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***Abstract*—Cortina is an energy-efficient indoor localization system, which leverages a wireless sensor network to support navigation and tracking applications. To improve the localization performance, we develop a hybrid ranging system, which incorporate both RSS and RToF-based techniques. To overcome effects from indoor multipath, we design and implement algorithms to take into account various contextual information. We evaluated the system over a 2000m^2 area instrumented with twenty-six fixed nodes. Evaluation results show the system achieved 2.5m accuracy in a pedestrian tracking application.**

***Index Terms*—Indoor Localization; Hidden Markov Model; Round-Trip Time-of-Flight; Particle Filter**

I. Introduction

Developments in pervasive computing have enabled a multitude of context-aware and location-based services [1]. These applications assist us in many everyday operations. With the emerging research in this area, users will soon be able to gather knowledge from their surroundings, interact with a variety of consumer electronic devices.

Cortina is a collaborative research platform that investigates potential techniques to enable context-aware services, applications, and tools. The long-term goal is to provide a platform to develop novel context-aware applications that interact with a large number of sensors and actuators embedded in the user's environment. Our short-term efforts have focused on using this distributed sensing infrastructure to implement a Real-Time Location System (RTLS) to track people or assets. Possible applications for our system include elderly and children monitoring, offender surveillance, security guard supervision, and tracking of test equipment and IT assets.

In many existing localization systems, accuracy is a significant design consideration [2]. The traditional radio signal strength-based (RSS) technique suffers from significant indoor multipath effects, making ranging measurements unreliable even within a few meters. Fingerprinting-based approach is time-consuming, vulnerable to infrastructure change, and affected by RF fading in indoor environment. Due to these factors, achieving accurate localization performance in indoor environments is still challenging.

Given these limitations, Cortina leverages simple and efficient onboard signal processing algorithms to achieve high localization accuracy. This paper highlights these algorithms by presenting three key modules in Cortina: 1) a hybrid ranging module, 2) a context sensing module, and 3) a back-end probabilistic localization module.

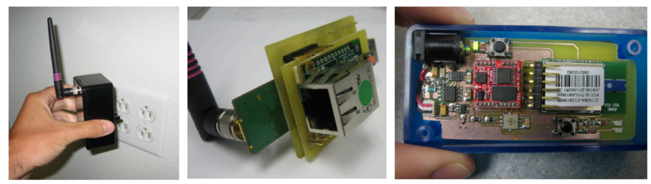

Figure 1: Left) Wall-plugged sensor node. Center) A coordinator with a LAN port to connect to the server. Right) A wireless tag (WTAG)

The contributions of this work-in-progress paper are:

- The design and implementation of Cortina, an indoor localization system that incorporates hybrid ranging and context sensing algorithms.
- The preliminary evaluation of the algorithms, with discussions about open challenges and ongoing work.

II. System Overview

Cortina is a real-time localization system that tracks assets and people moving indoors within a wireless sensor network (WSN). Using a low-power platform based on IEEE Wireless Personal Network (WPAN) standards, Cortina's infrastructure is composed of wall-plugged wireless sensor nodes distributed in the building, as shown in Figure 1. Objects being tracked wear wireless prototype tags (WTAGs). Each WTAG has a built-in IEEE 802.15.4 wireless microcontroller, a 3-axis accelerometer, a magnetic digital compass, and a barometric pressure sensor. Capable of sniffing beacons broadcasted from fixed sensor nodes, WTAGs periodically wake up and measure the RSS of the beacons. To compensate for inaccuracy of the RSS-based ranging technique, WTAGs also periodically initialize round-trip time-of-flight (RToF) measurements to nearby fixed nodes. Both the RSS and the RToF measurements are aggregated in packets and transmitted back to the WSN. Finally, this information is relayed to a central server where it is used to estimate the object's location. By incorporating both the RSS and the RToF techniques, Cortina achieves higher ranging accuracy than using either of the ranging techniques along.

Based on the distributed sensor network described above, we developed adaptive and efficient localization algorithms to provide accurate and robust navigation and tracking service.

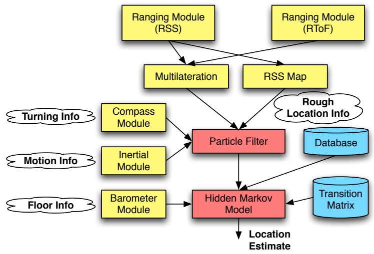

Figure 2: The algorithm architecture of the Cortina system. Yellow: Modules that gathers context information; Red: Probabilistic localization modules; Blue: Databases.

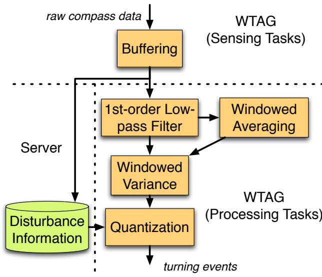

Figure 3: Adaptive compass module that collects raw compass data and detects turning events while the user walks.

III. LOCALIZATION ALGORITHM DESCRIPTION

As shown in Figure 2, Cortina leverages four types of user's context information to improve localization performance.

1) Rough location. A hybrid ranging module combines the RSS-based and the RToF-based ranging measurements to provide location information.

2) Turning events. An adaptive digital compass module detects relative directional change in user's movement.

3) Activity. An inertial module collects raw data from 3D accelerometers and determines user's activity.

4) Floor information. A barometric pressure sensor provides accurate height measurements.

At the back-end server, we developed a particle filter-based fusion engine to combine the above four information together, and a probabilistic Hidden Markov Model (HMM) to take into account location transitions in the user's movement history.

A. Hybrid Ranging Algorithms

Localization and tracking systems have been discussed for many years [2]. RSS-based and RToF-based techniques are two ranging approaches enabled by a number of commercial off-the-shelf wireless radios. However, previous work has shown that, neither of these two techniques alone can guarantee robust ranging performance under complex indoor scenario [3]. Given this situation, in the Cortina system, we investigate a hybrid ranging algorithm that leverages both of the techniques. We implemented these functions by using the latest version of Jennic JN5148 wireless microcontrollers [9], which provide RToF and RSS measurements in high resolutions. On the server side, we developed two algorithms to process RSS measurements sent from the WTAGs, i.e. the Multilateration and the RSSMap.

Multilateration: Since the propagation of RF signals varies largely from place to place, many RSS-based solutions rely on models that are manually calibrated. Cortina removes the need for time-consuming site surveys by leveraging a model that is calibrated in real-time. Since distances between fixed nodes are known, we leverage RSS ranging measurements collected among sensor nodes to derive a dynamically updated polynomial function that maps RSS values to distance. During our experiments, the polynomial parameters in this function are updated every 5 minutes. Then, the distances converted from both the RSS and the RToF measurements are used to estimate the user's location using mulilateration [2].

RSS Map: This approach bears similarities to a fingerprinting scheme, but our maps are automatically computed using RSS values collected by the sensor nodes. Every time a sensor node transmits a beacon, the RSS is simultaneously measured by all the nodes that are in its radio range. For each node, we create an RSS map using a 2D linear interpolation algorithm. Then, we estimate locations of the WTAGs by comparing its RSS values with those on the maps.

The RSS-based ranging results from these two algorithms are then fused with RToF results into a particle filter.

B. Context Sensing Algorithms

In this section, we present the context sensing functions in Cortina, which consist of an adaptive compass module, an activity detection module, and a height sensing module.

1) Adaptive Compass Module

Each WTAG is equipped with a digital compass that provides directional information as users move. Due to the existence of unknown surrounding magnetic fields, however, digital compasses in indoor tracking system are always hard to provide accurate readings.

In the design of Cortina, we investigate using relative angle changes instead of absolute changes. Our experiments showed that, measurements of the relative angle change are less sensitive to magnetic disturbance. Therefore, it can be used to determine user's turning events, such as a left or right turn. Such turning events can greatly reduce ambiguous location estimates in our particle filter-based fusion model.

The algorithm of the compass module is shown in Figure 3. First, a low-pass filter removes high frequency noise in the raw samples. Then a windowing operation computes an average value of the past compass readings. The difference between the current compass reading and the average value is subsequently computed to represent a time domain relative angle change, which is finally quantized to detect turning events.

2) Activity Recognition Module

The firmware on the WTAGs implements an algorithm that detects human body activity using a single tri-axial accelerometer [6]. Activity recognition allows us to gather additional information about the person being tracked and allows the WTAG to save battery energy by reducing the frequency of the location updates when the person is not moving.

Our firmware recognizes four main activities: motionless, fidgeting, walking, and running. Using 20Hz sampling rate

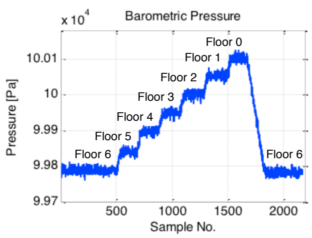

Figure 4: Barometric pressure readings collected when riding the elevator from the sixth floor to the basement. On the way down, the elevator was briefly stopped on each floor.

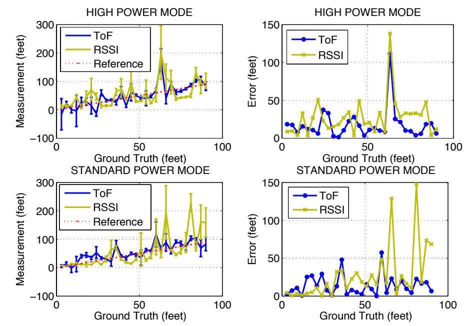

Figure 5: Comparison of ranging performance of the RSS-based and the RToF-based approach.

and data collected over a three second interval, we count the number of slope inversions for each of the three axes. The sum of slope inversions for the axes is distinct for different gaits like walking, running, standing, and fidgeting, and provides a good metric to classify the user's activity. Then, the activities are obtained by comparing the values against reference thresholds that we determined based on some preliminary observations.

It is worth noting that, this algorithm does not place restriction on the orientation or location for mounting the accelerometer. Using this approach, we are able to determine the user's activity with a high degree of accuracy.

3) Height Sensing Module

The barometric pressure sensors mounted on the fixed nodes and the WTAGs are used to improve 3D localization when tracking targets in multi-floor buildings. Figure 4 shows the output of the Bosh BMP085 sensor mounted on one of the WTAGs when riding the elevator from the sixth floor to the basement [8]. There is roughly a 50 pascal difference seen between floors. The fixed sensor nodes provide reference measurements which are used in conjunction with the measurements obtained on the WTAG to determine the floor. This preliminary data suggests that accurate floor detection is possible using barometric pressure measurements.

C. Particle Filter and Hidden Markov Model

The purpose of particle filtering is to track a user while he/she moves [7]. In Cortina, we incorporate the context information collected using multiple sensors as input into the particle filter. When the filter is initialized, a large number of particles are randomly distributed throughout the sensing area. Each particle represents a possible location of the user. In the "prediction" phase, the algorithm requests the user's turning events and moving speed from the compass module and the activity recognition module, respectively. These two pieces of information are leveraged to predicting the user's movement. Then, the particles change their locations according to the user's movement. In the "update" phase, localization results from the Multilateration and the RSSMap algorithms are used to assign the particles weights proportional to the distance from the particles to the localization results. A location estimate is then computed as the weighted average of the particles' locations.

The Hidden Markov model is built based on the given floorplan of the building. Movable area, such as offices, meeting rooms, and hallways, are represented by discrete states. Each state has links to adjacent states with transition probabilities. The location estimate from the particle filter is incorporated with the previous location estimates to form a possible path following the user's movement. Finally, a Viterbi algorithm is used to select the most probable state as the user's final location estimate.

IV. Evaluation

To validate our algorithms, we finished a number of experiments in realistic environments.

A. Hybrid Ranging Algorithm

We conducted controlled experiments along a hallway outside of our office. During the experiments, we set ground-truth distances from 1 feet (0.3m) to 90 feet (30m) with 3 feet (1m) step length. For each distance, 1000 RSS and RToF readings were collected. We tested the ranging performance by using both the high power and the standard power modes of the JN5148 radio.

As shown in Figure 5, when using RSS-based ranging technique, the high power mode and the standard power mode achieve 12.8 feet (3.8m) and 16.4 feet (5.0m) median errors, respectively. Using RToF-based technique, the high power mode and the standard power mode achieve 9.5ft (2.8) and 11.4 feet (3.4m) median error, respectively. This indicates the RToF-based technique has better accuracy than the RSS-based one, and using high power mode achieves smaller ranging errors. This result is consistent with our expectation.

B. Motion Correction

We used one WTAG to run the adaptive compass module and analyzed raw compass samples by using MATLAB. We selected six representative locations to cover different severity of magnetic disturbance.

Firstly, we conducted experiments in domestic scenarios including three sessions, i.e. kitchen, hallway, and living room. During each session, one colleague wore a WTAG on his waist, and walked in the three areas for 20mins, resulting in over 100 turning events. Experimental results, as shown in Figure 6, indicate that the compass module provided over 90% accuracy in the three sessions.

Secondly, we evaluated the system in our office building. As shown in the figure, obvious performance drops exist compared to that of the domestic sessions. We attribute this degradation to the relatively severe magnetic disturbance in office areas. However, although experiencing much higher interference, the adaptive digital compass still achieved over 80% accuracy. This significantly increases the accessibility of the proposed localization system.

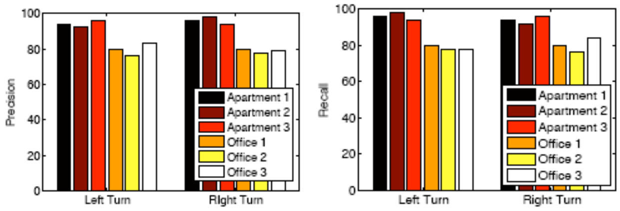

Figure 6: Performance of determing user's turning events using the adaptive digital compass module.

C. Activity Recognition

Qualitative results of the activity recognition module from one of our tests are shown in Table 1.

Table 1: Output of the activity classification algorithm with the WTAG mounted in different positions.

	Walking	Running	Motionless	Fidgeting
Ankle	Walking	Running	Motionless	Fidgeting
Knee	Running	Running	Motionless	Walking
Waist	Walking	Running	Motionless	Fidgeting
Shoulder	Walking	Running	Motionless	Fidgeting
Head	Walking	Running	Motionless	Fidgeting

In general, the algorithm determines the correct activity when the WTAG is mounted on the ankle, waist, shoulder, or head. We did preliminary tests with ten people in the age group from twenty to forty years, and the results were accurate in most cases without need to adjust the pre-determined thresholds. Less reliable results were instead produced with the WTAG mounted on the knee, which exhibits an extreme range of motion at all gaits. In this case, the algorithm's thresholds need to be adjusted based on the range of motion exhibited by an individuals' gait.

D. Particle Filter and Hidden Markov Model

During the experiments, one colleague walked along a hallway for 15 minutes, wearing a WTAG on the waist. In the analysis, we translate "left turn", "right turn" events to +90° and -90°, respectively, and translate "walking" activity to a walking speed of 1.4m/s and "motionless" to 0m/s, and do not consider other activities at this moment. Four different schemes are evaluated: 1) Multilateration, 2) RSSMap, 3) averaging the results of Multilateration and RSSMap, and 4) the particle filer and HMM-based algorithm.

As shown in Figure 7, the experimental results show that, the HMM scheme achieves the best localization accuracy (2.5m). The second best scheme is achieved by averaging the results of Multilateration and RSSMap, having 2.8m of average error. Both of the schemes can be improved further by tuning algorithm parameters.

V. Related Work

In the field of wireless sensor network, indoor localization has been researched for many years. However, due to the complexity of indoor environment, there still lacks a unified solution. In [2], Liu et al. provide a comprehensive survey of the indoor wireless positioning systems, comparing their performance based on accuracy, complexity, scalability, and cost. Combining sensing data of inertial modules, hybrid methods provide promising performance. For example, in [4], the authors present an indoor localization system that uses inertial sensors, in combination with a low precision RSS-based proximity determination technique and map information.

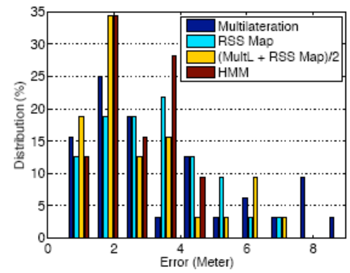

Figure 7: Localization performance by using various algorithms. Experimental results show that the HMM-based algorithm achieves the smallest localization error.

While inspired by the existing work, we would like to investigate the performance of combining both RSS and RToF ranging schemes together, since a hybrid ranging scheme is expected to generate more noise-tolerance and thus accurate localization results. In addition, sharing the cost and performance constraints with other work [5], Cortina combines context information with wireless ranging results to augment localization performance, and a novel compass module is designed to dynamically detect turning events based on relative angle changes.

VI. Conclusion and Future Work

In this paper, we outline the structure of the Cortina indoor localization system, focusing on its hybrid ranging algorithms and lightweight context sensing algorithms. We show the current system achieves 2.5m of indoor localization accuracy.

The current system, however, still relies on fixed anchor nodes. In the future work, we would like to incorporate the neural network paradigm of Self Organizing Maps (SOM) into our system, which enables anchor-free localization solution that works using connectivity information only. This approach would be necessary for deployments with strict cost constraints. In addition, the current Cortina system can leverage various additional context data, such as time of the day and users' identities, to design user-specific localization algorithms that are optimized for each individual user. In addition, all the algorithms mentioned in this paper can be optimized. Such improvements remain the focus of our work in the future.

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