$DECODE$: Exploiting Shadow Fading to DEtect CO-Moving Wireless DEvices

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Abstract—We present the DECODE technique to determine 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. The positioning errors from indoor RSS based localization systems tend to be too large making it difficult to detect whether two devices are moving together based on the inter-device distances. DECODE achieves accurate co-movement detection by exploiting the correlations in positioning errors over time. DECODE can not only be implemented in the position space but also in the signal space where a correlation in shadow fading due to objects blocking the path between the transmitter and receiver exists. This technique 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. We further show that DECODE is generic and could accomplish detection for mixed mobile transmitters of different technologies (IEEE 802.11b/g and IEEE 802.15.4), and our results are not very sensitive to the frequency at which transmitters communicate.

1 Introduction

Many location-aware applications benefit from higher-level information about the movements 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. Co-movement information could be used to infer containment relationships, indicating for example that two devices are owned and carried by the same person, or that several tagged objects are placed on the same pallet. It could also be used to infer social relationships if the transmitters are carried by different persons or for optimizing localization system performance.

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. Indeed, our evaluation of a bayesian WiFi localization system (M1) [1] shows that the location estimation errors lead to bias and variance in the Euclidean distance between two co-moving transmitters, making detection of co-movement difficult. Global Positioning System (GPS) accuracy is also frequently degraded in urban canyons [2], and even if signals are available, GPS receivers are not commonly used in portable devices due to their high 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 [3]. This, however, requires tracking software to be installed on all mobile devices, it can not easily be inferred through infrastructure solutions alone.

1.1 Overview of DECODE

In this paper, we propose the DECODE technique which detects co-movement through correlated signal variations over time rather than directly measuring the signal difference between two transmitters. The technique can either work in signal space, using Received Signal Strength (RSS) indicator values, or in position space, using location coordinates derived from the signals.

DECODE can exploit commonalities in signal power variations, because certain fading patterns of co-moving transmitters are similar. The wireless communications literature [4] distinguishes shadow and multi-path fading effects that attenuate or amplify 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 [5]). 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 if the position of the receiver changes by merely one-half the wavelength of the communication frequency used (about 59mm for ISM Band 2.4GHz [6] can result in signal strength changes exceeding 20dB). As transmitters or receivers move, the time varying attenuation due to these effects will be unique for each path in space. Two receivers co-moving with a separation of less than one-half wavelength can be trivially detected because they will experience nearly identical signal power curves, assuming same transmission power and antennas). For high communication frequencies in the unlicensed band, however, only few transmitters will be sufficiently close to allow such straightforward detection. Thus co-movement detection has to allow significant difference in signals due to multi-path fading.

Thus, this paper presents the DECODE technique, which detects co-moving transmitters by correlated signal changes introduced by the shadow fading component in measured signals. While the multi-path component of the signal differs, transmitters separated less than a few meters will often still observe commonalities in shadow fading since larger objects in the environment tend to block all direct signal paths to the co-located transmitters. To isolate the shadow fading component, DECODE first extracts periods of high signal variance from the observed signal strength traces over time. When operating directly in signal space, DECODE removes high-frequency multi-path components of the signal and calculates a correlation coefficient over the filtered signal. A high correlation coefficient indicates co-movement of the transmitters. When operating in location space, it calculates correlation over a time-series trace of coordinates reported by a localization algorithm. Localization algorithms typically average signals over time and thus also largely filter out multi-path effects. Shadow fading can manifest itself as errors in the localization output, which DECODE can exploit. One key advantage of applying DECODE in signal space is that, in typical indoor or urban outdoor environments where shadow fading exists [7], DECODE requires only one receiver to detect co-movement, while localization systems require signal measurements from multiple receivers.

1.2 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 an outdoor to an in-building location, it may be tracked by a variety of different technologies each using a different device identifier (usually a radio MAC address). 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 [3] 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. Section 6 discusses the advantages of the DECODE system in signal space compared to the location space and the effects of environmental mobility on DECODE's performance. Concluding remarks are given in Section 7.

2 Background

2.1 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 classify the related work into three main categories.

Mobility Detection: Several earlier studies have concentrated on distinguishing mobile and stationary transmitters. [8] determines mobility from GSM traces using seven different metrics one of which is the variance in Signal Strength which is similar to our approach. Similarly, [9] discusses detecting mobility from RSSI in WLAN. LOCADIO [10] again used variance to detect mobility and combined it with a two state Hidden Markov Model (HMM) to eliminate oscillations between the static and mobile states. We build on this work—

detecting mobility is an integral component of the DECODE technique.

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. The Reality Mining project [3] [11] 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 [12] used radio signal attenuation to estimate the relative distance between the special tags. Though these techniques look attractive for co-location detection, they require 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.

Distance Threshold Detection: This baseline detection technique involves estimating the locations of different transmitters and deriving conclusions about co-movement based on the distance between the estimated positions of the transmitters. Recent efforts have resulted in a plethora of methods to determine the locations of transmitters. [13] used infrared and [14] employed ultrasound to perform localization. However, both of them required specialized infrastructure to be deployed for performing localization. On the other hand, in spite of meter-level accuracy [15], using RSS [1], [16], [17] is an attractive approach because it can reuse the existing wireless infrastructure.

RADAR [16], the first algorithm for IEEE 802.11 transmitters in this category, uses RF Fingerprint information (vector containing known locations of transmitter along with a measure of the observed signal strength at different receivers) observed at three receivers and performs a nearest neighbor matching algorithm to determine the location of the transmitters with a three meters median accuracy. [1] 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 [18] 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 [17] and an active RFID system [19] is about the same with median errors around 3-4m when using four receivers.

While the recent papers [20], [21] have reported a higher accuracy localization techniques, these techniques require transmitters to perform synchronized communications which is not common across typical transmitters that we analyze in this paper. Further, these papers have not reported the accuracy in a mobile environment questioning its applicability for the detection of co-movement.

Intuitively one can derive co-movement information with threshold detection on the distance between two

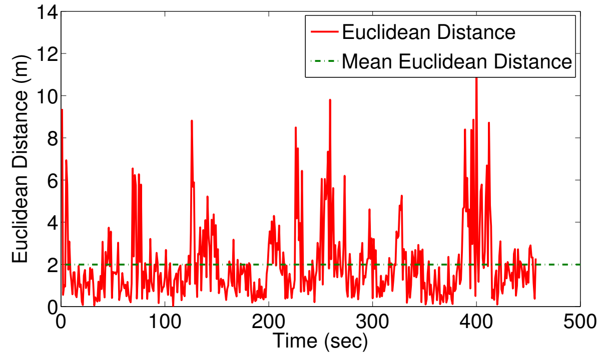

Fig. 1. Euclidean distance between the localized (X, Y) positions for a co-moving transmitter pair

transmitters. Compared to DECODE (in signal space) all these localization systems require three or more receivers to work in concert, whereas DECODE can be used even with only one receiver. In addition, the accuracy results reported for WiFi localization raise questions about the precision of such a detection approach. We will further address this question in the next section.

2.2 Accuracy of Distance Threshold Detection

If current indoor localization systems can provide sufficiently accurate location coordinates, one would detect co-movement based on the distance between the two transmitters remaining below a threshold of a few meters. To verify this intuition, we conduct an experiment in an office environment with coordinates reported by a WiFi localization system using the RSS bayesian localizer M1 [1]. M1 is a lateration-based bayesian algorithm which encodes the relationship between the RSS and 2-dimensional cartesian location coordinates using a simple log-distance propagation model. Using a training set (a vector of RSS for different known (x, y) locations), M1 determines the propagation parameters for each of the receivers. It then derives the joint probability density of (x, y) as a function of the observed RSS for the point to be localized and uses the mean of the derived pdf to estimate the unknown location (x, y). M1 has been shown to provide qualitatively comparable accuracy to current state-of-the-art WiFi localization algorithms [1].

In our experimental setup, two IEEE 802.11g (WiFi) transmitters, send 10 packets per second on the same channel, while moving together with about six inch separation within the office space at a constant speed of 1m/sec. Four receivers recorded the observed Received Signal Strength (RSS) from this transmitter pair. We localize these co-moving pair of transmitters in the $85m \times 50m$ cubicle office environment using M1 every second, based on the average RSS reported over the last second. More details on the testbed setup are provided in Section 4.1.

The Figure 1 plots the Euclidean distance in geographic space between the localized points for the pair of co-moving devices over time. We can see that the distance varies between 0.3m and 12m with a mean distance of 2m. This high variance in the Euclidean distance can be attributed to the following causes.

1) Typical RSS based localization algorithms exhibit a relatively high median localization error of 3m even under no mobility. This localization inaccuracy can increase with mobility thereby resulting in high distance variance.
2) The Localization algorithm estimates X and Y for every transmitter independently before the Euclidean distance metric combines the estimated X and Y from each transmitter. It is possible that errors add up temporarily. It is also possible that a bias in the estimated values for one of the parameters could result in continuously high Euclidean distance estimates.

These high distance errors suggest that the distance threshold detection approach cannot accurately determine co-moving transmitters. This further motivates the DECODE technique, which we will describe next.

3 DECODE System Design

The environment in which wireless communication takes place affects the received signal power (or 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. This similarity in signal strength in turn should also translate to correlations in localization errors.

DECODE captures these similarities by calculating the correlation coefficient over a time-series trace of signal strength or location coordinate values. The correlation coefficient measures the strength of a linear relationship between two random variables. Thus the correlation coefficient captures similarities in the changes of two values, even if the absolute values are different. DECODE uses the Pearson's product moment correlation coefficient [22], a preferred method for quantitative measures such as the RSSI traces used. For comparison, we also evaluated another measure of correlation, Spearman's Rank correlation coefficient [23]. Unless otherwise mentioned, correlation coefficient will refer to Pearson's product moment correlation coefficient r_{xy} in the remainder of this paper. For n samples each from two random variables X and Y, it is defined as

$$r_{xy} = \frac{\sum x_i y_i - n\overline{x}\ \overline{y}}{(n-1)S_x S_y} \tag{1}$$

where S_x and S_y are the sample standard deviations. The correlation coefficient 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 4.4), values that exceed this threshold indicate co-movement.

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 calculates a moving average over signals, which acts as a low-pass filter to reduce or remove multi-path effects.

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. Therefore, DECODE will focus on periods of high signal variance, which typically correspond to movement.

Figure 2 illustrates the system design and key pro-

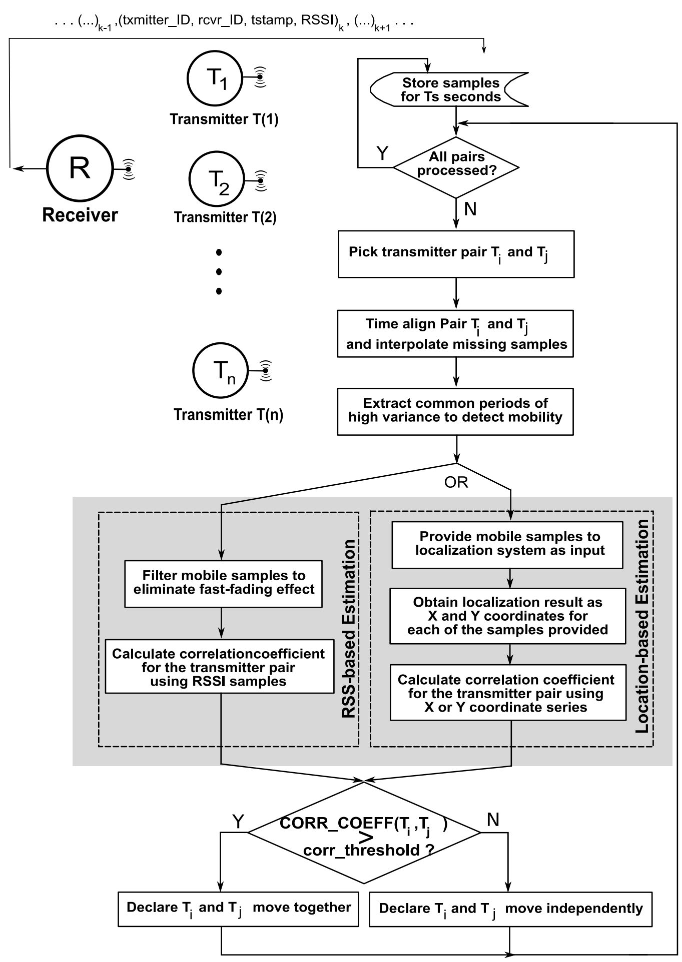

Fig. 2. System diagram and data flow

cessing steps of the DECODE system, which can use received signal strength or location-coordinates for estimation. Both approaches share a number of common data collection and preprocessing steps.

In both cases, the receiver measures the received signal strength for packets emitted from 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. 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 [24], 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. 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.

This is followed by RSS- or location-specific processing steps. Finally, correlation coefficients are calculated for each transmitter pair and correlation values exceeding a specified threshold indicate co-movement of a transmitter pair.

In the following subsections, we give details of the common, RSS-specific, and location-specific components of DECODE.

3.1 Common Components

The common preprocessing steps include time alignment and extraction of high variance periods.

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 from these different transmitters to arrive at the receiver on slightly different times. Depending on wireless channel conditions, packets are also lost due to collisions or path loss. Thus, the time alignment step synchronizes the 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 replaces 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 shadow fading, and during these periods it can filter out multi-path fading. Several techniques have been proposed to detect mobility [8]–[10], [25]. 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 variance threshold to be three (see 4.6 for further discussion) and a suitable block size of five seconds for variance calculation.

3.2 RSS-Estimation Components

If DECODE operates using RSS data, this is followed by filtering out multipath fading and computing correlation over RSS values.

Filtering out multi-path fading: While fading is common in communication channel, the fast fading component where the signal varies in amplitude and phase over short periods of times does not contain useful information about the shadowing profile of the environment. The variance due to fast fading should thus be removed from the RSSI traces to allow calculation of correlation primarily over shadow fading components. DECODE uses a moving window averaging process with a window size of 10 packets (1sec). Figure 3 shows an example of this filtering effect. Before filtering the received RSSI values vary by about 10 dB on timescales of less than 100 ms. After processing, only slow variations remain, which are expected from shadow fading.

Co-movement detection: The final step involves calculating correlation co-efficient on the processed signal strength values from the transmitter pair under consideration. If the resulting correlation co-efficient exceeds a certain threshold, we classify the transmitter pair to be co-moving. We give details on determining this threshold in Section 4.

3.3 Location-Estimation Components

The location based estimation approach calculates the same correlation metric over time-series location coor-

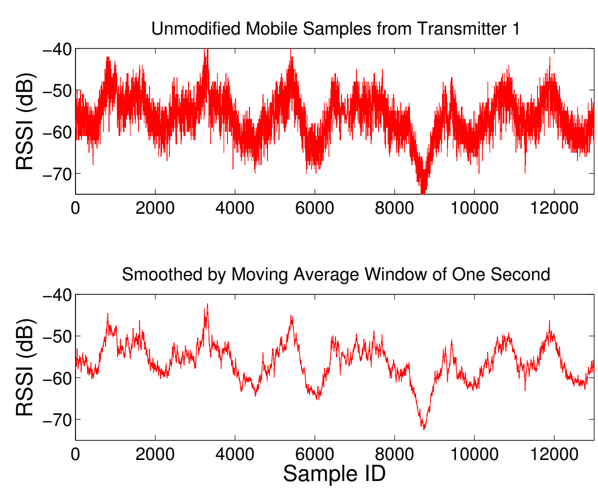

Fig. 3. Smoothing data to remove fast-fading.

dinate data, but it requires data from several receivers to be available and a calibrated localization system. Our localization system relied on an existing signal map of the building, which discretizes spaces and contains an observed signal strength vector (each value corresponding to a different receiver) for each known locations.

RSS Fingerprint Generation: The input to the location system is a fingerprint, an $R \times T_s$ matrix containing RSS values, where R refers to the number of receivers (four in our setup) and T_s to a time window in seconds. To generate these fingerprints, receivers report the *transmitter identifier*, *signal strength* and a *reception timestamp* for every transmitted frame to DECODE. After generating a time aligned sample for the transmitter pairs at each of the receiver and extracting the high variance periods, the resulting RSS samples for each transmitter-receiver pair are averaged over one second intervals and entered into the fingerprint matrix (one matrix per transmitter). If the interval contains no observations for a specific transmitter-receiver pair, the fingerprint generator fills in a localization algorithm-specific default value of -99.

Localization: We use a bayesian solver [1] called M1 to perform localization. M1 is initially provided with a signal map (or training set) containing measurements from 88 different locations in 2D space within the building we carried out the experiment. M1 then transforms each fingerprint matrix into a $2 \times T_s$ matrix of cartesian location coordinates over time, one location estimate per second.

Co-Movement detection: The final step involves detecting co-movement from the (X,Y) estimations at every second for different transmitters. To verify whether a pair of transmitters move together, we estimate their similarity in X or Y coordinates using correlation co-efficient. If the correlation co-efficient for X or Y is over a certain threshold, we declare the transmitter pairs to be moving together. While it may be possible to combine the inference about the correlation in X and the correlation in Y, we do not address this in this paper.

4 Results

4.1 Experimental Methodology

The measured environment is a typical office environment with partitioned cubicle offices. The experiments were performed during normal office hours where one could expect dynamic changes in the environment as a result of the mobility of the people within the office. We set up both IEEE 802.11b and IEEE 802.15.4 receivers within the office space and place them at strategic locations as shown by stars in Figure 4. The WiFi receivers(landmarks) in these four locations operated in promiscuous mode in 2.4GHz, ISM Band Channel 1 to capture all the packets in this particular channel. A Tmote Sky mote configured as receiver was attached to each of the landmarks to capture packets originating from Zigbee transmitters. These motes operated in 2.4GHz, ISM Band Channel 16.

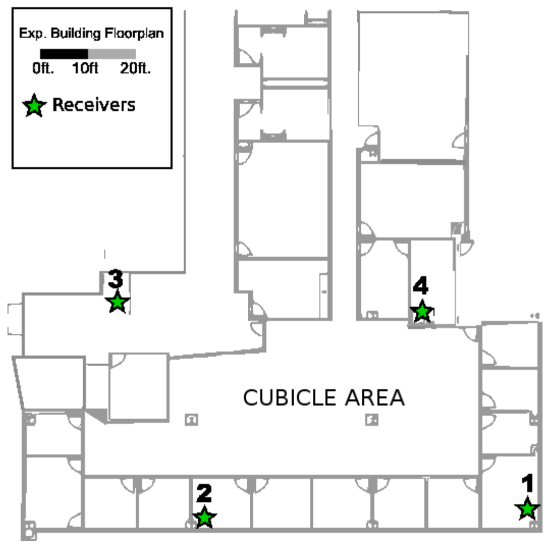

Fig. 4. Floorplan of the experiment environment and the node placement

We used four IEEE 802.11b cards and four Tmote Sky motes as transmitters where a pair of WiFi cards and a pair of motes were placed together in the first laptop and the other pair of WiFi cards and motes were placed together in the second laptop as illustrated in Figure 5. The motes were battery powered. The WiFi cards were connected to the configured APs and pinged the AP at the rate of 10packets/sec with a transmit power of 15dBm. And the motes were configured to transmit packets at the rate of 10 packets/sec at 0dBm. We use the ORBIT infrastructure for capturing and logging each IEEE 802.11 and IEEE 802.15.4 packet from these transmitters to be stored in a SQL database. For each packet, we logged the transmitter's MAC address(Mote ID in case of motes), the receiver's MAC address(Mote ID in case of motes), RSSI and the time when the packet was captured. We also recorded the ground truth about which transmitter pairs were moving together along with the speed and the start and the end times of the different static and mobile periods of these transmitters manually. We note that we set up pairwise transmitters in our experiments to show how DECODE works, but our approach could be applied to a set of transmitters

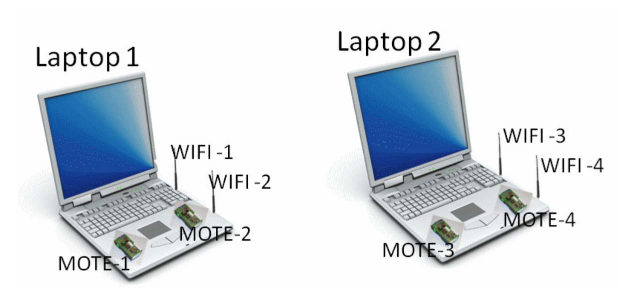

Fig. 5. Nodes and the transmitters used in experiments

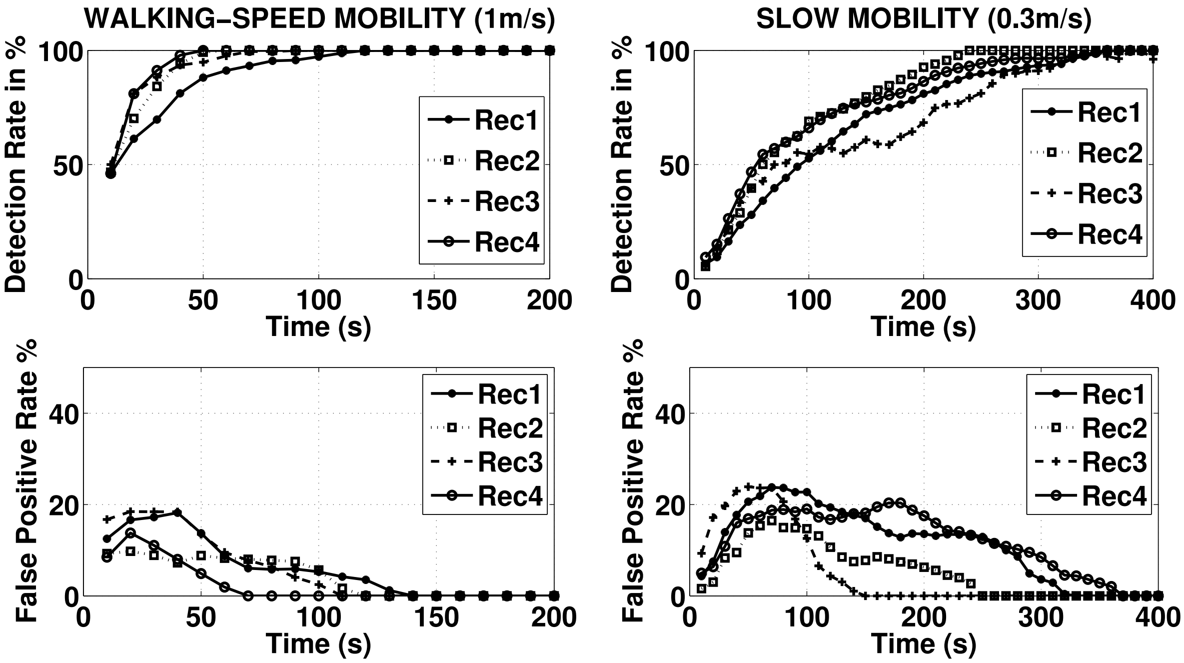

Fig. 6. IEEE 802.11 network: Effectiveness of DECODE in terms of detection rate and false positive rate. The left side plots are for the Walking-Speed Mobility experiment and the right side plots are for the Slow Mobility experiment.

that are co-moving.

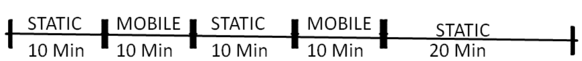

Fig. 7. The Experimental Procedure

Two experimenters carried one laptop each (that contains two WiFi and two motes) and conducted the experiment. The total experiment lasted for one-hour with alternating static and mobile periods as shown in Figure 7. The authors were walking at 0.3m/sec(1ft/sec) for about 20 minutes. We call this experiment period *Slow Mobility*. We chose very slow speeds because this represents the most challenging case. The same experiment was repeated once more where the moving speed of the transmitters was increased from 0.3m/sec to 1m/sec (normal human walking speed). We refer to this second experiment period as *Walking-Speed Mobility*. We refer to these experiment traces as the complete traces.

To analyze the effect of mobility on the results, we then also create mobile-only traces by extracting and concatenating the two 10 minute mobile periods into a 20 minute mobile trace. Using this technique we both create a slow-mobile and a walk-speed mobile trace. We then use a time-based sliding window of time interval T_s seconds to slice each of the above datasets into overlapping test traces. We vary the time interval T_s from 10 second to 400 seconds in steps of 10 seconds. For, example $T_s = 100s$ would generate 1101 test traces of duration 100s from the 1200s of data.We used these different sliced datasets with different time intervals T_s in our results to report the detection rates and false positives.

4.2 Evaluation Metrics

We will evaluate the effectiveness of RSS based DECODE in the following three categories: (1) performance evaluation in terms of the detection rate of co-moving transmitters and the corresponding false positive rate; (2) sensitivity study under different packet sampling rates and various correlation coefficient thresholds; and (3) generality investigation across different correlation methods and wireless networks. Finally, we will study the effects of mobility detection on the performance of DECODE.

4.3 Effectiveness of DECODE's RSSI based detector

To evaluate the performance of DECODE, we first examine the detection rate and the false positive rate of determining the co-mobile transmitters. Figure 6 depicts the detection rate and the false positive rate as a function of time with respect to each receiver for the IEEE 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 4.4. In our 20 minutes of mobile trace, we repeat the above procedure for all the generated data subsets of duration T_s seconds. We then estimate detection rate as the percentage of times DECODE correctly reports 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 6 shows that in both the Walking-Speed Mobility and Slow Mobility experiments, DECODE is able to detect all co-moving and non-co-moving pairs over all the data subsets accurately. We can also see that, increasing the observation time T_s improves the co-mobility detection rate while reducing the likelihood of observing spurious matches.

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 detect all co-moving data subsets. Whereas it takes around 370 seconds to achieve the same in the Slow Mobility experiment. This suggests that, with higher speed, more shadow fading effects can be observed within a shorter duration, leading to improved detection performance.

The results of the Slow Mobility experiment represent detection performance of DECODE under challenging conditions. For the rest of this section, we provide analysis by using the Walking-Speed Mobility experiment since it represents more typical scenarios for devices carried by humans.

4.4 Sensitivity to Sampling Rate and Correlation Coefficient Threshold

We now study the sensitivity of our scheme with respect to the different correlation coefficient thresholds and sampling rates, which we define to be the "packet transmission rate per transmitter". To this end, we further process the Walking-Speed mobile trace and extract 0.5,1,5 and 10 packets every second from the trace to generate datasets corresponding to sampling rates of 0.5,1,5, and 10 pps respectively. These four datasets are further sliced into several data subsets with time interval T_s seconds similar to our previous study for estimating detection and false positive rates.

Figure 8 presents the detection rate and false positive rate as a function of time for packet sampling rates of 0.5 packets per second (pps), 1 pps, 5 pps, and 10 pps, respectively, 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 pps, 5 pps, and 10 pps, the time taken to achieve 100% detection rate and 0% false positive rate is similar—about 130 seconds. With the low 0.5 pps 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 sampling rates in the 1 pps range. This insensitivity can be because, a higher sampling rate would not provide additional gain compared to lower sampling rate as long as the lower sampling rate is fast enough to capture the "shadowing events".

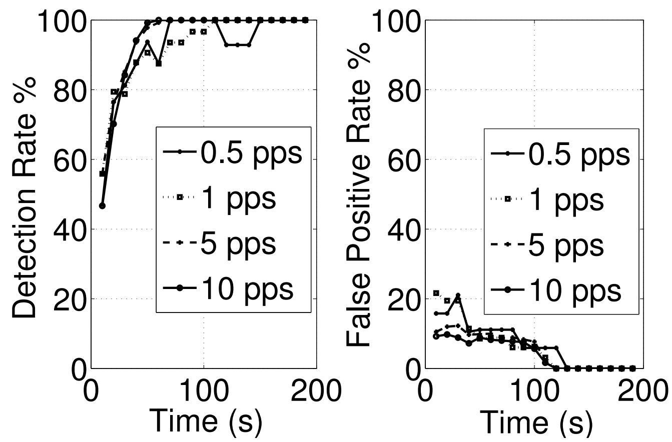

Fig. 8. IEEE 802.11 network: Sensitivity of DECODE vs. sampling rate.

This insensitivity to sampling rate also allows reducing the overall channel utilization, in a system design that relies on explicitly transmitted beacons to allow co-movement detection. The transmission overhead would be negligible. For example, assuming a minimum packet length of 29 bytes(28 Bytes of Frame and 1 Byte of Payload), an 802.11b station transmitting one packet per second at 11 Mbits/s PHY rate takes $603.27\mu sec$ [26] which accounts only for 0.06% of channel utilization.

We next analyze the sensitivity of DECODE to the correlation coefficient thresholds τ. Choosing an appropriate threshold will allow our detection scheme to be robust to false detections. Figure 9 presents the detection rate and the false positive rate for τ equaling 0.4, 0.5, 0.6, 0.7 and 0.8, respectively. As expected, we observe that the detection rate takes longer to reach 100% as the threshold goes up, while the false positive rate drops to 0% quicker. The threshold $\tau = 0.6$ achieves the best balance with a false positive rate remaining below 10% at all times and the detection rate reaching 100% nearly as fast as the smaller thresholds 0.4 and 0.5. Hence, we chose a threshold of 0.6 for all other experiments.

4.5 Generality of RSSI based DECODE

We now study the generality of DECODE in using different correlation methods to determine co-moving transmitters and its generality across both IEEE 802.11 as well as IEEE 802.15.4 networks.

Different Correlation Methods: We compare our correlation coefficient method (i.e., Pearson's product moment correlation coefficient) with Spearman's rank correlation coefficient in Figure 10(a) and 10(b) for the IEEE 802.11 network and the IEEE 802.15.4 network respectively. The correlation coefficients are computed for all the co-moving and non-co-moving pairs of transmitters.

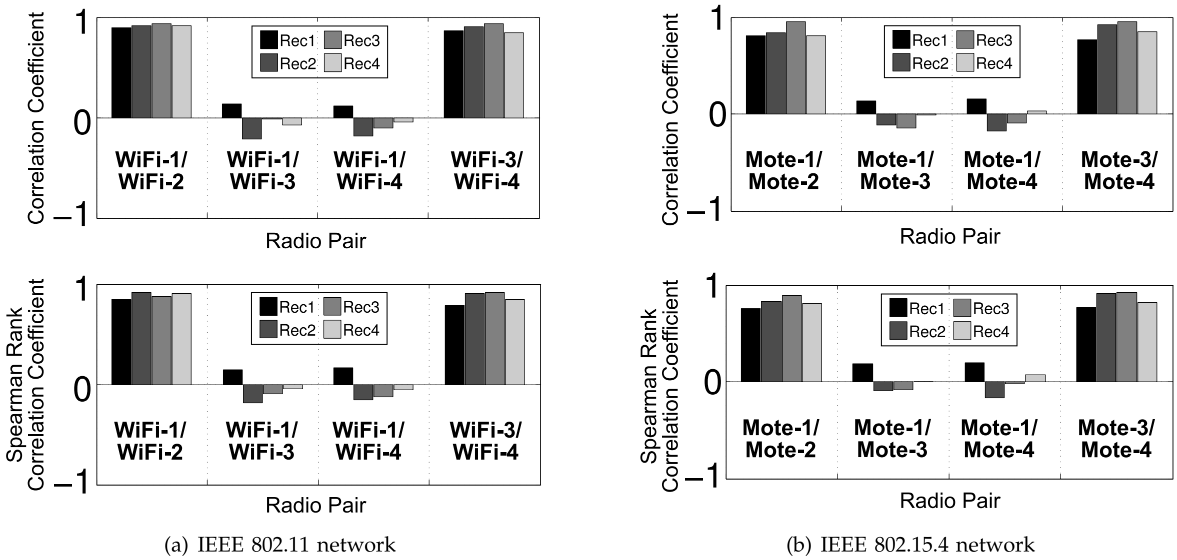

Fig. 10. Comparison of correlation coefficient methods for WiFi and Mote radio pairs.

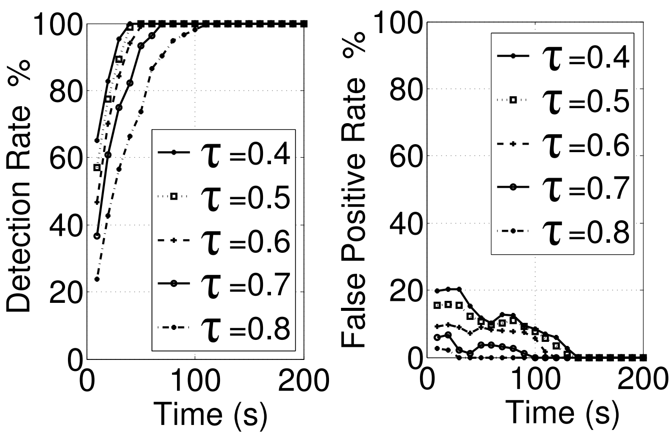

Fig. 9. Sensitivity of DECODE to Correlation Co-efficient Threshold. We pick a threshold of 0.6 for Co-Movement.

Note that we refer to the Pearson's product moment correlation coefficient method as correlation coefficient in the figure.

We observed that both the correlation coefficient methods perform similarly for the co-moving and the non-co-moving pairs of transmitters. For the co-moving pairs, the correlation coefficients from both methods are above 0.6, while for the non-co-moving pairs, both have values of correlation coefficient below 0.2.

Different Wireless Networks: Figure 11 presents the results of correlation coefficient calculated across an 802.11 transmitter and an 802.15.4 transmitter.

We found that the correlation coefficients for co-moving pairs for both the 802.11 as well as for the 802.15.4 are consistently high (larger than 0.6) across all receivers. This is because, when there is an obstruction to the Line-of-Sight signal component due to walls and other objects, both the WiFi and the mote transmitters experience similar shadowing effect as they are placed close enough. Though the actual amount of the degradation of signal differs, the relative effects are the same. Since Pearson's correlation coefficient method removes the sample mean from its estimation, similar relative performance is enough to capture co-moving transmitters. This result is strong evidence that our approach is generic across different networks.

4.6 Significance of Mobility Detection for DECODE

In this section, we examine how mobility detection impacts the performance of DECODE.

Effects of Mobility Detection: Figure 12 plots the correlation coefficient at all 4 receivers for co-moving transmitters in the Walking-Speed Mobility experiment. The correlation coefficient is computed over the entire duration of the experiment as well as just over the mobile periods.

We found that the mobility detection helps increasing the values of the correlation coefficient for co-moving transmitters by an average of 20%. During static periods, the co-moving transmitters do not experience significant changes in shadow fading, but may experience small

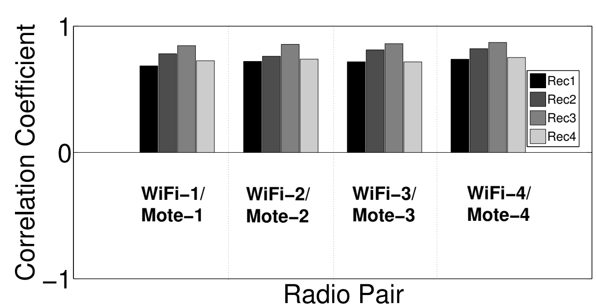

Fig. 11. Correlation Coefficient for Co-located Mote and Wifi

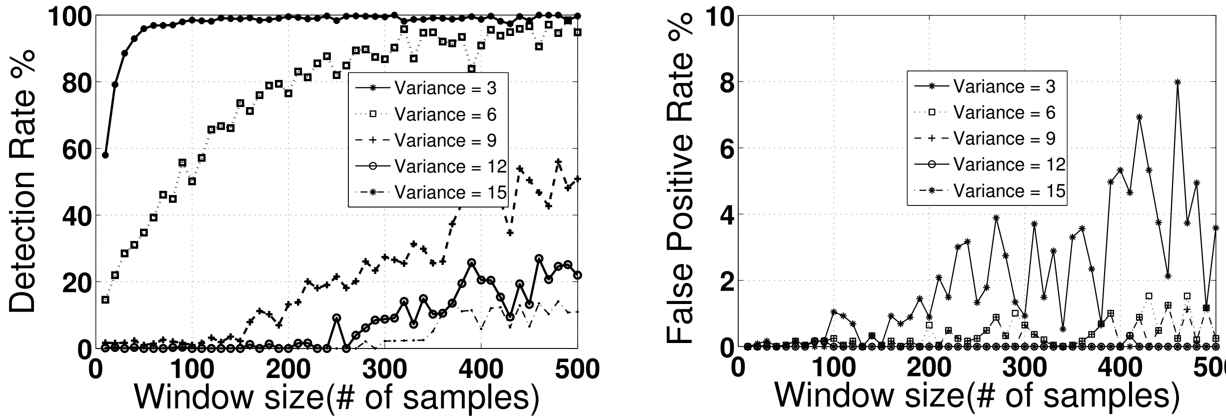

Fig. 13. Effects of variance threshold and sample window size on mobility detection.

scale fading effects that differ from one transmitter to the other (if the separation is more than about 6cm ($\lambda/2$) for 2.4GHz). Thus, including static periods in the calculations tends to reduce overall detection performance, particularly if the static periods are long compared to the mobile periods.

These results support our approach of first extracting mobile (high variance) periods.

Thresholds for Variance and Window Size: For mobility detection, there are several metrics available as shown in [8]. However, we found that using a simple metric, variance of RSS, is sufficiently effective. Further, two parameters are important when using the RSS variance to detect mobility: the threshold of variance and the number of RSS samples on which the variance is calculated. Figure 13 plots the trade off between the detection rate and the false positive rate for different variance thresholds and different window sizes for the co-moving WiFi transmitter pair.

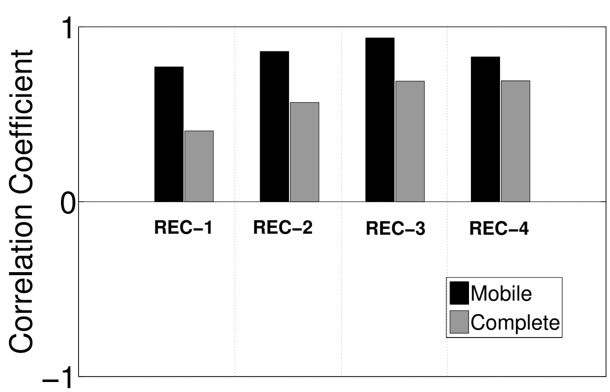

Fig. 12. 802.11 network: Calculation of the correlation coefficient over the entire experimental period and over the mobile periods only. There is a 20% improvement in the correlation coefficient values when applied over mobile periods only.

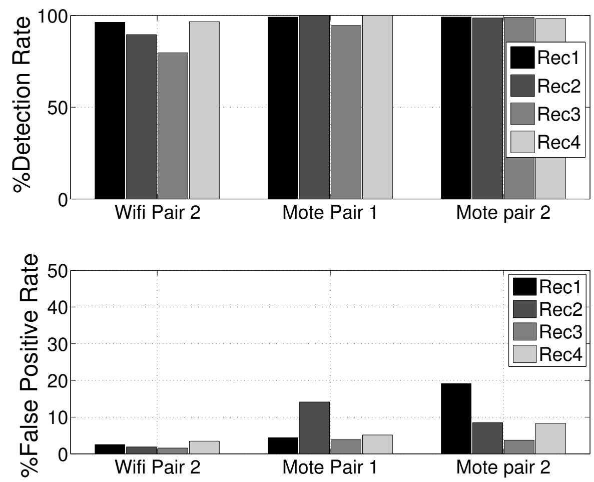

Fig. 14. Mobility detection of co-moving transmitters under windowsize =50, variance Threshold = 3.

We observed that the variance threshold of three has the highest detection rate with false positives less than 10% for all window sizes. We choose a window size of 50, where the detection rate is over 96% and the false positive is less than 1%. We estimate the correctness of these parameters across all transmitters to check the result consistency. Figure 14 plots the detection rate and the false positive rate for mobility detection across the rest of the 6 transmitters including both WiFi and mote transmitters. The results from Figure 14 proves that our results are consistent across all the transmitters with high detection rate and less than 10% false positive rate under a window size of 50 and a variance threshold of three.

4.7 Co-Movement Detection in Location Space

As pointed out in Section 2, the Euclidean distance between the pairs of transmitters is not a very accurate estimator for co-movement detection. In this section, we evaluate the DECODE correlation estimation applied to individual co-ordinates in location space.

Figure 15 plots the localized X and Y positions over time for a pair of co-moving WiFi devices that were attached to the laptop 1 and moving at a speed of 1m/sec. We can observe that the X and Y co-ordinates estimated by the localization system for the two co-mobile transmitters are very similar, but some differences exist. These differences can be attributed to the sensitivity of the localization algorithm to small scale fading, which can affect both transmitters differently and resulted in the high variance in Euclidean distance, as was shown in Figure 1.

However, by calculating the correlation coefficient over the localized X position and the correlation co-efficient over the localized Y positions, we can achieve similar detection performance to the signal space technique. This is possible because the correlation co-efficient can ignore the absolute values and can capture the relative trend in the way the X and Y co-ordinates vary (e.g, shadow fading is likely to lead to similar localization errors for both transmitters).

We evaluate the total time taken to achieve a 100% detection rate and 0% false positive rate. We define the detection rate as the percentage of times the correlation co-efficient computed for a co-moving pair is above 0.6 and false positive as the percentage of times the correlation co-efficient for a non-co-moving pair is above 0.6. Figure 16 plots the detection rate and false positives as a function of time. Note that for simplicity, we have calculated correlation separately for the X and Y coordinates. We can see that it takes nearly 200 and 90 seconds for the X and Y co-ordinates respectively to achieve a 100% detection rate with 0% false positive rate. The corresponding time taken by DECODE in signal space was 130 seconds. While these times are comparable, there are several advantages of using signal space DECODE over location space DECODE—we discuss them in the Section 6

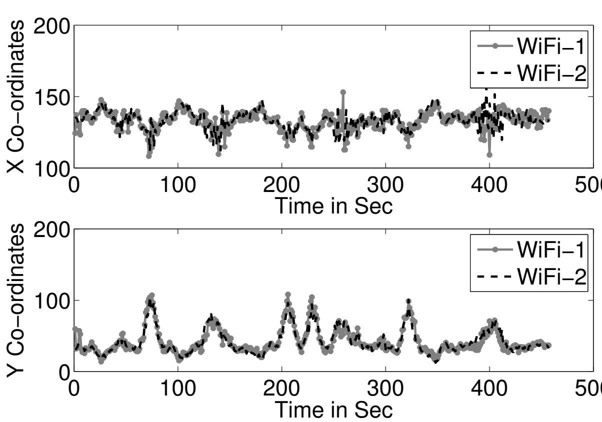

Fig. 15. Localized X and Y positions for a pair of co-moving wifi devices

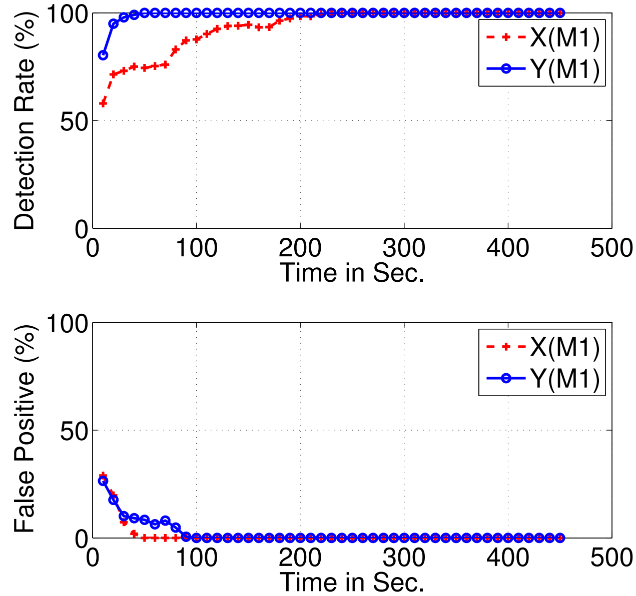

Fig. 16. Effectiveness of correlation coefficient applied over the localized X and Y locations for co-movement detection

5 Simulation with Different Channel Parameters

After observing encouraging results in the experimental indoor environment, we evaluate now whether these experimental results as presented in section 4 are consistent with results from simulation models and whether they can be generalized to indoor and outdoor environments with different propagation parameters. We also analyze the effect of shadow fading on the detection time.

Our simulation methodology involves generating the received power at a receiver from three transmitters, two of which are moving together on the same path and the third transmitter following a different path. To allow comparison with the experimental results, the path taken by the moving transmitters in the simulation was derived from the experiment paths described in section 4.1.

The simulator generates received power levels as follows. From [27], we know that the received power at a receiver from a transmitter can be modeled as

$$P(d) = P_0 - 10\gamma \log_{10}\left(\frac{d}{d_0}\right) + S_\sigma + \delta, \tag{2}$$

where d is the distance between the transmitter and the receiver; P_0 is the received power at the reference distance d_0 from the transmitter; γ is the path loss exponent; S_σ represents shadow fading (i.e. correlated shadowing) which follows zero mean and σ standard deviation Gaussian distribution and δ is the random noise.

To simulate correlated shadowing, the S_σ for different positions must satisfy the following exponential con-

Environment	PathLoss Exponent	De-Correlation Distance (m)	$\sigma_{CorrelatedShadowing(db)}$	$\sigma_{Noise(db)}$	Detection Time (sec)
Indoor-1	2.5	2	2	2.3	108
Indoor-2	2.5	2	4.3	0	81
Outdoor-1	2.8	5	2	2.4	94
Outdoor-2	2.8	5	4.4	0	70

TABLE 1
Summary of the Parameters Used in simulations along with the total detection time

straint [28]:

$$E[S_\sigma(P_i)S_\sigma(P_j)] = \sigma^2 e^{-D_{ij}/D_c}, \tag{3}$$

where $S_\sigma(P_i)$ and $S_\sigma(P_j)$ are the shadow fading at location P_i and P_j, respectively. D_{ij} is the distance between the positions P_i and P_j. D_c represents the decorrelation distance, which can range from 1-2m indoors to many tens of meters outdoors. We generate such correlated Gaussian random variables S_σ by multiplying uncorrelated Gaussian random variables with the upper triangular matrix from a cholesky decomposition of the correlation matrix [29]. In our case, the correlation matrix is initialized with the desired correlation values e^{-D_{ij}/D_c} between each transmitter (position) pair.

As shown in Table 1, we considered four scenarios with different propagation parameters, two for indoor environments and two for outdoor environments. For the indoor environments, we chose standard deviation of the received power by measuring in our experiment environment. Since this standard deviation combines both correlated shadowing and random noise, we simulate two indoor scenario with different assumptions on the level of shadowing and noise. While Gudmundson's exponential [28] decay model has been proposed for medium to large cellular networks in the outdoor environments, [7] has shown that this exponential model can be adapted for analyzing the spatial correlation arising from shadowing in the indoor environments. We obtained the other indoor and outdoor parameters including the propagation exponent from other reported measurements [7], [30]. The last column of the table also shows the result, the total time taken for detecting co-movement without false positives. The results show similar detection times across all four scenarios, indicating that DECODE is not very sensitive to propagation parameters. This is encouraging and shows that DECODE can be expected to also work in outdoor environments with typical parameter settings.

While the simulation results show slightly lower detection times, 80-108 seconds compared to 130 seconds in the experiment, the results are on the same order of magnitude. The difference can be attributed to modeling and measurement inaccuracies. We measured the standard deviation in power (4.3db) within the office environment several months after conducting the DECODE experiments. Also, the simulation model assumes that power measurements follow a Gaussian distribution $\mathcal{N}(P_0 - 10\gamma \log_{10}(d_n/d_0), \sigma^2_{RSS})$, which may not be fully accurate.

Receiver1	Receiver 2	Receiver 3	Receiver 4
0.4630	-0.1140	0.2753	0.4362

TABLE 2
Correlation Coefficient for the time interval t=3100 seconds to t=5100 seconds.

The indoor results also show that increasing the correlated shadowing reduces the overall detection time from 110 sec to 81 sec. A similar trend can be observed in the outdoor results. This indicates that the presence of correlated shadow fading leads to faster detection and is beneficial for DECODE.

6 Discussion

In this section, we discuss the feasibility of detecting transmitters that are static and located within close proximity. We continue the discussion by giving out the advantages of operating in the signal space in comparison to the location space. We finally conclude this section by discussing the impact of missing samples on co-mobility detection.

6.1 Feasibility of Detecting Co-Location

The co-movement detection results described so far raise the question whether the DECODE technique can also be used to detect stationary co-located transmitters. Ostensibly, an environment with high surrounding mobility could lead to similarly high signal variance even though the transmitters and receivers are stationary, because the moving objects can temporarily block transmission paths, which changes shadow and multipath fading patterns.

To investigate whether human mobility in a cubicle office environment is sufficient to also allow detection of co-located stationary transmitters, we performed an experiment where a pair of mote transmitters were attached to the main doorway within the WINLAB office, which is an area with frequent human traffic (it is located next to a printer and water cooler providing additional traffic).

Table 2 shows the correlation co-efficients obtained for the stationary transmitter pairs by each of the receivers over a 2000 seconds interval (the transmitters actually moved when the door was opened, but this occurred only twice in this period). Note that all correlation coefficients are far below the 0.6, our correlation threshold for co-movement detection. Note also that some of the receivers show correlation coefficient values near zero, which suggests that reducing the detection threshold would not be very effective. Thus, these results show that in a typical office environment, surrounding mobility is unlikely to induce sufficient correlated fading to allow use of the DECODE technique for detecting co-located transmitters (even with the extended 2000s measurement period, compared to the 130s period that was sufficient for co-movement detection as shown previously).

6.2 RSSI-Based vs. Location-Based Detection

While accuracy of DECODE in both signal and location-space is similar, applying DECODE in signal-space provides several advantages, particularly if location information is not needed for other applications. However, there are challenges to be addressed before one could assume localization systems are sufficient for the purposes of co-location detection:

- **Generality:** Most localization systems use the already computed training set to determine the location associated with any fingerprint. However, this approach requires the TX power settings during the training and the testing phase to be same in order to estimate the correct location. With a wide variety of wireless devices in the environment, this requirement makes localization technique highly sensitive and error prone, while RSS-based co-movement detection is more agnostic to these issues. Also, different radio technologies may need different localization systems with different accuracy limits, making co-location detection for radios belonging to different technologies non-trivial using these systems, while we showed that the RSS-based technique can be used across wireless technologies.
- **Localization Overheads:** Calculating absolute location of a device takes time and requires signal information from multiple points of contact (e.g., three reference points for trilateration), which may not be available at all times.
- **Infrastructure Costs:** Investing in the localization infrastructure, including the equipment costs as well as maintaining signal maps, beacon or landmark (receiver) positions etc., might be costly. The RSS-based co-movement detection techniques only requires a single receiver, in comparison.

6.3 Impact of Missing Samples on Co-Mobility Detection

As explained in section 3.1, the time alignment step involves replacing the missing samples from a transmitter with its last observed sample. While this step aids in comparison of signal strengths from transmitter pairs, excessive replacement of missing samples could overstate the correlation between transmitter pairs. To this end, we analyze the percentage of times the missing samples have been replaced during this step for a Wifi-Wifi pair at Receiver-1.

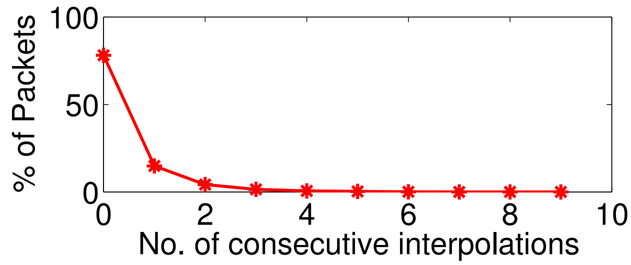

Fig. 17. Histogram of the percentage of consecutive missing samples from a Wifi transmitter observed at Receiver-1

Figure 17 shows that, very few consecutive packet losses occur. 80% of packets have been correctly received. 15% are intermittent single packet losses and only 5% of packets are consecutive packet losses. We also verified these packet loss rates across all the other transmitter receiver pairs and found similar results. Since DECODE uses a moving window average over 1 second of received packets to remove multipath fading, interpolation of these packet losses has little effect on the correlation results.

7 Conclusion

In this work we presented DECODE, a system that detects co-moving wireless devices. DECODE's strategy is founded on exploiting the similarity in shadow fading for the packets transmitted from a set of transmitters. We showed that our technique can work in both the signal space and its corresponding location space, but that the signal space approach provides the key advantage that only a single base station is needed. Our approach was general in that it could detect co-movement of wireless transmitters with different radios. We validated our approach through simulations for various indoor and outdoor environments. We further demonstrated that it works for both IEEE 802.11b/g WLAN and IEEE 802.15.4 Mote devices in real indoor environments.

Given 130 seconds of mobile data, DECODE can achieve a true positive rate of 100% with 0% false positive estimated over 1071 data subsets. 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 130 seconds was sufficient to achieve a 100% detection rate and 0% false positive rate.

Finally, because DECODE's effectiveness is quite sensitive to mobility, we examined using the RSSI variance for mobility detection. We found this technique to have a mobility detection rate of over 96% with the corresponding false positives to be less than 1%. Therefore, detecting mobility has a straightforward solution and does not limit the DECODE system.

8 Acknowledgments

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References

[1] E. Elnahrawy, X. Li, , and R. P. Martin, "The limits of localization using signal strength: A comparative study," in *Proceedings of the First IEEE International Conference on Sensor and Adhoc Communcations and Networks (SECON)*, oct 2004, pp. 406–414.

[2] Y. Cui and S. S. Ge, "Autonomous vehicle positioning with gps in urban canyon environments," *IEEE Transactions on Robotics and Automation*, vol. 19, no. 1, pp. 15–25, February 2003.

[3] N. Eagle and A. S. Pentland, "Reality mining: sensing complex social systems," *Personal Ubiquitous Comput.*, vol. 10, no. 4, pp. 255–268, 2006.

[4] Z. Rong and T. S. Rappaport, *Wireless Communications: Principles and Practice*. Prentice Hall, 2002.

[5] C. Hill and T. Kneisel, "Portable radio antenna performance in the 150, 450, 800, and 900mhz bands outside and in-vehicle," *IEEE Transactions on Vehicular Technology*, vol. 40, no. 4, pp. 750–756, 1991.

[6] P. Nepa, G. Manara, S. Mugnaini, G. Tribellini, S. Cioci, G. Albasini, and E. Sacchi, "Differential planar antennas for 2.4/5.2 ghz wlan applications," in *IEEE Int. Symposium of Antennas and Propagation Society*, July 2006, pp. 973–976.

[7] N. Jalden, P. Zetterberg, B. Ottersten, A. Hong, and R. Thoma, "Correlation properties of large scale fading based on indoor measurements," in *IEEE Wireless Communications and Networking Conference(WCNC)*, March 2007.

[8] T. Sohn, A. Varshavsky, A. LaMarca, M. Y. Chen, T. Choudhury, I. Smith, S. Consolvo, J. Hightower, W. G. Griswold, and E. de Lara, "Mobility detection using everyday gsm traces," in *UbiComp*, September 2006, pp. 212–224.

[9] K. Muthukrishnan, M. Lijding, N. Meratnia, and P. Havinga, "Sensing motion using spectral and spatial analysis of wlan rssi," in *EuroSSC*, October 2007.

[10] J. Krumm and E. Horvitz, "Locadio: inferring motion and location from wi-fi signal strengths," in *MOBIQUITOUS*, Aug 2004, pp. 4–13.

[11] N. Eagle and A. Pentland, "Social serendipity: Mobilizing social software," *IEEE Pervasive Computing*, vol. 4, no. 2, pp. 28–34, 2005.

[12] J. Hightower, R. Want, and G. Borriello, "SpotON: An Indoor 3D Location Sensing Technology Based on RF Signal Strength," University of Washington, Department of Computer Science, Technical Report UW CSE 2000-02-02, February 2000.

[13] R. Want, A. Hopper, V. Falcao, and J. Gibbons, "The active badge location system," *ACM Transactions on Information Systems*, vol. 10, no. 1, pp. 91–102, Jan. 1992.

[14] N. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system," in *Proceedings of the ACM International Conference on Mobile Computing and Networking (MobiCom)*, Aug 2000, pp. 32–43.

[15] A. Krishnakumar and P. Krishnan, "On the accuracy of signal strength-based location estimation techniques," in *Proceedings of the IEEE International Conference on Computer Communications (INFOCOM)*, March 2005.

[16] P. Bahl and V. Padmanabhan, "Radar: an in-building rf-based user location and tracking system," in *INFOCOM*, 2000, pp. 775–784 vol.2.

[17] Y. Chen, J. Francisco, W. Trappe, and R. P. Martin, "A practical approach to landmark deployment for indoor localization," in *Proceedings of the Third Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON)*, September 2006.

[18] A. M. Ladd, K. E. Bekris, A. Rudys, G. Marceau, L. E. Kavraki, and D. S. Wallach, "Robotics-based location sensing using wireless ethernet," in *MobiCom '02: Proceedings of the 8th annual international conference on Mobile computing and networking*. New York, NY, USA: ACM, 2002, pp. 227–238.

[19] Y. Chen, G. Chandrasekaran, E. Elnahrawy, J.-A. Francisco, K. Kleisouris, X. Li, R. P. Martin, R. S. Moore, and B. Turgut, "Grail: General real time adaptable indoor localization," in *Sensor Review*, 2008.

[20] M. Maróti, P. Völgyesi, S. Dóra, B. Kusý, A. Nádas, A. Lédeczi, G. Balogh, and K. Molnár, "Radio interferometric geolocation," in *SenSys '05: Proceedings of the 3rd international conference on Embedded networked sensor systems*. New York, NY, USA: ACM, 2005, pp. 1–12.

[21] B. Kusy, A. Ledeczi, and X. Koutsoukos, "Tracking mobile nodes using rf doppler shifts," in *SenSys '07: Proceedings of the 5th international conference on Embedded networked sensor systems*. New York, NY, USA: ACM, 2007, pp. 29–42.

[22] K. G. Calkins, "E-Book, An Introduction to Statistics," http://tinyurl.com/2jlrsu, 2008.

[23] MathWorld, "Spearman's Rank Correlation Co-efficient," http://tinyurl.com/3ymsre, 2007.

[24] K. Srinivasan and P. Levis, "Rssi is under appreciated," in *Proceedings of the Third Workshop on Embedded Networked Sensors (EmNets)*, May 2006.

[25] N. Patwari and S. K. Kasera, "Robust location distinction using temporal link signatures," in *Proc of ACM MOBICOM*, September 2007.

[26] "Cisco Inc., Maximum Throughput Calculations for 802.11b WLAN," http://tinyurl.com/kv3yjn.

[27] V. Erceg, L. J. Greenstein, S. Y. Tjandra, S. R. Parkoff, A. Gupta, B. Kulic, A. A. Julius, and R. Bianchi, "An empirically based path loss model for wireless channels in suburban environments," *IEEE J. Sel. Areas Commun.*, vol. 17, no. 7, pp. 1205–1211, Jul. 1999.

[28] M. Gudmundson, "Correlation model for shadow fading in mobile radio systems," in *Electronics Letters*, 1991, p. 21452146.

[29] J. H. Stapleton, "Linear Statistical Models," Wiley Series in Probability and Statistics, 1995.

[30] X. Zhao, J. Kivinen, P. Vainikainen, and K. Skog, "Propagation characteristics for wideband outdoor mobile communications at 5.3 ghz," in *IEEE Journal On Selected Areas In Communications*, April 2002.

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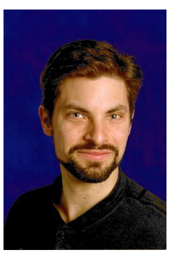

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