Contextual Occupancy Detection for Smart Office by Pattern Recognition of Electricity Consumption Data

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***Abstract*—The advent of IoT has resulted in a trend towards more innovative and automated applications. In this regard, occupancy detection plays an important role in many smart building applications such as controlling heating, cooling and ventilation (HVAC) systems, monitoring systems and managing lighting systems. Most of the current techniques for detecting occupancy require multiple sensors fusion for attaining acceptable performance. These techniques come with an increased cost and incur extra expenses of installation and maintenance as well. All of these methods are intended to deal with only two states; when a user is present or absent and control the system accordingly. In this paper, we have proposed a non-intrusive approach to detect an occupancy state in a smart office using electricity consumption data and introduced a novel concept of third state as standby for dealing with situations when the user lefts his seat for small breaks. We demonstrated our approach using electricity data collected within our research centre and detected occupancy state with efficiency up to 94%. Furthermore, our solution does not require extra equipment or sensors to deploy for occupancy detection as smart energy meters are already being deployed in most of the smart buildings.**

***Index Terms*—Contextual occupancy, classification, non-intrusive load monitoring, pattern recognition, smart office, internet of things**

I. Introduction

Occupancy Information plays an important role in intelligent buildings for providing optimized and automatic energy-efficient solutions for heating, ventilation and cooling (HVAC) systems, it also forms basis for automatic lighting systems, and also contributes in contextual models for defining user activities. According to [1], buildings are one of the main consumers of energy and accounts for 39% of total energy consumed in UK. The conscious and conservation behavior of the users can result into large amount of energy saving in buildings as demonstrated by authors in [2]. However, the actions of the users are likely to change over time. Thus recent research efforts are intended to provide automatic solutions for energy management by linking occupancy information to the HVAC and lighting control systems in intelligent buildings. For example, the authors in [3], used occupancy information to control home heating system and demonstrated significant decrease in gas usage for heating as compared to other traditional methods. Another example in [4] demonstrated that real time occupancy information can also be used for control of lighting systems resulting in significant amount of energy saved. Occupancy detection also find applications in intrusion detection systems by detecting an activity at abnormal times. This concept is also used to provide medical assist for old or elderly people.

In spite of many application scenarios, occupancy detection in buildings is still a complex and expensive process and offering research to overcome issues such as false detection, intrusive nature of visual sensors and energy issues with battery powered sensors [5]. The most common devices used for detecting an occupancy are based on Passive Infrared (PIR) and/or ultrasonic technologies, microwave and audible sensors, video cameras and Radio-frequency identification (RFID) based systems. PIR sensors are used extensively for detecting occupancy by detecting infrared direction radiated by human body movement. Microwave and ultrasonic sensors works on the Doppler shift principle, they transmit waves and depending on the change in patterns of the reflected wave, they detect occupancy. But one of the major drawback associated with such motion dependent sensors is if the user remains inactive for some time, they may not detect presence [4] and may result into annoying and uncomfortable situations such as switching off lights or switching off heating systems even in the presence of the user. Due to these drawbacks, they are mostly used in conjunction with audible sound sensors. But audible sound sensors are not able to distinguish between human and non-human noises and are proned to false alarms.

Video cameras and RFID systems have also been used to detect occupancy but mostly they have been applied for security purposes rather for building control systems. And most practical applications prefer to avoid using techniques which require changes in user behavior such as RFID or which are a concern to user privacy such as video cameras. The aim in most of the occupancy sensing infrastructure is to keep the overall costs low so that widespread use of such techniques can be promoted. This often implies that only few, cheap and possibly imprecise sensors are available, also, battery powered sensors are often used to avoid the deployment of power cables. It incurs extra cost of maintaining the batteries and as the batteries discharge, it can affect the performance of the sensors as well. Faulty installations and lack of maintenance also result in degradation of the sensors performance. Recently, the rise of IoT has initiated a trend towards the use of existing technologies such as mobile phones and Wi-Fi to detect occupancy in an opportunistic manner.

In our work, we have explored a non-intrusive approach based on pattern recognition of electricity consumption data to detect occupancy state using our existing Internet of Things (IoT) testbed [6] and introduced the novel concept of *standby* state in our work which can be defined as:
"A state when a user leaves his work desk temporary for a short period of time and switching off HVAC and other equipment associated with occupancy state is not optimal choice"
In short, following contributions are made in this paper.

- We measured the occupancy state in a smart office using different features of electricity consumption data and achieved accuracy up to 94%.
- We introduced the novel concept of *standby* state for occupancy detection to deal with annoying and uncomfortable situations.
- A qualitative and quantitative comparison is made between several pattern recognition algorithms which we implemented for occupancy detection from electricity consumption data.

The remainder of the paper is organized as follows. In section II we discuss briefly motivation for our research followed by related work in section III. Section IV explains our proposed architecture along with the different components involved for the implementation of our algorithm. In section V, we discussed the performance of different classification algorithms which we implemented for pattern recognition. A qualitative and quantitative analysis has been done to give more insight about the performance of different algorithms. Finally we conclude the paper in section VI.

II. Motivation

Although there is a growing interest in utilizing electricity data for minimizing energy usage, but much of the research is focused on households [7] and only little effort is put into minimizing energy use in offices. The pattern of electricity consumption data will be different for offices as compared to households because of two main reasons: the first one is that the nature of appliances which are present in offices like work stations, table lamps and printers are quite different as compared to the household appliances; and the second reason is that the occupancy pattern of users in offices is more random as the employees may have to leave their office or work desks frequently for meetings and short coffee breaks. In our work, we investigated a non-intrusive scheme which is based on analyzing the electricity consumption data measured by smart energy meters to detect occupancy state in office space. The installation of smart meters is already gaining popularity for monitoring real time energy usage in order to bring more awareness to users about their energy consumption [6]. In this regard, our proposed method requires no extra equipment for measuring occupancy as compared to approaches based on motion, audible and visual sensors which have to be purchased, installed, calibrated and maintained. All of the techniques discussed in the literature for detecting occupancy irrespective of their nature are intended for two states (either *present* or *absent*) which can result into annoying situations as discussed in [8]. But in our approach, the nature of electricity data enables us to have contextual sensing as the pattern of electricity data will be governed by user activities and with the help of it we introduced the novel concept of third state as *standby* in an office environment when the user leaves the office temporarily for short period of time for a meeting, coffee or lunch. In such cases, switching on and off the HVAC system is not optimal choice. If the standby state is detected, then the heating or cooling system associated can be tuned to some intermediate temperature in order to save energy and avoid uncomfortable situations.

III. Related Work

In [3], the authors used wireless motion sensors and door sensors to derive real time occupancy information. Their proposed smart thermostat used these sensors to infer when occupants are away, active, or sleeping and turns the HVAC system off as much as possible without sacrificing occupant comfort. Their model was able to achieve significant results by incorporating probabilities and exploiting historical data. In [4], the authors provide a survey about different techniques which have been used for detecting occupancy in the context of lighting control systems. They highlighted the use of PIR sensors, audible sound sensors, microwave sensors and video cameras. The use of video cameras for occupancy detection in buildings is not a preferred choice because of the intrusive nature of cameras and the cost associated with deployment and processing of images. PIR sensors are the most common choice for occupancy detection [9], but it is rarely deployed alone because it needs motion to get triggered. Hence in most practical applications, it is used in conjunction with other sensors. One such case is demonstrated by Agarwal [10] where PIR sensors are used in combination with magnetic reed switch door sensors to detect occupancy and occupancy information is used for controlling HVAC. RFID tags can also be used for occupancy detection as demonstrated in [11]. The authors put the RFID tags on the house keys and RFID receiver was plugged in the server to detect whenevr a user carrying a key enters in a house, and extend this information to predict occupancy patterns in order to control home heating. Only adults have the RFID keys with the assumption that kids will not be at home alone, hence RFID tag keys enabled the system to only detect the presence of adults. The extra motion sensors are not much effective if the user is in the room but not moving frequently. The false detection of occupancy may lead to switching off unnecessarily the HVAC system and hence prompting to discomfort of users.

All of the above mentioned techniques require additional cost of installing and maintaining extra sensors. However, there are also few methods discussed in the literature which do not require installation of additional sensors in order to detect occupancy in opportunistic manner. It was demonstrated in [12] that by analyzing Global Positioning System (GPS) travel data from the occupants mobile phone to estimate the arrival time of the users, an approximately 7% increase in the saving of energy can be achieved. The system will notify the heating control unit, when to start pre heating so that when the user arrives at home, the temperature of the room is optimum. However, their approach makes the system complex as calculating travel time from GPS data is itself a cumbersome task due to dynamic and unpredictable nature of road conditions and traffic congestion. The wrong estimate may prone the system to start pre heating too soon and result in the wastage of energy. A drained mobile battery or loss of connectivity can also fail the system. In [13], the authors discussed smart heating in the context of web enabled sensors and actuators. They proposed opportunistic sensing approach in order to incorporate GPS information, WiFi logins or NFC information whichever is available. They also discussed the possibility of using electricity usage to detect the occupancy as well. The same author later in his work [7] discussed occupancy detection based on electricity consumption data in households and achieved an accuracy up to 80 % using power features of electricity consumption data.

IV. Proposed Architecture

The proposed architecture for our approach is shown in the Fig 1 along with the block diagram. The intuition behind the proposed approach is when the employees or usres are at their work desk, the electricity consumption patterns will be different as they will be using their computer, laptop, table fan, lamp or other appliances as compared to when they are not present. The contextual nature of electricity data enables us to detect an extra state which we called as *standby* state when the users leave the office for small breaks. We have implemented classification algorithms for pattern recognition from electricity consumption data. More details about the different components involved in our approach are described below.

A. Data Acquisition

Data is acquired from employees work desks within our research centre using smart energy units. These smart energy units have in built energy meter and Zigbee module and keep track of energy usage at the desk by logging electrical data measurements. It is connected to the management gateway via ZigBee and gateway is connected to internet through WiFi module. The details about the test bed can be found in [6]. In our experiment, we have gathered data from the work desks of four employees which have different appliances connected with the smart energy unit as shown in the table I.

TABLE I
Appliances connected to smart energy unit

No.	Appliances Connected
Employee 1	work station, table lamp
Employee 2	work station, table lamp, table fan
Employee 3	work station, table lamp, laptop charger
Employee 4	work station, table lamp, table fan, laptop charger

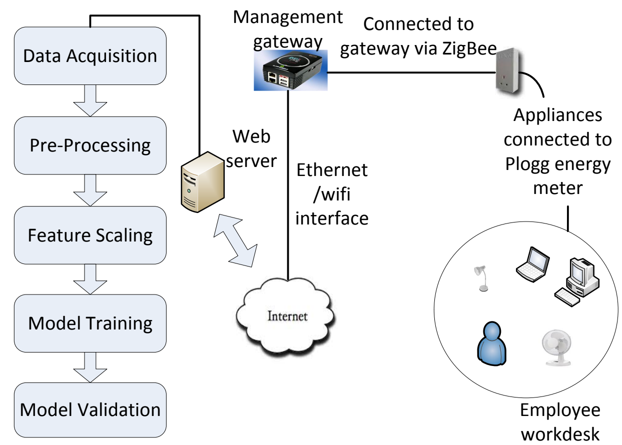

Fig. 1. Proposed Architecture and Block Diagram

Different employees have different behavior as far as energy saving and usage of their devices are concerned [8]. Most of the employees usually switch off the table lamp and table fan before leaving their offices, even if it is for a short period. And they might switch the work stations to standby mode, or it can automatically go to the standby mode depending on the employees behavior and settings. But nonetheless, there might be few employees who do not care much about switching off extra appliances as discussed in [8]. In this regard, we did not instruct the employees to follow any specific behavior, rather they followed their natural response. The ground truth data is gathered using a simple application on Samsung tablet, in which an employee can register his state as either *present*, *standby* or *absent* just by clicking on the appropriate icon. Data is gathered for approximately two weeks and the total gathered data is divided into two parts with ratio 70:30 after assigning ground truth realities and shuffling the data randomly. The larger data set is used for training the classifier models while the other data set is used for validation purposes.

B. Data Analysis

1) Pre-processing: Every smart energy node transmits the electricity consumption data every 10 seconds. In real time environment, a sensor node connection might be disconnected or crashed and it may fail to transmit the next reading. In order to overcome the missing values, a simple algorithm is implemented to fill out the missing values with the last recorded value. It is a reasonable assumption that the state did not change in consecutive readings for a sampling period of 10 seconds.

2) Feature Scaling: The range of values of different features are on different scale. If one of the feature has considerably wider range as compared to other features, the optimization function for classification will be governed by that particular feature and make the classifier unable to learn from other features correctly. Furthermore, it will take much longer time for the optimization objective to converge in that case. Feature scaling is a method to bring all the features on the same scale so they contribute equally to classification algorithm. Dealing with large data sets, feature scaling becomes an important step otherwise algorithms like Support Vector Machines (SVM) can take quite a longer time. We implemented standardization method for feature scaling which results in having each feature as zero mean and unit variance. The general expression for feature scaling using standardization is

$$X_1' = \frac{X_1 - \mu_1}{\sigma_1} \tag{1}$$

where X_1' is the new feature vector after scaling, X_1 is the initial feature vector, μ_1 is the mean value of feature vector and σ_1 is the variance of feature vector.

3) Feature selection: The selection of right features independent of the algorithm plays an important role in the performance of any classifier. An algorithm cannot find good features or create good features by itself. In this regard, we have used three different types of feature sets to compare their performances which are shown in Table II.

TABLE II
FEATURES USED FOR OCCUPANCY DETECTION

No.	Features selected
Feature Set 1, F1	P, Q
Feature Set 2, F2	V_{rms}, I_{rms}, ϕ
Feature Set 3, F3	$P, Q, V_{rms}, I_{rms}, \phi$

The first feature set, F1 consists of only power measurements and includes real power (P) and reactive power (Q). The second feature set, F2 consists of root mean square voltage(V_{rms}) and current measurements(I_{rms}) along with the phase angle (ϕ) between them. Finally, we have used all the five features for classification algorithms in F3. The complexity of algorithm increases with the number of features, and the selection of inappropriate features can result into complex decision boundary for classifiers effecting the performance of the algorithm as we discussed in the next section.

C. Model Implementation

Different variants of classification algorithms are implemented for pattern recognition from electricity consumption data. Classification is a supervised machine learning technique used widely for pattern recognition; it requires labeled data to learn and recognize the patterns. In our case, electricity consumption data with the ground truth reality acts as training data. As described earlier, we divide the total gathered data in the ratio 70:30, where the larger dataset is used for training the classifier and the smaller dataset is used for validating the model. We implemented four state of the art classification algorithms for pattern recognition which are shown in Table IV.

Support Vector Machines (SVM) is an efficient classification algorithm which is widely used for pattern recognition because of its two main advantages: 1) Its ability to generate nonlinear decision boundaries using kernel methods and 2) It gives a large margin boundary classifier. SVM requires a good knowledge and understanding about how they work for efficient implementation. The decisions about pre-processing of the data, choice of a kernel, and setting parameters of SVM and kernel greatly influence the performance of SVM and incorrect choices can severely reduced the performance of SVM [14]. The choice of a proper kernel method for SVM is very important as is evident from the results in the next section. The SVM algorithm requires extensive time in training but once the model is trained, it makes prediction on new data very fast.

TABLE III
CLASSIFICATION ALGORITHMS

No.	Technique	Parameters	Abbreviation
1	K Nearest Neighbor	k=10, weight = uniform	knn
2	SVM*	ker=rbf, gamma=0.7	SVM-RBF
3	SVM*	ker=lin, C=1	SVM-Lin
4	SVM*	ker=poly, deg=3, C=1	SVM-Poly

*Support Vector Machine

On the other hand, K Nearest Neighbor (KNN) is one of the simplest learning technique used for classification. It is a non parametric algorithm which means it does not make any prior assumptions on the data set. It works on the principle of finding predefined number of labeled samples nearest to the new point, and predict the class with the highest votes. The advantage of KNN lies in simple implementation and reduced complexity. Despite its simplicity, it works quite good in situations where decision boundary is very irregular. Its performance is also very good when different classes do not overlap in feature space [15]. KNN is also called lazy algorithm as it take zero effort for training but it requires full effort for the prediction of new data points [15].

V. RESULTS AND DISCUSSIONS

F-measure represents an accurate and widely used metric for comparing the performance of multi-class classifiers. We have also used F-measure to compare the performance of implemented algorithms. The equation for calculating F-measure is below

$$F - measure = \frac{2P.R}{P+R} \tag{2}$$

where P represents Precision and R represents Recall. And can be calculated as follows,

$$Precision = \frac{TP}{TP+FP}, \quad Recall = \frac{TP}{TP+FN} \tag{3}$$

where TP is true positive, FP is false positive and FN is false negative.

Fig 2 shows the F-measure plot of different classification algorithms implemented for all three feature sets, and table IV shows the results in tabular form. From the figure, it is obvious that KNN performs best for F1 and F3 and achieves accuracy up to 94.01% while SVM-RBF (SVM with Radial Basis Function as kernel) outperforms other algorithms for

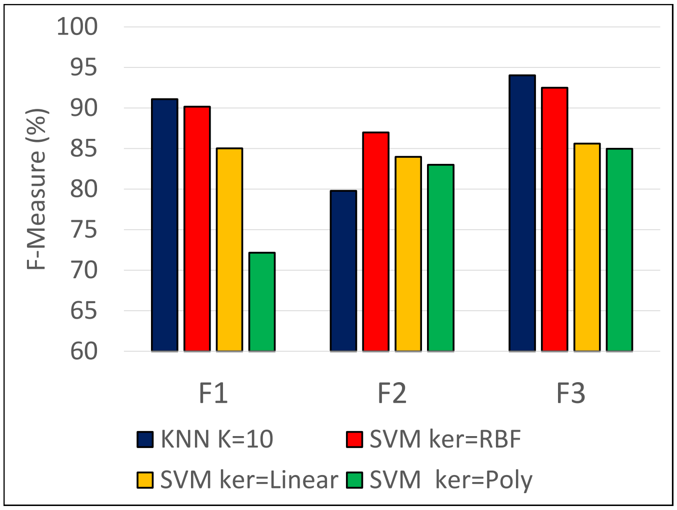

Fig. 2. Performance of Classifiers for Different Feature Sets

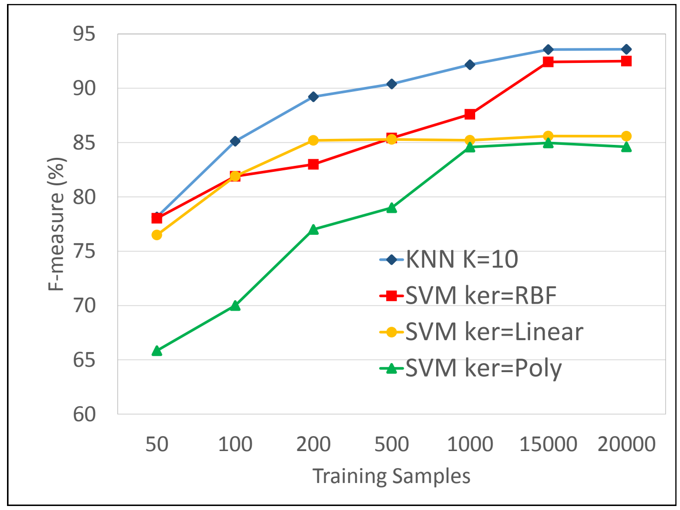

Fig. 3. F-measure relation with Training Data Size

TABLE IV
F-MEASURE FOR FEATURE SET 1, 2 AND 3

Method	feature set 1	feature set 2	feature set 3
KNN	**91.08**	79.79	**94.01**
SVM-RBF	90.16	**86.99**	92.5
SVM-Lin	85.02	83.97	85.6
SVM-Poly	72.15	83	84.97

F2 with maximum efficiency of 86.99%. The reason for good performance of KNN for F1 and F3 is that the power features involved in F1 and F3 for different states are non overlapping and distinct, and KNN performs very well in such situations. The overlapping nature of features in F2 resulted in the reduced performance of KNN, whereas SVM-RBF performs better as compared to other variants of SVM. In general, SVM forms an hyper-plane as a decision boundary between different classes in feature space, and the shape of hyper plane is governed by the kernel function chosen. The spherical nature of hyper-plane for RBF kernel enables to classify simple and complex problems accurately. SVM-Poly(SVM with Polynomial kernel) performance is degraded for F1 as it tries to overfit the problem by forming complex decision surface. We have used feature set 3 for all further analysis in the paper.

TABLE V
ACCURACY OF CLASSIFIERS FOR STANDBY STATE

Method	Accuracy(%)
KNN	**93.67**
SVM-RBF	79.12
SVM-Lin	56.58
SVM-Poly	55.37

F-measure reflects the overall performance of the classifier, whereas the performance of different algorithms might vary for identifying the patterns of certain class. In our case, *standby* state is of specific interest and is most difficult to detect because the feature values for *standby* state can lie very close to either *present* state or *absent* state depending on the users behavior and it is difficult to find any hard decision boundary. We calculated the accuracy of all four algorithms for *standby* state using confusion matrix and the results are shown in the table V. KNN outperforms all other algorithms for the correct classification of *standby* state.

The number of training samples plays an important role in the performance of a classifier. As the training samples increase, the decision boundary becomes more accurate and the performance of classifier improves. Fig 3 shows how the F-measure of different classifiers improve as we increase the training samples. After a certain number of training samples, increasing the training data set does not have much effect on the performance of a classifier. SVM-Poly has the greatest effect on the performance with increasing training samples. SVM-Poly tries to differentiate all training samples by making complex and non linear decision boundary. For low data sets, the decision boundary is very specific but when the same model is validated against new data, the same decision boundary may not work accurately and result into degradation of performance. But as the training data set increases, the decision boundary becomes more general and more fitting for new data and hence performance of the classifier increases with increasing data set.

A large commercial building can have hundreds of nodes and the amount of data can be huge. In order to provide further insight about the performance of different algorithms, we compared the total time which includes training and validation for each algorithm. The amount of time taken by each algorithm for different number of training samples on a personal laptop (Intel i7-4510, 12GB RAM, Ubuntu 64 bit operating system) is plotted in Fig 4. The size of validation data remains the same for all cases. For small number of training samples, the performance of all algorithms remains almost the same. But as the data size increases, complexity and hence the time

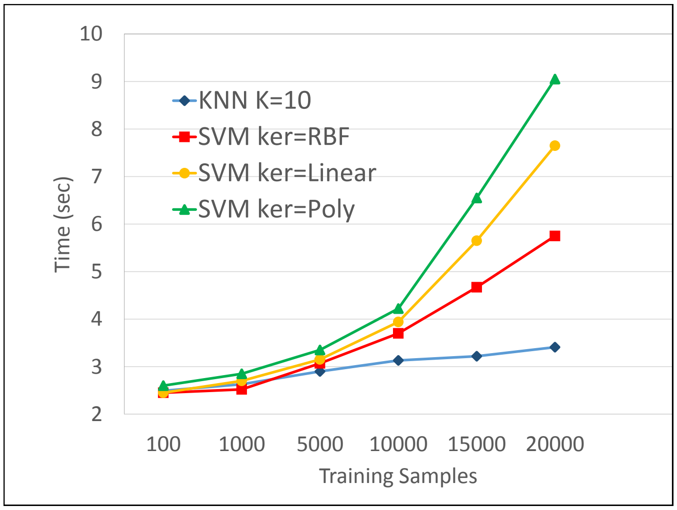

Fig. 4. Time Complexity of Different Classifiers for Feature Set 3

taken for all the variants of SVM increases rapidly; whereas, increase in time for KNN is significantly low. This is due to the instant learning nature of KNN. During training, KNN simply memorizes the all examples in the training data set and used it for comparing and predicting new samples with highest nearby votes. In contrast, SVM implements gradient descent algorithm for finding optimum decision boundary (which is an iterative optimization algorithm) and results in exponentially increasing time with increased number of training samples.

Finally, we measured occupancy state (only *present* and *absent* as detecting *standby* state is not possible) using PIR sensors data in order to make a comparison with our approach as PIR sensors are the most commonly used technique for occupancy detection. We used different threshold values and sliding window methods to reduce false detection as much as possible. The maximum efficiency we were able to obtain using PIR sensors was 67% which further supports the usefulness of our approach.

VI. Conclusion and Future Work

In this paper, we have demonstrated that electricity consumption data has the potential to detect occupancy state with high efficiency and provide contextual information at the same time as compared to other state of the art occupancy detection techniques. It also provides an edge in terms of cost as it does not not require extra dedicated occupancy sensors. In future, we aim to explore the possibility of fusing other sensors with electricity consumption data to provide more accurate and context aware models in smart buildings. In large buildings and offices, number of work desks and hence energy measurement units can be in hundreds or perhaps thousands. In this regard, we aim to explore our approach in the context of big data for processing many nodes in real time.

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