GroupWi-Lo: Maintaining Wi-Fi-based Indoor Localization Accurate via Group-wise Total Variation Regularization

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***Abstract*—Wi-Fi fingerprint-based localization is known to be prominent for indoor positioning technology; however, it is still challenging on sustainability of its performance for long-term use due to distribution drifts of the signal strength across time. Therefore, the laborious continual surveys on fingerprint are inevitable. In this paper, we propose a new scheme for solving the large cost of maintaining common Wi-Fi fingerprint-based localization with machine-learning-based way by efficient incremental learning (retraining). Specifically, we propose a brand new retraining method, called GroupWi-Lo, that focuses on minimization of parameter variation with respect to the incremental surveys on fingerprint (i.e., calibration). Our method tries to keep the parameters of the previously trained model unchanged while minimizing the error on the dataset obtained in the last surveys. This formulation is helpful to keep robustness against overfitting from the limited size of the dataset per survey. The experimental results both in the lab and the uncontrolled environment show that GroupWi-Lo achieves competitive performance among the state-of-the-art methods, while its computational cost retains independent of the number of surveys compared with existing the semi-supervised approach and standard incremental training approach.**

***Index Terms*—Wi-Fi fingerprinting, machine-learning-based indoor localization, total variation, model maintaining**

I. Introduction

The widespread use of smart devices has prompted the demand for accurate indoor localization [1]. Indoor localization has been researched in several ways [2]–[4] due to these demands. Among the various localization methods, Wi-Fi-based indoor localization is one of the most attractive solutions owing to the availability of Wi-Fi signals [5], [6].

Typically, Wi-Fi-based localization methods can be categorized as access point (AP)-based localization [7], [8] and fingerprint-based localization [9], [10]. AP-based localization assumes that the precise location of the APs has been announced in advance. Although AP-based localization is useful when the locations of the APs are known and controllable, this assumption itself is unrealistic in uncontrolled environments (such as shopping malls and subway stations) where the APs cannot be controlled. On the other hand, fingerprint-based localization is based on the RSSI information with unknown AP locations. This approach only requires "fingerprints with location" to obtain the RSSI distribution map to train a localization model. In this research, we focus on fingerprint-based localization because of its practicality.

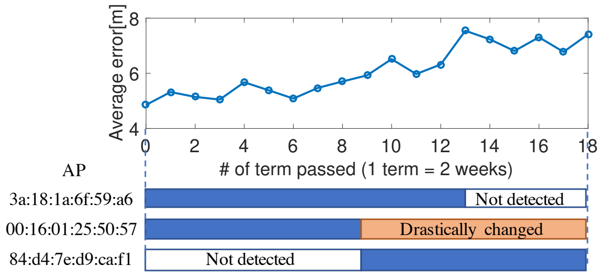

Fig. 1: The accuracy deterioration of the indoor localization due to RSSI change according to the environmental change (We employ the multi-class classifier-based fingerprinting)

However, fingerprint-based localization has a problem that accuracy deterioration is inevitable in ever-changing environments in actual errors as shown in Fig.1 (The drastically change in this figure means the RSSI change over 50 dBm between previous term and next term). This accuracy deterioration is caused by the changing the condition around AP, new AP installation, and removal of AP [11]. That is, the RSSI distribution at a specific location varies over time, making it uncertain and therefore unable to be used to determine the user's location. To overcome the deterioration problem, fingerprint-based localization needs continual fingerprint surveys to reconstruct the model with additional dataset. However, obtaining a completely new dataset in the whole environment is a labor-intensive and time-consuming task. To avoid this, some researchers have devised transfer learning frameworks to adapt the localization model to the current environment with few data from current environment [12]. These transfer learning frameworks enable construction of a new model using two types of datasets: a source domain data and a target domain data. The source domain data are gathered before the service is deployed and gathered after it has been deployed until the current time, and the target domain data are gathered in its current environment for calibration. Although the transfer learning approaches resolve the deterioration issue, they are regarded unsuitable for localization because their computational costs increase with time due to the increase in the amount of data in every calibration.

In this paper, we propose **G**roup **R**egularized **O**nsite **U**pdate of **P**arameters for **Wi-**Fi **Lo**calization (**GroupWi-Lo**), a new incremental learning method for fingerprint-based localization. The model can be thought of as a variant of online learning [13], that is, the model does not require the memory storage of fingerprints obtained by the previous calibration. This setting makes the model available for an unlimited number of calibrations. In each training, GroupWi-Lo only uses the small sized dataset obtained at the current calibration; thus, the computational cost can be reduced to reduce the computational cost to a constant level, and it is thus reasonable to run it for long-term deployment.

Similar to our model, the standard online training methods, such as [13], also offer reduction in memory consumption in large-scale learning; however, the incremental training with the limited number of calibration data is not so stable even though the parameters are considered to be kept across the training as a result of regularized learning.

Our model focuses on minimizing the total variation of the parameters as the standard online training methods while it also considers the structural property of features used in the localization model. To solve this issue in a systematic manner, we employ the idea of the total variation techniques explored in the computer vision community [14] and segmentation of time series analysis [15]. To the best of our knowledge, our work is the first attempt to install the idea of total variation for the training for Wi-Fi localization. Furthermore, we employ group lasso regularization term as a part of the regularization for total variation that aims to treat parameters of each AP as a group. We call this regularization as total variation regularization. With this formulation, our model updates the parameters corresponding to the APs with distribution changes that occurred after the previous training phase.

In summary, the main contributions of our proposed GroupWi-Lo are as follows.

- We propose a low-cost sustainable retraining method, GroupWi-Lo, for fingerprint-based localization using a new idea resembled from total variation minimization with sparsity inducing regularization.
- We conducted extensive experiments in a uncontrolled environment in a shopping mall and confirm that GroupWi-Lo can maintain the accuracy of Wi-Fi-based localization better than state-of-the-art methods with a practical computational cost.
- We confirmed that GroupWi-Lo can keep the parameters of non-deteriorated APs fixed while minimizing the localization error as we intended via AP movement detection application.

The rest of this paper is organized as follows. Section II formalizes indoor localization using a multi class classifier. We formulate the GroupWi-Lo and describe the order of calculation of our model in Section III. Section IV provides us with the contents of describing the experiment for all evaluation, and we discuss the results of the evaluation and the practicability of our model. In section V, we verify the ability of the GroupWi-Lo that can detect the AP movement with a controlled dataset. We review the related work in Section VI. Finally, section VII concludes this study.

II. Problem Setting

The fingerprint received from a device can be written as $\boldsymbol{x} = (x_1, \ldots, x_{|\mathcal{S}|})$, where $\mathcal{S}$ is the set of APs. If the device cannot obtain the RSSI from an AP, we substitute $x_i = \mathrm{V}$ with the constant value $\mathrm{V} \in \mathbb{R}$. We use a function that maps the fingerprint $\boldsymbol{x}$ to the location $\boldsymbol{y} \in \mathcal{Y} \subset \mathbb{R}^2$ that represents the location with 2D coordinates.

The fingerprint-based localization model can be divided into two approaches: a generative model and a discriminative model. In this paper, we formalize the indoor localization problem as discriminative model since Gaussian processes (GP) model has drawback in online model online phase. We compared with GP method as a generative method in experiment.

The discriminative localization model can be divided as two frameworks: regression and multi-class classifier. The regression framework infers the 2D coordinates of the position from the feature vector generated by the RSSI directly [16]. Multi-class classifier framework estimates the posterior of all labels that set in whole position in the environment. Since our approach can be applied in both setting, we formulate as a multi-class classifier method because accuracy of regression considers as low; actually, we compare the performance of both model in experiment (see section IV-D4). It should be noted that our proposed model can apply to the every machine learning-based localization method such as contains recent advanced localization method that handle other problems in indoor localization; however, to focused on the recover the accuracy deterioration in environmental changes, we employ the simple multi-class classifier-based localization method.

a) Formalization as multi-class classification: Following from [17], the discriminative function f can be formulated as the classifier $f(\boldsymbol{x}) \to \mathcal{L}$, where $\mathcal{L}$ depicts the labels of position, $l \in \mathcal{L}$ is the label that each label represent the 2D coordinate y. We assume that this quantization is given in advance for each target environment.

We build the classifier, $f(\boldsymbol{x}) = \mathrm{argmax}_l\, f_l(\boldsymbol{x})$, $f_l = \boldsymbol{\theta}_l^\mathsf{T} \boldsymbol{\phi}(\boldsymbol{x})$, where $\boldsymbol{\phi}$ is the basis function for creating a feature, $\boldsymbol{\theta}_l$ denotes a parameter vector for each location. As for the feature representation $\boldsymbol{\phi}$, we use the response of a Gaussian filter as the feature [17]. The number of features derived from a single RSSI value x_s from the s-th AP is equal to the number of Gaussian filters. With this featurization, the parameter could be represented as a structured collection as $\boldsymbol{\Theta} = \{\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_{|\mathcal{L}|}\}$, and $\boldsymbol{\theta}_l^\mathsf{T} = \left(\boldsymbol{\theta}_{l,1}^\mathsf{T}, \ldots, \boldsymbol{\theta}_{l,|\mathcal{S}|}^\mathsf{T}\right)$.

To optimize the classifier from the training dataset $\mathcal{D} = \{\boldsymbol{x}_i, l_i\}_i$, we use a cost-sensitive hinge loss function [17] as

$F_{\mathcal{D}}(\boldsymbol{\Theta}) = \frac{1}{|\mathcal{D}|}\sum_i F_{(\boldsymbol{x}_i,l_i)}(\boldsymbol{\Theta})$. The loss function per point can be depicted as

$$F_{(\boldsymbol{x}_i,l_i)}(\boldsymbol{\Theta}) = \left[\max_{\tilde{l}\neq l_i} \Delta(l_i,\tilde{l})(1-(\boldsymbol{\theta}_{l_i}-\boldsymbol{\theta}_{\tilde{l}})^{\top}\boldsymbol{\phi}(\boldsymbol{x}_i))\right]_+ ,$$

where Δ is a cost function defined as a distance function, $\tilde{l}$ is the estimated position, $[u]_+ = \max(0,u)$ for $u \in \mathbb{R}$ and constant 1 is the margin for the hinge loss function. We employ the Euclidean distance function as a distance Δ. With this cost sensitive loss, a regularized framework could be applied to the training of the model as $\hat{\boldsymbol{\Theta}} = \mathrm{argmin}_{\boldsymbol{\Theta}} F_{\mathcal{D}}(\boldsymbol{\Theta}) + \lambda R(\boldsymbol{\Theta})$, where $R(\boldsymbol{\Theta})$ is a regularized term for training and λ is the hyper parameter for the regularization. The parameter could be optimized by employing (stochastic) gradient based techniques such as Forward Backward Splitting (FOBOS) [18] and variants of the training methods.

III. Group-level total variation regularization

To recover the accuracy of localization, we need to reconstruct the new localization model. To achieve a constant low computation cost, we need a framework that can reduce the size of the dataset for learning the localization model.

We assume that we gather a dataset $\mathcal{D}^{(k)} = \{\boldsymbol{x}_i^{(k)}, l_i^{(k)}\}_{i=1}^{n_k}$ in term k for model maintenance, where n_k is the amount of data in term k, and also have the previously learned model $f^{(k-1)}(\cdot)$ i.e., the corresponding parameter $\boldsymbol{\Theta}^{(k-1)}$ is preserved. The dataset $\mathcal{D}^{(k)}$ in term $k \in \{1,2,\dots\}$ contains a few data acquired from the part of the target environment due to avoid the time consuming data acquisition process. At 0-th term before launching the localization deployment, we assume that n_0 is much larger than n_k at $k > 0$ that is the amount of data for retraining.

A. Model maintenance by retraining

When we construct a newer localization model for term k, we need to avoid using all data in term k considering the high computational cost. Instead, we construct the localization model for term k by using the current model constructed for $k-1$ and a small amount of new data in term k. To do this, we consider the following optimization problem:

$$\boldsymbol{\Theta}^{(k)} = \underset{\boldsymbol{\Theta}}{\mathrm{argmin}}\, F_{\mathcal{D}^{(k)}}(\boldsymbol{\Theta}) + \lambda R(\boldsymbol{\Theta}, \boldsymbol{\Theta}^{(k-1)}). \quad (1)$$

In contrast to the regularization frequently employed in the batch training methods, the regularization contains $\boldsymbol{\Theta}^{(k-1)}$. In other words, we construct a retraining method using the parameters of the existing localization model and only new data $\mathcal{D}^{(k)}$. Target domain data is much smaller than the entire dataset that was previously acquired; thus, this framework should reconstruct a new model with much smaller data.

Our approach is in the different class of online learning from the standard online learning. The important difference from the standard online learning such as AROW algorithm [13] is that they do not explicitly use the structure of the parameter $\boldsymbol{\Theta}^{(k-1)}$ in the regularization. That is, they do not use the structural property that causes performance deterioration in indoor localization. In contrast to the standard online learning methods, we use the structured property of the features in the regularization, especially on the AP information. We specify the regularization term R in our proposed method in the next section.

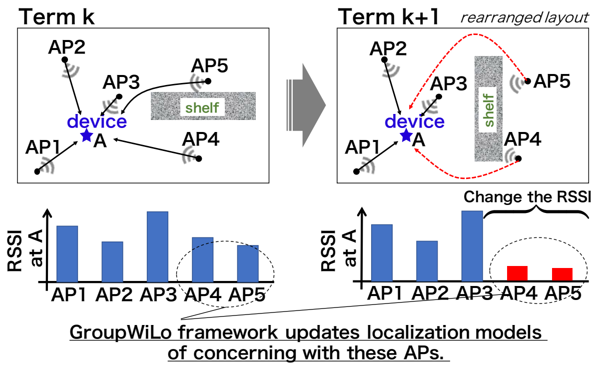

Fig. 2: The RSSI change due to the environmental change

B. Designing regularization term

Overfitting issues stemming from the effect of noise and biases are inevitable due to the small sized data (i.e., it only contains the data from a part of the environment) in recalibration phases if we employ the standard L1 or L2 regularization, i.e., $R(\boldsymbol{\Theta}, \boldsymbol{\Theta}^{(k-1)}) = \sum_l \|\boldsymbol{\theta}_l\|_1$, $R(\boldsymbol{\Theta}, \boldsymbol{\Theta}^{(k-1)}) = \sum_l \|\boldsymbol{\theta}_l\|_2^2$ in (1). To avoid this problem, we consider the model that restricts the updated parameters to parameters that need to be updated and other parameters should be fixed.

To limit the parameters change, we install the idea of the total variation regularization. By this technique, we can reconstruct the new localization model with keeping the knowledge of the previous model.

Moreover, in Wi-Fi-based indoor localization, environment change occurs with each AP individually. As an example with trivial visualization (see Fig. 2), as to the effect of the environmental change, the features of the 4-th and 5-th APs change, whereas those of the others remain the same. In real environments, the distributions of only the RSSIs from some APs change; hence, we will assume that this is the case. From this assumption, localization accuracy can be recovered by updating only the parameters relating to the APs that the distribution changed. Thus, by minimizing the total variation of the parameters of each AP, we can construct a new localization model with a small amount of new data and the current localization model.

To achieve the above requirement, we focus on the group norm of the parameter changes. Vert et al. [19] proposed the anomaly detection method that focused on regularization that considers parameter changes rather than parameter shrinkage. We extend the idea of that work to updating the parameter with minimizing total variation of the parameters. The norm of the parameters for s-th AP at location l between terms $k-1$ and k is $\|\boldsymbol{\theta}_{l,s}^{(k-1)} - \boldsymbol{\theta}_{l,s}^{(k)}\|_2$. This norm calculates the amount of

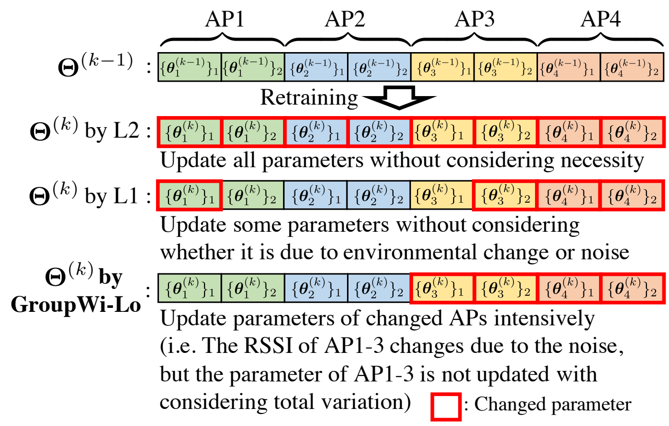

Fig. 3: The example of parameter updating of the proposed method and other regularization-based method

change in parameters with regard to s-th AP. We apply group sparsity regularization with these norms as follows:

$$R(\boldsymbol{\Theta}, \boldsymbol{\Theta}^{(k-1)}) = \sum_{s,l} \|\boldsymbol{\theta}_{l,s} - \boldsymbol{\theta}_{l,s}^{(k-1)}\|_2. \tag{2}$$

It should be noted that this group sparsity regularization makes parameter changes zero when the norm of parameters change in the same group is small.

It might be also natural to think that for L1 regularization, or L2 regularization for the regularization term within the total variation regularization framework, the effectiveness thanks to the group structure is more vivid than the others in the setting of indoor localization. Fig. 3 shows an overview of the parameter changes for each regularization term. L2 regularization updates all parameters because this technique does not have the effect that leads the sparsity. L1 regularization, i.e., $R(\boldsymbol{\Theta}, \boldsymbol{\Theta}^{(k-1)}) = \sum_l \|\boldsymbol{\theta}_l - \boldsymbol{\theta}_l^{(k-1)}\|_1$, can make parameters sparse independent of AP and location; however, this technique treats the parameters equally. As a result, it has to update many parameters and requires a lot of data to avoid overfitting. Thus, L1 regularization cannot recover localization accuracy effectively. Compared with L1 norm regularization, our model can induce parameters sparse with each group. Therefore, we can update only those parameters related to the APs whose distributions change. In other words, using group regularization for the parameters change, the model can minimize the total variation of the parameter groups while minimizing the error for the target dataset. This leads to the number of updated parameters being small. Therefore, Our method can recover accuracy without worrying about overfitting due to group constraints with this small updating.

C. Cost of Learning

The order of computation of the methods that use all term data related to the data size is $O(\sum_{j=1}^{k} n_j + n_0)$. The computational cost of the training with all data is $O((\sum_{j=1}^{k} n_j + n_0) im)$ where the data size is $\sum_{j=1}^{k} n_j + n_0$, n_k is the number of data in term k, i is the number of iterations for optimization, and m is the dimension of the feature vector. On the other hands, the computational cost of our approach is $O(n_k im)$ because our approach uses the only term k's data for retraining. The size of the dataset in the n-th term is much smaller than in the first term. Therefore, we can retrain the localization model constantly in terms of computational and labor cost no matter how many terms have passed.

IV. Experiments

We evaluate the performance of GroupWi-Lo from the viewpoints of performance and practicability with uncontrolled dataset.

A. Comparison methods

We compare our work with five state-of-the-art and baseline methods as follows. We implemented a localization model trained with only the first term's data as the baseline **(NotRetrain)**. It shows whether accuracy deterioration occurs [17]. The two types of conventional methods are Lasso for all data **(Lasso-AD)** and Lasso for parameter changes **(Lasso-PC)**. Lasso-AD updates the localization model using source domain data and a small target domain data [20], that is, the full dataset. The objective function of Lasso-AD is $F_{D^{(1)} \cup D^{(2)} \cup \cdots \cup D^{(k)}}(\Theta) + \lambda \sum_l \|\boldsymbol{\theta}_l\|_1$. Although Lasso-AD will certainly resolve the deterioration issue and avoid the overfitting issue because of using the all target position dataset, it will also incur a large computational cost as we repeat the calibrations. To confirm the effect of group regularization, we used lasso regularization for the parameter changes (Lasso-PC). The objective function of Lasso-PC is $F_{D^{(k)}}(\Theta) + \lambda \sum_l \|\boldsymbol{\theta}_l - \boldsymbol{\theta}_l^{(k-1)}\|_1$. Lasso-PC is similar to GroupWi-Lo, as both algorithms penalize parameter changes; however, Lasso-PC minimizes the total variation of the parameters independently. In addition to the comparison methods focusing on the design of the regularization term, we also employ a recent work [21] that called fingerprint spatial gradient (FSG) method that is reported to be robust against environmental changes. Moreover, to compare the generative method based indoor localization method, we employ the GP-based indoor localization [22] as comparison method.

1) Parameter settings: Gaussian filters are used in GroupWi-Lo, NotRetrain, Lasso-AD, and Lasso-PC. We determined the parameters of the Gaussian filters for the features as all pairs of $\mu \in \{-35, -45, -60, -80\}$ and $\sigma \in \{0.2, 1.0, 5.0\}$. Regarding the parameters of FSG, we use the Euclidean distance as the fingerprint distance and the cosine similarity as the FSG similarity metric. We use the same two parameters from the paper [21], that is, $r = 4$ for deciding the neighbor position number and $k = 3$ for the kNN algorithm.

B. Evaluation metric

We prepare 2 evaluation metric: p-value between first-term to target-term and Calculation time. We evaluate the p-value of the localization error defined as Euclidean distance between the true position l and the estimated position $\hat{l}$ as $e(l, \hat{l}) =$

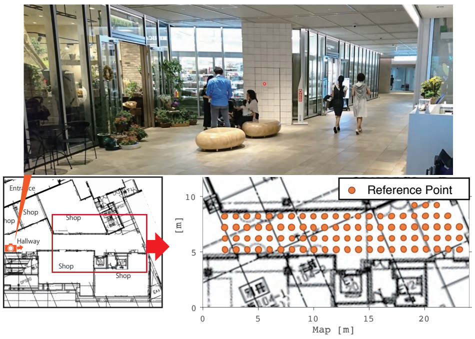

Fig. 4: Map and reference points of shopping mall dataset

$\|l - \hat{l}\|_2$. The accuracy deterioration turn to be occurred if p-value has a significant difference.

We use calculation time as a metric to verify the practicability on an Intel Core i7-3770 CPU with 32GB of memory.

C. Shopping mall dataset (Uncontrolled-Data)

The dataset was collected in a shopping mall constructed from reinforced concrete. Fig. 4 shows the reference points and scenery in collecting points. As shown in the figure, we set up the experiment in a wide corridor on the ground floor; the experimental area is $4\ \mathrm{m} \times 24\ \mathrm{m}$. A some people are exist in the target floor in every data acquisition timing, and sometimes the upper floor is crowded. We set up 90 reference points in total that are set on every $1\ \mathrm{m}^2$ grid. We used a Nexus5 to gather data from each point six times a day (each acquisition heads different direction) and gathered data once every two weeks for nine months. We select 20 reference points from 90 points in the training dataset randomly in each period respectively, and use the data from these reference points as training data.

D. Evaluation results with Uncontrolled-Data

In this experiment, we confirm the performance for recovering the accuracy and practicability with Uncontrolled-Data.

1) Robustness against accuracy deterioration: Fig. 5 depicts the localization performance of each method when we calibrate the model every two weeks. From this figure, it is clear from the results of NotRetrain that the accuracy deterioration issue actually does occur. The p-value of the difference between the 0-th term and the 18-th term is $p = 0.12$ (GroupWi-Lo), $p = 0.36$ (Lasso-AD), $p = 0.013$ (Lasso-PC), $p = 2.0 \times 10^{-15}$ (FSG), and $p = 6.4 \times 10^{-21}$ (GP). It should be noted that $p = 7.2 \times 10^{-8}$ (NotRetrain), and this persuades the need of additive data collection and retraining. In contrast, GroupWi-Lo achieves retaining localization performance against environmental changes compared with other methods. We also compared the performance of our approach with others at the 18-th term. We could not obtain a small p-value on the performance of GroupWi-Lo vs Lasso-AD ($p = 0.19$).

Lasso-AD has high resilience because it uses all the data. GroupWi-Lo has the same level of resilience with Lasso-AD but uses only the new target dataset and the parameters of the previous retrained model.

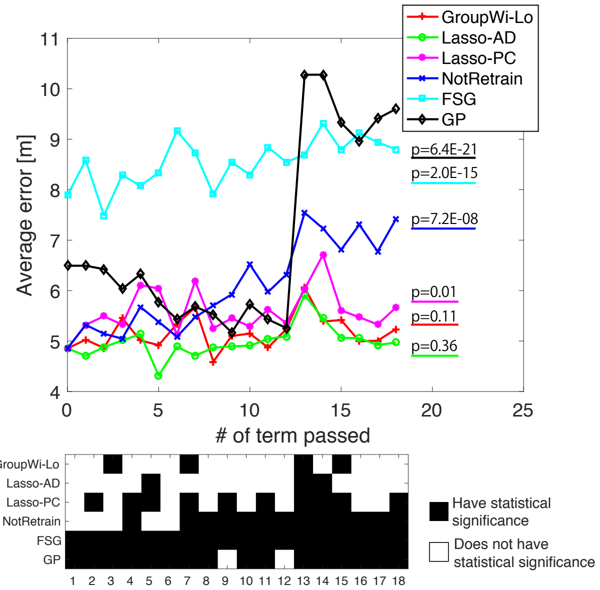

Fig. 5: Average change at error and p-value in the Uncontrolled-Data during 18 terms (1 term = 2 weeks): The upper figure shows the average error in each term. The p-values in the upper figure depict the difference between the 0-th term and the 18-th term. The lower figure depicts the statistical significance from 0-term in each term (The white cell represents it does not have statistical significance, i.e., accuracy is not deteriorated).

The results of Lasso-PC method show that lasso regularization is effective but not efficient. This result indicate that the retraining causes overfitting or bias in the new model because the k-th term dataset only contains the data from a part of target positions. Thus, the results of Lasso-PC have a large variance. This comparison shows that the group regularization is key to the deterioration recovery capability of GroupWi-Lo.

FSG has the worst accuracy among the methods tested. FSG uses a fingerprint database and the kNN algorithm; however, the quality of the database deteriorated during the experiment. Moreover, the database could not be updated for the current environment because it does not support the recalibration process. Even though FSG is powerful to deal with temporal deterioration such as shadowing and crowded space (we confirm that FSG can localize precisely in Lab. data sets used in application part), FSG cannot be used to recover from a permanent deterioration.

The accuracy of GP is drastically deteriorated in 13-term. In 13-term, many AP are changed, and GP can not deal with this changing. This result shows that GroupWi-Lo is more robust than the generative based indoor localization method.

We also conducts the experiment with sparse target point setting that select 24 reference points from Uncontrolled-data that are set on every $2\ \mathrm{m}^2$ grid. The error at first term is $4.93\ \mathrm{m}$. The error of 18-th term with GroupWi-Lo is $4.76\ \mathrm{m}$, while the Lasso-AD is $4.26\ \mathrm{m}$, the Lasso-PC is $5.62\ \mathrm{m}$, FSG is $6.39\ \mathrm{m}$, and GP is $8.35\ \mathrm{m}$. It should be noted that the error without retraining (NotRetrain) is $6.67\ \mathrm{m}$. From this result, our proposed method achieves accurate localization result with the

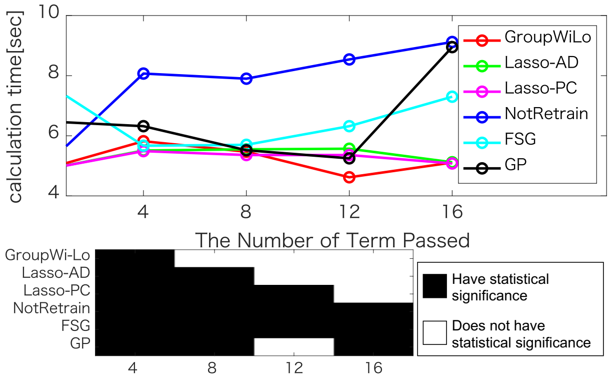

Fig. 6: Average change at error in the Uncontrolled-Data with long time duration (1 term = 8 weeks): Upper figure shows the average error in each method and lower figure depicts the p-value from 0-th term result of NotRetrain.

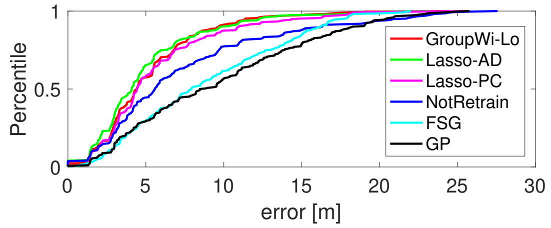

Fig. 7: CDF of the error distance of each method in the 18-th term calibration.

sparse target settings.

For long time period evaluation, we adopt 8 weeks span as 1 term. Fig. 6 which depicts the result show that our model can recover the accuracy with the long-term period compared with NotRetrain; however, it is better to employ our model per 2 weeks to ensure the effect of the recovery.

Fig. 7 shows the cumulative distribution function (CDF) of the error distance of each method. It shows that GroupWi-Lo and Lasso-AD have almost the same accuracy as in Fig. 5. The results demonstrate that the resilience of GroupWi-Lo is similar to the resilience of Lasso-AD. To conclude, the experiments show that GroupWi-Lo is a practical method from the viewpoint of resilience.

2) Computational cost: Fig. 8 depicts the relation between the computation time for retraining and the number of retraining on the Uncontrolled-Data. It should be noted that the calculation time of the GP and FSG is the not time for training but time for matching to the database time because these methods cannot retraining. Lasso-AD approach takes a long calculation time because it uses a large dataset (i.e., the all terms data sets).

GroupWi-Lo, FSG, GP, and Lasso-PC have constant calculation times independent of the number of retraining, whereas Lasso-AD becomes more costly as the number of retraining periods grow. Methods that require larger computational costs are impractical.

3) Discussion: GroupWi-Lo is a practical and efficient method for resolving accuracy deterioration. The resilience of

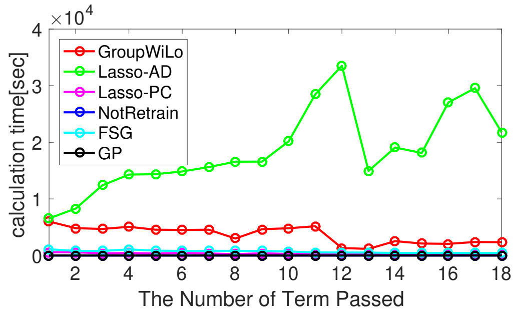

Fig. 8: Relation between computation time for retraining and the number of the retraining.

TABLE I: Average error and calculation time with 20 reference points in Uncontrolled-Data

	average error [m]	recover the accuracy?	constant calc time?
GroupWi-Lo	5.23	◯	◯
Lasso-AD	4.97	◯	×
Lasso-PC	5.66	×	◯
NotRetrain	7.41	×	◯
FSG	8.79	×	◯

GroupWi-Lo is equal to that of Lasso-AD, but its computational cost is at a constant and same low level as that of Lasso-PC. Lasso-AD and GroupWi-Lo have the lowest average errors. Compared with the NotRetrain approach, GroupWi-Lo recovers $2\ \mathrm{m}$ more accuracy (from $7.41\ \mathrm{m}$ to $5.23\ \mathrm{m}$). The calculation time of Lasso-AD increases as the calibration process is repeated (over 8 h). Lasso-AD approach is thus not practical in terms of the calculation time.

Although FSG is a state-of-the-art approach for robust temporary disturbances, it cannot resolve the accuracy deterioration issue. FSG is based on the kNN approach and cannot deal with new or untrustworthy APs, although it works in an ideal situation like a laboratory environment or situation which a white-list of APs is available for making an estimation.

4) Multi-class classifier vs regression: We show the comparison results between multi-class classifier and regression [16] with 6-fold cross validation.

As for the result, the mean of average error in each cross validation with the multi-class classifier is $\mathbf{4.65 \pm 0.02\ m}$, whereas that with the regression is $\mathbf{5.83 \pm 0.80\ m}$. Thus the regression methods have less performance than multi-class classifier. Regression method is told to be sensitive to data acquisition process.

V. Application: AP movement detection

GroupWi-Lo can detect the AP movement from the group norm of parameters change about each AP. We can check the changes of the AP by observing the result of parameter updating. This is, because our proposed method update only the parameters that related to deteriorated APs. We set the threshold value as 9 for the norm value defined at (2) to detect the AP changes.

We obtained the RSSI dataset in a $17\ \mathrm{m} \times 47\ \mathrm{m}$ area on a certain floor of a certain building in a university. We took the fingerprint data from the meeting room and corridor. We

L2Norm of parameter changes when a AP moves 20m

	AP1	AP2	AP3	AP4	AP5	AP6	AP7
GroupWiLo	**10.84**	1.51	**11.35**	2.63	3.28	6.65	3.07
Lasso-PC	**11.12**	**10.26**	**11.84**	**11.24**	**12.75**	**11.42**	**9.85**

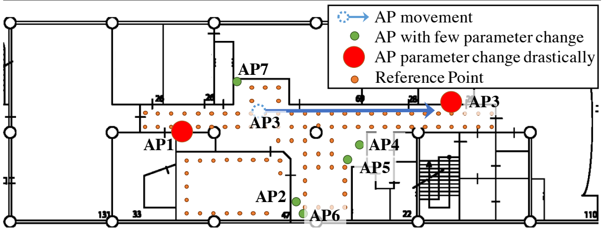

Fig. 9: Overview of single AP long distance movement and L2 Norm of parameter changes of GroupWi-Lo and Lasso-PC due to the distribution drift.

initially set seven APs in the corridor, as shown in Fig. 9; we then moved some APs in the experiment. We put a reference point every $1\ \mathrm{m}^2$, 105 reference points in total. We used a Nexus5 to gather data at each point ten times per day. We thus collected 5,250 fingerprints over the course of five days.

Fig. 9 shows intentional deterioration, and accompanying table shows the Frobenius norms of the parameter changes after updating the parameters. One long distance ($20\ \mathrm{m}$) movement in AP3 is simulated (Fig. 9). The large red circle indicates that the norm of the parameters change is significantly larger than others. In the case of using GroupWi-Lo, the changes to the parameters of AP3 and AP1 became large. This result shows that GroupWi-Lo can detect the AP movement about AP3. AP1 is also detected by GroupWi-Lo; this is because AP1 was located near AP3 before it was moved. On the other hand, Lasso-PC also minimizes the total variation of parameters; however, Lasso-PC updates every parameter regardless of whether the APs are affected by deterioration. Therefore, group constraints have the benefit of not only avoiding overfitting but also detecting the AP movement.

VI. Related Work

The RSSI-based indoor localization methods can be categorized into two types, that use the AP position, and that do not use the AP's position information.

Elbakly and Youssef [7] used Voronoi regions around the APs for localization and Liu et al. [23] used the AP's information to select the location. Most AP-based localization methods use the relation between the APs' position and the RSSI, so that supervised data is not required. Thus, even if the localization accuracy deteriorates because of changes in the environment, the AP's position only has to be updated for performance recovery.

Although AP-based localization is feasible in controlled environments such as office spaces where the location of the APs is known, it is hard to adapt it to a general uncontrolled environment which is not controlled (e.g., shopping malls and train stations).

Over the last few decades, many researchers have tried to construct localization methods from RSSI obtained from APs with unknown positions, that is, fingerprint-based localization [9], [24]. The fingerprint-based localization framework constructs a localization model from a supervised dataset. The supervised dataset consists of RSSI fingerprint vectors and precise location information in the target area. Thanks to using the relation between RSSI fingerprints and location information, the localization model is able to infer the device's position. However, the trained model deteriorates as time passes and environmental changes accumulate due to the environmental changing [25], [26]. Accuracy degradation is the central issue of fingerprint-based indoor localization. To overcome the accuracy deterioration problem, some researchers have tried to simplify the calibration process and transfer learning.

Some previous studies have attempted to reduce the calibration cost itself. Wu et al. [21] tried a new feature representation to reduce the effect of distribution changes. Wu's method [21] is a state-of-the-art of resolving temporal distribution changes such as shadowing and crowded space and is based on the kNN algorithm. Although these attempts are robust against temporal disturbances of the RSSI distribution that are caused by differences in device signal sensitivity, device direction and so on, among others, they do not deal with environmental changes. Montoliu et al. [27] tried to fill the empty RSSI with not constant value but regression techniques. This is also state-of-the-art of resolving empty RSSI due to the environmental changes; however, this method cannot handle the RSSI distribution changes because this method only focused on the empty RSSIs.

Other approaches to simplify the calibration process use supervision (i.e., location information as well as RSSI fingerprints) from additional sensors such as cameras as proposed by Chen et al. [28], image and RSSI by Xu et al. [29]. While these approaches improve accuracy, they make the RSSI fingerprint systems more expensive. To improve practicality, it is necessary to avoid installation for the environment and use only a smartphone sensor.

Recently CSI-based indoor localization is also explored as high accurate localization techniques [30], [31]. These techniques use the channel state information such as angle of arrival and time of arrival, and achieve decimeter level accuracy in indoor localization. However, these technique needs specific hardware such as multi-antenna Wi-Fi receiver and specific software setting in operating system (i.e., iOS, Android). That is, that technology cannot apply to the common mobile device on the market now. Thus, it can be say that the CSI-based indoor localization is not practical.

Although crowd sensing-based approaches [32], [33] reduce the effort of fingerprint distribution construction, the costs of adaptation are still non-negligible. Moreover, Yu et al. combined the crowd-sensing and the pedestrian dead reckoning (PDR) [34]; however, battery consumption issue on users prevent the practicability.

In the last decade, transfer learning and domain adaptation have been explored as ways of dealing with the environmental changes. In transfer learning of indoor localization, the source domain data is acquired before the service is deployed and acquired until the current term, and the target domain data is gathered in current environment for recalibration. Yin et al. [35] predicted RSSI distribution using regression analysis. Wang et al. [36] and Le et al. [37] used unlabeled data and acceleration data, while Ferris et al. [38], and Luo et al. [39] created temporary labeled data from unlabeled data using the characteristics of fingerprints predicted from a map or user trajectories, as the biggest issue of transfer learning methods, large computational cost in long term operation is reported.

VII. Conclusion

We proposed a brand new retraining method, called GroupWi-Lo, that has high resilience and low computational cost for tackling accuracy deterioration of fingerprint-based localization. We focused on the total variation of the parameters between the current and new model. We formalize this with the total variation of parameters with group structure per AP; thus, GroupWi-Lo only needs to use the parameters of the localization model and the new calibration dataset. The results show that our proposed method can recover accuracy to the same level as that of the existing methods while our model is more sustainable than existing methods because of a low and constant level computational cost. Moreover, we confirm that GroupWi-Lo can detect the AP movement thanks to the property of our algorithm. In future work, we enhance our work to unsupervised scenario that use the data that uploaded by users. This enhancement makes indoor localization more practical.

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