LOCATION-PREDICTION FOR SMART BUILDINGS

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**INTRODUCTION**

There is an increasingly popular trend within the mobile community of tracking users’ locations. Every time a picture is taken or someone updates his or her status a geo-tag is associated with it. Geo-Fencing, a more sophisticated that has been developed to use this data to provide contextual awareness of a user’s location to software developers, marketing teams, and others. Geo-Fencing is used with virtual wallets, asset management (RFID), and law enforcement; however, it is not yet fully developed to break into a broader, consumer market.

Predicting location in conjuncture with geo-fencing could be the key that provides advantage to applications wishing to utilize contextual intelligence. Current reminder systems, social networks and recommender systems are only as good as the data that the user feeds them. Lack of sophistication or accuracy prevents the systems from understanding the user. By predicting when someone will be at a location, systems can also react to the user in an appropriate manner.

Location prediction in smart building has been previously studied, but only with algorithms that preform predictions based on what the next location will be or when someone will be returning. These systems do not perform well enough because they lack a general integration into the business. By predicting not only where someone will be next, a system should also provide when someone will be at certain locations. For example, if your supervisor goes to lunch late on alternating days and you need to run into him or her for a quick meeting then the system should be able to show the best times to run into him or her.

**Background**

Ingrid Burbey [1] summarized that the common ways of predicting location does not allow for predicting two vectors and that a unique algorithm would have to be used to predict both time and location. Jan Petzold [5] applied a multitude of learning algorithms to predict location, specifically office worker’s location. He found that using just one did not work for everyone. Utilizing a heuristic method and keeping track of historical data, Burbey’s algorithm has an accuracy of 77%-91%.

**Project Goals**

The project’s goal as described in this paper was to provide a model to integrate location prediction into a building’s A/C system. The project utilizes a custom-made simulation of an office floor and A/C system to provide location data and temperature data for the algorithm to predict both the locations of users at certain times and how the A/C system should be optimized to maximize comfort and reduce cost.

**METHODOLOGY**

Utilizing the .Net platform the simulation was built with a graphical interface and a file based backend to keep track of historic data. The simulation uses an OOD to represent sources of heat, cold, and the agents themselves. The simulation keeps track of the locations of all the objects, the temperatures of all of the agents, and the heat/cold outputs for the heaters and air vents in the historical data file. The system also implements an encoding function to track only meaningful location names instead of coordinates, an implementation of geo-fencing.

The prediction algorithm is used at each time step to adjust the A/C system based on the next time step. An interval of 30 min was chosen based on research into common A/C systems’ cooling capabilities. The pseudo code for location-time prediction is listed below.

**Prediction Function**

predictLocation(QLocation, CTime, CLocation)

{

Search through all of the historic data by sequence for the QLocation,

else continue to the next sequence

Search through the selected day for the time closest to CTime

Then search for the time of QLocation that occurs after CTime

Increment the counter for that time and continue to next sequence

}

The goal of the function is to calculate the probability that the person will be at location X at some time. If the location is never found then the result is zero. If the person is always at location X at the same Time T then the function will return that result with complete confidence. In order to increase accuracy of returned results fuzzy logic was necessary for searching through times. When the algorithm searches for a time that is before CTime it searches for nearest and not the same time, and times have windows of error.

**RESULTS**

Analysis of the predicted results versus the actual results yielded 86% accuracy. This is comparable with other studies on the matter [1, 2, 3, 4]. Integrating to the building’s A/C system and letting the prediction algorithm decide when to turn on the air caused the A/C system to run less while still keeping the temperature of the relevant rooms at an acceptable level. While some simulation runs or days had lower power savings, even a 1.5 degrees Fahrenheit increase during summer can reduce energy consumption by 15% for the day [7].

**CONCLUSIONS**

Through a heuristic model and some simple location data, a building could cut its energy cost throughout the year by anticipating when the system should be operating. This system could be implemented with low cost RFID tags and a central low voltage unit, such as an Ardinuo or Raspberry-Pi. Further work could be taken on optimizing the historic data records and using a compression algorithm to increase the efficiency of the system.

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