Autonomous Robot Localization Using WiFi Fingerprinting

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ABSTRACT

We are using widely available 802.11 wireless networks to determine the location of autonomous robots. Before a robot can accomplish a simple task, such as moving to a specific coordinate, it must accurately know its current location with a certain degree of accuracy. We often take our eye sight and spatial awareness for granted, where, for a robot; the computational difficulty of solving the same problem becomes apparent. Our implementation creates a database of wireless signal strengths of a given area and uses the current signal strength reading within said area to find a weighted signal space distance. The "closest" point in the database should also correlate with the current position of the robot. Given the robots correct location, we can successfully navigate any area with sufficient Wi-Fi coverage.

Categories and Subject Descriptors

C.2 [**Computer-Communication Networks**]: Miscellaneous

General Terms

Algorithms, Design, Experimentation, Theory

1. INTRODUCTION

Existing Global Positioning Systems require line of sight communication with geosynchronous satellites in order to function. This requirement renders their utility to indoor environments minimal. However, indoor localization can still be accomplished using multiple techniques. Vision based systems attempt to identify certain known landmarks within an area using image processing algorithms, but are computationally expensive and require significant training. [3] Odometer based localization methods measures distance traveled and orientation changes, but experience increasing error due to impercise measurements. [1] And radio based methods attempt to measure radio signal delay and signal strength from known sources, but require transmitters to be installed within the indoor environment to function.

Thanks to the prevalence of wireless networking, most indoor environments have preexisting infrastructure in place that can be utilized for both communication and localization. We were tasked with using the University of North Texas's existing 802.11n wireless networks to solve the indoor localization problem using four Acroname Garcia Robots.

2. HARDWARE

The Acroname Garcia Robot is composed of the following components:

- Gumstix Verdex-Pro XL6P COM
  -600mhz ARM processor
  -128mb Ram
  -USB Port
  -32MB flash memory (file system)
  -MicroSD expansion (file system)
  -Openembedded Linux Distribution

- Wifistix 802.11b/g Expansion Board
  (Marvel 88W8385 Module)

- Acroname Brainstem Processor

- Two Maxon 250443 Motors

- Two HiTech 322HD Servos (camera tilt / rotate)

- Six Infrared Range Fingers

- Hokuyo URG-04LX Laser Ranger

3. LOCALIZATION METHODS

After researching existing techniques to accomplish our goal we decided upon wifi fingerprinting. Despite previous work done by others at UNT in way of trilateralization, we quickly came to realize that they completely ignored the issue of converting the RSSI (Received signal strength indicator) to distance. Using freespace path loss models as a basis to solve for real world distances in indoor environments simply does not work in practice. [2] Indoor environments are subject to shadowing and multipath distortion, which are completely ignored by these models. Most implementations of the trilateralization methods rely on taking signal strength samples and performing a log fit to create a model of the sampled data. The fingerprinting method, however, uses the sampled data directly and correctly accounts for any nonlinear changes in signal strength that are regularly seen within a typical indoor environment.

3.1 Fingerprinting

The fingerprinting method is primarily composed of two phases, a database creation phase and an usage phase. In order to implement this method one must create a wireless signal strength database, also known as a radio map, as a preprocessing step. This is accomplished by physically taking measurements of signal strengths at regular intervals within the desired area at any granularity that achieves the desired results while minimizing the physical effort required to generate the data. After the database is created software is used to determine location in real time by searching for the closest matching database signal given the current signal reading. We collected signal samples at approximately one meter intervals in a grid pattern of two separate locations – A common area between the CS and EE departments and an embedded systems computer lab within the CS department.

3.2 Design

After placing tape to mark one meter intervals in the desired location we placed the acroname garcia robot on these markers in a single orientation. (Facing the positive x axis of generated data and images.) We used the linux iwlist scan command to collect data from the robot which was piped into a plain text files. Multiple samples were taken at each point one to two seconds apart. Originally we took three samples per reference point and later took ten samples per reference point in one of our two locations. Using standard ANSI C code we wrote programs that created a binary database of the collected text data and used this database to perform various tasks. These tasks include an implementation of the fingerprinting algorithm just discussed as well as generating visual heatmap images of the collect data, robot path finding, as well as creating programs to inspect the contents of the database. This free and open source code will be available at http://lineofsight.awright2009.com along with our collected data.

```
Input: signal sample vector
Output: (x,y) position
float diff = 0.0f;
float min_diff = 1000.0f, old_diff = 1000.0f;
int matches = 0;
foreach reference point i in database do
    foreach cell j in reference point do
        foreach cell k in signal sample do
            if cell k in sample == cell j in database then
                diff += abs(sample signal - database signal);
                matches++;
            end
        end
        if matches then
            diff /= matches;
            min_diff = MIN(min_diff, diff);
            if old_diff != min_diff then
                old_diff = min_diff;
                ref_index = i;
            end
        end
    end
end
```

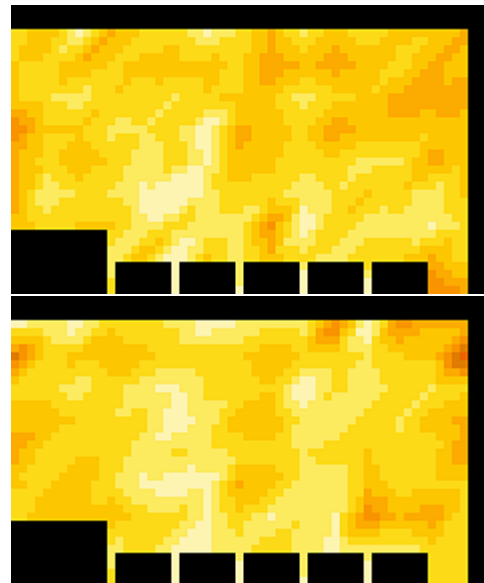**Algorithm 1:** Our original unoptimized matching algorithm

Figure 1: Signal strength images from access point 00:1A:1E:8B:47:60 displaying signal fluctuation of embedded lab from different scan sets taken roughly two weeks apart.

3.3 Access Point Transmit Power

The University of North Texas uses Aruba AP-125 802.11n antennas which act as terminals that are centrally controlled by a single master controller. As our selected method makes the assumption that wireless signal strength is relatively constant over time, our accuracy is limited by the fluctuation of signal power transmitted by these access points. We requested that the school enable a constant transmit power as well as disable any dynamic load balancing or power saving features offered by the aruba network system. Any changes we requested to the school's network settings would be temporary in nature and due to the lead time required to get changes in place we attempted as best we could to work with the dynamic settings. When collecting our first dataset, the area between the CS and EE departments, the school had a constant transmit power enabled. The first two sets of embedded lab data, however, have the schools normal dynamic settings. We are unaware as to what settings were changed and what these settings are.

3.4 Results

Our results varied greatly depending on where the robot was placed. Certain locations returned a perfect match regularly while most areas were within 2-3 meters of the robots actual location. Other areas, such as those near walls or between computer desks within the embedded lab lead to results that were off by as much as 5 meters. However, in cases where perfect matches occured the signal space difference between the sample and the matched location was consistantly low, ranging between 0.5 and 1 dBm, for only a single point. In cases where the matches were between 2-3 meters a small subset of points near the robot had similar dBm differences between 0.75 and 2dBm. This allows one to give a rough confidence level of the results received and provides the robot with enough information as to whether or not it should rely

on the fingerprint localization coordinate. Assuming worst case results, this still gives the robot a general idea of where it is located within a space when placed randomly. This information, when combined with information from other sources, such as laser range fingers and odometer data, can be used to help determine the robots actual location based on other known feature identification.

4. CONCLUSIONS

The accuracy of wifi fingerprinting depends heavily on the quality of the data collected and the variation of signal strength power. The results given by our matching program can be improved without making any changes to the code itself. Minimizing transmission power variability as well as reducing any inaccuracy that may occur between the true RSSI value and what is recorded by the linux driver can improve our system. Probabilistic methods may also improve the accuracy of fingerprinting at the cost of complexity, but I feel that larger gains will be made through the use of hardware designed with localization in mind. The Horus method [4] claims results accurate to 1.4 meters 90 percent of the time, however, they made use of custom linux drivers and much more sophisticated, probabilistic, modeling methods. However, customizing drivers and firmware for our purposes would be a huge undertaking in and of itself. Detailed knowledge of the factors influencing the transmit power for the deployed Aruba 802.11 access points would be helpful as well as any methods one may employ to ensure that there is little to no variation of signal strength over time. Accurate odometer data is crucial to the correct operation of any autonomous system as any small error in direction exacerbates the localization problem.

5. ACKNOWLEDGMENTS

6. REFERENCES

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