DECODE : Detecting Co-Moving Wireless Devices

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Abstract

We present the DECODE technique to determine from a remote receiver whether a set of transmitters are co-moving, i.e., moving together in close proximity. Co-movement information can find use in applications ranging from inventory tracking, to social network sensing, and to optimizing mobile device localization. DECODE detects co-moving transmitters by identifying correlations in communication signal strength due to shadow fading. Unlike localization systems, it can operate using measurements from only a single receiver. It requires no changes in or cooperation from the tracked devices other than sporadic transmission of packets. Using experiments from an office environment, we show that DECODE can achieve near perfect co-movement detection at walking-speed mobility using correlation coefficients computed over approximately 60-second time intervals.

1 Introduction

Many location-aware applications benefit from higher-level information about the movement of transmitters. One instance of such higher-level information is *co-movement*, which describes whether a set of transmitters are moving together on a common path. While it is straightforward to derive co-movement relationship from position coordinates and trajectories generated by a localization system, sufficiently accurate and precise data is not always available. Global Positioning System (GPS) accuracy is frequently degraded in urban canyons [5] or not used in portable devices due to its energy consumption. For indoor environments, localization systems require the presence of multiple landmarks or receivers, which adds infrastructure cost. Coarse co-movement information can also be obtained from connectivity through short-range radios [7]. This, however, requires tracking software to be installed on all mobile devices, it can not easily be inferred through infrastructure solutions alone.

Overview of Decode: In this paper, we study a co-movement detection technique that operates solely on communication signal strength traces, requires only a single receiver (or landmark), and does not rely on modifications of the tracked devices (under the assumptions that the devices will periodically transmit messages to communicate). It exploits commonalities in the received signal power fading patterns observed from a set of co-located transmitters. The wireless communications literature [17] distinguishes shadow and multi-path fading effects that attenuate a signal in addition to the path loss due to communication distance. Shadow fading refers to obstacles in the environment that attenuate the transmitted signal, when it travels through the object. The magnitude of this effect depends on the material and width of the object (e.g., about 10dB attenuation was observed when an outside antenna was moved inside of a vehicle [10]). Multi-path fading describes the effect that objects in the environment reflect and scatter the transmitted signal, so that the signal often arrives at the receiver along multiple paths. The signal components constructively or destructively interfere, leading to fast changes in received signal strength. Also, if the position of the receiver changes by merely one-half the wavelength of the communication frequency used (59mm for ISM Band 2.4GHz [14]), it will experience a very different multi-path fading channel, resulting in signal strength changes that can exceed 20dB. As transmitters or receivers move, the time varying attenuation due to these effects will be unique for each path. Two receivers co-moving with a separation of less than one-half wavelength, will experience nearly identical signal power curves and thus can be distinguished from transmitter pairs separated by larger distances. For high communication frequencies in the unlicensed band, however, only few transmitters will be sufficiently close to allow such straightforward detection.

Thus, this paper presents the DECODE technique, which allows detection of co-moving transmitters through similarities in the shadow fading component of the received signal. These similarities persist even if the separation between

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transmitters is larger than one-half the wavelength. DECODE records, at one receiver, the signal power changes over multiple frames emitted from each of several transmitters. It then applies a three-step detection algorithm, which begins with extracting periods of high signal variance from each of the traces. It then filters out fast fading effects and calculates correlation values over the resulting data for each transmitter pair. High correlation indicates co-movement of the transmitter pairs.

Uses of Co-Movement Information Many applications can benefit from co-movement information. Some of the important ones are:

Mapping Devices to Persons: Many location-aware application such as Friend finders are tracking devices as a proxy to infer the position of the device owner. The proliferation of mobile devices and distinct radio technologies on each mobile device make monitoring this mapping of devices to their owners increasingly cumbersome. For example, as a mobile device moves from outdoors to building location it may be tracked by a variety of different technologies, where each uses a different identifier (usually the radio MAC address) to identify the device. By monitoring co-movement of different transmitters a localization system may be able to infer which devices belong to the same owner, or which addresses represent the same device.

Social Network Mining: Recent work [7] has sought to infer social relationships from mobile device connectivity patterns. Applications for such techniques include automatically determining access control policies and viral marketing. Current techniques monitor Bluetooth advertisement messages to determine when and how long devices from different owners meet. This requires software on mobile devices. The co-movement techniques could also extract this information through external observations (from a communications base station).

Localization optimizations: Knowing that two mobile devices move together helps collaborative positioning mechanisms that provide lower energy consumption or better accuracy. For example, one device could power down its GPS receiver to conserve energy, while the other device's receiver still provides accurate position updates. In challenging environments for localization, position estimates may also be improved through redundancy.

The remainder of the paper is organized as follows: In Section 2, we review related research and Section 3 presents the DECODE technique. In Section 4, we discuss our experimental methodology and results. Concluding remarks are given in Section 5.

2 Related Work

The previous work on detecting co-located and co-moving objects have either been based on absolute location of the transmitters obtained using localization indoors and GPS outdoors or from proximity sensing using short range infrared (IR) or Bluetooth devices. We know of no other work that infers co-location or co-movement directly from signal strength measurements. In this section we divide the related work into 2 main categories.

Location based inference: There have been active prior efforts in determining the locations of transmitters. RADAR [1] which works for 802.11 uses RF Fingerprint information observed at three receivers and performs a nearest neighbor matching algorithm to determine the location of the transmitters with a three meters median accuracy. [8] uses Bayesian learning algorithm on RF fingerprints observed at three or more receivers to obtain a median 802.11 localization accuracy of 3-4 meters. The most accurate 802.11 location system to date is [12] which uses Hidden Markov Model and Bayesian inference derived from observations at nine different receivers yielding a median accuracy of one meter. Further, the average localization accuracy employing RSS in a 802.15.4 (Zigbee) network [4] and an active RFID system [3] is about the same with median errors around 3-4m when using four receivers. All of these localization approaches need three or more receivers to work in concert to perform co-location detection . Whereas our scheme only needs to work with one receiver.

Proximity Based inference: Proximity based co-location inference techniques mainly consist of using short range IR or Bluetooth devices to estimate distance between the transmitters. Reality Mining project [7] [6] used Bluetooth capable GSM phones to record the other nearby bluetooth devices and transmit them to the central server for inferring social interaction patterns. SpotOn system [9] used radio signal attenuation to estimate the relative distance between the special tags. Though these techniques look attractive for co-location detection, they requires tracking software on the devices themselves and are effective only for detecting devices that have the same technology. Our scheme is more generic as it involves measurement of RSSI which is common to GSM, WLAN, Zigbee, Bluetooth.

3 DECODE SYSTEM DESIGN

The environment in which wireless communication takes place affects the received signal power (i.e., Signal-to-Noise ratio). The key idea underlying the DECODE technique is exploiting shadow fading, signal attenuation due to objects blocking the path of communication. Two transmitters in close proximity will be similarly affected by surrounding buildings, furniture, or passing people. Therefore, the observed signal power from these transmitters should be correlated.

Received signal strength, however, also significantly varies due to multi-path fading. It can introduce received signal strength changes of more than 20dB between locations separated only by half the wavelength of the carrier frequency, if no line-of-sight path to the transmitter is available. These variations render the similarities due to shadow fading difficult to detect. To address this challenge, DECODE uses a filter that reduces or removes multi-path effects by calculating the mean of the signals observed from the moving path of a transmitter.

Movement also helps detection of shadow fading similarities, because co-moving transmitters will experience received signal strength changes due to shadowing at similar points in time (e.g., two co-moving transmitters would pass a building corner at the same time). Intuitively, higher speed of the transmitters will increase the frequency of these changes and thus facilitate co-movement detection.

Figure 1 illustrates the system design and key processing steps of the DECODE system. A receiver measures the received signal strength for signals emitted from the transmitters. It reports a *transmitter identifier*, *signal strength* and a *reception timestamp* for each observation to the DECODE processing unit, usually over an existing wired network infrastructure. For each transmitter, DECODE first performs time alignment and interpolation to facilitate later processing in the face of missing samples. It then extracts periods of high signal variance, which are likely to correspond to movement of transmitters. In the next step, it uses moving window averaging to eliminate fast fading components from the received signals of all transmitters. Finally, correlation coefficients are calculated for each transmitter pairs and correlation values exceeding a specified threshold indicate co-movement of a transmitter pair.

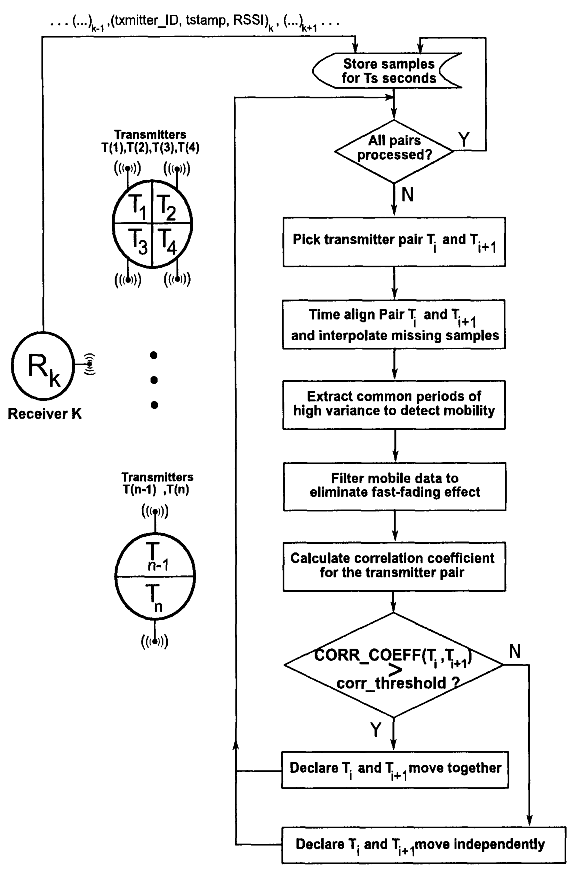

Figure 1. System diagram and data flow

In our prototype, we have implemented DECODE by monitoring the RSSI indicators reported for each packet reception by the receiver. RSSI has been shown to be a good indicator of channel quality [19], hence it should provide adequate information about fading patterns. RSSI is also available across all wireless technologies, which allows measuring co-movement across different transmitters.

In the following subsections, we give details of each of the components of DECODE.

3.1 Alignment and Filtering Steps

Time alignment. The following co-movement detection seeks to compare RSSI values observed at the same time from different transmitters. The packets originating from transmitters attached to different devices may not be synchronized in time. Even if one attempts to synchronize transmitters attached to the same device, the inherent channel access delays will cause packets to arrive at slightly different times. Depending on wireless channel conditions, packets are also lost due to collisions or path loss. Thus, the time alignment step synchronizes and interpolates samples received from two transmitters. Given the packet traces for two transmitters, our implementation matches every packet from the first transmitter with the last prior packet transmission from the second transmitter. If a sample is missing from the second transmitter, this procedure interpolate the missing sample with the last observed sample from the second transmitter.

Extracting high variance periods. Recall that DECODE focuses on periods of mobility because during these periods it can observe correlated signal changes due to large scale fading. Several techniques have been proposed to detect mobility [18, 13, 15, 11]. Of these, we choose the straightforward signal strength variance threshold detection technique. DECODE divides the RSSI traces into blocks. It then extracts and concatenates all blocks where the variance exceeds the specified threshold. We empirically determined the optimal variance threshold to be three and the period over which it has to be estimated to be 5s.

Filtering multi-path fading. Variance due to fast fading should be removed from the RSSI traces to allow calculation of correlation primarily over large scale fading components. DECODE uses a moving window averaging process with a window size of one second for the elimination of fast fading components.

3.2 Detection of co-movement

DECODE determines co-movement by monitoring whether two transmitters experience similar changes in RSSI. To this end, DECODE calculate a correlation coefficient, which measures the strength of a linear relationship between the two RSSI streams. DECODE uses the Pearson's product moment correlation co-efficient [2], a preferred method for quantitative measures such as the RSSI traces used. For n samples each from two random variables X and Y, Person's product moment correlation coefficient $r_{x,y}$ is defined as

$$r_x y = \frac{\sum x_i y_i - n\overline{x}\,\overline{y}}{(n-1)S_x S_y} \qquad (1)$$

where S_x and S_y are the sample standard deviations. The correlation co-efficient lies in the interval $[-1, 1]$, where 0 indicates no correlation, +1 indicates maximum positive correlation, and -1 indicates maximum negative correlation. We empirically determined a correlation coefficient threshold of 0.6 (see section 4.2), values that exceed this threshold indicate co-movement.

4 Experimentation

The measured environment is a typical office environment with partitioned cubicle offices. We use the ORBIT nodes [16] to setup IEEE 802.11b/g(Wifi) receivers at 4 different locations inside the office space as shown in Figure 2. The Wifi receivers were configured to monitor Channel 1 in promiscuous mode.

We used four IEEE 802.11b/g cards as transmitters where a pair of WiFi cards were placed together in the first laptop and the other pair of WiFi cards were placed together in the second laptop as illustrated in Figure 2. The WiFi cards generated ICMP ping packets on channel 1 at the rate of 10packets/sec. We use the ORBIT infrastructure for capturing and logging each IEEE 802.11 packet from these transmitters and store them in a postgres database. For each packet, we logged the transmitter's MAC address, the receiver's MAC address, RSSI and the time when the packet was captured. We also recorded the ground truth about the mobility of the transmitters. We note that we set

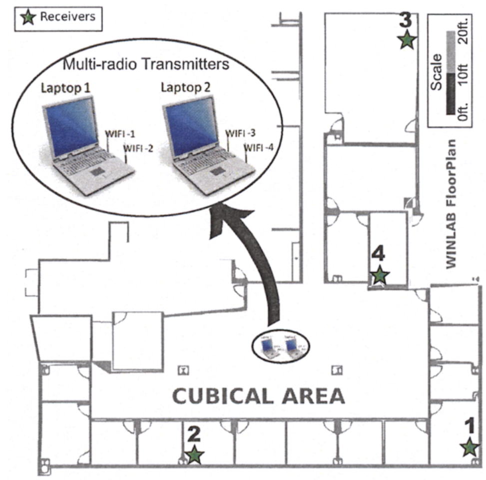

Figure 2. Floorplan of the experiment environment and the node placement

up pairwise transmitters in our expreriments to show how DECODE works, but our approach could be applied to a set of transmitters that are co-moving.

Two of the authors carried one laptop each (that contains two WiFi cards each) and conducted the experiment. The experiment was one-hour long with alternative static and mobile periods. In that one hour duration, the authors were walking at a speed of 1ft/sec for about 20-minutes. We call this experiment *Slow Mobility*. We chose very slow speeds because this represents the most challenging case. The same one hour experiment was repeated once more where the moving speed of the transmitters was increased from 1ft/sec to 4-5ft/sec (normal human walking speed). We refer to this second experiment as *Walking-Speed Mobility*.

4.1 Effectiveness of DECODE

To evaluate the effectiveness of DECODE, we first examine the detection rate and the false positive rate in determining the co-mobile transmitters. Figure 3 depicts the detection rate and the false positive rate as a function of time with respect to each receiver for the 802.11 network for both Slow Mobility as well as Walking-Speed Mobility experiments.

We compute the correlation coefficient for the samples accumulated over the last T_s seconds and if the computed correlation coefficient is larger than 0.6, the pair of transmitters are declared to be co-mobile. Otherwise, this pair of transmitters are declared to be not moving together. A detailed discussion of the choice of the threshold is presented in Section 4.2.We then estimate Detection rate as the percentage of times DECODE correctly reports Co-Mobility

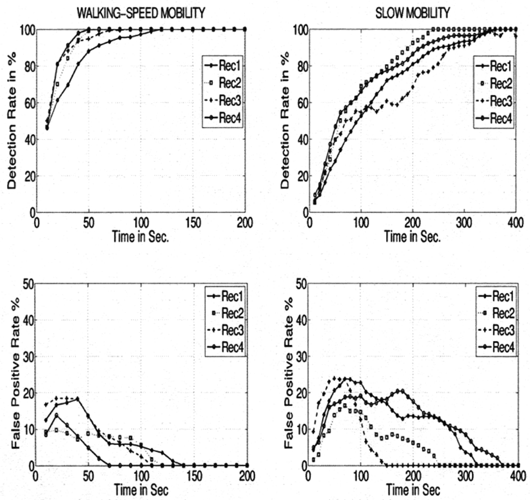

Figure 3. Effectiveness of DECODE in detecting Co-Mobility

when the pair of transmitters are indeed moving together and False positive rate as the percentage of times DECODE incorrectly reports Co-Mobility when the Transmitters are NOT moving together.

Figure 3 shows that in both the Walking-Speed Mobility and Slow Mobility experiments, the detection rate increases to 100% and the false positive rate drops to 0% as T_s increases. This is because, with more time, a better shadow fading profile that is common to the two co-mobile transmitters but completely different for the two non-co-mobile transmitters can be extracted.

We found that the mobility speed also has an impact on the time required to achieve high detection rate and low false positive rate. In the Walking-Speed Mobility experiment, it takes about 130 seconds to achieve 100% detection rate with 0% false positive rate. Whereas it takes around 370 seconds to achieve the same in the Slow Mobility experiment. This indicates that, with a higher moving speed, more of the shadow fading effects could be observed within a shorter duration and since we are essentially capturing the shadow fading effects for detecting co-mobile transmitters, a high detection rate could be achieved quicker in the experiment conducted under the walking speed. The results of the Slow Mobility experiment represent the worst case detection performance of DECODE. In the next sections, we provide our analysis for the Walking-Speed Mobility experiment since it represents more typical scenarios for devices carried by humans.

4.2 Sensitivity to Sampling Rate and Correlation Coefficient Threshold

In this section, we study the sensitivity of our scheme with respect to the different sampling rates and various correlation coefficient thresholds.

The sampling rate is defined as rate at which the transmitter transmits packets. We study the impact of varying the sampling rate on DECODE's effectiveness at detecting Co-Mobility.

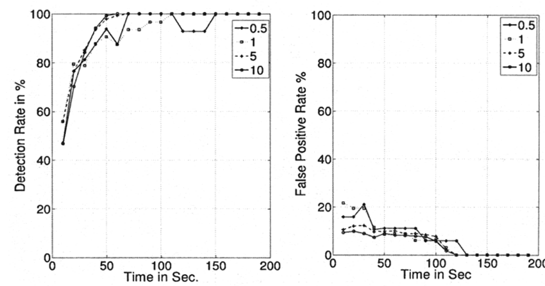

Figure 4. Sensitivity of DECODE to Sampling rate.

Figure 4 presents the detection rate and false positive rate as a function of time for packet sampling rates of 0.5 pkt/sec, 1 pkt/sec, 5 pkt/sec, and 10 pkt/sec observed at Receiver-2. We do not present the results from other Receivers as the performance is very similar. The threshold of the correlation coefficient is empirically determined to be 0.6. We found that for the sampling rates of 1 pkt/sec, 5 pkt/sec, and 10 pkt/sec, the time taken to achieve 100% of detection rate and 0% of false positive rate is similar, about 130 seconds, although when the sampling rate is 0.5 pkt/sec (i.e., one packet every 2 seconds), the time to reach 100% detection rate increases marginally to 150 seconds. This is encouraging as it indicates that DECODE is not very sensitive to the sampling rates.

We next analyze the sensitivity of DECODE to the various thresholds τ of correlation coefficients. Choosing an appropriate threshold will allow our detection scheme to be robust to false detections. Figure 5 presents the detection rate and the false positive rate when τ equals to 0.4, 0.5, 0.6, 0.7 and 0.8 respectively. As expected, we observed that the detection rate takes longer to reach 100% as the threshold goes up, while the false positive rate drops to 0% quicker. When τ is 0.6, the false positive rate remains below 10% at all times and the detection rate reaches 100% at almost the same time as that of smaller thresholds 0.4 and 0.5. Hence, we chose a correlation coefficient threshold of 0.6.

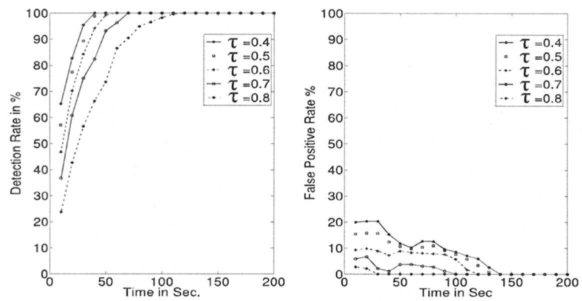

Figure 5. Sensitivity of DECODE to Correlation Co-efficient Threshold. We pick a threshold of 0.6 for Co-Movement.

5 Conclusion

In this work we presented DECODE, a system that detects co-moving wireless devices. DECODE's strategy is founded on observing the correlation coefficient of streams of RSSI values from the transmitters.

Given one minute of mobile data, DECODE can drive the true positive rate to 100% and the false positive rate to 0%. However, a key finding of this work is that mobility is critical for our approach, and that the DECODE's effectiveness scales with both the time and speed of the devices mobility. We also showed that DECODE's performance is insensitive to the sampling rate and a sampling rate of 1 packet/sec for 60 seconds was sufficient to achieve a near perfect co-movement detectioin at Walking Speeds indicating that the approach is practical.

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