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Visible Light Based Occupancy Inference Using Ensemble Learning

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ABSTRACT As a key component of building management and security, occupancy inference through smart sensing has attracted a lot of research attention for nearly two decades. Recently, a cutting edge technique visible light sensing (VLS) that utilizes the LED luminaires as light sensors has shown its promising application potentials in occupancy inference as it piggybacks on pervasive lighting infrastructure without extra equipment deployment. Although existing inference algorithms based on the VLS data set can achieve high accuracy, the performance degrades when the occupants are moving. This paper focuses on the occupancy inference issue and presents an ensemble learning algorithm to improve the inference accuracy. We use heterogeneous learning algorithms to generate diverse learners. Consequently, we adopt forward sequential pruning to enhance the ensemble that pursues inference error minimization. We conduct extensive experiments based on the field data. The experiment results show that the proposed algorithm is able to improve inference accuracy, especially for highly dynamic occupancy data set.

INDEX TERMS Ensemble, occupancy inference, visible light sensing.

I. INTRODUCTION

Heating, Ventilation and Air Conditioning systems (HVAC) and illumination systems account for 17-49% typically for the energy consumption of the total amount of a commercial building [1]. It's estimated that the energy use of HVAC systems can be reduced by up to 42% in enterprise-scale buildings [2] by utilizing real-time occupancy information for flexible controlling. As a crucial input component of HVAC controlling system, occupancy inference has been extensively studied for nearly two decades, thereby avoiding energy waste in unoccupied indoor environment. Most solutions heavily rely on additional equipment deployment, including CO_2 sensors [3], [4], image sensors [5], passive infrared (PIR) sensors [5], [6], acoustic/ultrasonic sensors [7], and etc. In order to release the heavy reliance on additional equipment deployment, recent efforts on indoor occupancy detection have been made to leverage existing pervasive infrastructure such as powerline [8], speakers (potentially already in place) [9], RF signals [10], geomagnetism [11]. However, many of these solutions suffer from the issue of scale [8], complex functionality in client devices [12], or extensive war driving [10], [11], and so on.

Until very recently, a novel VLS based occupancy inference system has emerged. The seminal system *CeilingSee* [13] demonstrated the effectiveness of leveraging existing illumination infrastructure for occupancy detection. CeilingSee re-designed the driver of Commercial Off-The-Shelf (COTS) LED and thus enabled it to serve as both a light emitter and a light sensor. Consequently, the occupancy can be inferred by detecting the variance of the diffuse reflection caused by the presence of occupants using mounted LED luminaries.

CeilingSee employed Support Vector Regression (SVR) algorithm for occupancy inference. The algorithm works well when the occupancy is relatively static, whereas it yields unsatisfying accuracy when the occupancy changes dynamically, especially in the early morning and leaving time in the afternoon. In this case, it only achieves the accuracy from about 65% to 94% and the accuracy degrades significantly as the occupants increase. The performance even degenerates to

TABLE 1. Summary of existing indoor occupancy inference solutions.

Reference	Input feature	Inference method	Performance
[3]	Environmental data	linear discriminant analysis, random forest, classification and regression tree	Accuracy of 95% to 99%
[16]	Environmental data	NN	Accuracy of 75%
[15]	environmental data	duo output NN and stacking	Accuracy of 90%
[4]	CO_2	Feature Scaled ELM	Accuracy of 94%
[18]	Temperature and heat	RNN	Error less than 0.288
[6]	PIR sensors and thermal sensor	NN, KNN and linear regression	RMSE of 0.35
[23]	Vision	Markov Chain model	JSD of 0.2 and NRMSE of 0.4
[26]	Context resource	C4.5 classifier	Accuracy of 86%
[27]	Electricity consumption	HMM, KNN, SVM	Accuracy of 80%.
[5]	Vision and PIR	KNN Transition Classification	Accuracy of 94%, Miscount of 1.83
[13]	Light diffusion	SVR	Accuracy of 97% for static occupancy, 65% to 94% for dynamic occupancy

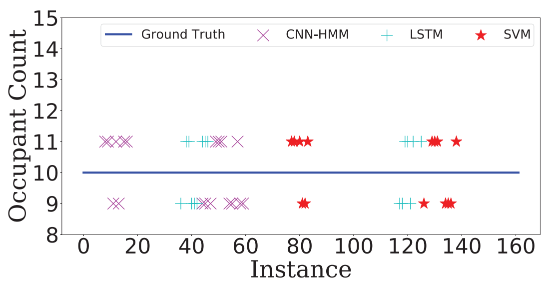


FIGURE 1. Diversity of inference errors.

about 50% under the interference caused by furniture moving and etc. Therefore, we aim to propose an inference algorithm to improve the accuracy in dynamic occupancy scenarios.

When we break down the inference results of different learning algorithms, we observe that the prediction errors of the different algorithms happen in different instants. Fig. 1 shows the inference results of 160 instances when the occupant count is 10 using three inference algorithms including Support Vector Machine (SVM), Convolutional Neural Network-Hidden Markov Model (CNN-HMM) and Long Short Term Memory networks (LSTM). We can clearly see that the inference errors occur on different instances. This observation motivates us to employ an ensemble learning algorithm that combines several weak learners so as to produce a strong learner.

In the following, a brief literature survey is firstly provided in Section II. We analyse the properties of VLS data in Section III before we present our occupancy inference algorithm in Section IV. We report the performance evaluation of the proposed inference algorithm in Section V. Section VI concludes the paper finally.

II. RELATED WORK

Although the indoor occupancy inference has been extensively studied, few of them are related to VLS based occupancy inference. In this paper, we only focus on the inference algorithms used in existing occupancy inference systems. Some typical solutions of indoor occupancy inference are summarized in Table 1.

Initially, the most used input features are indoor environmental data including CO_2, light, humidity, temperature data. A typical data set can be found from occupancy detection data set in UCI Machine Learning Repository [14]. Based on a (sub)set of the input features, Linear Discriminant Analysis, Random Forest, as well as classification and regression tree are used to predict occupancy of a room in [3] while Neural Networks (NN) is used in [15] and [16]. The accuracy is beyond 95% in [3] and roughly 75% in [16]. Extreme Learning Machine (ELM) is used in [4] and [17] and the accuracy can reach up to 94%. RNN is used in [18] which results in a very low average error 0.0056. Ortega *et al.* [19] prove Support Vector Machine (SVM) is able to provide more accurate occupancy detection than Hidden Markov Model (HMM) and K-Nearest Neighbors (KNN). Kraipeerapun and Amornsamankul [15] combine duo output NN and stacking technique and achieve the average accuracy of about 90%.

As a simple approach to detect if a room is occupied or not, passive infrared (PIR) sensors are widely used for binary detection [20]. ThermoSense [6] deploys PIR sensors and thermal sensor arrays and compare three inference algorithms, NN, KNN and linear regression. It showed that three models had similar results with KNN having the best root mean square error (RMSE) of about 0.35 occupants. However, PIR based solution is not always sufficient for HVAC control according to Erickon *et al.* [2] and Erickson and Cerpa [21].

Taking visual features as the input data set, SCOPES [22] consisting of 16 cameras achieves up to the accuracy of 80%. Utilizing SCOPES system, Erickon *et al.* design Markov Chain model [23] and achieve Jensen-Shannon divergence (JSD) of about 0.2 and Normalized-Root-Mean-Square-Error (NRMSE) of the occupancy durations of most 0.4. POEM [5] combines PIR and image sensors and uses KNN Transition Classification resulting in 1.83 miscount.

RF signals including WiFi, Bluetooth and cellular signals can be used as input features as well [10], [24], [25]. In addition, context sources, electricity consumption and etc. can also be used as input features. Ghai *et al.* [26] use the context sources such as WiFi access points, instant

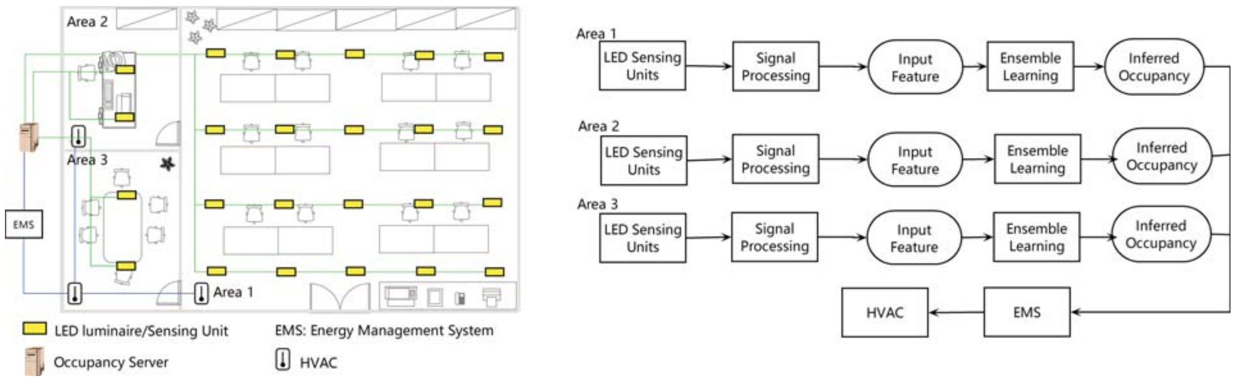


FIGURE 2. System architecture of VLS based occupancy inference.

messaging and calendar as input features and C4.5 classifier as the learning algorithm. The accuracy is beyond 90%. Kleiminger *et al.* [27] focus on the occupancy of households. The electricity consumption of appliances such as kettle and television are considered as input features and HMM, KNN, SVM and shareholding as classifiers. The highest accuracy exceeds 80%.

The most related work to ours is VLS [28]. Zhou and Campbell [30] and Varshney *et al.* [31] leverage VLS to position the users and further identify the users and their postures [31], [32]. In particular, Li *et al.* [31] propose to deploy light sensors on the floor to sense the shadows of a user so as to deduce the postures. The learning algorithms in the exiting VLS literature mainly focus on the gesture/posture recognition which is quite different from the occupancy inference. In comparison, CeilingSee [13] that innovates in using LED luminaires as light sensors is designed specifically for the occupancy inference. Based on the measurement of ambient light diffusion, CeilingSee performs SVR with Gaussian kernel for occupancy inference. It achieves the accuracy up to 97% based on static data set but performs unsatisfying when the occupancy changes dynamically. In this paper, we present an ensemble learning method that boosts the inference accuracy, especially for dynamic occupancy data set.

III. PRELIMINARY

Considering that the HVAC system in a commercial building deploys the aforementioned visible light based occupancy inference system as in CeilingSee [13], the occupancy inference system is naturally divided into areas, e.g. halls and rooms as shown in Fig. 2. The LED luminaries are redesigned into sensing units which are capable to capture the ambient diffused light. As the reflected light is strongly impacted by the change of occupancy, the measurements can be used to infer the occupancy. In each area, the LED lighting/sensing units are mounted on the ceiling, sense the reflected light and take the measurements periodically. The collected measurements are transmitted to an occupancy server. The server then infers the occupancy for each area and feeds the inference results into the actuators in HVAC, e.g. heater and air conditioners. The system architecture is shown in Fig. 2.

Before presenting the indoor occupancy inference framework and algorithm, we conduct an empirical analysis on the collected data from a laboratory and extract the properties of the data. Considering there have been plenty of research work on the property of the occupancy in commercial buildings, such as the periodicity, we only focus on the property of the LED sensing values in this section.

A. SPATIO-TEMPORAL CORRELATION

It's well known that the occupancy has temporal correlation, thus accordingly the LED sensing values naturally have temporal correlation. As the LED sensing units are usually densely deployed, an occupant could be sensed by multiple nearby sensing units. Thus, LED sensing values also have spatial correlation that is shown in Fig. 3. Fig. 3 plots the sensing values of two adjacent LED sensing units when an occupant passes by the two adjacent LED sensing units. Roughly from 1 s to 2 s, the occupant is sensed by both sensing units. From this figure, we can clearly see the spatio-temporal property of the sensing values. Therefore, intuitively the inference algorithm should take advantage of the spatio-temporal property.

B. ERROR DIVERSITY

In the pioneer work CeilingSee [13], the occupancy is considered to consist of static patterns and dynamic patterns. In static patterns the occupants stand or sit at arbitrary locations, and dynamic patterns are collected when all occupants move freely in the monitored area. The experiment results show that the accuracy based on static patterns is always higher than 97% for all occupancy counts while the accuracy varying from 60% to 90% for dynamic patterns appears to be rather disappointing. However, in reality the occupancy varies continuously, especially in rush hours, e.g. in the early morning and leaving time in the afternoon. Therefore an inference algorithm that can achieve satisfying accuracy in the dynamic situations need to be designed.

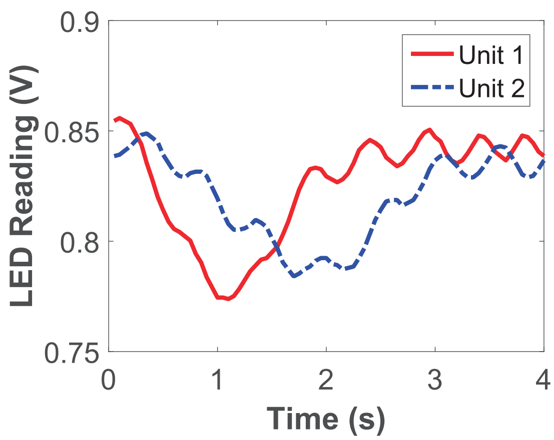


FIGURE 3. Spatio-temporal property of LED sensing values.

When we apply different learning algorithms as shown in Fig. 1, we observe that the prediction errors occur on difference instances. This is a encouraging observation for it inspires us to employ ensemble learning method for the occupancy inference purpose.

IV. INFERENCE ALGORITHM

In order to improve the inference accuracy under dynamic occupancy, we present an ensemble learning algorithm in this paper. Instead of ordinary learning that constructs a single learner from training data, an ensemble algorithm firstly constructs a set of first-level learners and then combines them to produce a final hypothesis. Ensemble is an effective learning method for its capability to combine weak first-level learners to a much stronger learner. Diversity among the first-level learners is one of the key issues for the ensemble learning method. Thus, we prefer heterogeneous learners generated by different learning algorithms [33] and each learning algorithm generates several learners through parameter variations to enrich the ensemble.

The occupancy inference is neither a pure regression problem nor a classification problem. On one hand, the occupant count must be an integer (in comparison, regression might produce a decimal); One the other hand, the deviation of the inferred occupant count from the ground truth dose matter in this problem, which is different from classification. Therefore, in this ensemble generation phase, we treat the inference problem as classification while we adapt the pruning criterion considering the deviation from ground truth.

A. DATA SET

In VLS based occupancy inference system, each LED sensing unit takes a sensing value periodically. The sensing values from all the n LED sensing units taken at time slot i form a snapshot $\mathbf{x}_i$. Thus, the data set can be formulated as $L = \{\mathbf{x}_i, y_i\}_{i=1,\cdots,m}$, where $\mathbf{x}_i \in \mathbb{R}^n$ denotes the input snapshots and $y_i \in \mathbb{R}$ denotes the labels (i.e. the occupancy count), m is the size of the data set. Please note, before feeding into the inference algorithm, the raw data are smoothed and normalized [13]. Given the data set L, the task of occupancy inference is to learn a mapping function $f(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}$ to map $\{\mathbf{x}_i\}$ to $\{y_i\}$ by optimizing a certain criterion, e.g. minimization of the classification error.

B. ENSEMBLE GENERATION

Diverse learners are generated using three classic learning algorithms, i.e. Support Vector Machine (SVM), Convolutional Neural Network-Hidden Markov Model (CNN-HMM) and Long Short Term Memory networks (LSTM). These learning algorithms are chosen because of their different principles.

The design of SVM follows that in CeilingSee [13]. In order to take advantage of the spatio-temporal correlation, SVM first processes the input data by multiplying Geographically Weighted Regression (GWR) and then applies a Gaussian kernel $\mathcal{K}(\mathbf{x}_i, \mathbf{x}_j) = e^{-\gamma\|\mathbf{x}_i-\mathbf{x}_j\|^2}$ with $\gamma > 0$. Plentiful of learners are generated with varying parameters including those in GWR and Gaussian kernel.

By feeding the probability of an observation sequence learned by CNN to the HMM model, CNN-HMM shows its promising performance compared to traditional GMM-HMM (HMM with Gaussian Mixture Model) and has been drawing increasing attention in the area of speech recognition, activity recognition and etc. recently. As the data has spatial-temporal correlation, CNN-HMM is a natural choice as one learning algorithm. In reality, the LED sensing units are usually deployed in a grid manner so that we can reshape $\mathbf{x}_i$ into a two-dimensional matrix according to the geographic layout of LED sensing units. For those cases that $\mathbf{x}_i$ can not be reshaped to a two-dimensional matrix, zeros are added to fill the vacant entries. The diverse learners are generated by initializing the parameters of CNN differently including the convolution kernel size, the number of kernels, dropout keep probabilities and etc.

LSTM, a species of Recurrent Neural Network (RNN), is another efficient learning algorithm that handles sequential characteristics of the input data. Compared with traditional RNN, LSTM can store longer temporal information. A gate mechanism is adopted to determine whether information is retained or dropped through the cell, thus enabling the network to forget old knowledge and preserve new knowledge. We set different dropout keep probabilities, time steps and etc. for each LSTM learner.

The computational complexity of ensemble learning linearly scales with the ensemble size. As there are many off-the-shelf implementations of the base learners with low computation cost, the ensemble generation is in general efficient.

C. ENSEMBLE PRUNING AND INTEGRATION

The ensemble generation usually produces an unnecessarily large set of learners whereas it had been found that "Many could be better than all" [34]. In other words, using a subset of the generated learners usually performs better than using all of them. In order to improve generalization performance and reduce the storage or computation resource costs, pruning is carried out to select a subset of the learners according to some performance metric.

For pruning and integration, we use the forward search based approach that is similar with complementariness pruning [35] for pruning and plurality voting for integration. Given the original learner set $F_0 = \{f_1, f_2, \dots f_{|F_0|}\}$, the selected set through pruning is denoted as $F = \{f_1', f_2', \dots f_{|F|}'\}$, where $| * |$ is the size of $*$. In this pruning, $|F|$ is pre-determined. The integrated learner by plurality voting is denoted as $\hat{f}$. In complementariness pruning [35], the learner selected in the tth iteration f_t' is the one that maximizes

$$\sum_{k=1}^{m} I(f_l'(\mathbf{x}_k) = y_k \textit{ and } \hat{f}^{(t-1)}(\mathbf{x}_k) \neq y_k), \tag{1}$$

where $\hat{f}^{(t)}$ is the selected ensemble model in the tth iteration and $I(\textit{true}) = 1, I(\textit{false}) = 0$. Considering the deviation from ground truth does matter in occupancy inference problem, we adapt the pruning objective to minimize the error of the ensemble and the error is defined as

$$Error = m^{-1} \sum_{k=1}^{m} [\hat{f}(\mathbf{x}_k) - y_k]^2. \tag{2}$$

With this aim, the pruning is carried out as shown in Algorithm 1. Initially, F is initialized as empty. In the first iteration, the learner with the highest accuracy is put into F. Subsequently, the learner selected in the tth iteration is the one that minimizes

$$m^{-1} \sum_{k=1}^{m} [\hat{f}^{(t)}(\mathbf{x}_k) - y_k]^2 \; I(\hat{f}^{(t-1)}(\mathbf{x}_k) \neq y_k). \tag{3}$$

In this case, this criterion favors the inclusion in the selected ensemble that minimizes the deviation of inferred results from ground truth in which the partial sub-ensemble miscounts. The computational complexity of pruning is $O(|F_0|^2 m)$, which is not higher than the original complementariness pruning [35]. The overall computational complexity of ensemble learning should be the aggregation of that of ensemble generation and pruning.

V. EVALUATION

In this section, we evaluate the performance of the proposed ensemble learning algorithm in terms of accuracy and Mean Square Error (MSE) based on extensive experiments. The accuracy is defined as

$$\frac{\sum_{i=1}^{c} I(\hat{f}(x_i) = y_i)}{c},$$

where c is the size of the test set. MSE is defined as

$$\frac{\sum_{i=1}^{c} (\hat{f}(x_i) - y_i)^2}{c}.$$

Algorithm 1 Ensemble Pruning

Input: $F_0 = \{f_1, f_2, \dots\}$, data set $L = \{\mathbf{x}_i, y_i\}_{i=1,\cdots,m}$ and $|F|$

Output: F and $\hat{f}$

$F^{(1)} \leftarrow \{f_1'\}$ where f_1' has the highest accuracy among F_0
$\hat{f}^{(1)} \leftarrow f_1'$
for t from 2 to $|F|$ **do**
  minimum $\leftarrow +\infty$
  for f_k in $F_0 \setminus F^{(t-1)}$ **do**
    $\hat{f}^{(t)} = \textit{plurality} - \textit{voting}(F^{(t-1)} \cup f_k)$
    $\textit{value} = m^{-1} \sum_{k=1}^{m} [\hat{f}^{(t)}(\mathbf{x}_k) - y_k]^2 \; I(\hat{f}^{(t-1)}(\mathbf{x}_k) \neq y_k)$
    if value < minimum **then**
      $f_t' \leftarrow f_k$
      minimum = value
    end if
  end for
  $F^{(t)} = F^{(t-1)} \cup f_t'$
end for
return F

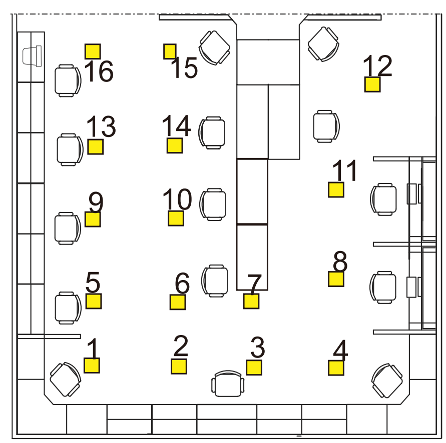


FIGURE 4. Sensing units layout in CeilingSee testbed [13].

A. EXPERIMENTAL SETTING

The field data set is obtained from the CeilingSee testbed [13] in which 16 LED lighting/sensing units are deployed in the ceiling of a 5m×6m laboratory in Nanyang Technological University. The layout of 16 LED sensing units is illustrated in Fig. 4. As the proposed ensemble aims to improve the performance for the frequently changing occupancy, the experimental data set is gathered through an experiment during which 3 to 12 volunteers keep walking or running freely in the lab. The volunteers even freely move the furnitures such as chairs and portable cabinets.

To generate diverse learners, the tuned parameters in SVM include the penalty parameter, gamma in Gaussian kernel, and the bandwidth in GWR. For CNN-HMM, according to the layout of the LED sensing units shown in Fig. 4, each input snapshot is reshaped to a 4×4 matrix. Considering

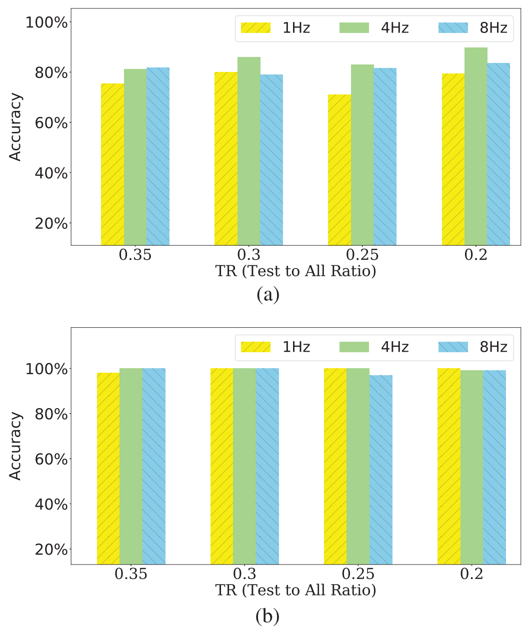


FIGURE 5. Inference accuracy with varying sampling rate.

the small size of the input matrix, we use a simplified CNN in which for each learner, 2 or 3 hidden layers are chosen, 16 or 32 filters for the layers, 2 or 3 for kernel size. Each LSTM learner has 3 hidden layers and 30 neuron units per hidden layer. Its time step is chosen from 5, 10, 20 and 30, and dropout keep probability as 0.6 or 0.7. For each learning algorithm 8 learners are generated respectively and 24 learners are generated in total among which 20% [35], i.e. 5 learners are selected after pruning.

B. SAMPLING RATE

Although a higher sampling rate generates a bigger data set that might improve the inference performance, it highly increases the workload of the occupancy inference system. We firslty explore the appropriate sampling rate in this subsection. Fig. 5 plots the performance with varying sampling rate. In addition to better evaluate the performance of our algorithm, we also show the performance when one miscount is allowed. We can see that the accuracy under sampling rate of 1 Hz is lower than that of 8 Hz. But overall, the accuracy stays stable with the sampling rate of 4 Hz and 8 Hz and in some cases the accuracy under 4 Hz is slightly higher than that of 8 Hz.

We attribute this to the fact that the monitored laboratory has only one entrance so that only one occupant can enter or leave once. In this case, the occupancy changing frequency is roughly the same with walking frequency of the occupants. The walking frequency of occupants indoors is typically 1-2 Hz, hence according to Nyquist Sampling Theory LED sensing units should adopt the sampling rate of roughly 4 Hz. This indicates that with a much lower data rate, the proposed ensemble can achieve high accuracy while largely saving the communication resource, computation resource as well as storage resource. Apparently, the sacrifice under a low sampling rate is the real-time response. In order to achieve a good trade-off between the resource cost and real-time requirement, we deem at most 0.25 s is acceptable for response delay, thereby suggesting the sampling rate as 4 Hz.

TABLE 2. Accuracy and MSE.

	Ensemble	CNN-HMM	SVM	LSTM
Accuracy	88.0%	70.1%	50.6%	65.0%
MSE	0.130	0.298	0.493	0.343

TABLE 3. Performance under one miscount-tolerance.

	Ensemble	CNN-HMM	SVM	LSTM
Accuracy	99.8%	100%	100%	99.3%
MSE	0.009	0	0	0.132

C. ACCURACY AND MSE

In this subsection, we demonstrate the effectiveness of the ensemble algorithm based on high dynamic occupancy data set. In this experiment, test-to-all ratio is 0.3 and the training/validation ratio keeps 9:1. SVM, LSTM, CNN-HMM shown in this experiment are the learners with the highest accuracies among all, respectively. As shown in Table 2, among the four algorithms, SVM performs the worst in terms of both accuracy and MSE while the proposed ensemble algorithm is superior to the other three algorithms. The accuracy can be improved to about 88.0% by ensemble algorithm compared with about 50.6% by SVM, 70.1% by CNN-HMM and 65.0% by LSTM. The ensemble method has MSE of only 0.130, which is the lowest among all methods.

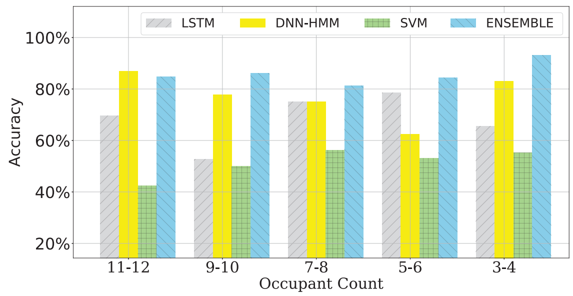
Table 3 shows the performance with one miscount tolerance. The accuracy of the ensemble algorithm is up to 99.8%. We also observe that LSTM has slight lower accuracy and higher MSE while the other three have the accuracy of nearly 100% and MSE of nearly 0. This is because the miscounts of SVM, CNN-HMM and the ensemble are almost one while LSTM yields more miscounts of 2 and 3.

Fig. 7 illustrates the distribution of inference miscount. We can see that most algorithms have miscounts of at most 1. LSTM has higher accuracy, yet it has higher miscounts too. It confirms to the fact that LSTM has higher MSE as shown Table 2 and 3. In comparison, SVM, CNN-HMM and the ensemble lead to much lower miscounts.

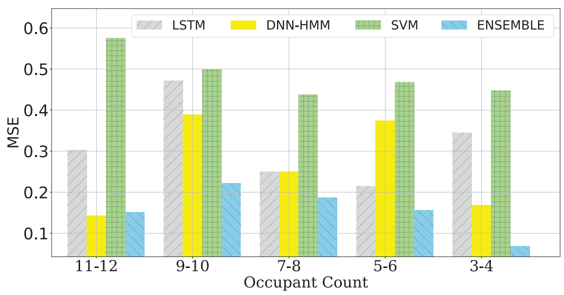
Fig. 6 demonstrates the performance under different occupant count. From this figure, we can see that compared with SVM, LSTM, CNN-HMM, the ensemble algorithm works stable as the accuracy is all beyond 80% and MSE is below 0.22. This figure verifies again the improved performance of the proposed ensemble algorithm.

D. PERFORMANCE BASED ON DAILY DATA SET

We also demonstrate the effectiveness of the ensemble algorithm based on *daily data set* which was collected for about 6 months by monitoring the daily routines of the occupants



(a)



(b)

FIGURE 6. **Performance with varying occupant count.**

TABLE 4. **Performance based on daily data set.**

	Ensemble	DNN-HMM	SVM	LSTM
Accuracy	93.3%	85.4%	79.7%	86.6%
MSE	0.088	0.150	0.208	0.153

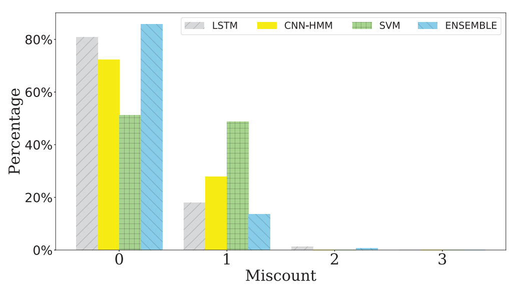


FIGURE 7. **Miscount distribution.**

in the lab [13]. Again, from Table 4 we can see that the proposed algorithm performs superior to the other algorithms in terms of both accuracy and MSE. Fig. 8 shows the miscount distribution which is rather similar with that in Fig. 7.

E. DISCUSSION

The daily data set is collected in a university lab in which the occupancy has relatively less intense changes. We believe in more dynamic scenarios, e.g. shopping malls and airport lounges, the improvement of the ensemble over the others would be more obvious. Moreover, the testbed only consists of 4×4 sensing units. In a large scale indoor environment, the algorithms might have different performance. For example, CNN-HMM that takes advantage of spatial correlation

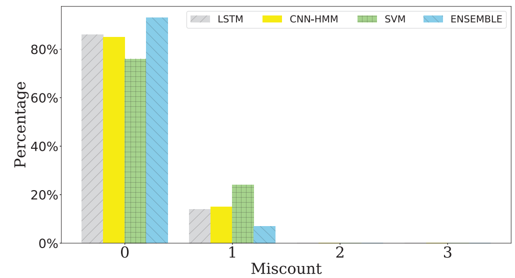


FIGURE 8. **Miscount distribution under one miscount-tolerance.**

might have better performance. There are lots of methods to improve the ensemble. Just to name a few, we can employ sophisticated bagging method for LSTM [36], orientation ordering [35] to accelerate the pruning, or optimization based method to refine the pruning and integration [37]. We leave these refinement for future work.

VI. CONCLUSION

In this paper, we focus on the problem of inference problem based on VLS data and aim to propose an inference algorithm that boosts the accuracy based on dynamic occupancy data. We present an ensemble learning algorithm. We use heterogeneous learning algorithms to generate diverse learners and pruning to enhance the performance of ensemble. Consider the specialty of occupancy inference, we design a new pruning criterion to reduce the inference error. Extensive experiments based on the field data demonstrate that the proposed algorithm can achieve the accuracy up to 88% and MSE of 0.13 based on dynamic occupancy data set and accuracy of 93% and MSE of 0.088 based on daily occupancy data set. In the future work, we plan to deploy the VLS based occupancy inference system in a shopping mall and evaluate our algorithm in such large scale and dynamic scenarios.

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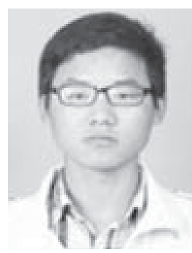

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