proximity detection problem is finally converted into a sparse vector reconstruction problem which is described as follow,

$$\hat{\mathbf{b}} = \arg\min_{\mathbf{b}} \|\mathbf{r}_{RSSI} - \Psi\Phi\mathbf{b}\|_2^2 + \lambda\| \ \mathbf{b}\|_1 \tag{5}$$

where λ is a tuning parameter related to the sparsity of **b**, and the index of non-zero entry in $\hat{\mathbf{b}}$ refers to the index of PoI where the target mobile device is allocated.

The above objective function can be solved by taking use of compressive sensing based algorithms, like orthogonal matching pursuit (OMP) [9], Compressive sensing matching pursuit (CoSaMP) [10], etc. Considering the tradeoff between performance and complexity, CoSaMP has an impressive performance and a computational perpective. Moreover, CoSaMP is applicable to implemented in our framework for discovering the targets in sparse beacon network [7].

III. Similarity and Distance measure

Numerous theoretical derivations and formulas show that it has achieved a better performance using CoSaMP in coping with a sparse recovery problem for a PBS context. However, the performance of CoSaMP is relatively unstable especially when considering the following two issues. The first issue comes from that the number of samples utilized in generating the sensing matrix is not large enough, which results in serious sensing errors. And the second one is the area of each PoI is relatively small, so the difference in two reference RSSI vectors $\bar{\phi}_i$ and $\bar{\phi}_j$ which are the ith and jth columns of the sensing matrix Φ, respectively received in neighboring PoIs is not obvious, which may let the mobile device feel confused and make a incorrect decision.

In order to overcome the first problem, it is usually adopted by increasing the number of samples, nonetheless, the second one may not be easy to deal with since the size of a PBS region, which may refer to the area or space of a store in a shopping mall, is fixed generally and not easy to be enlarged according to a lot of practical reasons. Therefore, a robust and generalized PoI detection technique is necessary for a sparse beacon deployment to enhance the detection performance.

The phenomenon that the difference in the reference RSSIs respectively received in two adjacent PoIs is not obvious, as a similarity of two PoIs. Intuitively, the more similarities, the worse detection performance will be attained. Hence, it probably put forward some improvement on making comparison the similarities between the target PoI and the mobile device before applying compressive sensing, for example, to delete some PoIs which have a lot of similarities between a mobile device.

In terms of similarities, there have many coefficients that express similarity in the range $[0, 1]$, can be categorized as metric, semimetric or nonmetric [11]. Moreover, depending on the purpose of a measure of similarity, in this paper, we focus on metric distance measures which it ought to satisfy the following principles:

1) The minimum value is zero when two items are identical.
2) When two items differ, the distance is positive.
3) The distance from object A to object B is the same as the distance from B to A.
4) With three objects, the distance between two of these objects can not be larger than the sum of the two other distances.

According to the above principles, it is discussed three kinds of distance measures to convert into a similarity for the scenario we mentioned in this paper.

A. Euclidean distance

The general similarity computation is based on euclidean distance between two vectors. In particular, [7] uses Euclidean distance to compute the similarity between the received instantaneous RSS vector $\mathbf{r}_{RSSI}$ and the reference RSS vector $\bar{\phi}_i$ of the ith PoI is utilized and represented as

$$d_{Eucli}(\mathbf{r}_{RSSI}, \bar{\phi}_i) = \|\mathbf{r}_{RSSI} - \bar{\phi}_i\|_2^2 \tag{6}$$

where $\|\mathbf{x}\|_2$ refers to 2-norm of a vector **x**. Two PoIs with high similarity should result in the similar Euclidean measures for the mobile device's perspective. But there is one PoI must be the real PoI area where the mobile device is located, and the other PoI will cause some confusion to the mobile device's decision and should be removed from the set of PoIs candidates. The reminded PoIs set will take part in the excution of compressive sensing algorithms.

However, considering the testbed conditions (e.g., size, power of beacons etc). Euclidean-based similarity computation may not be always proper. Other similarity computation such as Mahalanobis distance and Chordal distance, may provide better similarity filtering performance since they can measure the distance more precisely and enlarge the difference between two confused (or neighboring) PoIs.

B. Mahalanobis distance

The Mahalanobis distance between the received RSSIs and the reference RSSI of the ith PoI is achieved via

$$d_{Maha}(\mathbf{r}_{RSSI}, \bar{\phi}_i) = \sqrt{(\mathbf{r}_{RSSI} - \bar{\phi}_i)C^{-1}(\mathbf{r}_{RSSI} - \bar{\phi})^H} \tag{7}$$

where the cross correlation matrix C is given as

$$C = \mathbb{E}(\mathbf{r}_{RSSI}\bar{\phi}_i^H) \tag{8}$$

where $\mathbb{E}(x)$ denotes the expection value of a random variable x.

C. Chordal distance

The Chordal distance between the measured RSS and the reference RSS of the ith PoI is achieved via

$$d_{Chor}(\mathbf{r}_{RSSI}, \bar{\phi}_i) = \frac{1}{2}\|\mathbf{r}_{RSSI}\mathbf{r}_{RSSI}^H - \bar{\phi}_i\bar{\phi}_i^H\|_F \quad (9)$$

where $\|X\|_F$ refers to a Frobenious norm of a matrix A.

Finally, the similarity of two PoIs is defined as

$$s_{ij} = d(\mathbf{r}_{RSSI}, \bar{\phi}_i) - d(\mathbf{r}_{RSSI}, \bar{\phi}_j), i, j \in \{1, 2, ..., m\} \quad (10)$$

and the similarity filter algorithm is officially summarized in the following table

Algorithm I	Generalized similarity filter
Step 1:	Compute distances between the instantaneous RSSI and the reference RSSI of PoIs with Beacons, d_i
Step 2:	Compute the similarity of the ith and jth PoIs, s_{ij}
Step 3:	**if** $\|s_{ij}\| \leq \epsilon$
	if $sign(s_{ij}) \geq 0$
	The filtered PoI set $\mathcal{S}$ consists of
	all neighboring PoIs of the jth PoI except the ith PoI
	else
	The filtered PoI set $\mathcal{S}$ consists of
	all neighboring PoIs of the ith PoI except the jth PoI
	else
	Increase the value of ϵ and repeat step 3 until find a $\mathcal{S}$
Step 4:	return $\mathcal{S}$

where ϵ is a threshold to judge whether two PoIs have too much similarity to accurately detect the index of the targeted PoI, and achieved experimentally.

IV. SIMULATION AND RESULTS

In this section, we illustrate the performance of similarity filter via simulation results. First, in Fig.2, we chose a classroom for an experimental testbed to collect the necessary data sent by beacons. Total nine PoIs are established, and four corner PoIs are associated with four beacons, respectively, as shown in Fig.3. The reason that we keep four beacons that is because according to compressive sensing theorem that the number of observations m should at least be $Cs\log(n^2)$ for an accurate detection with an overwhelming probability [12]. Meanwhile, the difficulties in practical setting should be taken into account, for example, in a gallery, there may not have a suitable position at every PoI to set up the beacons that the arrangement of beacons at four corners can be thought of the best way without affecting the overall coordination of the gallery.

The beacons are built with CC2541 BLE chips and all the beacons are powered by a CR2450 3V lithium coin cell battery. An Asus zenfone 2 Deluxe ZE551ML mobile device was used to collect the data during an offline phase. All the collected data were then forwarded to Matlab program for simulation.

The performance comparison among different similarity computation are given in Fig.4. From the simulation results, we observe that the chordal-based similarity filter achieves the best performance compared to two other distance-based similarity filter for all PoIs. Especially, at the 5th PoI which is the worst area for detection with this four corner settlement, the chordal-based similarity filter can reach up to 60% which

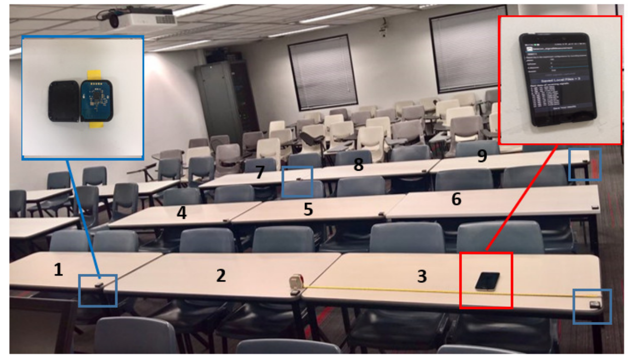

Fig. 2. Classroom Testbed with 4 working beacons in table 1,3,7,9

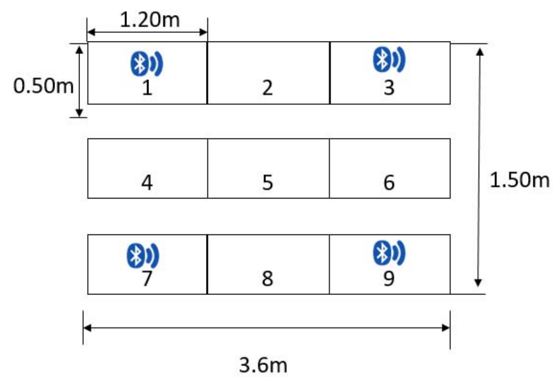

Fig. 3. Testbed with 4 Beacons positioning.

is much higher than the mahalanobis-based similarity filter (around 30%) and the standardized Euclidean-based similarity filter (around 27%).

The detection accuracy for CoSaMP and CoSaMP with the proposed generalized similarity filter are compared and the results are presented in Fig.5. It is clear that after applying the similarity filter to remove some confused PoI for the target PoI, a much higher possibility of accurate detection can be guaranteed. Particularly, at the 5th, 6th and 8th PoIs, CoSaMP doesn't work at all, but CoSaMP with the generalized similarity filter can improve the accuracy rate up to 60%, 80% and 85% for those PoIs respectively. We also consider several different layouts of beacons, illustrated in Fig.6. By exploiting the proposed generalized similarity filter, the detection accuracies of CoSaMP for all PoIs are significantly improved, which are shown in Fig.7 and Fig.8.

V. CONCLUSION

In this paper, for a scenario with sparse beacon deployment, we propose a generalized similarity filter for refining the

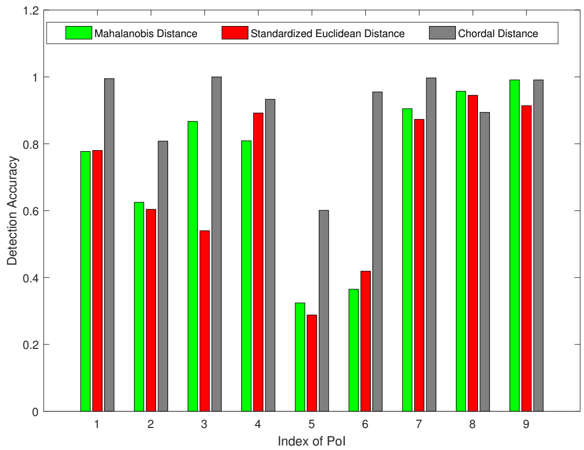

Fig. 4. Performance comparison among different distance-based similarity filters.

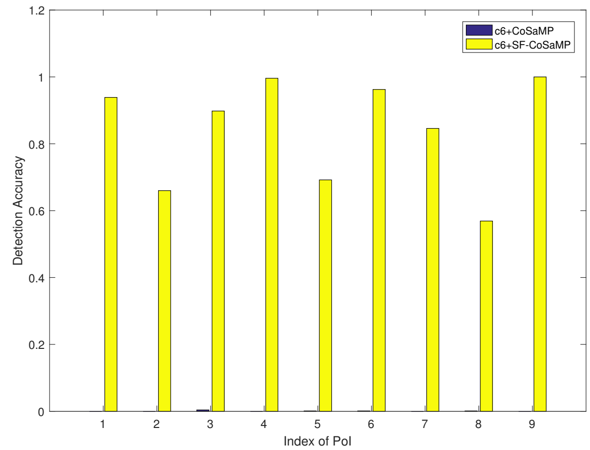

Fig. 7. Performance comparison bewteen CoSaMP and CoSaMP with generalized similarity filter in c6 beacons placement case

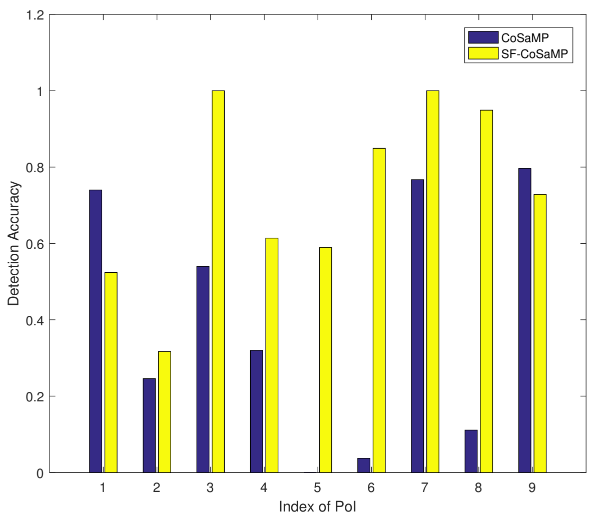

Fig. 5. Performance comparison bewteen CoSaMP and CoSaMP with generalized similarity filter

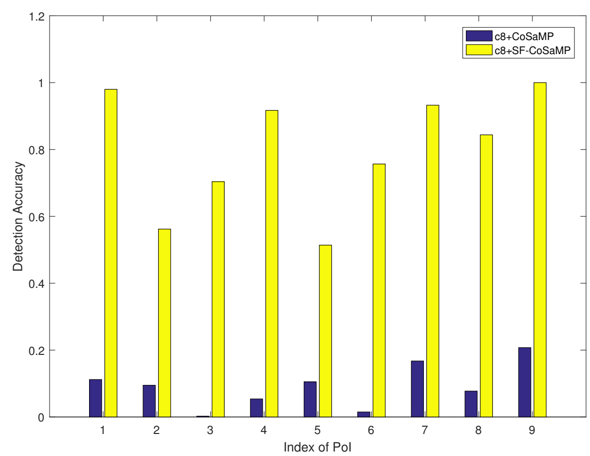

Fig. 8. Performance comparison bewteen CoSaMP and CoSaMP with generalized similarity filter in c8 beacons placement cases

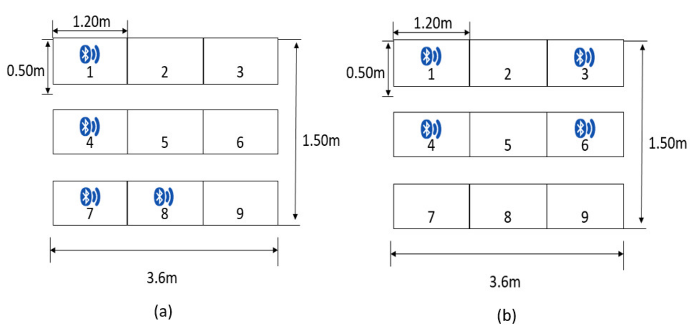

Fig. 6. 4 beacons in two different layouts (a) c6 beacon placement case (b) c8 beacon placement case

detection performance of compressive sensing based method. We also consider the effect of using different similarity computation. Simulation results show that the proposed algorithm can significantly increase the detection accuracy rate achieved by CoSaMP, and Chordal-based similarity filter performs better than other for the given experimental testbed. How to design a problem-oriental similarity computation which is able to adapt for arbitrary scenarios would be our future work.

ACKNOWLEDGMENT

This work was supported by HKUST-NIE Social Media Laboratory and the frame of international cooperation program managed by the National Research Foundation of Korea under Grant 2017K2A9A2A06016102. All the beacon equipment are sponsored by CyPhy Media Limited.

REFERENCES

[1] F. Palumbo, P. Barsocchi, S. Chessa, and J. C. Augusto, “A stigmergic approach to indoor localization using bluetooth low energy beacons,” in

Advanced Video and Signal Based Surveillance (AVSS), 2015 12th IEEE International Conference on. IEEE, 2015, pp. 1–6.

[2] Z. Li, T. Braun, and D. C. Dimitrova, “A passive wifi source localization system based on fine-grained power-based trilateration,” in *World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2015 IEEE 16th International Symposium on a*. IEEE, 2015, pp. 1–9.

[3] R. Faragher and R. Harle, “Location fingerprinting with bluetooth low energy beacons,” *Selected Areas in Communications, IEEE Journal on*, vol. 33, no. 11, pp. 2418–2428, 2015.

[4] M. Papandrea, S. Giordano, S. Vanini, and P. Cremonese, “Proximity marketing solution tailored to user needs,” in *World of Wireless Mobile and Multimedia Networks (WoWMoM), 2010 IEEE International Symposium on a*. IEEE, 2010, pp. 1–3.

[5] R. Tabata, A. Hayashi, S. Tokunaga, S. Saiki, M. Nakamura, and S. Matsumoto, “Implementation and evaluation of ble proximity detection mechanism for pass-by framework,” in *Computer and Information Science (ICIS), 2016 IEEE/ACIS 15th International Conference on*. IEEE, 2016, pp. 1–6.

[6] P. C. Ng, J. She, and S. Park, “Notify-and-interact: A beacon-smartphone interaction for user engagement in galleries,” in *2017 IEEE International Conference on Multimedia and Expo (ICME)*, July 2017, pp. 1069–1074.

[7] P. C. Ng, L. Zhu, J. She, R. Ran, and S. Park, “Beacon-based proximity detection using compressive sensing for sparse deployment,” in *2017 IEEE 18th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, June 2017, pp. 1–6.

[8] C.-W. Fan, Y.-H. Wu, and W.-M. Chen, “Rssi-based localization for wireless sensor networks with a mobile beacon,” in *Sensors, 2012 IEEE*. IEEE, 2012, pp. 1–4.

[9] T. T. Cai and L. Wang, “Orthogonal matching pursuit for sparse signal recovery with noise,” *IEEE Transactions on Information theory*, vol. 57, no. 7, pp. 4680–4688, 2011.

[10] M. A. Davenport, D. Needell, and M. B. Wakin, “Signal space cosamp for sparse recovery with redundant dictionaries,” *IEEE Transactions on Information Theory*, vol. 59, no. 10, pp. 6820–6829, 2013.

[11] B. McCune, J. B. Grace, and D. L. Urban, *Analysis of ecological communities*. MjM software design Gleneden Beach, OR, 2002, vol. 28.

[12] E. Candes and J. Romberg, “Sparsity and incoherence in compressive sampling,” *Inverse problems*, vol. 23, no. 3, p. 969, 2007.