No-Sweat Detective: No Effort Anomaly Detection for Wi-Fi-Based Localization

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***Abstract*—At present, Wi-Fi localization is the main approach to estimating location indoors. However, age deterioration of the localization model due to dynamic environmental changes degrades its accuracy. Therefore, periodic model recalibration is inescapable. Existing methods for doing this use transfer learning and a small set of additional and supervised datasets. However, the reference points to obtain these datasets are determined either randomly or comprehensively. Such poor datasets catastrophically destabilize model recovery after recalibration because overfitting occurs. We propose a new approach that detects anomalous reference points to gain felicitous supervised datasets in order to prevent overfitting. Unsupervised datasets obtained from off-the-shelf mobile navigation applications, i.e., user logs uploaded from phones, are used. Our approach is implemented in a system we call "No-Sweat Detective". The results of an experiment in a controlled environment demonstrate that No-Sweat Detective can detect anomalies caused by environmental changes, and the results of a five-month experiment show that No-Sweat Detective has redundancy against a complex open-space environment in the real world. In addition, it could suppress model age deterioration by up to 10.9% compared to existing methods.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Location-based computing is becoming increasingly important in the Internet of Things (IoT) market [1]. Wi-Fi localization based on received signal strength (RSS) is getting the most attention due to the ubiquity of Wi-Fi accessibility [2]. Unlike indoor localization methods using Bluetooth Low Energy (BLE) or Indoor MEssaging System (IMES), Wi-Fi localization does not require the installation of additional devices or equipment. While several algorithms are available for Wi-Fi localization, the fingerprinting algorithm [3] is the most commonly used and has become the industry standard. However, we have come up with a crucial assumption in the Wi-Fi localization problem: namely, we do not know the accurate location of Access Points (AP). Although this assumption makes the Wi-Fi localization problem difficult, it is undeniably realistic in "wild" environments (such as shopping malls and subway stations) where APs cannot be controlled.

Wi-Fi localization typically consists of two phases: training and operation. In the training phase, a localization model is initially created from labeled observations (a set of Wi-Fi observations obtained manually and labeled as reference points). In the operation phase, a target location is estimated by comparing the model with the current observation.

However, the model suffers from age deterioration due to environmental changes such as furniture movement, obstacle construction, AP movement, and any other phenomena that attenuate the Wi-Fi propagation, and these phenomena can affect the accuracy of localization. In addition, the automatic power adjustment module implemented in modern APs, which optimizes the transmission power, can create fluctuations in the Wi-Fi environment. Age deterioration is defined as the problem that the RSSI distribution at a specific location varies over time, making it uncertain and therefore unable to be used to determine a user's location. These factors affect not only the fingerprinting algorithm but also all the other localization algorithms based on a model created from radio wave observations, such as localization using a Kalman filter or a particle filter [4]. Thus, the model must be recalibrated periodically. Another problem is that obtaining labeled observations manually requires considerable effort and involves a high overhead [5]. Model recalibration and manual obtainment have thus been the main drawbacks of Wi-Fi localization.

Much research has been aimed at overcoming these drawbacks. Some studies have focused on recalibrating or reconstructing the model with less or no effort [6]–[14], while others have explored fixing the effect by deterioration in Wi-Fi environments by detecting environmental changes [15]–[17]. However, these methods require additional infrastructure such as motion sensors and rich devices. They also require map information including AP location information, which requires a lot of effort. They are thus not suitable for practical use.

A recently developed approach to reducing the effort involved in recalibration is to use transfer learning [18]–[22]. The idea is to reflect the current Wi-Fi environment in the localization model by retraining the model. This is done by adding a small number of labeled observations during each model recalibration [23]. This approach reduces the number of labeled observations required to recalibrate the model, but the reference points to obtain these labeled observations are either randomly or comprehensively taken from the localization site. The resultant poor datasets catastrophically destabilize model recovery after recalibration, as overfitting occurs. In short, existing methods for anomaly detection require significant manual effort and a sensor-rich infrastructure, and methods for transfer learning do not take recovery stability into account.

In response to the above issues, we have developed a system that enables no-effort anomaly detection targeted at Wi-Fi localization with stable model recovery by gaining felicitous labeled observations at every recalibration of the model. In other words, model recovery will be stable if we choose the appropriate reference points for recalibration, and the trained fingerprinting model can estimate user location with higher accuracy and lower variance. Our No-Sweat Detective system can detect reference points that are close to places where the environment has changed by analyzing user logs automatically uploaded from off-the-shelf location-based services, namely, mobile navigation applications. Therefore, the No-Sweat Detective does not require any manual effort other than obtaining labeled observations at the detected reference points to recalibrate the model, the same as with existing methods. The No-Sweat Detective is run on user logs, i.e., the unlabeled observations (obtained from Wi-Fi observations without reference point labels). User logs can be obtained with no effort as long as the location-based services are running. Utilizing the co-occurrences derived from the user logs, the No-Sweat Detective vectorizes each AP as a vector model that describes the AP's position relative to that of the other APs. The similarity of the vector model is then calculated chronologically to detect anomalous areas that are likely to be environmentally changed. This detection is done using density-based clustering and nullification of untrustworthy Wi-Fi signals coming from APs that are close to where the environmental changes occurred. Finally, the No-Sweat Detective determines the reference point at which it can convergently obtain labeled observations. This approach enables recalibration of the model with stable model recovery by preventing the model from being overconfident. The No-Sweat Detective method can be applied even for Transfer Learning Model for recalibration, and the selected reference points to be observed is helpful for learning more accurate model with less calibration efforts.

The main contributions of this work can be summarized as follows.

- We propose the No-Sweat Detective system, which requires no effort for anomaly detection, targeted at Wi-Fi localization with stable model recovery following recalibration.
- We present the results of a five-month study showing that No-Sweat Detective works even in an actual dynamic environment, i.e., a complex underground shopping arcade.
- We valid the proposed detective method by evaluating with two types of transfer learning methodologies.

II. Related Work

In this section, we give a brief overview of existing localization algorithms based on Wi-Fi RSS and of research aimed at suppressing age deterioration of the localization model due to environmental changes.

A. Countermeasures Against Age Deterioration of Localization Model

Naturally, the localization model could be completely recalibrated by obtaining new labeled observations from all the reference points; however, this would make deployment and maintenance of localization systems prohibitively expensive. Therefore, there has been much research aimed at reducing the cost of recalibration.

Various research groups have addressed the localization model age deterioration issue by focusing on signal changes in the wireless network. Song et al. [15] were able to detect network node redeployment by focusing on changes in node neighborship and changes in measured distances between nodes as estimated from signal changes. Meng et al. [16] proposed a probabilistic localization method for detecting severe signal distortions due to unexpected environmental changes. Ohara et al. [17] showed that they could detect environmental changes by observing Wi-Fi channel state information (CSI).

The use of transfer learning is a recent major step toward reducing the effort involved in recalibration [18]–[22]. The idea is to reflect the current localization environment in the localization model through retraining in which a small number of labeled fingerprints are added during each recalibration [23]. While this approach reduces the number of labeled observations required to recalibrate the model, the reference points to obtain them are randomly taken from the localization site. Such poor datasets catastrophically destabilize model recovery after recalibration because overfitting occurs.

B. Signal Source Displacement Detection

Ngewi et al. [24] proposed an anomaly detection method for autonomously detecting the displacement of a signal source using only measurements collected by active users of the system. The proposed idea is realistic and useful, but there is room for improvement in terms of the anomaly detection method. Their paper focused on the probability that a signal from the AP to be investigated is included in the user's total signal measurement, and thus only drastic displacement is detectable.

Yu et al. [25] combined Wi-Fi fingerprinting based localization and Pedestrian Dead Reckoning (PDR). Since accurate PDR can tell users' position, they can get labeled data easily. Then, we can calibrate fingerprinting database with detecting anomaly signals. Zhou et al. [26] also introduced PDR for fingerprinting based indoor localization and anomaly signal detection. They got labeled calibration data from crowd-sensing users. Though existed crowd-sensing calibration methods need the workers' actual position or trajectory, this research can estimate workers' position by PDR, so frustrated process for workers to input their true trajectory or position is not required. Collecting crowd sourcing workers can be the additional labor cost.

III. Localization Protocol of No-Sweat Detective

In this section, we describe our system and methodology with respect to existing methods.

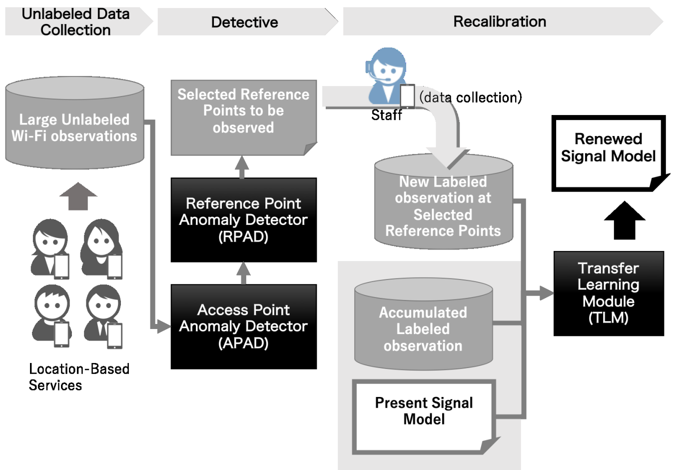

Fig. 1. No-Sweat Detective architecture

A. Two Types of Observation

Two types of observation are used in our system: labeled and unlabeled. They share a common data structure: Time, BSSID, ESSID, and RSSI (RSS indicator) (in dBm). These correspond to the absolute time when the observation was obtained or scanned, the BSSID that uniquely identifies each AP, the ESSID that also uniquely identifies each AP, and the RSSI that is a measurement of the power present in a received radio signal. Generally, Wi-Fi localization uses the BSSID to individuate each AP, as the ESSIDs sometimes overlap among frequency bands coming from different APs. The difference between the two types of observation is whether they are labeled with the reference points.

B. Challenge of No-Sweat Detective

No-Sweat Detective aims to reduce the labor cost of recalibrating a Wi-Fi fingerprint localization model with a large amount of unlabeled observation data. As discussed in Related Work, many researchers have developed learning methods for updating the localization model during recalibration. However, most of these methods select recalibration samples at random, whereas No-Sweat Detective focuses on the detective process of the calibrated reference points.

In summary, the main challenge tackled by No-Sweat Detective is how to decide the reference points to be observed for recalibration with a huge amount of unlabeled data. The concept of No-Sweat Detective can be applied to the recalibration process of any existing transfer learning method.

C. System Overview

As depicted in Fig. 1, No-Sweat Detective has three process.

First, we collected a huge amount of unlabeled observation data from the end users of a location-based service. Users install this application on their smartphones to obtain information on barrier-free locations, toilets, and area facilities and receive directions when heading to their destination. Their smartphones obtain Wi-Fi information and send this data to the server. However, the observation records do not include the true position of the users, resulting in data that is unlabeled and accumulates quickly.

Next is the detection phase, which includes access point anomaly detector (APAD) and reference point anomaly detector (RPAD). The APAD obtains unlabeled observations as input for detecting APs close to where environmental changes have occurred and forwards them to the RPAD. The RPAD uses the detected AP information to detect the reference points that should be used for the next recalibration.

The last phase is recalibration, at which point we obtain the reference points to be measured from the detection phase. In the recalibration phase, maintenance staff move to the designated reference points and observe the Wi-Fi signals there. Then, new data at the selected reference points are uploaded, and these data are labeled data because the staff uploaded Wi-Fi signals with their true position.

After obtaining the labeled observation data by the data collection process by maintenance staff, the TLM re-trains and recalibrates the model using the labeled observations obtained for the detected reference points. TLM retrains and uploads the models with newly collected observation data, observation data accumulated so far, and the present conventional signal model. This process continues as long as location-based services are operating.

D. Access Point Anomaly Detector (APAD)

As described above, unlabeled observations automatically uploaded from the users of location-based services and mobile applications are used to detect anomalies. Although the APAD handles the detection of anomalous APs close to where the Wi-Fi environment has changed, the unlabeled observations are those for which the point of observation is unknown. The APAD thus detects changes in the environment by analyzing the co-occurrence of relative positions with other APs.

The APAD does not use all the unlabeled observations for analysis. It uses only the ones for which the maximum RSSI is greater than the upper threshold $vecFilt$, as the APAD primarily works on the premise that the unlabeled observation is most likely to be the one observed close to a certain AP. The unlabeled observations $\mathbf{R}$ to be used are referenced as follows, where B_i indicates the observed BSSID from AP i, and $r(B_i)$ indicates the observed RSSI of B_i.

$$\mathbf{R} = \left(r\left(B_1\right), r\left(B_2\right), \ldots, r\left(B_n\right)\right) \qquad (\max \mathbf{R} > vecFilt) \quad (1)$$

The unlabeled observations are then modeled as a vector. For example, a vector model for B_ρ (BSSID from AP ρ)is created as follows.

$$\vec{B_\rho} = \left(r^*\left(B_1\right), r^*\left(B_2\right), \ldots, r^*\left(B_n\right)\right) \quad (2)$$

$$\rho = r\left(B_i\right) \qquad (\max r\left(B_i\right) > vecFilt) \quad (3)$$

If the unlabeled observation in (1) indicates that the RSSI of B_ρ is the strongest, it is vectorized as vector model B_ρ. This vector model expresses the relative positions of AP ρ with

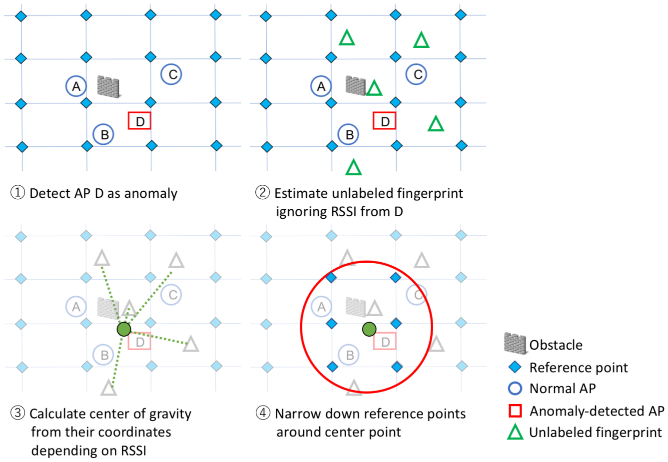

Fig. 2. Steps in detecting reference points when AP is singularly detected.

respect to the APs around ρ. Then, $r^*(B_n)$ in (2) satisfies the following condition of threshold $vecWidth$.

$$r^*(B_i) = \begin{cases} r(B_i) & (vecWidth < r(B_i)) \\ 0 & (vecWidth \geq r(B_i)) \end{cases} \tag{4}$$

This condition of $vecWidth$ means that the RSSI value is regarded as 0 when the weak radio wave has an RSSI value smaller than $vecWidth$. Weak radio waves become noise in the calculation of cosine similarity, so this formula aims to adopt only strong RSSI values when calculating cosine similarity.

When vector model $\vec{B'_\rho}$' of AP ρ is created, its cosine similarity is given as

$$\cos(\vec{B_\rho}, \vec{B'_\rho}) = \frac{\vec{B_\rho} \cdot \vec{B'_\rho}}{|\vec{B_\rho}||\vec{B'_\rho}|} = \frac{\sum_{i=1}^{|V|}(B_{\rho,i} \cdot B'_{\rho,i})}{\sqrt{\sum_{i=1}^{|V|} B_{\rho,i}^2} \cdot \sqrt{\sum_{i=1}^{|V|} {B'}_{\rho,i}^2}} \tag{5}$$

Vector models $\vec{B_\rho}$ and $\vec{B'_\rho}$are compared on the basis of their dimensions. For instance, if the dimension of $\vec{B_\rho}$ does not contain the dimension of $\vec{B'_\rho}$, 0 is designed to be assigned to the null dimension of $\vec{B_\rho}$. This process is chronologically applied to the other APs as well. When environmental changes occur, the similarity of the APs close to the changes decreases, and this decrease is measured using the threshold of cosine similarity $CosSim$ as it shows the normality of the APs and of the Wi-Fi environments around the APs.

E. Reference Point Anomaly Detector (RPAD)

Following execution of the APAD, the next step is to detect areas where the Wi-Fi environment has changed. We must address two cases: the case in which an AP is singularly detected by the APAD and the case in which an AP is multiply detected by the APAD.

In the first case, the RPAD detects the reference points as shown in Fig. 2. Consider the situation in which there are four APs (A, B, C, and D) and many unlabeled observations

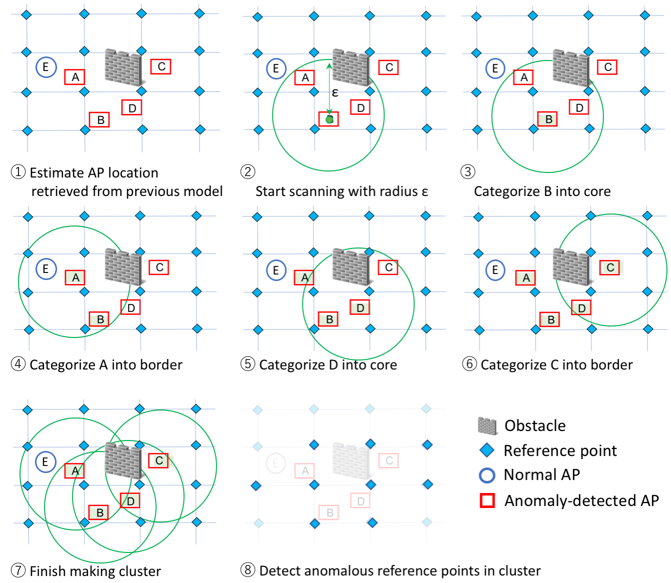

Fig. 3. Steps in detecting reference points when AP is multiply detected.

are obtained before the Wi-Fi environment changes. Then the environment changes. The APAD detects D because it is close to where the environment changed, and the RPAD roughly estimates the location where each unlabeled observation was observed, ignoring the signal coming from D as it is considered an anomaly. Next, the RPAD calculates the weighted average center coordinates. The unlabeled observations with an RSSI greater than or equal to -45 from the anomalous AP are targeted since using unlabeled observations with a weak RSSI may not return a trustworthy location estimate. The weighted average center coordinates are calculated using roughly categorized weights: unlabeled observations from the anomalous AP with an RSSI greater than or equal to -46 and less than -40 are given a weight of 1.0, those greater than or equal to -40 and less than -35 are given a weight of 1.5, and those greater than or equal to -35 are given a weight of 2.0. Finally, the RPAD detects the reference points within a radius ϵ m from the center. In the second case, it is likely that huge changes occurred in the Wi-Fi environment; therefore, the above algorithm described in the first case cannot be used because the RPAD has to ignore too many key Wi-Fi signals to estimate the center. This degrades the reliability of the RPAD in the search for areas where anomalous APs and/or environmental changes are most likely located. To overcome this problem, we use the density-based spatial clustering of applications with noise (DBSCAN) algorithm [27], as shown in Fig. 3.

DBSCAN, which was introduced by Ester et al., is the most commonly used algorithm for density-based clustering in the field of data mining.

F. Transfer Learning Module (TLM)

We applied the No-Sweat Detective to two existing transfer learning methods [23] to evaluate the performance of our

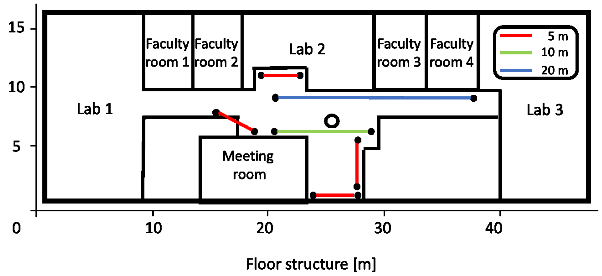

Fig. 4. Placement of AP pairs in laboratory setting.

methodology: the MixTrain and Lasso methods. The MixTrain method is closer to the basis of transfer learning than the Lasso method. It learns parameter θ from all datasets such that the transfer learning can recalibrate the model by adding the regularization term L1 norm, written as $(\sum_{i=1}^{|\theta|} |\theta_i|)$; this is done simply to keep the weights given to features from being overfitted by the general L1 norm. The Lasso method learns parameters from the variation in parameters by using L1 norms, written as $(\sum_{i=1}^{|\theta|} |\theta_i^{(k-1)} - \theta_i^{(k)}|)$. This regularization term enables regularization by minimizing the variation between the values of parameter θ at period $k-1$ and at period k.

IV. Evaluation

We evaluated the capability and performance of No-Sweat Detective in two different real-world environments: a laboratory and an underground shopping arcade. In the experiments at the laboratory, we arbitrarily created an environment of AP displacement. This experiment verified the performance of APAD. The experiment at the underground shopping arcade investigated how much the indoor positioning performance changes in TLM with No-Sweat Detective and TLM without No-Sweat Detective in a real environment. In a real environment, we cannot know whether or not the abnormality of the AP has actually happened. Therefore, we prepared a laboratory environment that can simulate displacement of APs, and we first confirmed that APAD can properly detect abnormalities.

A. Environmental Settings

1) Laboratory Area: We first investigated whether No-Sweat Detective can detect anomalies in a relatively uncomplicated area. We did this by simulating environmental changes on the fourth floor of a ten-story building at a university. The floor is 17 m $\times$ 47 m (799 m^2) and contains three labs, one meeting room, four faculty rooms, and one hallway. We created the meeting room and hallway localization sites and set 105 reference points on the floor at intervals of around 1 m, covering 348 m^2 (12 m $\times$ 29 m) to obtain labeled observations. We obtained one labeled observation for each reference point for each scan, and conducted ten scans a day for two days using the Google Nexus 5 Android smartphone. We obtained 2,100 labeled observations in total (1,050 per day). Moreover, we additionally deployed six pairs of APs in the hallway, as shown Fig. 4.

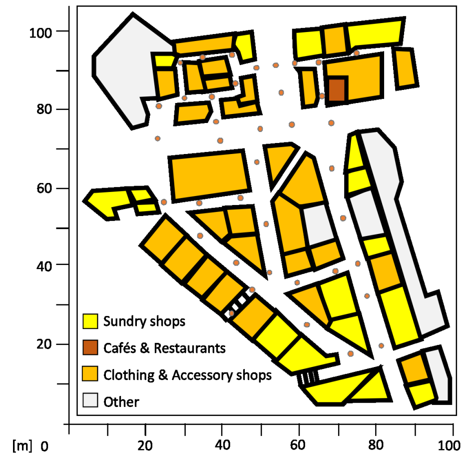

Fig. 5. Underground setting with reference points.

We assume that the radio wave received from APs is distorted due to the environmental changes such as appearance of new obstacles, movements of APs, and so on. It is thus reasonable enough to simulate the environmental changes in the Wi-Fi environments by displacements of APs [16] [24]. Therefore, to evaluate the detection performance of No-Sweat Detective, we simulated changes in the Wi-Fi environment by periodically moving the APs: six movements consisting of four 5-m shifts, one 10-m shift, and one 20-m shift. We then observed whether No-Sweat Detective could detect the anomalies.

2) Underground Shopping Arcade: We then investigated the actual performance of No-Sweat Detective in a more complicated area. These experiments were conducted in an underground shopping arcade in Osaka , Japan, as shown in Fig. 5. We chose this arcade because it is notorious for having a spatially complex maze-like structure and open space structure, which makes indoor localization further challenging. Several location-based services have been implemented in this area to support users, so we can easily obtain unlabeled observations in large quantities.

As shown in Fig. 5, we set 39 reference points at intervals of around 8 m, which follows industry practice, since we would like to obtain labeled observations at reference points actually used in existing off-the-shelf location-based services based on Wi-Fi. The localization site is 71 m $\times$ 65 m (4615 m^2) and contains clothing and accessory shops, cafes and restaurants, sundry shops, and so on. We obtained labeled observations, around six scans per point, every two weeks for five months with the Nexus 5 smartphone (2,693 labeled observations in total). We obtained unlabeled observations through the off-the-shelf indoor navigation application “Umechika-Navi (Underground Navigation)”. The number of installations conducted by July 2017 was around 9,500, and considering the release date was June 2016, we would like to emphasize that this number is high enough to gather the study dataset. There have been 350 different types of devices (including iOS and Android) obtained from the release date of June 2016 to July

2017. We can thus say that the study dataset contains data from a variety of devices. We obtained 764 unlabeled observations in total over five months from the same site.

To evaluate the performance of No-Sweat Detective, we ran it continuously during the five months with model recalibration every two weeks. We also investigated how the number of reference points used for recalibration affected age deterioration of the localization model due to environmental changes by varying the number of reference points used for each recalibration: 10%, 20%, 30%, 60%, and 100% of the reference points. Then, we evaluated the effect of No-Sweat Detective recalibrated points selection (detective method) by comparing it with usual randomly recalibrated points selection (without detective method). Methods without detective such as MixTrain or Lasso won't mention whether observed signals are irregular or not, so these methods update the localization model with just picking the reference points within the radius of the anomalous AP.

The labeled observations of the detective method used to recalibrate the model were obtained from the reference points detected by No-Sweat Detective. In the case that the number of labeled observations from the reference points detected by No-Sweat Detective was less than the total number of observation, the remaining observations were randomly obtained. We determined the accuracy of the model by recalibrating it using the same number of labeled observations after ten iterative trials. We compared its accuracy with that of existing methods and of the model without recalibrating (NonTrain) as a baseline. Note that we evaluated using the average of ten trials in order to eliminate the influence of random selection of all recalibration points in without detective methods and remaining recalibration points in detective methods.

In total, we compared five methods — NonTrain (baseline), MixTrain (without detective), Lasso (without detective), MixTrain (detective), and Lasso (detective), where the two detective methods are the ones proposed in this paper.

B. Results and Discussions

1) Laboratory Area: After No-Sweat Detective had been run with provisional parameters ($vecFilt$,$vecWidth$) = (-35, -35), 18 vector models were created covering the six pairs of APs. In Fig. 6, the vertical axis represents the normality of AP and of the Wi-Fi environments around the AP, and the horizontal axis represents the pairs of APs without environmental changes. In Fig. 7, the vertical axis represents the normality of each AP and of the Wi-Fi environments around the AP, and the horizontal axis represents the pairs of APs with environmental changes; the numbers on the horizontal axis are the displacement. As shown in Fig. 6, the APs had high normality overall, with 1.00 as the maximum and 0.74 as the minimum. Conversely, as shown in Fig. 7, the APs had low normality overall, with 0.20 as the maximum and 0.00 as the minimum.

These results demonstrate that No-Sweat Detective can detect anomalies caused by environmental changes. A key finding is that five of the six pairs of APs were judged to be

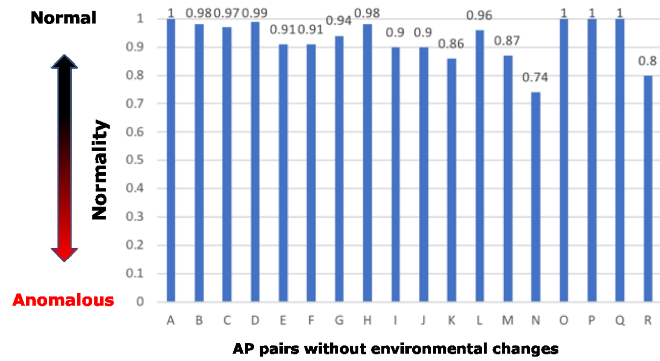

Fig. 6. Normality of AP and Wi-Fi environments around AP without environmental changes over two days.

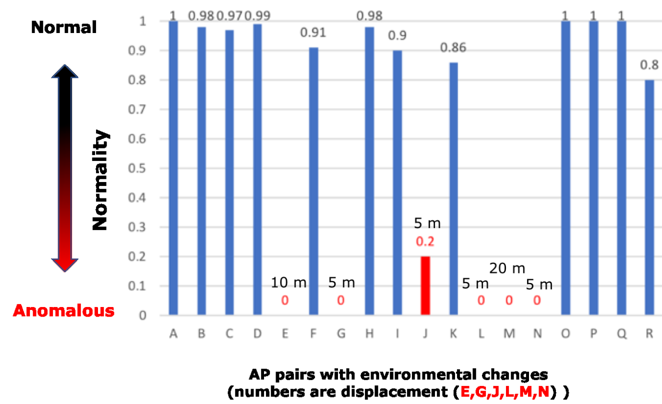

Fig. 7. Normality of AP and Wi-Fi environments around AP with environmental changes over two days.

completely different vector models by No-Sweat Detective, as shown in Fig. 7.

2) Underground Arcade: After ten trials using labeled observations with the provisional parameters ($vecFilt$,$vecWidth$) = (-43, -54), 36 BSSIDs were observed; four BSSIDs were detected as anomalous. They were all covered by ten BSSIDs in the unlabeled observations detected as anomalous. After creating the initial model using the initial dataset of labeled observations, we determined that the average error of the model was 2.32 m, and that for the NonTrain (non-recalibrated) after five months, it was 15.96 m. This demonstrates that the model had suffered age deterioration due to environmental changes.

3) Average Error: Fig. 8 shows the accuracy (average error) of MixTrain, MixTrain plus No-Sweat Detective (Detective + MixTrain), Lasso, and Lasso plus No-Sweat Detective (Detective + Lasso) after ten trials over five months. The vertical axis represents the average error and the horizontal axis represents the number of reference points used for each recalibration. Accuracy was about the same for the two existing methods with and without No-Sweat Detective when 60% and 100% of the reference points were used. In contrast, when 10% were used, the average errors for Detective + MixTrain and Detective + Lasso were dramatically lower than those for

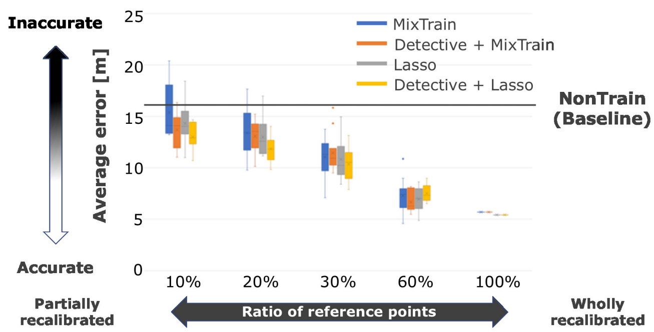

Fig. 8. Average error of final model for two existing methods with and without No-Sweat Detective using various numbers of reference points: 10%, 20%, 30%, 60%, and 100% of all reference points.

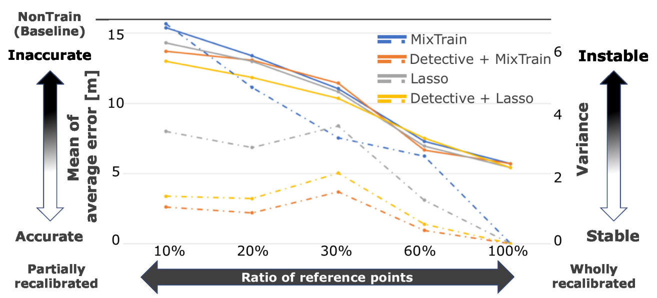

Fig. 9. Mean and variance of average error after ten trials over five months.

MixTrain and Lasso alone, which greatly stabilize the recovery of the model after recalibration.

Most importantly, although the average error for MixTrain exceeded that of NonTrain (baseline) when 10% of the reference points were used, that for Detective + MixTrain was lower than the baseline. This means that No-Sweat Detective can prevent the existing transfer learning methods from overfitting additional datasets selected by random sampling. Moreover, we clearly confirmed the difference in performance between with detective method and without detective method (especially in 10% reference point selecting case), which indicates that the number of unlabeled observation data used for the anomaly detection process was enough to confirm the effectiveness of No-Sweat detective.

4) Mean and Variance of Average Error: Fig. 9 shows the mean (solid lines) and variance (dash-dotted lines) of the average error after ten trials over five months. The left vertical axis represents the mean of average error, the right vertical axis represents the variance of average error, and the horizontal axis represents the number of reference points used for each recalibration. The means for all methods converged to around 5.5 m as the ratio of reference points used for recalibration increased. The variances for all methods converged to lower values as the ratio increased.

Focusing on the mean, we see that the mean for both Detective + MixTrain and Detective + Lasso was lower overall compared with MixTrain and Lasso alone. When 10% of the reference points were used, Detective + MixTrain had a larger suppression effect on age deterioration (mean of 13.70 m vs. 15.38 m) than MixTrain. When 20 % were used, Detective + Lasso had a larger suppression effect (mean of 13.00 m vs. 14.31 m) than Lasso.

Focusing on the variance, we see that both Detective + MixTrain and Detective + Lasso greatly reduced the variance overall compared with MixTrain and Lasso. When 10% of the reference points were used, Detective + MixTrain had a larger suppression effect on the variance (2.61 vs. 6.85) than MixTrain, and Detective + Lasso had a larger suppression effect (1.48 vs. 3.50) than Lasso.

C. Deciding parameters of $vecFilt$ and $vecWidth$ for detecting anomalos APs.

The performance of APAD and RPAD depends on the parameter set ($vecFilt$,$vecWidth$). We adopted ($vecFilt$, $vecWidth$) = (-35, -35) in the laboratory area experiment and ($vecFilt$, $vecWidth$) = (-43, -54) in the underground arcade experiment as provisional parameters. These parameters were determined on the following grounds.

In the laboratory area experiment, six APs were actually displaced and all of them were detected as 'displaced AP'. We can find that a set of ($vecFilt$, $vecWidth$) = (-35, -35) can detect the displaced AP the most accurately with the highest recall rate. So, we adapt ($vecFilt$, $vecWidth$) = (-35, -35) Then we got the confusion matrix shown in Table I, which describes the confusion matrix of detected displaced APs out of actually displaced APs in sliding scale ($vecFilt$, $vecWidth$). For example, "4/6" is confirmed in ($vecFilt$, $vecWidth$) = (-45, -45), which means that we can observe the signal from six APs and 4 APs among 6 APs are detected as displaced APs. Actually, we prepared six APs in total for laboratory experiment, and all of them were displaced as shown in Fig. 4, so 6/6 is correct score.

As the results show, if the threshold become strict (bigger score), since anomaly detection is done only with strong RSSI value information, the accuracy of detection becomes high. On the other hand, if the threshold is too strict, we cannot even detect APs unless users are very close to them and we can catch a very strong RSSI from the AP.

From these observation, we could lead the rule of deciding parameters. In this paper, we explicitly selected as large as parameters of ($vecFilt$, $vecWidth$) as possible under the condition that the existence of the AP can be detected exhaustively.

V. Conclusion

In this paper, we have presented a system, No-Sweat Detective, that detects environmental changes (i.e., anomalies) with no effort and recovers the model at a more stable rate. No-Sweat Detective detects reference points close to where changes in the environment have occurred by using the co-occurrences derived from unsupervised datasets (user logs), i.e., unlabeled observations automatically uploaded from off-the-shelf location-based services. Model recovery from age deterioration can be drastically alleviated by re-measuring only

TABLE I
CONFUSION MATRIX OF DETECTED APS OUT OF DISPLACED APS IN SLIDING SCALE {VECFILT AND VECWIDTH}

VecFilt\VecWidth	-25	-30	-35	-40	-45	-50	-55	-60
-25	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
-30	-	4/4	4/4	4/4	3/4	2/4	1/4	0/4
-35	-	-	**6/6**	**6/6**	4/6	2/6	1/6	0/6
-40	-	-	-	**6/6**	4/6	2/6	1/6	1/6
-45	-	-	-	-	4/6	2/6	1/6	1/6
-50	-	-	-	-	-	2/6	1/6	1/6
-55	-	-	-	-	-	-	1/6	1/6
-60	-	-	-	-	-	-	-	1/6

the detected reference points. Moreover, the proposed detective method is independent of recalibration methods, therefore it can apply any transfer learning methodologies in recalibration.

Two experiments in greatly different real-world environments were conducted, and confirmed effective performance of our anomaly detection module. The first experiment in a controlled indoor environment with simulated environmental changes demonstrated that No-Sweat Detective can detect anomalies. The second experiment in a complex underground shopping arcade over five months showed that No-Sweat Detective has redundancy against fluctuations in Wi-Fi signals.

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