AutoEncoder based Active Signal Map Crowdsourcing

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ABSTRACT

Signal map is of great importance, especially in the dawn of 5G network, location-based services (LBS) and cellular planning. But due to participants and budget issues, the signal map constructed by crowdsourcing is often sparse and incomplete. In this work, we study how to effectively reconstruct and update the signal map in the case of partially measured signal maps 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 online. Secondly, AER consists of an active query mechanism which further reduces the measurement cost to a large extent. Thirdly, 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 with parallel acceleration is proposed. The simulation results demonstrate the advantages and effectiveness of our approach in both accuracy and cost.

KEYWORDS

Signal map, active matrix completion, auto-encoder, crowdsourcing

1 INTRODUCTION

Signal maps, which consist of signal strengths at different locations, play an important role in site spectrum monitoring [1], LBS [2], and network construction [3]. But constructing the signal maps through on-site surveys, is time-consuming and laborious. And 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. Crowdsourcing schemes are proposed to address this issue, but 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 with signal propagation model[4], matrix completion[5] or compressive sensing[6]. These algorithms either have higher computational costs which are not conducive to updating the signal map in time, or lower reconstruction accuracy which does not meet the actual requirements. In order to solve these problems in a comprehensive way, we propose a novel signal map reconstruction algorithm based on auto-encoder based active matrix completion.

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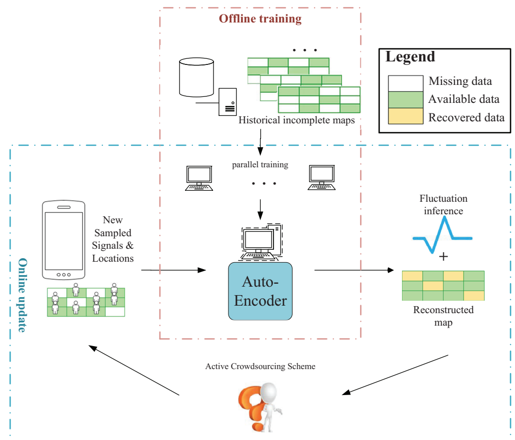


Figure 1: The workflow of the AER

2 METHODOLOGY

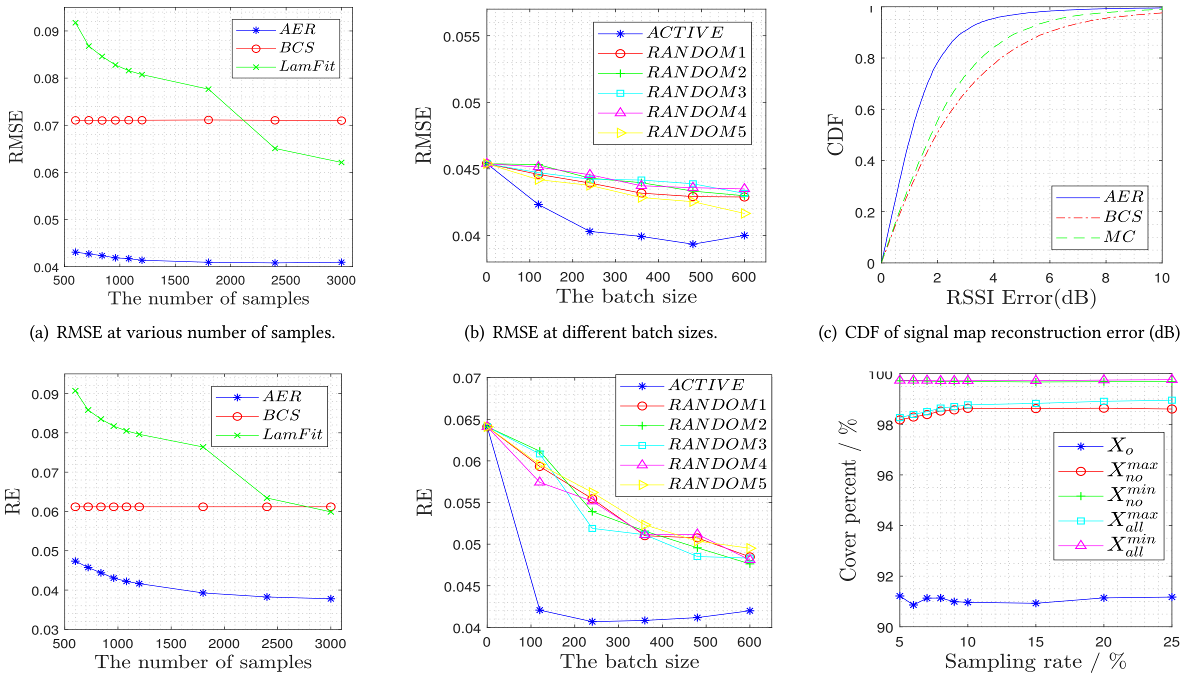
In this section, we will propose an auto-encoder-based signal map reconstruction method (AER in Fig.1). The algorithm is divided into the offline training phase and the online update phase.

Offline training phase: faced with a large amount of incomplete historical data, we extend the training of auto-encoder with parallel training method.

- We divide the massive crowdsourced historical signals and then use each compute node to train part of the fragmentation data.
- We combine the gradient parameters and update them through the parameter server.

Online update phase: we use the uploaded signal to reconstruct the signal map in time.

- The AER takes the partial signal collected at time t as input and reconstructs the signal map using the previously learned features.
- A fluctuation inference method infers the fluctuation range of the reconstructed signal map.
- An active crowdsourcing method finds the signal with the highest informativeness.



(a) RMSE at various number of samples.

(b) RMSE at different batch sizes.

(c) CDF of signal map reconstruction error (dB)

(d) RE at various number of samples

(e) RE at different batch sizes

(f) CP at different sampling rates

Figure 2: Experiment Result(The upper part is the result of no noise and the lower part is the result of noise.)

3 RESULTS

In this section, we will verify the effectiveness of our algorithm. The experimental data is the simulated WiFi indoor positioning data set. And we compare the performance of our algorithm to two state-of-the-art missing value inference algorithms, compressive sensing[6] and matrix-completion[5].

Relative Error: from Fig.2(a) and Fig.2(d), we can clearly see that our algorithm is far superior to the other two algorithms. And we find that the Relative Error of our algorithm is 1% lower or even 2% lower than the error of BCS, and AER is much better than MC. Then we compare the cumulative distribution of errors in Fig.2(c) and we can see that the performance of our algorithm far exceeds the other two algorithms. AER's RSSI error is about 90% less than 3.5dB, MC's RSSI error is about 90% less than 5dB, and BCS's RSSI error is about 90% less than 5.5dB.

Active Crowdsouring Scheme: for the active crowdsourcing problem, we use the active AER algorithm to compare with the random sampling AER algorithm. And we found that the signal obtained by the active method is much better than the random sampling method, and under the same errors, the active AER only needs less than half of the number of random sampling in Fig.2(b) and Fig.2(e). So active AER algorithm can greatly reduce the collection cost required to reconstruct signals.

Fluctuation Estimation: we use the fluctuation estimation algorithm to estimate the signal fluctuation range, making the reconstructed signal map more practical. From Fig.2(f), we can see that even at the lowest sampling rate, we can still guarantee that more than 90% of the signal range contains the ground-truth of the signal.

4 CONCLUSIONS

In this work, 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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