Cost-effective Signal Map Crowdsourcing with Auto-Encoder based Active Matrix Completion

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***Abstract*—Signal map is of great importance, especially in the dawn of 5G network, for site spectrum monitoring, location-based services (LBS), network construction, and cellular planning. Despite its significance, the traditional signal map construction, e.g., through full site survey, could be time-consuming and labor-intensive as the signal varies frequently over time and the accuracy requirement grows rapidly with the emergence of new applications. Even with crowdsourcing scheme, the participants tend to be unevenly distributed in space while the encouragement budgets for the participants could be far from enough to collect adequate high-quality measurements. Therefore, the signal map constructed by crowdsourcing is often sparse and incomplete. To this end, in this paper, we study how to effectively reconstruct and update the signal map in the case of partially measured signal maps with minimum cost and propose an auto-encoder-based active signal map reconstruction method (AER). Our method is mainly innovative in three parts. Firstly, AER can effectively update the signal map with only a small number of observations while also fully using the incomplete historical signals to effectively update the signal map online. Secondly, AER consists of an active query mechanism which quantitatively evaluates the most valuable measurement site for reconstruction, which further reduces the measurement cost to a large extent. Thirdly, to cope with the measurement dynamics, we give a new signal map model describing not only the signal strength but also the signal dynamics, based on which an advanced AER algorithm is proposed. The simulation results demonstrate the advantages and effectiveness of our approach in both accuracy and cost.**

***Index Terms*—Signal map, active matrix completion, auto-encoder, crowdsourcing**

I. INTRODUCTION

Signal maps, which consist of Received Signal Strength Indication (RSSI) at different locations, play an important role in site spectrum monitoring [1], location-based services (LBS) [2], [3], network construction [4], and network distribution. For example, signal maps can be used for fingerprint based indoor location to provide better location services, while users can use signal maps to understand current network conditions to select the right location to experience better mobile network services. ISPs can use signal maps to understand network conditions and optimize network architecture to provide better coverage. Especially, in the dawn of 5G network, signal maps could also be used to analyze the current 4G network to guide the deployment of 5G network. Despite its importance, constructing the signal maps, mostly through on-site surveys, is time-consuming and laborious, which often takes several

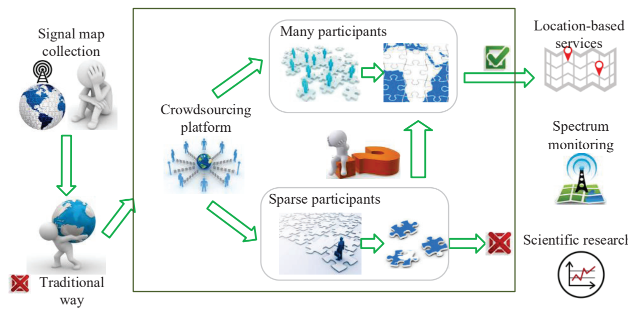

Fig. 1. Application scenario and the dilemma

days or months. However, the signal may change with time and surroundings, which leads to a dilemma that the acquisition and updating of the signal map could hardly meet the requirements of the applications, no matter in quality or timing.

Therefore, crowdsourcing schemes are proposed to address this issue[4], [5] by acquiring the signal measurements from nonprofessional participants instead of professional surveys. At present, many organizations, e.g. Sensorly[1] and OpenSignal[2], have obtained signal maps through crowdsourcing for analysis and optimization. However, collecting signals through crowdsourcing suffers from random and insufficient participants, which leads to incomplete or low-quality measurements.

To cope with this, existing works mainly try to complete the signal map in condition of partial observations (Fig.1) with signal propagation model, matrix completion or compressive sensing. For example, Gaussian process[6], [7] requires complex signal propagation model for specific environment, which is also quite difficult and not scalable. The traditional matrix completion algorithms[8], [9] require the prior knowledge of rank of the signal map, which is impossible in reality. Recent work [1], [10] uses Bayesian compressed sensing to reconstruct the signal map and uses the confidence provided by the Relevance Vector Machine (RVM) to determine the location of the next crowdsourced signal acquisition. However, Bayesian compressed sensing reconstruction method requires low-rank and sparse property of the genuine signal map, which is often not the case in reality.

[1]Sensorly:https://www.sensorly.com/

[2]OpenSignal:https://www.opensignal.com/

Therefore, in this paper we mainly solve this problem by answering the following questions: given the historical signal map with incomplete observations, how to effectively reconstruct the signal map online without the assumption of prior map structure knowledge, and further, whether we could actively guide the crowdsourcing process, e.g. encourage the clients to report the measurement on intended sites with reward, so that the cost could be reduced to the minimum without compromising the accuracy.

The main contributions of this paper are summarized as:

- **Accurate construction in general situation:** we use the auto-encoder to solve the problem of signal map reconstruction. Firstly, we learn the nonlinear temporal features of the signal in the target area by means of the auto-encoder, and then apply this temporal features to the signal map reconstruction process. Compared with the current popular signal map reconstruction algorithm (BCS, MC), our algorithm can achieve lower reconstruction error with the same number of crowdsourced signals.
- **Active crowdsourcing for minimum cost:** with the help of auto-encoder and a large amount of historical data, we propose an algorithm to further reduce the cost of signal map reconstruction by actively acquiring the data in certain most valuable position rather than as randomly reported by the participants, which requires far more measurement to achieve the same level of reconstruction accuracy.
- **A new signal model with fluctuation estimation:** in the real process of signal collection, the signals often fluctuate around a certain value. Therefore, we estimate the fluctuation of the reconstructed signal map to make the reconstructed signal map more realistic. Corresponding construction algorithm is proposed for this model.
- **Comprehensive evaluation:** we conduct extensive evaluations based on simulation data sets for indoor WLAN positioning. The experimental results further show the effectiveness and applicability of the proposed algorithm. Compared with the state-of-the-arts, the proposed algorithm can further improve the accuracy of signal graph reconstruction with fewer observations, and the algorithm has better robustness.

II. RELATED WORK

Signal maps have received much attention due to its important role [4], [11]. However, the acquisition of the signal map is very time consuming and labor intensive. In many recent works, crowdsourcing-based approaches [12] have been proposed to replace professional website surveys with explicit and unprofessional user participation. These studies focus on how to motivate more participants to be enrolled and how to improve the signal collection quality, and the algorithm we propose is complementary to the above work. The main consideration we have is to reconstruct the entire signal map more accurately using the small amount of signal we have collected. Some approaches have also been proposed to address the issues above. Typical algorithms include Gaussian processes [6], [7], compressive sensing [10], [13], and matrix completion [8], [9]. The Gaussian Process (GP) models the relationship between the signal fluctuation and distance between reference points based on measurements by WiFi sniffer. In contrast to GP, our proposed algorithm does not assume any signal propagation model, so our algorithm is more versatile and can be used in more complex indoor environments. The compressive sensing algorithms [1], [10] are based on the sparsity of the reconstructed signal. But the actual signal is often not sparse, and it is cumbersome to construct a suitable observation matrix. Our algorithm does not need to consider these, so our algorithm is much simpler. Some recent studies[8], [9] have used matrix completion to construct missing RSSI values in the signal map. But the traditional matrix completion is a deterministic algorithm that considers only the linear relationships of matrix elements and needs to know the rank of the matrix in advance. Recently, studies have shown that the auto-encoder can learn the nonlinear relationship in the matrix [14], [15], [16]. Inspired by this, our algorithm learns the continuous temporal features by means of auto-encoder and realizes online update of the signal map, so there is no need to know the rank in advance. Classical active learning research [13], [17] uses labels as a measure of the informativeness. However, signal map reconstruction is unsupervised learning and cannot be classified by labels in advance. Therefore, how to define the informativeness and find the largest informativeness in this case is a huge challenge. The algorithm proposed by us can effectively solve this problem, which seeks the most informative signal from the encoder and historical data to effectively reconstruct the signal map with very little observed signal.

III. PRELIMINARIES & SYSTEM FRAMEWORK

In this section, we first introduce the signal map and the auto-encoder in Section III-A and Section III-B, then we define the key concepts used throughout this paper in Section III-C, followed by the system framework in Section III-D.

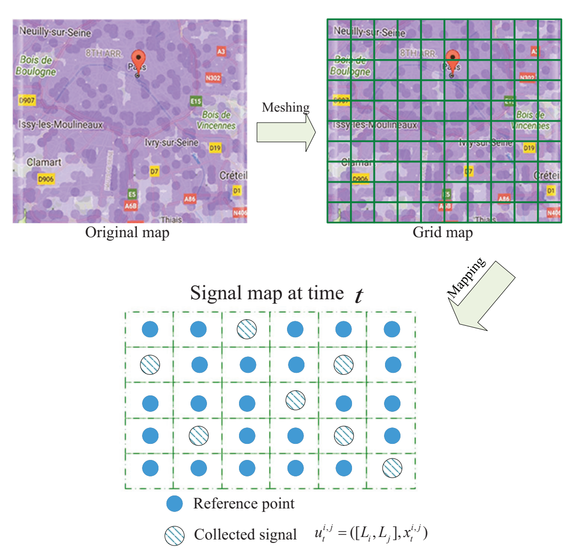

Fig. 2. The signal map at time t

A. Signal Map

Signal map consists of signal strength at different locations. And we first divide the signal collection area into a finite (for example, m rows and n columns) grid. Then we assume that there is only one access point (AP) and $m \times n$ reference points (RPs) in the target area. We use $u_t^{i,j} = ([L_i, L_j], x_t^{i,j})$ to represent the collected signals (Fig.2) uploaded by the crowdsourcing participants at time t, where $x_t^{i,j}$ presents RSSI at time t and $[L_i, L_j]$ indicates geographical coordinates. And we use X_t to represent the signal map at time t, the elements of which are $x_t^{i,j}$. In this paper, we assume that the grid granularity is given in advance.

B. Auto-Encoder

The auto-encoder is a machine learning model which includes two parts (the structure is shown in Fig.4): an encoder and a decoder. The encoder is responsible for extracting latent features $z \in \mathbb{R}^d$ (d is the dimension of the latent feature) in the input data $x \in \mathbb{R}^n, n >> d$ (n is the dimension of the input data), and the decoder restores the latent features z extracted by the encoder to the reconstructed data $\hat{x} \in \mathbb{R}^n$. To realize the auto-encoder by neural network, it can be expressed by the following formula:

$$\begin{aligned} z &= f(x) \Leftrightarrow \sigma(W_{en}x + b_{en}), \\ \hat{x} &= f^T(z) \Leftrightarrow \sigma(W_{de}x + b_{de}), \end{aligned}$$

where $f(\cdot)$ is a nonlinear map, $f^T(\cdot)$ is an approximation for the inverse of $f(\cdot)$, σ is the activation function, W_{en}, W_{de} are the encoder and decoder weight matrices respectively, and b_{en}, b_{de} are the corresponding bias vectors. Therefore, in the training phase, given a data matrix $X \in \mathbb{R}^{m \times n}$, auto-encoder solves the following problem:

$$\begin{aligned} \min \frac{1}{m} \sum_{i=1}^{m} (||x_i - \sigma(W_{de}\sigma(W_{en}x_i + b_{en}) \\ + b_{de})||^2) + \frac{\lambda}{2}(||W_{en}||_F^2 + ||W_{de}||_F^2), \end{aligned} \tag{1}$$

where λ is a hyperparameter which can be set in advance.

C. Definitions

We model this problem as a matrix completion (MC) problem, and in order to understand this paper more conveniently, we first define some related concepts about MC.

Definition 1. *Ground-Truth Matrix. For a signal collection task which has already been divided into grids according to the requirement, involving m rows and n columns, its ground-truth matrix is denoted as $M_{m \times n}$, where each entry $M(i,j)$ denotes the true signal in $[L_i, L_j]$.*

Definition 2. *Observed Matrix. A observed matrix $O_{m \times n}$ denotes the actual collected observed signal:*

$$O = \Omega \bullet M,$$

where $\bullet$ denotes the Hadamard product and if the entry of $[L_i, L_j]$ is observed : $\Omega(i,j) = 1$, otherwise, $\Omega(i,j) = 0$.

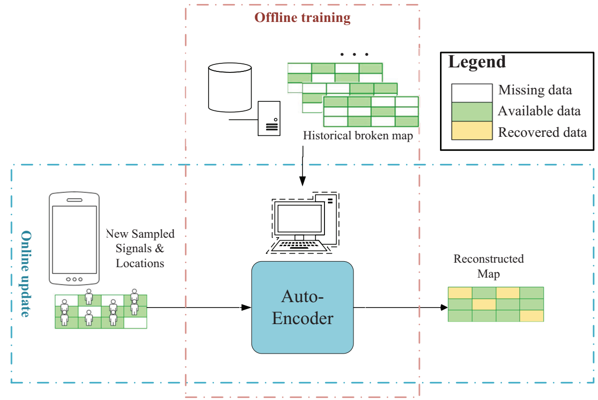

Fig. 3. The workflow of the AER

Definition 3. *Reconstruction Algorithm. A matrix completion algorithm Ψ_{old} attempts to reconstruct a complete matrix $\widetilde{M}_{m \times n}$ from the observed matrix $O_{m \times n}$:*

$$\Psi(O_{m \times n}) = \widetilde{M} \approx M$$

D. System Framework

Wireless signal maps tend to change over time due to the randomness of signal gain, and such changes are often random and non-linear. The work of [15], [16] shows that the auto-encoder can learn the nonlinear relationship in the matrix. And compared with many other methods (GP, BCS, CNN), the auto-encoder is simple in structure (as shown in Fig.4).So we consider using a large amount of historical incomplete signal map to train the auto-encoder and we reconstruct the current incomplete signal map using the temporal features of the auto-encoder learning. Therefore, we propose an auto-encoder-based signal map reconstruction method (AER). The framework of AER (as shown in Fig.3) consists of two phases: the offline training phase and the online update phase.

IV. BASIC MODEL AND SOLUTION

In this section, we consider a simple version of our problem and propose the corresponding solution in terms of active sample collection and signal map reconstruction.

A. Assumptions and Formulation for Basic Problem Model

We make the following assumptions for the basic problem.

Assumption 1. *A large amount of historical incomplete signal maps. For the target area, signal maps at different times are collected.*

We believe that this assumption is realistic in many realities, especially when sparse crowdsourcing and crowdsourcing participants are unevenly distributed in space and time. This assumption is correct.

Assumption 2. *High quality observations. In other words, there is no noise in any of the observations (every crowdsourced signal is an element in Ground-Truth matrix) and any locations can be observed.*

Although in real life, errors often occur when making observations. This assumption is also reasonable if attractive incentives are used. After that, we will relax this assumption.

Assumption 3. *No movement during observation. Each time the signal observation of the position is determined, the signal observation of the next position cannot be performed until the observation is completed. In other words, the observation value at each position is only the exact value of the signal at the position.*

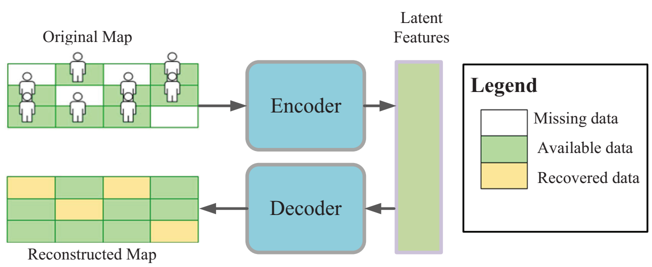

Fig. 4. Auto-Encoder Construction

Assumption 3 ensures that if we assign an collection task to a participant in in $[L_i, L_j]$, the upload RSSI will actually represent the location (i, j). This assumption can usually be met if the collection task does not take too much time.

Based on these assumptions, we define the research problem as follows: Given a signal map reconstruction task in the target area, how to use the incomplete signal O collected randomly at time t and a large amount of incomplete signal maps at different times to reconstruct a complete signal map $\widetilde{M}$ and minimize the error between the $\widetilde{M}$ and M. The formulation is as follows:

$$\begin{aligned} \min \quad & \varepsilon = error(\widetilde{M}, M) \\ s.t. \quad & \widetilde{M} = \Psi_{old}(O_{m \times n}) \\ & O = \Omega \bullet M \end{aligned} \tag{2}$$

B. Basic Algorithm

In this section, we will solve the above signal map reconstruction with auto-encoder and we propose an auto-encoder-based signal map reconstruction method (AER). The workflow of AER is as shown in Fig.3. The algorithm is divided into the offline training phase and the online update phase.

In the offline training phase, the input data of the auto-encoder is a large number of incomplete historical signal maps at different times and the loss function is the formula (1). In order to reduce the number of parameters, we set $W_{de} = (W_{en})^T$ and unified with W, W^T instead. Since our input data is incomplete, the formula (1) cannot be processed directly, so we convert it to the following formula:

$$\begin{aligned} \min \frac{1}{t-1} \sum_{i=1}^{t-1} (\Omega_i \bullet ||x_i - \sigma^{(2)}(W^T \sigma^{(1)}(W x_i + b^{(1)}) \\ + b^{(2)})||^2) + \frac{\lambda}{2} ||W||_F^2 \end{aligned} \tag{3}$$

Algorithm 1 The Active Crowdsourcing Algorithm

Input: Small batch query quantity b;
Output: b upload signals
if no upload signals **then**
  compute the informativeness by formula (6) and sort;
else
  compute the informativeness by formula (5) and sort;
end if
Select the first b signals with the largest informativeness to query;
Set the corresponding elements of Ω to 1;

In the online update phase, we use the incomplete signal maps uploaded by sparse crowdsourcing participant at time t as input. We use formula (3) to fine tune and then the signal map is reconstructed using formula (4). The formula (4) is as follows:

$$\widetilde{M} = \sigma^{(2)}(W^T \sigma^{(1)}(W x + b^{(1)}) + b^{(2)})) \tag{4}$$

C. Active Crowdsouring Scheme

In reality, the uploaded signals we get may be very sparse (crowdsourced participants are few) or even no uploaded signals (crowdsourcing tasks just released). In this case, the signal map reconstruction accuracy is low. In order to deal with this situation, we have designed an active crowdsourcing method which mainly uses a large amount of existing historical data and an auto-encoder that has been trained to find the signal with the highest informativeness and then we acquire these signals through some kind of incentive. In traditional active learning, the informativeness is defined as the degree of prediction of the instance. Inspired by this, in this paper, we define the informativeness as the degree of changes in signal. In this part, we define the acquisition cost of the signal as the number of signals.

$$I^{i,j} = abs(x_{t-1}^{i,j} - x_t^{i,j}) \tag{5}$$

Here $I^{i,j}$ represents the informativeness in $[L_i, L_j]$, $abs(\cdot)$ denotes absolute value. We reconstruct the crowdsourced signals of the two batches by the auto-encoder and then select the signal with the highest informativeness in the un-uploaded signal as the candidate point for active crowdsourcing. In order to make the active crowdsourcing mechanism work better, we defined another informativeness in the case of the crowdsourcing task (no upload signal) as follows:

$$I_{initial} = abs(\widetilde{M}_0 - mean(M_{his})), \tag{6}$$

where $I_{initial}$ represents the informativeness at different locations without an upload signal. $\widetilde{M}_0$ indicates a signal map reconstructed formula (4) by setting the initial value of the auto-encoder without uploaded signals, $mean(\cdot)$ represents the element-wise mean and M_{his} represents the historical signal we used to train the auto-encoder. The active acquisition algorithm has been summarized in Algorithm 1.

V. ADVANCED MODEL AND SOLUTION

In Section IV, we simply consider that the data uploaded by the crowdsourcing participants are all ground-truth signals (Assumption 2). However, in the actual measurement, due to the influence of the surrounding environment and the existence of noise, we cannot directly obtain a ground-truth signal. Therefore, in the actual signal collection process, we usually collect the mesh multiple times and finally use the mean as the signal value of the grid. At the same time, the signal map formed by the signal map reconstruction algorithm is a certain value, but this is not consistent with the actual situation. So we will further expand our base model next.

A. Advanced Problem Model

In order to make our model more consistent with the actual signal acquisition situation, we extend the signal of each grid to the signal fluctuation range.

For the problem model, we still model this extension problem as a signal map reconstruction problem as in Section IV-A and we further extend the previous related concepts.

Extended Signal Map : we still divide the signal collection area into finite grids. And we assume that there is only one access point (AP) and $m \times n$ reference points (RPs) in the target area. At time t, each grid has k measurements, and the upload data of the (i,j)-th RP at time t is given by $\mathbf{u}_t^{i,j} = ([L_i, L_j], \mathbf{x}_t^{i,j})$, where $\mathbf{x}_t^{i,j}(\mathbf{x} \in \mathbb{R}^{k\times 1})$ presents the k-time RSSI measurement of that RP at time t. And we use $\mathbf{X}_t$ to represent the signal map at time t, the elements of which are $\mathbf{x}_t^{i,j}$.

In order to solve this problem better, we have also extended the Assumption 2.

Extended assumption. *Temporal Relative stability. In a round of signal collection at time t, the signal has relative stability. And the signals of multiple measurements do not change much, that is, when measuring a certain grid, many of the measurements are fluctuating around a certain value due to the influence of ambient noise.*

This is very common in the actual signal acquisition process, especially when the acquisition process of each signal is very fast. Therefore, in a round of signal collection at time t, the multiple measurements made on a certain grid do not change much. This assumption is easy to satisfy.

B. Advanced Algorithm

In order to solve this problem, we propose an extended AER algorithm.

Extended offline training phase : The offline training process is roughly the same as the Section IV-B. For the multiple measurements $\mathbf{X}_t \in \mathbb{R}^{m\times n\times k}$ affected by noise obtained at time t, we consider the mean $\bar{\mathbf{X}}_t \in \mathbb{R}^{m\times n}$ as the signal observation at time t. Therefore, we represent the signal map collected at time t as $\Omega_t \bullet \bar{\mathbf{X}}_t$. We will use historical signal maps $\Omega_T \bullet \bar{\mathbf{X}}_T, T = 1, ..., t-1$ as input to train our auto-encoder model by formula (3).

Algorithm 2 The advanced AER algorithm

Input: Historical incomplete data $\bar{\mathbf{X}}_T, T = 1, ...t-1$;
Initialization hyperparameter λ;
Current sampled incomplete data $\bar{\mathbf{X}}_t$;
Output: Reconstructed signal map $\widetilde{M}$ and fluctuation s_x^2;
The Offline Training Phase
1)Initialization parameters $W, b^{(1)}, b^{(2)}$;
while $i < t$ **do**
2)Set initial values X_{ini} for unobserved signals and calculate the input matrix $\bar{\mathbf{X}}_i = \Omega_t \bullet \bar{\mathbf{X}}_t + (1-\Omega_t) \times X_{ini}$ at different times $T, T = 1, ...t-1$;
3)Convert matrix $\bar{\mathbf{X}}_T, T = 1, ...t-1$ into a one-dimensional vector $\bar{\mathbf{X}}_T \in \mathbb{R}^{1\times mn}$;
end while
4)Stack historical signal map $\bar{\mathbf{X}}_{his} \in \mathbb{R}^{(t-1)\times mn}$;
5)Train auto-encoder by formula (3);
The Online Update Phase
if no upload signals **OR** quite a small number of signals **then**
Using **Algorithm 1** to actively acquire b signals
end if
1)Convert matrix $\bar{\mathbf{X}}_t$ into a one-dimensional vector $\bar{\mathbf{X}}_t$;
2)Fine tune the auto-encoder by formula (3);
3)Reconstruct signal map by formula (4);
4)Calculate fluctuation by formula (8);

Extended online update phase : In the extended online update phase, we divide the process into two steps:

1) In the online recovery phase, which is basically consistent with the basic algorithm. we use the mean $\bar{\mathbf{X}}_t$ of multiple signals collected at time t as the signal value and we use this $\Omega_t \bullet \bar{\mathbf{X}}_t$ as input and fine-tune the auto-encoder model and reconstruct the signal map; 2) The fluctuation inference phase, which mainly draws on the relationship between the sample variance s^2 and the population variance δ^2 in statistics (as shown in formula (7)). And it uses the multiple signal measurements obtained in each observation grid to infer the fluctuation range of the reconstructed signal map.

$$\delta^2 \approx s^2 = \frac{1}{k-1} \quad \sum_{i=1}^{k} (x_i - \bar{x})^2 \tag{7}$$

Here x_i is the sample, $\bar{x}$ is the sample mean, and k is the number of measurements.

Because the signal map we collected is incomplete, we draw on this relationship and design a formula that fits our model, as follows:

$$s_x^2 = \frac{1}{k-1} \quad \sum_{i=1}^{k} \frac{\Omega_t \bullet ||X_i - \chi||_F^2}{|\Omega_t|}, \tag{8}$$

where s_x represents the fluctuation range of the signal map, k represents the number of measurements at time t, $X_i, i = 1, ...k$ represents the i-th signal map at time t, Ω_t represents which grid is collected at time t, $|\Omega_t|$ represents the number of meshes collected at time t. For collected grids ($\Omega_t = 1$), χ represents the observed mean matrix $\bar{\mathbf{X}}_t$ at time t, and for uncollected grids ($\Omega_t = 0$), we set χ to the maximum $\bar{\mathbf{X}}_{his}^{max}$ or minimum $\bar{\mathbf{X}}_{his}^{min}$ of the grid signal in the historical signal.

So the Ground-Truth of the signal map should be mostly concentrated in $(\widetilde{M} - s_x, \widetilde{M} + s_x)$.

C. Active Crowdsourcing Scheme

We found that the active crowdsourcing strategy mentioned in Section IV-C can still be applied to the advanced model, but the advanced model has new features. Therefore, we have extended the original active crowdsourcing strategy to make it more consistent with the advanced model. We extend formula (6) to the following :

$$I = abs(X_0 - mean(\bar{\mathbf{X}}_{his})), \tag{9}$$

where I represents the informativeness at different locations. X_0 indicates a signal map reconstructed formula (4) by setting the initial value of the auto-encoder without uploaded signals, $mean(\cdot)$ represents the element-wise mean and $\bar{\mathbf{X}}_{his}$ represents the mean of multiple historical signals collected.

The entire algorithm flow of advanced AER has been summarized in Algorithm 2.

VI. EXPERIMENTAL EVALUATION

In this section, we will verify the effectiveness of the proposed algorithm through some experiments. The experimental dataset we selected is the simulated WiFi indoor positioning dataset. The randomness of wireless signal map is mainly derived from channel gain. Therefore, we use ray tracing technology to generate 5000 signal maps with random changes of channel as historical signal maps at different times, in which each signal map has a missing rate of 50%, then we randomly generate 4 samples from the same channel random variation as incomplete signal maps at time t.

Baseline algorithms: we compare the performance of our algorithm to two state-of-the-art missing value inference algorithms, compressive sensing (BCS)[1], [10] and matrix-completion (LmaFit[9]).

BCS: the algorithm uses signal sparsity to model signal map reconstruction as a compressive sensing model, which reconstructs the signal with a small number of observations by Relevance Vector Machine (RVM)[18].

LmaFit: a popular alternating least-squares method for matrix completion. In our experiments, we selected the best matrix rank r for each signal map to ensure that its performance is optimal.

A. Experiment Setup

In this paper, both the encoder and the decoder use a single-layer neural network and we use cross-validation to determine the best model parameters in the training phase and the fine-tuning phase. We consider basic experiments (no noise) and advanced experiments (random Gaussian noise), mainly to compare the reconstruction errors of the three algorithms on the missing data at a lower sampling rate (5%-10%, 15%, 20% and 25%). At each sampling rate, we have set 11 different random sampling methods (the same number of samples, different Indicator matrices). In order to evaluate the reconstruction errors, we use the Relative Mean Squared Error [16] defined as $RMSE = \frac{||\hat{\Omega} \bullet (\widetilde{M} - M)||_F}{||\hat{\Omega} \bullet M||_F}$ and $RE = \frac{||(\widetilde{M} - M)||_F}{||M||_F}$ to evaluate three algorithms. Firstly we compare the recovery effects of three different algorithms on different test signal maps at different sampling rates, where RMSE is the average of the errors in 11 different indicator matrices. Secondly, we compare the RSSI error cumulative distribution function and coverage percentage ($CP = \frac{\sum(|(\tilde{\mathbf{X}} - M)| < s_x)}{|M|}$). Finally, we compared the different batch signals with active acquisition and 5 random samples at the beginning of the crowdsourcing task (no upload signals).

B. Experiment Result

Table I is the RMSE comparisons of the three algorithms. From the table we can clearly see that our algorithm is far superior to the other two algorithms. The RMSE of our algorithm is between 4% and 5%, while the RMSE of BCS is between 6% and 7%. The RMSE of MC varies greatly, but the minimum RMSE also exceeds 6%. Then we compare the cumulative distribution of reconstruction errors for the three algorithms in Fig.5. The higher the curve, the better the reconstruction effect. We can see that the performance of our proposed algorithm far exceeds the other two algorithms.

For the active crowdsourcing problem, we use the active AER algorithm to compare with the random sampling AER algorithm. Fig.6 shows that in the absence of crowdsourcing participants, we actively obtain reconstruction errors under different batch signals. As can be seen from Fig.6, we found that the signal obtained by the active method is much better than the random sampling method, and under the same RMSE, the active AER algorithm only needs less than half of the number of random sampling. And active AER algorithm can greatly reduce the collection cost required to reconstruct signals.

In the extended experiment, we compared the RE of the three algorithms at different sampling rates. The experimental results are shown in Fig.7. We found that in the presence of environmental noise, the performance of the three algorithms is almost unaffected, and the reconstruction accuracy is similar to that in the absence of noise.

For the active crowdsourcing problem in the presence of noise, from Fig.8, we found that the active AER performs better. Under the same RE, random sampling AER requires more than 5 times the number of signals required for active AER. In an active way, AER can greatly reduce the number of signals and reduce the cost of signal map reconstruction under the same RE. At the same time, we use the fluctuation estimation algorithm to estimate the signal fluctuation range, making the reconstructed signal map more practical. From Fig.9,where X_o represents the coverage of the collected grid, X_{no}^{max} represents the coverage of the uncollected grid calculated by $\bar{\mathbf{X}}_{his}^{max}$, X_{no}^{min} represents the coverage of the uncollected grid calculated by $\bar{\mathbf{X}}_{his}^{min}$, X_{all}^{max} represents the coverage of the reconstructed signal map calculated by $\bar{\mathbf{X}}_{his}^{max}$, and X_{all}^{min} represents the coverage of the reconstructed signal map calculated by $\bar{\mathbf{X}}_{his}^{min}$, we can see that even at the lowest

TABLE I
IMPUTATION PERFORMANCE IN TERMS OF RMSE(AVERAGE ± STD)

Test signal map	Algorithms	RMSE								
		5%	6%	7%	8%	9%	10%	15%	20%	25%
signal map (a)	AER	**0.0530±0.0011**	**0.0523±0.0000**	**0.0517±0.0011**	**0.0510±0.0013**	**0.0507±0.0015**	**0.0502±0.0015**	**0.0489±0.0020**	**0.0486±0.0022**	**0.0484±0.0020**
	BCS	0.0716±0.0000	0.0716±0.0000	0.0715±0.0000	0.0716±0.0000	0.0716±0.0000	0.0716±0.0000	0.0715±0.0000	0.0715±0.0000	0.0715±0.0000
	MC	0.0908±0.0024	0.0859±0.0017	0.0831±0.0015	0.0810±0.0013	0.0797±0.0000	0.0786±0.0000	0.0752±0.0000	0.0714±0.0124	0.0611±0.0000
signal map (b)	AER	**0.0431±0.0000**	**0.0427±0.000**	**0.0423±0.0000**	**0.0419±0.0011**	**0.0417±0.0011**	**0.0414±0.0000**	**0.0409±0.0000**	**0.0408±0.0011**	**0.0409±0.0010**
	BCS	0.0710±0.0000	0.0711±0.0000	0.0710±0.0000	0.0710±0.0000	0.0711±0.0000	0.0711±0.0000	0.0711±0.0000	0.0710±0.0000	0.0710±0.0000
	MC	0.0917±0.0028	0.0868±0.0019	0.0846±0.0015	0.0828±0.0012	0.0816±0.0000	0.0807±0.0000	0.0777±0.0000	0.0651±0.0024	0.0621±0.0000
signal map (c)	AER	**0.0500±0.0000**	**0.0496±0.0000**	**0.0492±0.0000**	**0.0489±0.0000**	**0.0485±0.0000**	**0.0483±0.0000**	**0.0475±0.0011**	**0.0471±0.0010**	**0.0471±0.0000**
	BCS	0.0592±0.0000	0.0592±0.0000	0.0591±0.0000	0.0591±0.0000	0.0591±0.0000	0.0591±0.0000	0.0591±0.0000	0.0595±0.0000	0.0591±0.0000
	MC	0.0924±0.0024	0.0872±0.0022	0.0849±0.0016	0.0829±0.0015	0.0816±0.0012	0.0805±0.0000	0.0773±0.0000	0.0633±0.0014	0.0620±0.0027
signal map (d)	AER	**0.0506±0.0000**	**0.0502±0.0000**	**0.0498±0.0000**	**0.0495±0.0000**	**0.0491±0.0000**	**0.0488±0.0000**	**0.0480±0.0011**	**0.0476±0.0010**	**0.0475±0.0000**
	BCS	0.0608±0.0000	0.0608±0.0000	0.0607±0.0000	0.0608±0.0000	0.0608±0.0000	0.0608±0.0000	0.0608±0.0000	0.0608±0.0000	0.0608±0.0000
	MC	0.0926±0.0026	0.0873±0.0023	0.0851±0.0017	0.0831±0.0015	0.0817±0.0013	0.0805±0.0000	0.0774±0.0000	0.0638±0.0028	0.0620±0.0026

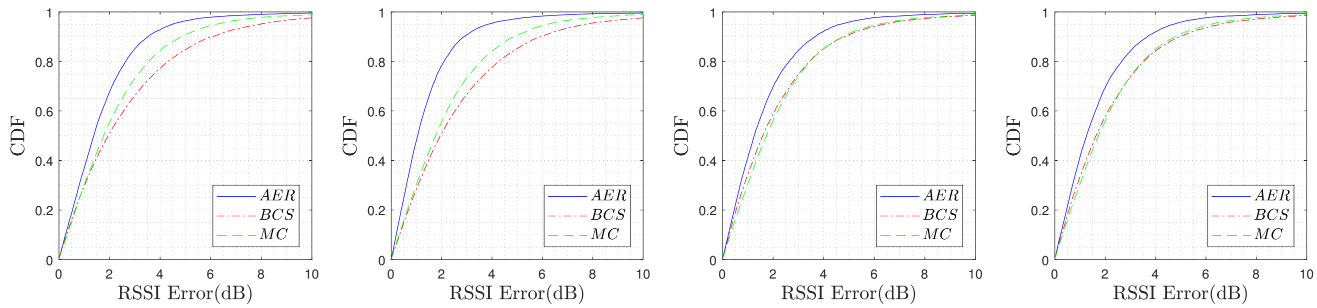

Fig. 5. CDF of signal map reconstruction error (dB)

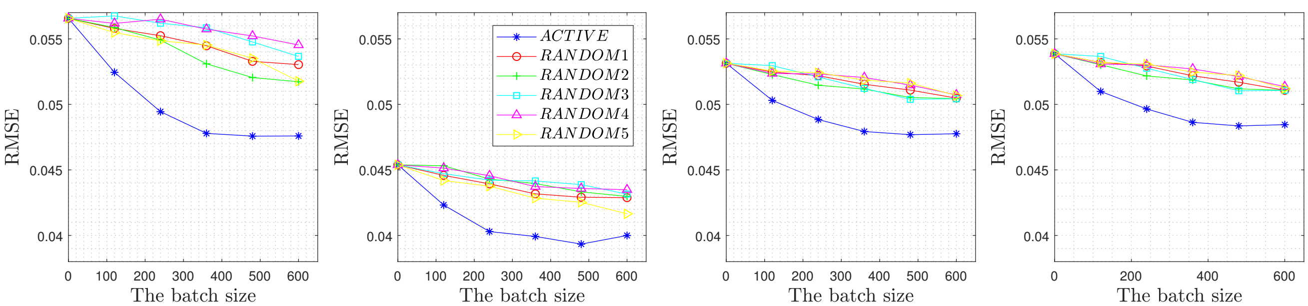

Fig. 6. RMSE at different batch sizes

sampling rate, we can still guarantee that more than 90% of the signal range contains the ground-truth of the signal.

From the above experimental results analysis, we can see that our proposed algorithm is far superior to the other two algorithms in RMSE. At the same time, AER can guarantee that more than 90% of the signals have small deviations. Moreover, we can further reduce the number of signal observations while ensuring reconstruction accuracy through active crowdsourcing.

VII. CONCLUSIONS

In this paper, we propose a comprehensive solution for signal map acquisition, where auto-encoder is used to learn the nonlinear features of and compose an algorithm called auto-encoder(AER) firstly. The AER can effectively utilize historical incomplete signal maps collected and learn the nonlinear temporal features therein and effectively reconstruct the signal map; Secondly, we propose an active crowdsourcing scheme for better performance of AER. This method can reveal the more valuable measurement sites for reconstruction algorithm and effectively reduce the reconstruction error with lower crowdsourcing budget. Finally, we also propose a more realistic signal map model with the description of the signal dynamics in the same location over time, and correspondingly, an extended AER algorithm is proposed to solve the reconstruction problem on this model. The simulation experiments results demonstrate the effectiveness of our solution.

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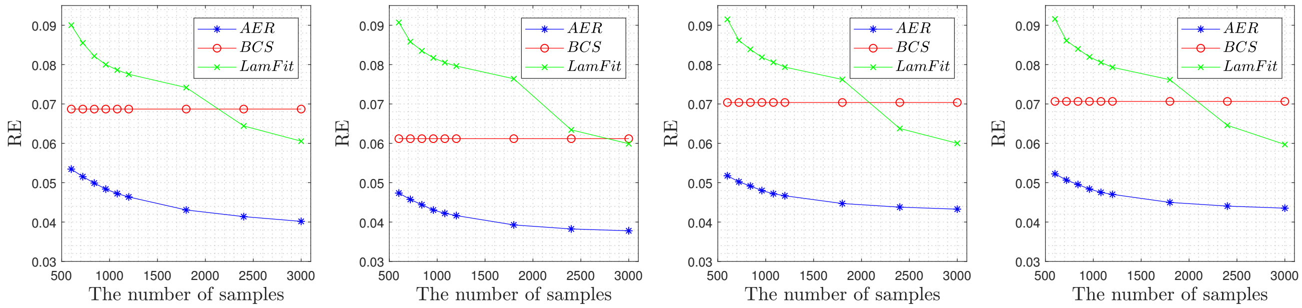

Fig. 7. RE at various number of samples

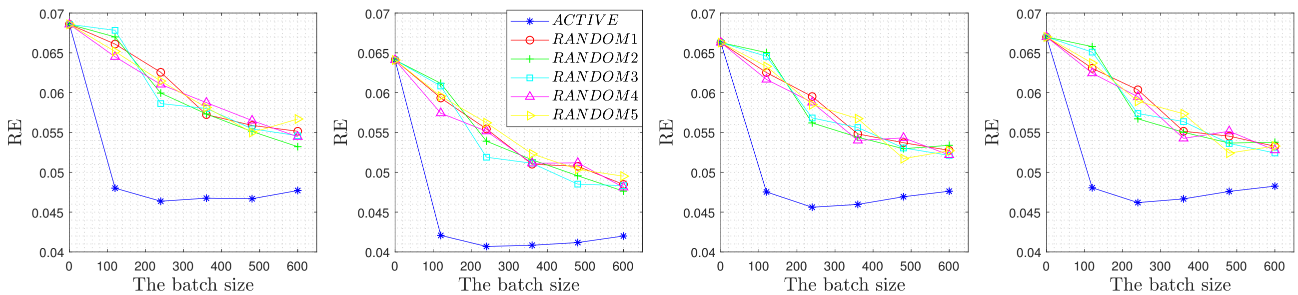

Fig. 8. RE at different batch sizes

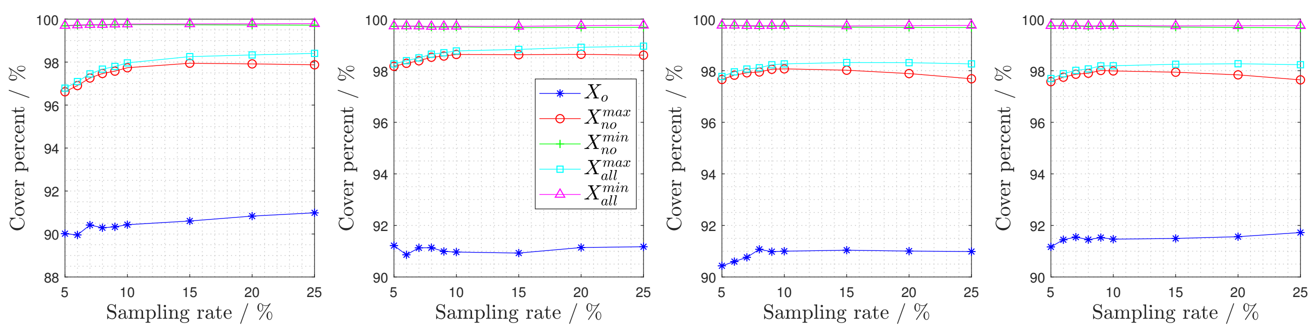

Fig. 9. CP at different sampling rates

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