Motion Tracking Device With Wifi Power Measurements

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Abstract— *This Project titled "motion tracking device with wifi power measurements" facilitates to count the total number of people walking in an area based on only WiFi received signal strength indicator (RSSI) measurements between a pair of stationary transmitter/receiver antennas. This work proposes a framework based on understanding two important ways that people leave their signature on the transmitted signal: blocking the Line of Sight (LOS) and scattering effects. By developing a simple motion model, this work first mathematically characterizes the impact of the crowd on blocking the LOS. This work probabilistically characterizes the impact of the total number of people on the scattering effects and the resulting multipath fading component. By putting the two components together, developing a mathematical expression for the probability distribution of the received signal amplitude as a function of the total number of occupants, which will be the base for our estimation using Kullback-Leibler divergence. In order to confirm the proposed framework, extensive indoor and outdoor experiments were conducted with up to 9 people and show that the proposed framework can estimate the total number of people with a good accuracy with only a pair of WiFi cards and the corresponding RSSI measurements.*

Keywords—motion Tracking, WiFi received signal strength, stationar transmitter

1. INTRODUCTION

In recent years, there has been considerable interest in understanding what WiFi signals can tell us about our environment. There are several potential applications that can benefit from such a sensing that relies only on the available WiFi signals. Search and rescue, robotic exploration, location aware services, and smart health systems such as elderly monitoring, are just a few examples. Work on WiFi-based localization can be broadly categorized into two groups: device-based active and device-free passive localization.

A survey of the literature shows several work in the area of device-based sensing and localization, where a user's WiFi-enabled gadget, for instance, actively tries to position itself. In passive device-free sensing, on the other hand, WiFi-enabled nodes/network sense and map their environment, for instance objects and humans, without any communication from those objects. Along this line, there has been work on seeing through walls with only WiFi, motion tracking, and gesture recognition.

Most people counting systems are sensor-based and make use of different types of sensors, such as pressure sensors, infrared sensors, thermal sensors, and video cameras.

However, these sensor-based approaches have limitations. As sensors are preinstalled in some fixed checkpoints, these systems can count people only in the areas with these checkpoints. Counting results will be misleading if a person moves randomly without passing any checkpoint and if the same person walks across checkpoints multiple times.

Such high dependence on the exact locations of the preinstalled infrastructure generally leads to low accuracy. Some environments such as open environments are not suited for sensor deployment. A people counting system based on the existing Wi-Fi infrastructure and smartphones could address these limitations.

2. LITERATURE SURVEY

A. DEVICE-FREE INDOOR PEOPLE COUNTING USING WI-FI CHANNEL STATE INFORMATION FOR INTERNET OF THINGS

This paper proposes a non-imagebased people counting system based on the deep neural network (DNN) model using fine-grained physical-layer wireless signatures such as Wi-Fi channel state information (CSI). Only one Wi-Fi transmitter and one laptop receiver are required, and people are not required to wear or carry any equipment (i.e., device-free). A novel feature space expansion scheme that incorporates the dynamic information of CSI measurements is proposed for the DNN model to enhance its performance. Real test bed experiments showed that the proposed system can achieve as high as 88% average correct classification rate in estimating the exact number of the crowd of size up to nine people in the most general indoor scenario.

B. A TRAINED-ONCE CROWD COUNTING METHOD USING DIFFERENTIAL WIFI CHANNEL STATE INFORMATION

This paper focuses on the problem of providing a rough count of the number of people in a room using passive WiFi Channel State Information (CSI) measurements taken by a single commodity receiver. The feature which mainly distinguishes our work from others is the attempt to emerge with an approach which does not require any dedicated training inside the specific environment where the system is deployed. Our proposal stems from the intuitive observation that features which account for variations of CSI are expected to be less sensitive to the surrounding environment as opposed to features which account for absolute CSI measurements. We turn such intuition into a concrete proposal, by suitably identifying a set of differential CSI feature candidates, and by selecting the (two) most effective ones via minimization of the summation of the Davies-Bouldin indexes. We preliminary assess the effectiveness of the proposed approach by training once for all the system in a room, and testing the system in two different rooms having different size and furniture, and involving people freely moving in the rooms with no a-priori movement constraints.

C. WI-COUNTER: SMARTPHONE- BASED PEOPLE COUNTER USING COWDSOURCED WI-FI SIGNAL DATA

This paper, proposes a smartphone-based people counting system, Wi-Counter, by leveraging the pervasive Wi-Fi infrastructure. To collect comprehensive Wi-Fi signals and people count information based on crowdsource, Wi-Counter first adopts a preprocessor to overcome the noisy, discrepant, and fragile data based on the Wiener filter and Newton interpolation. It then makes use of the designated five-layer neural network to learn the relation model between the Wi-Fi signals and the number of people. By analyzing the received Wi-Fi signals, Wi-Counter can estimate the number of people based on the resulting model. We have conducted experiments by implementing a prototype of Wicounter based on smartphones and evaluated the system in terms of accuracy and power consumption in an indoor test bed covering an area of $96x^2$. Wi-Counter achieved a counting accuracy of up to 93% and exhibited reliable and robust performance resisting temporal environmental changes with negligible power usage.

D. PEOPLE COUNTING SYSTEM FOR COUNTING SYSTEM FOR GETTING IN/ OUT OF A BUS BASED ON VIDEO PROCESSING

This paper presents an automatic people counting system for getting in/out of a bus based on video processing. The basic scheme is to set a zenithal camera in the bus for capturing the passenger flow bidirectionally. The captured frame is firstly divided into many blocks and each block will be classified according to its motion vector. If the block quantity of similar motion vectors is more than a threshold, those blocks are regarded as belonging to the same moving object. As a result, the number of such moving objects is counted to be the passenger number of getting in or out of a bus. can be segmented for counting. Experimental results show that the proposed bus passenger counting algorithm can provide a high count accuracy of 92% on average.

E. TOWARDS A ROBUST SOLUTION TO PEOPLE COUNTING

This paper investigates the possibilities of developing a robust statistical method for people counting. To maximize its applicability scope, In contrast to the majority of existing methods from this category - not to require prior learning of categories corresponding to different number of people. Second, it searches for a suitable way of correcting the perspective distortion. Finally, this paper links the estimation to a confidence value that takes into account the known factors being of influence on the result. The confidence is then used to refine final results.

3. PEOPLE COUNTING UUSING WIFI POWER MEASUREMENTS

This paper proposes a new approach for estimating the total number of people walking in an area with only WiFi power measurements between a pair of stationary transmitter/receiver antennas. More specifically, we separated the impact of the crowd on the transmitted signal into two key components: 1) blocking of the LOS and 2) MP effects caused by scattering. By developing a simple motion model, this work first mathematically characterized the impact of the crowd on blocking the LOS.

Then, further probabilistically characterized the resulting multipath fading and developed an overall mathematical expression for the probability distribution of the received signal amplitude as a function of the total number of occupants, which was the base for our estimation using KL Divergence. In order to confirm our approach, this work has been ran in several indoor and outdoor experiments with up to and including 9 people and showed that the proposed framework can estimate the total number of people with a good accuracy.

4. PROBLEM FORMULATION

Consider a scenario where N people are walking casually. A WiFi transmitter (TX) and receiver (RX) are positioned (both stationary) at the border of this area to collect measurements. The goal of this paper is to estimate the total number of people based on only the received signal strength measurements over a small period of time. In this section, we present the mathematical formulation of our motion model. It should be noted that in our experiments, we have no control over how people walk and they are simply asked to walk casually. Thus, the purpose of this section is to derive a simple mathematical model for a casual walk.

A. Workspace Model

Consider a rectangular region of dimension L * B. We discretize it to form a 2-D discrete workspace W consisting of cells, wherein the position of each cell is specified by the coordinates of its center. The origin is taken to be at the lower left corner. Moreover, the length and breadth are partitioned into Ndiv;x and Ndiv;y segments respectively. (L=2; 0) and (L=2;B) respectively.

N people are moving in this workspace. In our mathematical modeling of this section, we discretize the position of each person to the center of a cell. This is solely for modeling purposes and people are not walking in a discretized manner in our experimental setup.

B. Motion Model

In general, mathematical modeling of the motion of people is a challenging problem and not the focus of this paper. Instead, we are interested in a simple probabilistic motion model in order to characterize the stationary distribution of the position/heading of the people in the next section. In our experiments, people were asked to walk casually. We observed that people had a tendency to maintain their direction for a while before changing it. In this section we come up with a simple mathematical model to characterize the movement of the people. For the sake of mathematical characterization, we assume that each person moves around the workspace independent of the others and at a speed of dstep per iteration.1 At each iteration, we assume that a person chooses a direction and moves a distance of dstep in that direction. If a step results in a person crossing the boundary, we assume that the person reflects off the boundary and lands back inside the workspace. Note that the total distance traveled is still dstep. At every iteration, the position of a person would be quantized to the center of the cell in which she currently resides. At each iteration, we assume that each person maintains the same heading of the previous iteration. The motion of person i can then be characterized by the following,

5. ESTIMATION OF THE TOTAL NUMBER OF PEOPLE BASED ON WIFI POWER MEASUREMENTS

In this section, we discuss our proposed approach for estimating the total number of people based on only WiFi power measurements. A person will leave her signature on the received signal in two ways. First, when she crosses the LOS path between the TX and RX, she blocks the transmitted signal, resulting in a drop in the received signal power. Second, she acts as a scatterer of the signal, contributing to multipath fading (MP). As a result, we have two underlying effects: possible blockage of the LOS and multipath fading, both of which carry implicit information of N. This shows an example of a received signal power measurement (N=5 in this case). Sample arrow shows the impact of LOS blockage as well as MP. For a lower level of occupancy, the blocking effect typically results in more pronounced drops as compared to MP. However, as the number of people increases, MP can result in similar levels of drop. As such, it is important to consider both effects.

This proposed approach is thus based on the understanding and characterization of the impact of N on these two phenomena 2. We start by modeling the probability of blocking the LOS path in Section III-A. This characterization is then utilized in Section III-B, to mathematically model both effects and find an expression for the overall probability density function (PDF) of the received signal amplitude as a function of N.

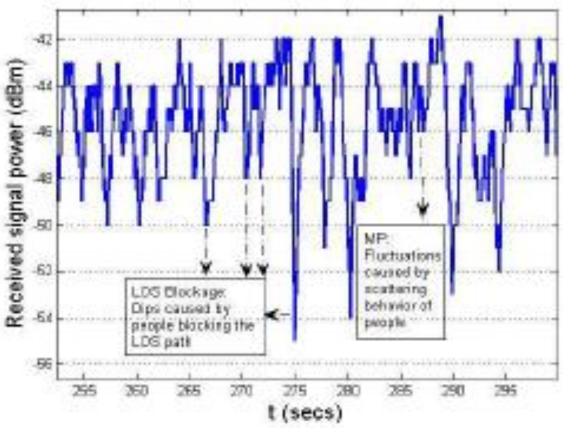

FIG.5.1 POSSIBLE BLOCKAGE OF THE LOS

The position along the y-axis, Lemma 1 and 2 shows that the position and heading of a person takes a uniform distribution asymptotically. Remark 1: While we derived the uniform asymptotic distribution for the angle model of (1), constant speed, and boundary behavior, we expect that an asymptotic stationary distribution will be achieved whenever there is a small amount of randomness in the motion model. A more rigorous characterization of this, however, is a subject of further studies. 2) Characterization of the Probability of Blocking: In this part, we derive a mathematical expression for the probability of blocking the LOS. Definition 1: We say a blocking (crossing)4 has occurred at time t + 1 if either xi(t) is L=2 and xi(t + 1) is L=2 or xi(t) is L=2 and xi (t + 1) is L=2. Based on the definition above, a cross has also occurred if a person lands exactly on the LOS path or moves along it. Thus, this probability of crossing considers slightly more cases than the case of only cutting the LOS, which is of interest to us. However, as we shall see, since we take x ! 0, the probability of these special cases tends to zero, resulting in the desired probability of crossing.

6. CONCLUSION

This paper further probabilistically characterizes the resulting multipath fading and developed an overall mathematical expression for the probability distribution of the received signal amplitude as a function of the total number of occupants, which was the base for our estimation using KL Divergence. In order to confirm this approach, several indoor and outdoor experiments with up to and including 9 people were conducted and this showed that the proposed framework can estimate the total number of people with a good accuracy.

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