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An experimental study on the effect of pattern recognition parameters on the accuracy of wireless-based task time estimation

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ABSTRACT

Task time estimation is a core industrial engineering discipline. However, the process to collect the required data is manually intensive and tedious, thus making it expensive to keep the data current. Radio frequency signals have been used to automate the required data collection in some applications. However, such radio frequency data is subject to systemic and random noise, leading to a reduction in the accuracy of the task time estimation. This research investigates the use of a pattern recognition method, the *k*-nearest-neighbor algorithm, to improve the accuracy of task time estimation in a simulated assembly work area. The results indicate that the parameters of the *k*NN algorithm can be experimentally tuned to improve the accuracy and to dramatically reduce the necessary computational time and the costs of performing real-time task time estimation.

1. Introduction

Task time estimation is important in manufacturing as it is one of the core elements of industrial engineering tasks such as workstation layout, capacity planning, cost estimation and line balancing. However, traditional task time estimation techniques such as work sampling and time studies are time consuming and tedious.

A novel approach to task time estimation involves monitoring the strength of a radio frequency (RF) signal within a wireless sensor network (WSN) to estimate an operator's position within a workstation in real-time and then use this position information to derive task duration (Atichat, 2011). A key part of this approach is to utilize a pattern recognition technique called *location fingerprinting* based on the *k-nearest-neighbor* (*k*NN) classification algorithm to analyze and classify the data generated by the WSN, and then use that processed data to estimate the task time at a specific location. The location fingerprinting process consists of two phases: the offline data collection phase (or calibration phase), and the online data collection phase.

Once all the new RF signals are assigned to estimated locations in the online data collection phase, the task times are estimated from those locations. The results reported by Atichat (2011) indicated that the quality of the resultant estimated task times using this approach was sensitive to the *k* parameter of the *k*NN algorithm. Therefore, this study focuses on the pattern recognition phase by investigating the effects of several pattern recognition parameters on the accuracy of task time estimation. Different levels of these pattern recognition parameters were identified and tested via a designed experiment on offline and online datasets collected wirelessly in a simulated assembly area covered by a WSN. More specifically, this paper analyzes how using the *k*NN pattern recognition algorithm to classify WSN signals affects the accuracy and computational performance of task time estimation using those signals, and identifies a limitation of the *k*NN algorithm in detecting task transition events. The results obtained in this research show that the parameters of the *k*NN algorithm can be experimentally tuned to improve the accuracy of task time estimation and to dramatically reduce computational time.

The remainder of this paper is organized as follows. The rest of Section 1 describes the problem, related work and the research contribution. Section 2 presents some background on the work that motivated this research. The research methodology and experimental results are presented in Section 3. Section 4 contains a discussion of the results, and the paper ends with conclusions and recommendations for future work in Section 5.

1.1. Problem definition

Location fingerprinting relies on the fact that an RF signal degrades (i.e., attenuates) with distance. This phenomenon, referred to as *free space loss*, is modeled by the radio propagation model which expresses the RF signal power received by an antenna as a function of the signal power transmitted by another antenna (Ahson and Ilyas, 2011; Stallings, 2005):

$$P_r = P_t\left(\frac{\lambda}{4\pi d}\right)G_tG_r \tag{1}$$

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where P_r is the received signal power, P_t is the transmitted signal power, λ is the wavelength of the RF signal, G_t and G_r are the transmitter and receiver gains, respectively, d is the distance between the transmitter and receiver, and n is a signal path loss coefficient which is determined by the environment and typically ranges from 2 to 6. The received signal power, P_r, is generally reported by a surrogate measurement such as the link quality indicator (LQI) or the received signal strength indicator (RSSI). The strength of an RF signal transmitted from a source can then be measured (as the LQI or RSSI) at several receivers and the relative degradation in the power of the signal at each of the receivers is then used to estimate the location of the signal source relative to the receivers.

The RF signal transmitted from a source encounters several forms of interference in its path to the receiver, which affect the measured strength and stability of the signal. For example, obstacles like walls and human bodies cause the RF signal to attenuate (i.e., lose signal strength), whereas signal reflection, scattering, and refraction result in losses due to the multipath effect. Therefore, the signal measurement used in a location fingerprinting system has to be processed to compensate for the variation introduced by these sources of noise.

This variation in location accuracy is compounded when the locations classified by location fingerprinting are used to estimate the duration of a transmitted signal at each of those locations. The issue is that the key to task time estimation is the ability to accurately detect the transition from one task to the next, which is represented by the transmitted signal moving from one location to another. In an RF-based location fingerprinting system, there is no easy way to discriminate (from two consecutive signals in time) whether an apparent change in the source of the RF signal from one location to another is due to the signal transmitter moving from the first location to the next, or whether it is due to variation in a noisy signal environment.

To address the specific problem of location accuracy due to RF signal propagation variation and its resultant effect on task time estimation, the effects of various pattern recognition parameters on the accuracy of task time estimation were investigated in this research. More specifically, experiments were conducted using different levels of the *k*NN classification algorithm that was used in location classification (the level of the *k* parameter), alternate methods of recording the offline fingerprinting data (the fingerprinting method), different methods for calculating the proximity of a new signal to existing signals in the offline database (the distance metric), as well as alternate formulations for detecting the transition of a signal transmitter from one task (as represented by a location) to the next (the segmentation algorithm).

1.2. Related work

Related work in the area of wireless task time estimation can be aggregated into two main areas, i.e., *work measurement* and *location fingerprinting*.

The most accurate manual work measurement methods involve time studies, but time studies are not effective at measuring the task times of non-cyclical or long tasks, like those in healthcare (Ben-Gal et al., 2010). In such situations, work sampling is the preferred work measurement method. Moreover, time studies are also subject to an "observer effect" where the time study subjects change their behavior due to being observed (Franke and Kaul, 1978). In such a situation, work sampling is again a less intrusive form of work measurement. However, work sampling often requires a large number of labor-intensive observations to meet the desired accuracy (Finkler et al., 1993).

Several examples exist in the literature where measurement and estimation techniques have been used to extract location information from RF signals. RADAR, developed at Microsoft Research, was the first RF-based technique for location estimation and user tracking (Bahl and Padmanabhan, 2000). RADAR is built on top of the IEEE 802.11 Wireless Local Area Network (WLAN) standard, commonly known as WiFi. In their experiments, the researchers used location fingerprinting to build an offline database of signal strengths received at three base stations from specific physical locations whose (x, y) coordinates they recorded. They then used a *k*NN algorithm to classify new signals in signal space according to the offline database and, by extension, to estimate the physical locations of the new signals. This study was one of the first to provide localization via WiFi technology, and documented the impact of node orientations, the number of sampling data points, and the fact that signal strength was a stronger indicator of location than signal-to-noise (SNR) ratio. An accuracy of 80% was achieved in location estimation with a position error smaller than three meters. However, the *k*NN algorithm consumed significant amounts of computing power and time, which would prevent the implementation of this technology in a real-time tracking system (Honkavirta et al., 2009). Researchers have worked on improving the RADAR approach by using more access points during fingerprinting (Honkavirta et al., 2009; Jan and Lee, 2003) and by applying additional fingerprinting methods like weighted *k*NN, Bayesian filtering, and Kalman filtering (Honkavirta et al., 2009).

Location fingerprinting has also been used with other RF technologies. For example, SpotOn is a three-dimensional (3D) location sensor based on radio frequency identification (RFID) technology (Hightower et al., 2000). SpotOn utilizes an RSSI distance interpolation technique which includes a unique calibration technique that results in a high precision radio map between RSSI values and the distance between an RFID reader and the tag. In the calibration phase, the custom design of the SpotON RFID device allowed the researchers to fine-tune the RF signal level for both the readers and the tags to achieve a linear relationship between distance and RSSI in the radio map. This study claimed that the system can achieve very precise 3D location accuracy within a small area. However, a complete system has not been made commercially available yet. A two-dimensional (2D) location sensor system based on SpotOn demonstrated 2D location precision of 2–8 cm with more than 80% accuracy in a real inventory application (Ehrenberg et al., 2007).

From the review of the work measurement literature, it is evident that the amount of data collected is one of the most important factors for both time studies and work sampling techniques. The increase in data points proportionally enhances the accuracy of the estimated time but is either expensive (time studies) or may not meet the accuracy requirements (work sampling). The location fingerprinting literature suggests that wireless technologies can be used as the foundation for an automated method to collect the necessary data for work measurement applications. For example, the location of a person relative to certain areas in a workstation can be identified, so that the period of time spent by that person in these areas can be allocated to the appropriate positions.

1.3. Research contribution

As documented above, several studies have addressed *location accuracy* of location fingerprinting systems, and have attempted to reduce the time required to convert a signal into a position. While some research has been published on identifying activities over a time horizon (Ward et al., 2006), there is no current evidence of research employing the signal strength characteristics of WSN RF signals to support task time estimation applications. Moreover, *time accuracy* of a task time estimation system based on location fingerprinting has never been addressed. It is expected that this research would fulfill this gap in the body of literature.