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Abstract

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Preface

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I would like to thank my supervisor Ashish Pandharipande(Philips Research), David(Philips Research) , Venkatesh Prasad(TU Delft) for all the support and guidance provided during the course of this 9 months. I would also like to thank my parents for all the support and love they have provided me all these years. A special thanks to all the people of FO 52 past and the present who made the stay in Eindhoven so much more pleasant.

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Chapter 1

Introduction

The European Union (EU) has pledged to cut the consumption of primary energy by 20% by the year 2020. It is estimated that buildings consume 40% of the energy produced[1]. This has resulted in an increase in the demand to reduce the energy consumption of buildings. To reduce the consumption of energy, building automation systems (BAS) are being widely employed. BAS are computer-based systems that help to manage, control and monitor building technical services (HVAC, lighting etc.) and the energy consumption of devices used by the building. BAS deploy huge amount of sensors, which provide inputs to perform efficient control of various services like HVAC and lighting. BAS brings with it various benefits,at the same time, offers numerous challenges too.One of the primary challenges is generating and updating the locations of the installed sensors. For performing effective control, information about the location is highly important. As the size and distribution of the deployed sensors are high, it is highly cumbersome and error prone to manually maintain the meta-data about the sensor placement. Also as building evolve and change managing this spatial information becomes a cumbersome process. Hence to ease the process of sensor location verification an automatic process to locate the sensors in a building is required.

[1] according to value published at https://ec.europa.eu/energy/en/topics/energy-efficiency/buildings

Chapter 2

Literature Review

2.1 Sensors Localization in Buildings

Various approaches have been taken to automate the process of determining the sensors location in buildings using various data analytics and signal processing tools. Hong et al.[4] apply empirical mode decomposition to 15 sensors in 5 rooms to cluster sensors which belong to the same room by analyzing the correlation coefficients of the intrinsic mode functions. They characterize the correlation coefficient distribution of sensors in the same room and different rooms and show that there exists a correlation boundary analogous to the physical boundary and can be discovered empirically. [1] Akinci et al. propose a feature: energy content in HVAC delivered air, which can be derived from HVAC system sensors which could lead to identification of the space in which the sensors are located . They combine sensor measurements and building characteristics(floor area) .
Lu et al.[5] describe a method to generate representative floor plans for a house. Their method clusters sensors to room and assigns connectivity based on simultaneous firing of the sensors placed on the door and windows jamb. The algorithm gives a small set of possible maps from which the user has to choose the right map. The authors were able to calculate the floor map of 3 out of the 4 houses they evaluated. There method requires special placement of the sensors . Ellis et al.[3] proposed an algorithm to compute the room connectivity using PIR and light sensor data. They compute room connectivity based on the artificial light spill over between rooms ; occupancy detection due to movements between two rooms. They calculate the transition matrix for light sensor and occupancy sensor. Fuse both the data together to compute the connectivity graph. Here the authors have considered a situation where there is only one PIR and light sensor per room.

2.2 Subgraph Isomorphism

In our work we reduce the problem of mappings the sensors to its location in the grid to graph monomorphism problem. Graph monomorphism is widely used in pattern recognition for comparing the graph representing an object to a model graph, or prototype. Various algorithms have been developed so far to solve the problem of graph monomorphism. In our work here we make use of the VF2[2] algorithm to solve for monomorphism.

Chapter 3

Conclusions and Future Work

3.1 Conclusions

TODO CONCLUSIONS

3.2 Future Work

TODO FUTURE WORK

Chapter 4

Methodology

4.1 Data Description

As it has been shown in [4] correlation values Data obtained from the PIR sensros is binary in nature. 1 indicates occupancy and 0 indicates non occupancy.

4.2 Feature Extraction

Energy feature is computed on 36 sample windows of pir sensor data with 18 samples overlapping between consecutive windows. At sampling frequency of 100ms, window length of 36 corresponds to 3.6s data. The energy of bianry signal x(n) is computed as given in 4.1.

$$E_s = \sum_{n=-\infty}^{\infty} |x(n)|^2 \tag{4.1}$$

Energy of PIR signal along with giving the indication that the region is occupied it also gives information about the extent of activity in the region of occupancy. To diffrentiate between the neighboring nodes and non neighboring nodes we use pearson correlation coefficient given by 4.2.

$$r(x,y) = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{4.2}$$

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