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Recognizing energy-related activities using sensors commonly installed in office buildings

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Abstract

Automated control based on user activities and preferences could reduce energy consumption of office buildings. In this paper, we investigated generalisation properties of an office activity recognition approach using sensors that are frequently installed in modern and refurbished office buildings. In particular, per-desk passive infrared (PIR) sensors and power plug meters were considered in an evaluation study including more than 100 hours of data from both, a single-person room and a three-user multi-person office room. Layered hidden Markov models (LHMM) were used for the recognition. Results showed that 30 hours and 50 hours of training data were needed to achieve robust recognition of desk activities and estimate people count, respectively. The recognition can be performed independent of a particular occupant desk. In further simulations considering different energy profiles, we show how energy consumption due to lighting and office appliances is related to occupant behaviour.

Keywords: Activity recognition, office buildings, Green ICT, energy saving, BEMS

1. Introduction

Todays' office workers engage in various activities during an office day. In simulations it has been observed that different office worker activities are related to substantial energy consumption variances in buildings. Subsequently, automated control based on user activities and preferences could improve comfort while reducing energy consumption [1, 2]. By recognising office desk activities using screen-attached proximity sensors, we controlled the operation of computer screens in a previous study and switched displays off when users were not present [3]. The approach showed savings of up to 43% per display, compared to using the computer's screen saver. Furthermore recognising desk-related activities, such as computer-based work vs. desk-based work could save energy of overhead lighting. By comparison, for computer-based work, a 30% lower light level is suitable according to the EC Standard BS EN 12464-1 [4]. As it was shown in a previous investigation [5], desk activities could be automatically discriminated using sensors and overhead lighting could be dimmed accordingly, resulting in energy savings close to 30%. Similarly, the people count per office room affects heating, ventilation and air-conditioning (HVAC) needs. According to the ASHRAE Standard 62.1, air flow rate and occupant population are directly related [6]. Therefore, HVAC could be dynamically controlled according to actual people count in a building space rather than building design estimates.

To leverage energy savings in office buildings and maintain user comfort at the same time, additional ambient sensors had been considered in previous investigations. However, many sensor systems and modalities that are considered as informative sources for activity recognition, such as cameras and ambient sound, often require complex processing, additional maintenance, and introduce privacy concerns. Moreover, the required installation and networking effort creates substantial hurdles for building owners and managers to use additional sensors. By contrast, many modern or refurbished buildings already provide sensors, e.g. used to control overhead lighting per desk or measuring the power consumed by appliances. Often these sensors and controls are integrated into a building energy management system (BEMS), which provides the required network infrastructure to add further advanced control features.

In this paper, we discuss an office activity recognition approach targeting desk-related activities and estimate people count. We consider sensors that are often already installed in modern or refurbished office buildings. In particular, we utilise per-desk passive infrared (PIR) sensors and power plug meters and use layered hidden Markov models (LHMM) for the recognition. In an evaluation study including more than 100 hours of data from a single-person room and a three-user multi-person office room, we evaluate the performance of our approach.

The paper provides the following contributions:

1. We investigate the amount of training data required for the HMM-based recognition of office desk activities and to estimate people count. Based on this analysis, the initial training dataset required to use our approach in other buildings can be estimated.
2. We investigate the recognition performance for a desk-independent operation of our recognition approach by performing a leave-one-desk-out cross-validation across all desks of our evaluation dataset. With this analysis, we confirm that the recognition approach can be used independent of a particular office desk.
3. We present an exploratory energy consumption analysis to detail energy needs for different behaviour profiles. For this simulation, we modify the HMM transition probability distributions and estimate energy consumption based on generated state sequences. This analysis provides insights into the relation of energy requirements and occupant behaviour.

The remainder of this paper is structured as follows: in Section 2 we describe previous works, related to our approach. In Sections 3 and 4 the methods and evaluation study are detailed. Results and conclusions are presented in Sections 5 and 6.

2. Related work

PIR sensors are commonly used for motion and presence detection. Authors in [7] used PIR sensors together with door switches, light sensors, and energy controllers to manage stateless devices such as monitor, printer, coffee pot, and microwave according to occupancy. Their prototype system achieved energy savings of 7.1% to 14.6%, implementing a relatively simple control policy. Agarwal et al. [8] showed that fine grained occupancy information is critical for increasing energy efficiency of HVAC systems. Using a pilot deployment across ten offices for the period of over a two weeks, they discovered significant opportunities for energy saving in the period of non-working hours. Using the data collected during the study, HVAC energy consumption was simulated and showed that by considering occupancy only, energy consumption could be decreased between 10% to 15%. Delaney et al. [9] introduced LightWise, a wireless tool, which aims to evaluate lighting control systems in office buildings. They used motion and light sensors to discover points in the control system that have unnecessary high energy consumption. Their optimization considered available level of natural and artificial light and current occupancy. The results showed options to save up to 58% by highlighting areas of energy loss. Information about occupancy proved to be valuable for controlling lighting and HVAC systems and save energy in the previously described works. Our work focuses on occupant activity and behaviour as a key element for adaptation and energy saving potential, not limited to occupancy only.

Besides occupancy detection, PIR sensors were used for activity recognition and tracking of users in previous works. The solution proposed in [10] used a network of PIR sensors, grouped in clusters and superclusters making several levels of hierarchy for activity recognition. The first level was used for motion detection, while sequences of motions on the second level represented movements, such as turning, entering, leaving, joining and splitting. The final level of superclusters was used for detecting sequence of movements, i.e. the actions visiting, chatting, and meeting. Wojek et al. in [11] used one camera and one microphone per room. Multi-level HMMs were used for evaluating features captured from audio and video sources in order to perform activity recognition and room-level tracking. The authors showed that with their approach it was possible to recognize whether a user is in a meeting, involved in a discussion, performing paper work, or having a phone call as well as room occupancy. Oliver et al. [12, 13] used binaural microphones and cameras in their setup. Layered HMMs were introduced for office activity recognition. The first layer was used for estimating audio and video features. The second layer, was used for fusion of features from the first layer deriving specific classes necessary for detecting activities such as phone and face-to-face conversation, working on computer, presentation, distant conversation and nobody present at the highest layer. All activities were recognized with average accuracy higher than 92%. Authors in [14] proposed a method for indoor activities detection by using PIRs, pressure sensors, and microphones. They designed a system using a wireless sensor network that can identify different activities. Although use of cameras and microphones would provide rich information about user activities, this approach is often considered privacy intrusive, and it could affect a user's behaviour and comfort. PIR sensors and plug-in power meters, as used for motion detection and power measurements of computer screens in our study, provide sufficient information for activity recognition purposes without introducing privacy issues.

Opportunistic sensing approaches have been investigated to combat the constraints in obtrusiveness, privacy, and cost associated to the previously mentioned concepts, which are key to our application too. In the context of smart homes, infrastructure-mediated sensing or 'home bus snooping' was investigated to recognize user activities by single-point sensing. Patel et al. [15] analyzed electricity line noise of different device in homes. By observing the device operation, the authors derived information about user location and activity. In the approach of Froehlich et al. [16] water fixtures were monitored, including sink, toilet, shower, bathtub, clothes washer and dishwasher. Another approach was proposed by Patel et al. [17] for detecting human movement by differential pressure sensing at the home-based HVAC system. According to differential pressure it was possible to determine location of pressure disturbances and determine when people were passing through doorways as well as to detect door opening and closing. Although these approaches are easy to deploy and very promising, they are mainly applicable to private houses. Our approach focuses on identifying activities in office buildings, where the opportunistic single-point sensing approaches would not be feasible due to the larger variability in installed appliances, variety in occupant behavior patterns, and need for widely scalable sensing solutions.

3. Recognition approach

This section details our approach to recognise activities from PIR sensors and power meters installed in office rooms. In particular, the feature extraction and layered HMM modelling are described. Finally, three analyses methods are described, related to estimating the amount of training data needed, the desk-independent recognition performance, and the simulation of energy profiles.

3.1. Feature extraction and recognition method

For the recognition analysis, we considered office activities that are relevant for energy-based control at desk level, as well as room level. Individual desk activities included *Presence*, *Away*, *Computer work* and *Desk work*. When recognized, the activities could be used to control appliances, such as overhead lighting, e.g. to decrease lighting level during computer-based activities. Moreover, we estimated *People count*, which represents the actual number of occupants present in an office room. *People count* can be used for room conditioning, i.e. change the fresh air rate or reference temperature.

In order to recognize office activities we used different features provided from PIR sensors and power meters. The PIR sensor state (s_{PIR_i}) was used as feature for recognizing *Presence*, *Away* and *People count*. By using the actual screen energy consumption provided by power meters (v_{Energy_i}), *Computer work* and *Desk work* were recognised. Our approach assumes that the computer's screen power management is configured to switch off the screen, when not used. Thus, if the screen energy consumption was above the standby threshold ($v_{Energy_i} > \phi_{Energy}$), the office worker used the computer. In contrast, if no computer-based activity was recognized, the screen will enter standby mode ($v_{Energy_i} \leq \phi_{Energy}$). The energy consumption threshold was set to ϕ_{Energy}=2.2 W, according to Directive 2005/32/EC [18].

Hidden Markov Models (HMMs). A hidden Markov model (HMM) is a Markov model in which the observation is a probabilistic function of hidden states. To specify an HMM, two model parameters are needed: N representing the number of individual model states, and M, describing the number of distinct observation symbols per state. The individual symbols are denoted as $V = \{v_1, v_2, ... , v_M\}$. Moreover, the HMM description requires specifying three sets of probability measures A, B and π, which are state-transition probability distribution, observation symbol probability distribution, and initial state distribution, respectively [19].

In order to derive HMM model parameters, unlabeled sequences of observations and states were used in a training step. The model parameter estimation, $\lambda = (A, B, \pi)$ was done using MATLAB [20]. In particular, the following parameters were determined:

$$\bar{\pi}_i = \text{expected frequency (number of times) in state } i \text{ at time (t = 1)} \tag{1}$$

$$\bar{a}_{ij} = \frac{\text{expected number of transitions from state } i \text{ to state } j}{\text{expected number of transitions from state } i} \tag{2}$$

$$\bar{b}_j(k) = \frac{\text{expected number of times in state } j \text{ and observing symbol } v_k}{\text{expected number of times in state } j} \tag{3}$$

Layered Hidden Markov Models (LHMMs). Considering that *Computer work* and *Desk work* could exist only if the system is in a *Presence* state, we chose a layered HMM approach for recognizing activities. The classic LHMM approach used a bank of HMM classifiers to discriminate observation sequences [13]. The HMMs at the next level *L+1* took the outputs of the HMM at level *L* as inputs.

In our study, the first layer consisted of three nodes to model *Presence*, *Away* and *Temporary Away* states as shown in Figure 1. The *Temporary Away* state is an intermediate state between *Presence* and *Away*, introduced to prevent false deactivations of PIR sensors.

Unlike the classical LHMM approach, we used the Viterbi algorithm [19] to find the most probable sequence of hidden states that resulted from a sequence of observed events. This was done by using the Bayes Net Toolbox (BNT) [21], an open-source MATLAB package for directed graphical models. The result of the first layer was then used as an input for the second layer, which had two nodes representing *Computer work* and *Desk work* states. To estimate the number of people in the room, we combined the outcome of *Presence* states from individual desks in an office room. Changing the number of people thus represents changes in *Presence* states per desk.

3.2. Estimating training data amount

One of the main challenges associated with the training of HMMs is the size of a training dataset. Very often training dataset contains inadequate number of occurrences of low-probability events and it cannot give good estimates of the model parameters [19]. Therefore, we analysed the influence of training data amount on the recognition accuracy to determine the minimal data amount requirements. The training dataset was divided in 1 hour sections and sequentially added to the training dataset. For each iteration, recognition accuracy was evaluated. Since our approach uses unsupervised data for training, performance was evaluated on the same data.

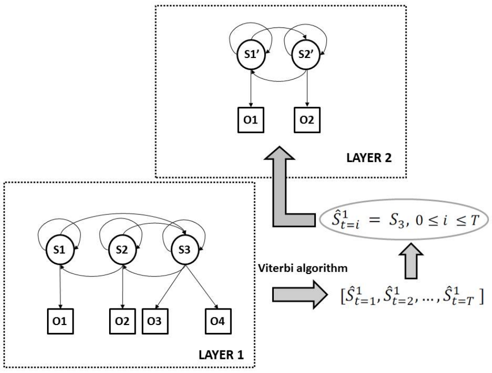


Figure 1. Layered representation of HMMs used in the recognition. Layer 1 consists of three states S_1-*Away*, S_2-*Temporary away* and S_3-*Presence*, where different PIR states and power measurements represent observations (O_1, O_2, O_3, O_4). The Viterbi algorithm was used to find the optimal state sequence associated with a given sequence of observations. The estimated state sequence represented the input for the second layer, where S'_1- *Desk work* and S'_2-*Computer work* states were activated during the S_3 (*Presence*) state.

3.3. Desk-independent analysis

To analyse whether the recognition can be performed independent of training data from a particular desk, a leave-one-desk-out cross-validation was performed where data for one desk was used as a testing set, while data for remaining desks was considered for the HMM training. This procedure was repeated until all desks were used once for testing and the performance results were averaged.

3.4. Simulation of energy profile per desk

In order to confirm that office worker activities affect energy consumption, we simulated different occupant behaviours and estimated the effect on energy needs using our LHMM modeling. The activities considered in our study were selected according to their relevance for energy-related control. Desk activities, *Presence* and *Away* could be used for controlling office appliances e.g. computer screens could be switched off when user is away. Furthermore, light level could be decreased during *Computer work*, since lighting requirements are lower comparing to desk-based activities.

In our simulation, we assumed that computer screens could be controlled according to the user's presence. The average consumption of the screens in our living-lab installation during operation was ~40 W. We assumed that screens will consume the operating energy whenever users were present. According to the EC Standard BS EN 12464-1 [4], when user is working with computer, lights could be dimmed by 30% of the value when involved in desk activities. In the energy consumption simulation we considered modern LED lighting, e.g. the Philips Master LEDtube at 1200 mm tube length and 19 W power. We assumed that at least four light tubes were dedicated to each desk, in order to provide the necessary light amount per desk. If no presence was detected, lights were considered to be off.

We generated data for five working days from the HMM model derived from the entire study dataset. The initial parameter estimation of generated data was improved by the expectation maximization (EM) algorithm. The most probable sequence of states for a set of generated observation was determined using the Viterbi algorithm. For this analysis, we excluded weekends from the dataset. Occupant behaviour and hence the HMM state distribution differs for working days and weekends. According to our ground truth reference, users were absent for 71.5% of work days and present for 19.5%. The remainder was spent in the *Temporary away* state. Regarding *Computer work* and *Desk work* during working days, the ratio was 89.6% to 10.4%. During weekends, only *Away* state was present.

To evaluate how different occupant behaviour and thus state distributions influence energy consumption, we modified the transition probability distributions $A = \{a_{ij}\}$ [19], where each element is given by:

$$a_{ij} = P[q_{t+1} = j \mid q_t = i], 1 \leq i, j \leq N. \tag{4}$$

where N represents the number of states in the model. The individual states were labeled as {1, 2, ..., N} and denoted as q_t at time t. For the simulation, we carefully modified single states in the transition matrices to obtain models, where individual states are more probable than in the original dataset. For each simulation, only one state was modified to explore its effect on energy consumption.

4. Living-lab implementation and evaluation study

Since the overall goal is to make buildings more energy efficient, the resulting system should consume as little energy as possible. We used a wireless PIR sensors per desk, mounted at the ceiling facing desk area. The living-lab installation in 3-user multi-person office is shown in Figure 2. The PIRs work based on EnOcean wireless protocol and harvest solar energy necessary for their operation (Eltako FBH63AP and Thermokon SR-MDS). For monitoring energy consumption of the users' screens, we used Plugwise 'Circles', a plug-in power meters based on wireless ZigBee protocol. The plug-in power meters measured power consumption of the screens at a sampling frequency of 1 min. Maximal consumption of the screens was ~40 W/h, while their standby consumption was ~2 W. Standby time for the screen was configured to 2 min. This setting was observed to be suitable to maintain user comfort. The Context Recognition Network Toolbox [22] was used for recording and synchronization of sensor data streams. Wireless USB interfaces for EnOcean and Plugwise protocols were used for data acquisition.

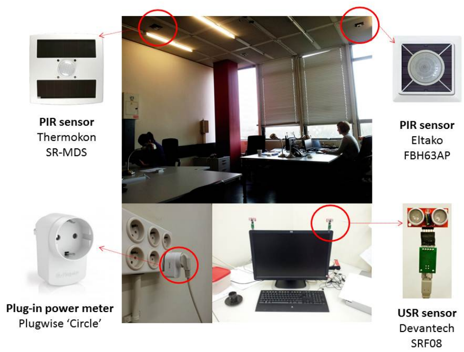


Figure 2. Illustration of the living-lab installation for the 3-user multi-person office. Different types of PIR sensors and plug-in power meters were used. Ultrasound range finders (USRs) were used for obtaining reference information on occupant behaviour only.

In the evaluation we considered a single-person and a 3-user multi-person office room. Recordings were conducted for five days in the single-person office and for seven days in the multi-person office room. Activities were not scripted in any form during the recordings as the office workers regularly worked in these rooms. Participants were asked to fill in a diary, with a resolution of 1 min to annotate their activities. In addition, two ultrasound range finders (USRs) with sampling frequency of 1 s, were attached to computer screens as reference for *Presence* and *Away* states. In a preliminary analysis the accuracy of the USR sensors was estimated to 94% compared to manual annotations of the user, who reported to be precise in filling the form. From the participant annotations and the USRs, ground truth was derived on the activities performed during the study.

5. Results

The results of the HMM analysis confirmed that activities can be recognized with high accuracy. *Presence* and *Away* states were recognized at average accuracies above 87%, with class-specific accuracies for *Presence* up to 84%, and for *Away* up to 99%. The performance for distinguishing *Computer work* and *Desk work* was 98%. Average class-specific accuracies for *Desk work* was lower (~60%) than for *Computer work*, since users spent significantly more time working with the computer, than being involved in desk

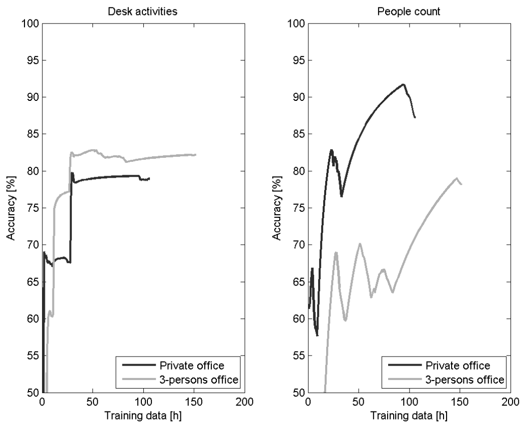


Figure 3. Results for estimating training data amount in relation to recognition performance. Left: for desk activities, a performance of 80% can be achieved with approximately 30 hours of training data. Right: for people count estimates, an accuracy above 70%, 50 hours of training data were needed.

activities. People count was estimated with accuracy of 87% in the single-person and 78% in multi-person office room.

5.1. Estimating training data amount

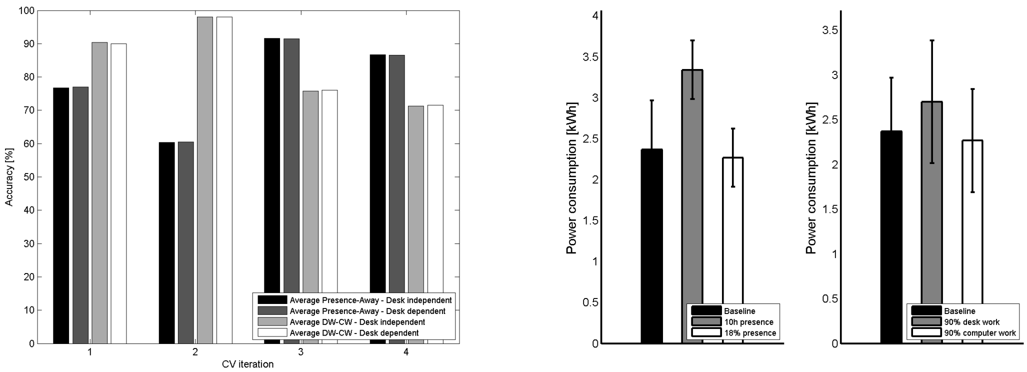
We analysed the influence of training data availability on accuracy to determine minimal data amount requirements. The results of the incremental data analysis are presented in Figure 5. The analysis showed that an activity recognition accuracy of ~80% can be achieved with not more than 30 hours of training data. To achieve accuracy of 70% for people counting, the system needs ~50 hours of training data. The performance of the *People count* is manly affected by the recognition performance for *Presence* and *Away* states. In our dataset, the classification between these two states was biased in favor of *Away* class, totalling to 86% of dataset. While this class skew is a natural phenomena, it may occur differently for different users or offices.

5.2. Desk-independent analysis

The comparison between desk-independent and desk-dependent analysis is presented in Figure 4(a). In order to validate our approach, we chose leave-one-desk-out cross-validation. Results of desk-independent and desk-dependent conditions were very similar, which confirmed that our approach can be implemented independently from the desk. The average accuracies across validation iterations were for *Away* and *Presence* 97.7% and 61%, respectively, while for *Desk work* and *Computer work*, 69% and 98.7% was achieved.

5.3. Simulation of energy profile per desk

We simulated different user behaviour by modifying the transition probability distributions (according to Eq. 4) in order to investigate the effect on energy consumption. Here, we considered five different cases. Each case was simulated 10 times and average results with error bars are presented in Figure 4(b). As "baseline", we used the dataset obtained from the evaluation study measurements, which showed two dominant classes (*Away* and *Computer work*), as shown in Sec. 3.4. The estimated energy consumption for the baseline was 2.37 kWh on average for five working days. In "10h presence", we simulated the consumption for users present at least 10 hours per day, by modifying the transition probability distribution for the layer 1 HMM. Since 10 hours represent 40% of entire day, transition probabilities to get from any state to *Presence* state were 0.4. Transition probabilities for layer 2 remained unchanged. Since, the amount of time spent in *Presence* was higher than in the baseline, energy consumption increased to 3.34 kWh. In "18% presence",



(a) (b)

Figure 4. (a): Comparison between desk-independent and desk-dependent recognition. Average accuracies for joint *Presence-Away* and *Desk work-Computer work* are presented per cross-validation iteration. The desk-independent case was validated by leave-one-desk-out cross-validation. (b): Simulation of the energy consumption for five different behaviour cases. "Baseline" corresponds to the consumption according to real measurements. Please refer to the main text for details on the simulation procedure.

we changed transition probabilities to simulate a decrease of presence hours to ~18%, which resulted in a lowered consumption (2.26 kWh).

Influence of desk activities on energy consumption was investigated in two cases: "90% Desk work" and "90% Computer work" simulating a dominance of *Desk work* and *Computer work*, respectively. We modified transition probability distributions for the layer 2 HMM, while maintaining probabilities for the layer 1 unchanged. For "90% Desk work", we assumed that user will be involved in desk activities 90% of the baseline presence time. Since lights assumed to be on their maximal level during *Desk work*, the consumption in this case was higher (2.7 kWh) compared to the baseline. For "90% Computer work", we modelled that user will work with the computer for 90% of the baseline presence time. Here, each time when *Computer work* was determined, overhead lights were set to a 30% lower consumption compared to their maximal value. Therefore, the overall energy consumption was decreased to 2.27 kWh.

6. Discussion and Conclusions

The recognition performances achieved in our analysis confirmed that the use of already installed sensors in office buildings is a feasible strategy to improve energy efficiency without extensive installation needs. This result is essential to dynamically save energy in modern buildings, while providing comfort where needed.

Our results confirm and complement previous work [5] of investigating training data needs, desk-independent operation, and simulation of behavior profiles. The incremental training data analysis showed that at ~30 hours of training data a robust recognition of 80% can be achieved. Hence, for controlling lighting according to presence and desk-related activities, it is sufficient to deploy the system in learning mode for approx. two days in an occupied office. Since the HMM recognition model states are known and only model parameters need to be trained, our approach does not require ground truth information during the learning mode. Due to the more complex model, people count required ~50 hours of training data for a good estimation performance. Our further analysis of the desk-independent recognition performance confirmed similar performances as in the desk-dependent setting. Thus our approach does not require to be trained for each desk individually.

The simulation of energy profiles illustrated the influence of occupant behaviour on energy consumption. We chose to modify individual parameters of a trained LHMM to explore energy profiles. While this could not replace future empirical analyses, it provided indicators for the effect of occupant behaviour on energy needs. Future work will moreover include large scale evaluations of the approach proposed in this work.

7. Acknowledgments

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