Observing Walking Behavior of Humans using Distributed Phenomenon Detection and Tracking Mechanisms

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Abstract

The utility of walking parameters such as stride length, cadence and gait velocity for monitoring motor functions of patients suffering from brain injury, Parkinson's disease and obesity is well established. The application of sensor networks in this context has also been actively researched however; most of the research has focused either on construction of formal models of walking or design of wearable monitors. Unfortunately these approaches are not always practical for real-life monitoring, since they either require users to continuously wear monitoring equipment or rely on mathematical models which can be susceptible to significant prediction errors. In this paper we propose distributed mechanisms which utilize the concept of phenomenon detection and tracking for monitoring walking parameters. Our mechanisms do not require patients to be encumbered with monitoring devices and can track a subject's walk in real-time, in an energy efficient manner without a priori knowledge of a fixed mathematical model, thereby making it suitable for practical deployments.

1. Introduction

Contemporary research in observation of human walking behavior using sensor networks has either focused on sensing motion using wearable monitoring devices [1] [2] or construction of mathematical models of walking patterns using techniques such as Switched Hidden Semi-Markov Models (S-HSMM) [3]. The former approach encumbers people with monitoring devices and requires them to carry it on their person at all times. This might be a cause of discomfort to some people and is also susceptible to large gaps in observations if the subject forgets to wear the monitor. The latter approach can be susceptible to significant prediction errors due to inherent challenges of modeling human behavior. Moreover, it assumes the *a priori* existence of sensor data streams and only concentrates on centralized aggregation and modeling of data. This requires all sensor nodes in the network to continuously stream up their data and does not work well in long-term practical deployments due to issues such as network and processing costs, latency and energy consumption amongst sensor nodes. In this paper, we propose distributed mechanisms for observing walking patterns in an unencumbered manner without requiring the construction of formal walking models. Distribution of the tracking process amongst sensor nodes also ensures that only a small sub-set of nodes is involved in monitoring walking parameters of the subject at any given time, thereby significantly reducing network, processing and energy costs of the sensor network as compared to centralized methods. The key contributions of this paper are:

- Characterization of human walk as a phenomenon, based on our work in [4].
- Distributed energy-efficient mechanisms for observing walking parameters in an unencumbered manner using a smart floor consisting of a grid of force sensors embedded underneath floor tiles.

The rest of this paper is organized as follows. Section 2 describes the basic hardware and software setup of our system. Section 3 begins by introducing our concept of a phenomenon cloud. It then characterizes the walking motion of a human in terms of phenomena clouds and describes distributed energy-efficient mechanisms for tracking it. Finally it describes how our mechanisms can be used to monitor walking parameters in an unencumbered manner. Section 4 covers related work. Section 5 concludes this paper and provides a brief discussion of future work.

2. System Setup

The tracking mechanisms described in this paper run on a floor based sensor network deployed in the

Gator Tech Smart House (GTSH) [5], a 2,500 sq. ft pervasive computing environment located at the Oak Hammock retirement community in Gainesville, Florida. The Smart Floor [6] deployed in the Gator Tech Smart House consists of a grid of piezoelectric force sensors embedded under raised residential grade floor tiles which cover the entire living area of the house. Each floor tile block has one force sensor attached to its central support (as shown in Fig. 1) which enables the detection of a foot step on any part of the block. In this manner, the movement of a resident can be tracked anywhere inside the house in an unencumbered fashion without requiring the use of wearable monitoring devices or cameras.

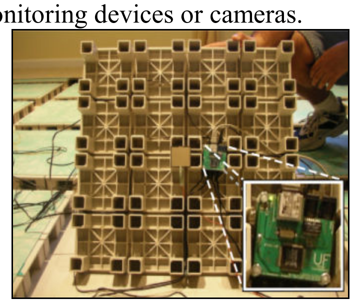

Figure 1. Smart Floor tile

All floor sensors are connected using the Atlas Platform [7], a plug-and-play service oriented sensor platform. Each sensor is physically connected to one of the sensor nodes which make up the hardware layer of Atlas. On powering up a node the sensors connected to it are automatically registered as software services (which also contain properties such as sensor type and location) in an OSGi service framework. This abstracts away low-level hardware details of the sensors and allows applications to access them using high level method calls. The sensor nodes in the hardware layer communicate with each other and with the service framework using ZigBee mesh-networking protocol.

3. Monitoring the Phenomenon of Walking

In this section we demonstrate how we apply the concept of phenomenon detection and tracking to monitor walking patterns. First we describe our concept of a phenomenon cloud and give its formal definition. Next we describe why and how human walk can be described in terms of a phenomenon cloud. Then, we discuss distributed detection and tracking mechanisms for monitoring a resident's walk using the Smart Floor in the GTSH and how it reduces network, processing and energy costs of the sensor network as compared to centralized methods. Finally, we discuss the practical application of our mechanism for monitoring walking parameters such as stride length, cadence and gait velocity.

3.1. What is a Phenomenon Cloud?

A Phenomenon cloud can be defined as a manifestation of a number of simultaneous events reaching "critical mass" and spanning a contiguous space. The shape, size and direction of movement of such phenomena clouds either cannot be modeled accurately or have models which are usually too complex for real-time computing by sensor networks, which largely consist of low-end nodes with limited processing capabilities. Examples of such phenomena can include gas clouds, oil spills or even movement of tourists in a museum. A phenomenon cloud can exhibit non-deterministic behavior over time making it difficult to anticipate its path and motion. The concept of phenomenon clouds was originally proposed by us in [4] to track motion of phenomena such as oil spills and gas leaks however, in section 3.2 we shall see how it can be adapted for tracking the motion of an individual.

We characterize a phenomenon cloud as a 5-tuple, P = <a, b, p_T, m, n>. We define a sensor's neighborhood as the set of sensors immediately surrounding that sensor, including the sensor itself. A sensor is said to participate in a phenomenon cloud given by P = <a, b, p_T, m, n> (or satisfy the *Phenomenon-Condition*), if at least n% of sensors in its neighborhood have readings in the range [a, b] with probability p_T during the last 'm' observations. This criterion ensures that a sensor must have a sufficient number of neighboring sensors in agreement before it can claim the existence of a phenomenon cloud, thereby reducing the occurrence of false positives. We define Phenomenon-Set to be the set of sensors participating in a phenomenon cloud.

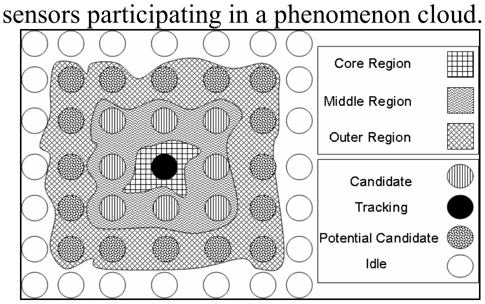

Figure 2. Regions of a phenomenon cloud

We consider a phenomenon cloud to be comprised of multiple regions as shown in Fig. 2. Depending on the location of a sensor in the phenomenon cloud and the role its plays, we classify each sensor in the grid as one of the following:

- **Candidate Sensor**: A candidate sensor is one which is currently not part of the phenomenon but is actively monitoring its readings to determine if it will become part of the phenomenon cloud or not. Candidate sensors make up the middle region of a phenomenon cloud.

- **Potential Candidate Sensor**: All sensors which are immediate neighbors of candidate sensors but are not candidates themselves are called potential candidate sensors. The role of a potential candidate sensor is to notify its neighboring candidate sensors whenever its readings satisfy the output range and probability conditions of the cloud definition. Potential candidate sensors make up the outer region of the phenomenon cloud.
- **Tracking Sensor**: A tracking sensor is one which has already detected a phenomenon event and is now actively engaged in tracking it. A candidate sensor becomes a tracking sensor after it determines that it satisfies the *Phenomenon-Condition* as defined above. Tracking sensors make up the core region. The Phenomenon-Set is the collection of all tracking sensors in the network.
- **Idle Sensor**: All sensors which do not belong to any of the above three categories are called idle sensors. These sensors are not engaged in phenomenon detection or tracking and do not execute any monitoring conditions.

3.2. Walking as a set of Phenomenon Clouds

From the perspective of a floor based grid of sensors such as the Smart Floor, the walking motion of a human has very similar characteristics to that of phenomenon clouds. The action of a foot hitting the floor is defined as a step. The walking motion in humans consists of steps where each foot alternately hits the floor with its heel. Our experience from the Smart Floor deployment has shown that when a person steps on a floor tile, not only does the force sensor directly beneath that tile register a strong reading, but the sensors corresponding to the tiles immediately surrounding it also register readings which are comparatively weaker but nevertheless have significant magnitude. Hence, the stepping motion of a foot on a floor tile causes a ripple effect in the immediate neighborhood of the tile. We use this observation to describe walking as a phenomenon by defining a step in terms of a phenomenon cloud.

A step can be described as a phenomenon cloud S = <a, b, p_T, m, n>, where a & b denote the lower and upper bounds of a force sensor reading indicating that a foot has stepped on a tile or in its immediate vicinity. This value depends on the particular sensor being used. For example, based on empirical study, we found that for the Interlink Inc. force sensors used in the Smart Floor (having an output range of [0, 1023]), a = 150 and b = 600 for an individual weighing between 110 to 240 pounds. p_T can be set between 0.7 and 0.9 to ensure that the readings are due to someone walking and not random vibration. The term m depends on the sampling rate of the floor sensors. Walking is a transient activity where a person's foot remains at one spot only for a very short period of time. Hence, if the sensors are capable of being sampled rapidly then m is set to a higher value, otherwise m has to be set lower.

Fig. 3 shows what a walking motion looks like as a phenomenon occurring on a grid of force sensors on the floor. The core region of each phenomenon cloud corresponds to the sensor beneath the tile a foot is currently stepping on, whereas the neighboring tiles make up the middle and outer regions of the clouds.

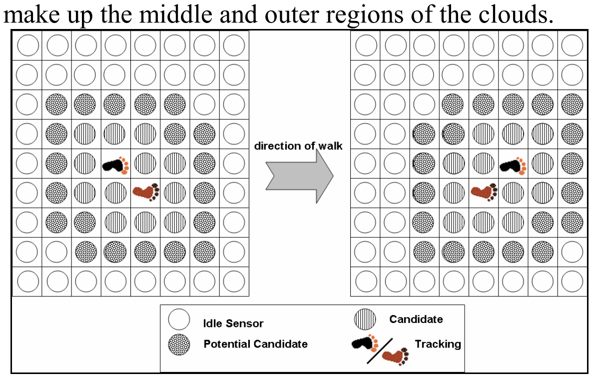

Figure 3. Walking as a Phenomenon Cloud

3.3 Distributed Tracking

We use a distributed in-network tracking mechanism which requires minimal interaction with the monitoring application. When the system is powered on from a cold state for the very first time, a number of sensors are initially chosen as candidate sensors based on their location. Sensors located at doors and passageways make good initial candidates since the probability that a person will step on them is very high. These sensors act as early warning systems for detecting the first step of the resident. Suppose a step is defined as S = <a, b, p_T, m, n>. Once a candidate sensor detects that its readings fall between 'a' and 'b' with probability p_T during last m readings and at least n% of its neighbors notify it of the same, it determines that the resident is stepping on it. It transitions from candidate to tracking category thereby becoming a member of the Phenomenon-Set and also notifies the application that it is being stepped on. It also notifies its neighboring potential candidate sensors to transition into candidate category. These new candidates in turn notify their neighbors which are idle to transition into potential candidates. Due to the use of ZigBee protocols these notifications are sent via inter-node communications usually occurring over a small number of hops thereby, reducing latency and enabling real-time tracking. In this manner, the task of tracking the resident's walk automatically propagates through the network without requiring intervention from the application. At any given time, this process is localized to a small sub-set of sensors in the immediate vicinity of the resident and all processing is done on the distributed nodes reducing the networking and processing overhead of the central application. Due to lack of space, we are unable to give a detailed description of the entire process including the formal rules which govern it. Interested readers are urged to refer to [4] for detailed treatment of these topics including fault tolerance and experimental evaluation of performance and energy consumption. The monitoring application is notified only when a sensor transitions from candidate to tracking category or vice versa (respectively corresponding to when a foot steps on or off a floor tile). This enables it to track the resident's motion in real-time without requiring periodic updates from all the sensors in the grid. We found that our mechanisms on an average result in 80% fewer updates, 90% decrease in number of sensors involved in tracking at any given time and 80% decrease in average power consumption of sensor nodes as compared to centralized stream-based methods.

3.4 Monitoring Walking Parameters

Walking motion is characterized by stride length (the distance between two footfalls of the same foot), gait velocity (speed at which a person walks) and cadence (the number of steps a person takes per minute). The observation of these parameters is of paramount importance for monitoring patients suffering from obesity and Parkinson's disease. For example, people with Parkinson's disease have significantly shorter stride length and slower gait velocity as compared to healthy individuals. Similarly, people suffering from morbid obesity typically have comparatively low gait velocity and cadence.

Our techniques can be used to monitor all three walking parameters in the privacy of one's home without encumbering the resident in any way. Stride length can be instantaneously calculated as twice the distance between two sensors which send consecutive update messages. Gait velocity can be calculated over an observation period P whose length depends on the how long the resident walks in a straight path without turning. If tiles 'i' and 'j' are the first and last tiles stepped on respectively during P, then gait velocity can be calculated as $V = (distance_i - distance_j)/|P|$. Finally, cadence can be easily calculated as one-half of the number of update messages received by the monitoring application in one minute.

4. Related Work

[1] and [2] propose wearable devices for monitoring motor functions of Parkinson's disease patients. However, their current prototypes are not well suited for long-term monitoring since they encumber users by requiring them to wear sensors on their arms and legs. Duong et. al [3] describe a Switched Hidden Semi-Markov Model (S-HSMM) for recognizing daily activities and detecting abnormalities in them. However, their work assumes *a priori* existence of sensor data streams and does not consider practical issues such as energy consumption and processing and networking costs of the sensor network.

5. Conclusions and Future Work

In this paper, we described distributed mechanisms for observing human walking behavior by adapting phenomenon cloud detection and tracking techniques. As part of future work, we plan on gathering data from test subjects residing in the GTSH so that we can fine tune our approach and evaluate its effectiveness in monitoring patients suffering from illnesses such as obesity and Parkinson's disease.

6. References

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