Building Complete Training Maps for Indoor Location Estimation

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of an appropriate sparse position-indicator vector based on the theory of Compressive Sensing, which takes advantage of the inherent sparsity of the data and the physical space. Finally, the system recovers accurately sparse signals, in conjunction with the efficiency of a Kalman filter, which updates the states of a dynamical system and predicts the user's estimated position. The main drawback of that method was the time required for collecting the fingerprints on the physical phase [4]. In this paper, we build complete maps by reconstructing the fingerprint maps from a small number of measurements based on Matrix Completion (MC) [5].

The paper is organized as follows: Section II gives motivation and presents the MC framework, while Section III shows the performance of the proposed method compared with our recent fingerprint-based algorithm [3].

II. MOTIVATION AND PROPOSED FRAMEWORK

In order to address the exhaustive collection of fingerprints, we perform random sampling on the fingerprint maps. Random sampling reduces the time needed to build the fingerprint maps and as a result the energy consumption at the mobile device. In order to succeed on this, we need the existence of correlation between the fingerprints at different locations on the physical space, which depend on some characteristics of APs.

Because of transient phenomena, such as shadowing and multi-path fading, the fingerprints have a spatial correlation since closer locations show similar measurement vectors. Since fingerprints are correlated, the degrees of freedom of the fingerprint matrix are much lower than its dimension. If a matrix has a low rank property, then it presents a limited number of degrees of freedom.

Assume that we have the fingerprint maps from the received signal strength from the i-th AP at the j-th location on the physical space $S \subset R^{i \times j}$. While the recovery of the $i \cdot j$ entries of matrix S is impossible from a number of measurements m (where $m \ll i \cdot j$), MC shows that such a recovery is possible when the rank of matrix S is small enough compared to its dimensions. In fact, the recovery of the unknown matrix is feasible from $m \geq cj^{6/5}r \log j$ random measurements, where $j > i$ and $\text{rank}(S) = r$. The original matrix S can be recovered by solving the following optimization problem:

$$\min ||S||_* \ s.t. \ A(S) = A(M), \quad (1)$$

where $||S||_* = \sum_{k=1}^{\min\{i,j\}} \sigma_k(S)$ with $\sigma_k(S)$ being the k-th largest singular value of S. M is the matrix S after sub-

sampling, while A is a linear map from $R^{i,j} \to R^m$, that has uniform samples in rows and columns and satisfies the Restricted Isometry Property (RIP).

Sampling on the measurements vectors of S will provide an incomplete fingerprint map. The mobile device that has to be localized uses a subset Ω of the measurements of S, which randomly chooses by sensing a random number of the $k < h$ channels of APs. Finally the mobile device receives $\Omega \subseteq |i| \times |j|$ measurements, with $|\Omega| = \frac{k(i \times j)}{h}$, while the sampling map $A_\Omega(M)$ has zero entries at the j-th position of the i-th AP if $S(i,j) \notin \Omega$.

During the runtime phase we need to recover the unobserved measurements of matrix S, denoted by S^-, by solving the following minimization problem,

$$\min ||S^-||_* \ s.t. \ ||A_\Omega(S^-) - A_\Omega(M)||_F^2 < \epsilon \qquad (2)$$

where F denotes the Euclidean norm, and ϵ is the noise parameter. The convex optimization problem in (2) can be solved by an interior point solver, *e.g.* CVX [6], or via singular value thresholding, *e.g.* SVT and FPC [7], which applies a singular value decomposition algorithm and then projection on the already known measurements in each step.

III. EXPERIMENTAL RESULTS

In this section, the performance of the proposed fingerprint completion technique is evaluated and compared on a *real dataset*, which was acquired at INRIA in Paris. The wireless coverage is achieved by employing an infrastructure consisting of five IEEE802.11 APs. The area used in the formation of the fingerprint map is discretized in cells of equal dimensions 0.76 m $\times 0.76$ m. The time intervals during the acquisition in the training and runtime phase were set to 90 sec and 30 sec, respectively. The estimation accuracy is evaluated in terms of the *completeness* of the fingerprint maps and the localization error, which is defined as the Euclidean distance between the centers of the estimated cell and the true cell where the mobile user is located at runtime.
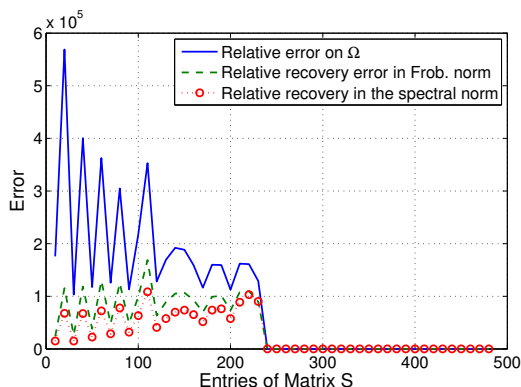

Fig. 1. Reconstruction error of S for the SVT algorithm.

Fig. 1 and Fig. 2 show the recovery error of the fingerprint map S based on SVT and FPC respectively, while we increase the number of the entries of S. Fig. 3 shows the cumulative distribution functions (CDFs, P($X < x$)) of the localization
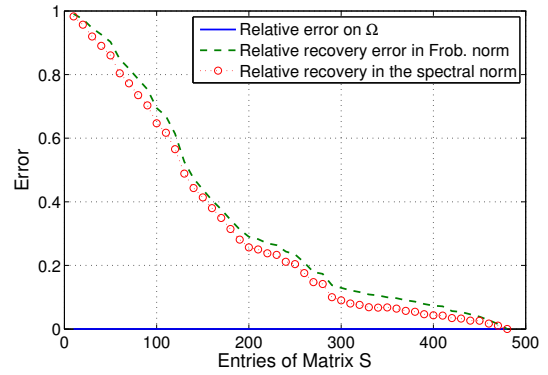

Fig. 2. Reconstruction error of S for the FPC algorithm.

error of the proposed method in [3] based on a percentage of measurements used (25% to 100%). The method obtains a median location estimation accuracy of 2.38 m, 1.87 m, 1.67 m, and 1.36 m for $\{25, 50, 75, 100\}\%$ complete measurements of the fingerprint map, respectively. More specifically, by using 75% of complete measurements the location accuracy is decreased by 17%, while addressing the problem of exhaustive collection of fingerprints.
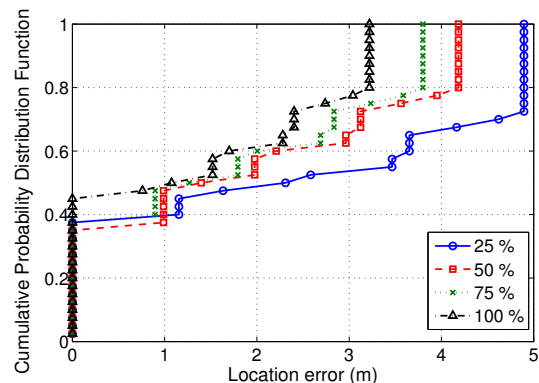

Fig. 3. Impact of the percentage of fingerprint map measurements on location error.

REFERENCES

[1] D. Milioris *et. al*, "Empirical Evaluation of Signal-Strength Fingerprint Positioning in Wireless LANs", in *Proc. 13th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM'10)*, Bodrum, Turkey, Oct. 2010.

[2] C. Fretzagias and M. Papadopouli, "Cooperative location sensing for wireless networks", in *Proc. IEEE PERCOM'04*, Orlando, Florida, Mar. 2004.

[3] D. Milioris, G. Tzagkarakis, P. Tsakalides and P. Jacquet, "WLAN-based Indoor Path-Tracking using Compressive RSS Measurements", in *21st European Signal Processing Conference (EUSIPCO'13)*, Marrakech, Morocco, Sep. 2013.

[4] P. Mirowski *et. al*, "Probabilistic Radio-Frequency Fingerprinting and Localization on the Run", in *Bell Labs Technical Journal*, Vol. 18, No. 4, 2014 (doi: 10.1002/bltj.21649).

[5] E. Candès and B. Recht, "Exact matrix completion via convex optimization", *Foundations of Computational Mathematics*, Vol. 9, pp. 717–772, 2009.

[6] M. Grant and S. Boyd, "CVX: Matlab software for disciplined convex programming, Version 1.21", 2011.

[7] J. Cai, E. Candès, and Z. Shen, "A singular value thresholding algorithm for matrix completion", in *SIAM Journal on Optimization*, Vol. 20, pp. 1956–1982, 2010.