A THEORETICAL ANALYSIS OF PATH LOSS BASED ACTIVITY RECOGNITION

Iberedem N. Ekure, Shuangquan Wang[1,2], Gang Zhou[2]
[1]*Institute of Computing Technology, Chinese Academy of Sciences;*
[2]*Computer Science Department, College of William and Mary*

***Abstract*—Body area networks are used extensively in the medical field and elderly care. These networks perform a collection of roles including monitoring an individual's activities, through a process known as activity recognition. Current approaches to activity recognition require specialized hardware for advanced sensors which puts stress on battery life.**

We show that it is theoretically possible to distinguish between different human activities/postures by using radio signal propagation only and provide strategies for doing this. This is immensely beneficial to the field of sensor networks for two reasons: 1) It removes the need for more energy intensive components thus reducing strain on limited power resources and thus 2) reduces form factor for sensor network nodes. We show that activity recognition can be done using only radio signals at low transmit power levels with good accuracy. Lower power consumption and reduced form factor are desirable features for body networks and have been identified as being essential for wide adoption of body networks.

I. INTRODUCTION

ACTIVITY recognition via body sensor networks is used in the fields of sports [4][5], gaming [5], fitness [3], medical and elderly care [4]-[7]. Most of the approaches are dependent on accelerometers, gyroscopes and light sensors. These additional components add bulk to sensor node units and compete with the radio for scarce power resources. The form factor and energy challenges are important because the aesthetics and battery longevity of sensor networks are key determinants of wide spread adoption [5].

In this paper, we tackle both challenges by showing that activity recognition is theoretically possible using nothing more than a radio transmitter and receiver. No other components are necessary at the sensor nodes. We use on-body transmitter-receiver distances to generate path loss information as input to our Path Loss based Activity Recognition (PLAR) methodology to distinguish between varying activities. We are able to successfully classify a range of activities into six broad activity groups with two transmitters on the wrist and ankle and one receiver on the belly. We are also able to show that the PLAR method is feasible with common sensor hardware. The main contributions of this paper are:

- We are the first to show that the theoretic path losses experienced in the communication channel across the body can be used for activity recognition and explain the fundamental reasons for this.
- We propose a path loss based activity recognition method which is theoretically feasible with common sensor hardware and power constraints in use today.

The rest of the paper is organized as follows: first we take a look at related work and discuss the motivation for this paper in section II. Section III describes the PLAR methodology in detail and IV discusses our experimental results. In section V, we present discussion and future work and VI concludes the paper.

II. RELATED WORK AND MOTIVATION

In this section, we highlight current approaches to activity recognition in sub-section A. In sub-section B, we examine path loss in the communication channel around the human body.

A. BSN BASED ACTIVITY RECOGNITION

Most work in the area of activity recognition has focused on advanced sensing capabilities such as accelerometers, gyroscopes and light sensors [8]-[11]. Other creative solutions include [12] which adds a microphone and temperature sensors to the above mentioned. In [13], a micro-vibrational sensor is used in conjunction with an accelerometer while [14] measures the voltage between the body and the environment to passively detect human body motion. All the above solutions require additional components to sensor nodes or specialized hardware.

In [15], only radio wave properties are used to

*This work is supported in part by the NSF under the following grants: CNS-1253506 (CAREER) and CNS-1250180, Beijing Natural Science Foundation under Grant No.4144085, and China Scholarship Council fellowship program.

978-1-4799-6036-1/14 $31.00 © 2014 IEEE
DOI 10.1109/MASS.2014.58

perform activity recognition but with no underlying propagation model to explain results. Varying doppler signatures associated with different activities are used in [21]-[22] to perform classification but all require specialized transmitter/receiver hardware.

B. COMMUNICATION CHANNEL AND PATH LOSS AROUND THE HUMAN BODY

Much work has been done on characterizing the communication channel and path loss models around the human body for sensor networks operating in the 300 MHz to 30 GHz bands. In [2], it was determined that the energy from transmitted waves does not penetrate the human body for frequencies within the 2-6GHz range. The energy rather diffracts around the body and thus path losses are not related to direct LOS paths through the body but rather paths along the body. The path loss for the channel along the body has been modelled by [2] [16] [17] based on the following empirical power decay law.

$$P = P_0 + 10n \log_{10}(d/d_0) \qquad (1)$$

where n is the path loss exponent and P_0 is the path loss at reference distance d_o.

Suggested path loss exponent values are in the 3 – 7.5 range and the path loss at a reference distance of 0.1m ranges between 20.5dB and 60dB. Other methods for characterizing path loss include the IEEE 802.15.4 body network model [1] where the path loss is specified as

$$P = P_0 + \gamma(d - d_0) \qquad (2)$$

where γ is in dB/m and the reference distance is 0.1m.

It can be inferred from the above that path loss is heavily dependent on the distance between transmitter and receiver and the path loss exponent. Given the significant impact of the exponent on path loss (10dB per unit increase in path loss exponent), it is important to determine a path loss exponent that is most suitable for the on-body channel. This will be discussed in section III.

C. MOTIVATION

Human body movements are mostly facilitated by diarthrosis joints which allow a wide range of free movements. The major diarthrosis joints are the knee joint, the elbow joint, the shoulder joint, the waist joint, the wrist and the neck joint. Of these joints the knee joint, the waist joint, the elbow joint and the shoulder joint allow maximum displacement of the two body segments that they connect. Depending on the path loss model used, the range of on-body path losses around these joints from minimum to maximum displacement/extension around the joint is between 35dB and 160dB.

With sensors placed strategically to take advantage of the body's joint structure, the varying magnitudes of on-body path loss can be used to identify and classify different human activities. In the next section, we discuss the PLAR method in detail.

III. PATH LOSS BASED ACTIVITY RECOGNITION

The PLAR method has two stages: the training stage and the classification stage. The training stage has four steps: 1) data collection; 2) path loss calculation; 3) feature extraction; 4) Support Vector Machine (SVM) classifier training. The classification stage uses the trained SVM to perform classification on test data.

The first step in the training stage is to have the individual subjects perform the activities to be classified and measure on-body distance between transmitter and receiver. The distance data collected is an input in step 2, path loss calculation using equation (3). In step 3, statistical features of the path losses calculated such as differences from the max, mean and median are derived and the data set of statistical features is used in step 4 to train SVM classifiers. The classification stage involves using the trained SVM classifier on the set of data that was not used in training to perform activity classification.

$$P = 3.2*(10*\log_{10}(d))-9.3 \qquad (3)$$

where d is in cm.

As mentioned in section II, using an appropriate path loss exponent is critical to obtaining reasonable path loss values. Past research has set the path loss exponent for body networks from 3 [17] to 7.5 [2] which leads to as much as a 45dB difference in path loss for the same transmitter-receiver distance. Given this wide discrepancy, we decided to use the path loss model of the approach with the transmitter-receiver setup that was closest to ours. In [2] there was no actual transmitter or receiver used and for [16] and [17], the transmitter receiver placement was very different from our approach. In [18], Nachayev et al took on-body measurements with a sensor placement that was almost identical to ours: one receiver at the waist and transmitters on different parts of the body, including the wrists and shins. The path loss values they recorded were modelled by equation (3).

Equation (3) is used to model the path loss in our proposed method because of the similar sensor node deployment. Besides, other approaches had transmitter receiver placement mostly around the chest circling the torso and around the waist. The power decay works to our advantage as shorter transmitter-receiver distances have more pronounced path loss differences for each incremental distance unit while longer transmitter-receiver distances have less differentiation.

IV. EXPERIMENTAL RESULTS

We performed a set of experiments to validate the PLAR methodology proposed above with the goal of identifying groups of activities. We took on-body measurements from 8 individuals performing a defined set of activities: 3 females, F1 to F3, and 5 males, M1 to M5. The female participants had heights between 5ft 6in and 5ft 7in and weights between 145lbs and 175lbs. The male participants had heights between 6ft and 6ft 2in and weights between 160lbs and 270lbs.

A. ACTIVITY CLASSIFICATION

The goal of this experiment was to validate the PLAR method by classifying a number of activities into 6 broad activity groups: activities performed while **(i)/(ii)** standing/sitting with hands close to torso; **(iii)** standing with hands by the side, raised to the neck and face or stretched forward or backward around the shoulder joint; **(iv)** sitting with hands by the side, raised to the neck and face, below the knees but above the ankles or stretched forward or backward around the shoulder joint; **(v)** standing with hands held up; **(vi)** sitting with hands held up or touching ankles and feet. These are shown in Figure 1 below. The sensor locations chosen were the wrist on the right hand and the right ankle for transmitters and the abdomen on the belly button for the receiver. We defined the activity groups in this way to take advantage of both ankle and wrist transmitters: The ankle transmitter to differentiate between an individual standing vs. sitting and the wrist transmitter to identify the location of the hand.

1) Data collection and path loss: We used bands to mark the location of the transmitters and receiver and for each individual, measured the shortest distance around the body between the transmitters and the receiver while they performed the activities listed in table 1 below. We took two measurements per activity: One for the on-body distance between the wrist transmitter and the receiver and another for the on-body distance between the ankle transmitter and the receiver.

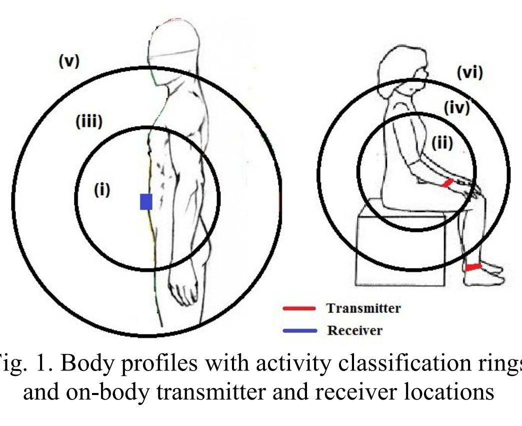

Fig. 1. Body profiles with activity classification rings and on-body transmitter and receiver locations

While taking measurements from some individuals, there was one activity, sitting with arms folded under the chest (#17 in Table 1 below), where the receiver was completely covered by a body part hence there was no path around the body between the transmitters and the receiver. There was no distance recorded in these cases.

#	Description	#	Description
1	Standing	14	Arms stretched forward
2	Walking1	15	Sitting
3	Walking2	16	Hands on knee
4	Arms folded	17	Arms folded under chest
5	Arms in pocket	18	legs crossed
6	Bicep curl1	19	Leg on table
7	Bicep curl2	20	Arms stretched on couch
8	Arms behind head	21	Hands behind head
9	Hands to face	22	Sleeping in chair
10	Praying hands	23	Hands on Table
11	Leaning against wall	24	Sleeping on Table
12	Quadriceps Stretch	25	Leg Stretch forward
13	Arms in the air	26	Legs tucked under seat

Table 1. 4-7,10 are in group (i), 15,17-19,22,25,26 are in group (ii), 1-3,9,11,12,14 are in group (iii), 16,23,24 are in group (iv), 8,13 are in group (v), 20,21 are in group (vi). 1-14 are performed standing while 15-26 are performed sitting

A couple of activities had periodic body motion, walking and performing a bicep curl. For these, we took two measurements to capture maximum displacement at both extremes of the periodic motion. The on-body distance measurements collected were used as inputs in the path loss equation (3).

2) Feature extraction and training

With the path loss values calculated for all individuals, we used the difference from the max, mean and median path losses per transmitter, per individual as statistical features for two SVMs; one for the wrist transmitter to determine the position of the hand and another for the ankle transmitter to distinguish between sitting and standing. We split the individuals into two groups, the training group (F1, M1, M2, M3) and the test group (F2, F3, M4, M5). The features from the training group were used to train the two linear SVMs.

3) Classification

We used the trained SVM classifiers on the test group features and combined the results from the wrist SVM and the ankle SVM to make classification decisions. We were able to achieve the following classification results in Table 2.

Accuracy (%)

F2	F3	M4	M5
68	60	64	69

Precision

%	F2	F3	M4	M5
i	57	44	38	57
ii	83	80	100	100
iii	67	67	60	71
iv	50	40	60	50
v	100	100	100	100
vi	100	100	100	100

Recall

%	F2	F3	M4	M5
i	80	80	60	80
ii	83	67	67	57
iii	57	29	43	71
iv	67	67	100	100
v	50	100	100	50
vi	50	50	50	50

Table 2. Classification performance by individual and activity group

B. PACKET LOSS AND PACKET DELIVERY RATES

The purpose of this experiment was to determine whether the PLAR method was feasible using commonly used sensor network hardware with a focus on packet loss and packet delivery rates. Thus far, we have assumed that data packets sent from the transmitter are received at the receiver. Data packets could however be lost and leave no way to decipher received signal strength and path loss. Receivers have sensitivity values and signals that arrive with strength below this sensitivity threshold are not picked up.

We calculated theoretical signal strength values for the experimental activities to determine what kind of packet delivery rates we would get using a commonly used transceiver for body networks, the CC2420. We assumed that the CC2420 was used in both the transmitters and the receiver. The CC2420 has the following important specs: transmit power between -54dB and -30dB and receiver sensitivity of -120dB. With a transmit power of -54dB, we calculated theoretical received power values for each individual and activity combination. We compared these values to the receiver sensitivity to see if data packets would be received or lost at the receiver. We found that the minimum received power for each individual would be at least 8dB above the receiver sensitivity.

While it is necessary to have a transmit power high enough to ensure that received power is above the receiver sensitivity, this does not guarantee that all packets sent will be received correctly at the receiver. Some packets will still be dropped at the receiver due to bit errors. Below, we analyze the relationship between transmit power, packet size and packet delivery rates. We aim to show that reasonable packet delivery can be achieved at low transmit power levels of sensor networks.

The CC2420 transceiver has sensitivity of -120dB, transmit power range of -54dB to -30dB and 20dB noise figure for a 250kbps transmit rate. With the transmit power known and noise figure at the receiver, we calculate Signal to Noise Ratio [19], Bit Error Rate, Packet Error Rate [17] and Packet Delivery Rate.

$$\text{Noise Pwr.} = k*T*Np*B \tag{4}$$

$$\text{SNR} = \text{Received power/Noise Pwr.} \tag{5}$$

$$\text{BER} = 0.5*\text{erfc}\,(\sqrt{SNR}\,) \tag{6}$$

$$\text{PER} = 1 - (1 - S)^{2m} \tag{7}$$

$$\text{PDR} = 1 - \text{PER} \tag{8}$$

where 'k' is Boltzmann's constant, 'T' is the temperature in Kelvin (we assumed room temperature 293K), 'Np' is the receiver noise figure, 'B' is the bandwidth in Hz, 'm' is the byte size of each packet and S is given below

$$S = \sum_{n=1}^{32} \binom{32}{n} BER^n (1 - BER)^{32-n} \times P_{se}(n) \tag{9}$$

$P_{se}(n)$ is the probability of symbol error when n chips are received in error. Table 3 below shows the probabilities of symbol error for given numbers of chip errors.

n	<=5	6	7	8	9	10	11	12	13	>= 14
Pse(n)	0.00	0.002	0.01	0.05	0.15	0.35	0.65	0.92	1.00	1

Table 3: Symbol Error Probabilities

We used the ankle transmitter data for individual M2 who had the weakest receive power values to calculate packet delivery rates. We did this for transmit power values spanning the transmit power range of the CC2420 and for varying packet sizes. We find that a transmit power of at least -48dB is required to achieve PDR > 50% for packet sized greater than 10bytes. This is within the CC2420 transmit power range and is on the low end of the range. Effective packet delivery thus, does not require very high transmit power level.

V. DISCUSSIONS AND FUTURE WORK

We are aware of the following limitations to the current approach: The transmitter and receiver are on only one limb. This is not too much of an issue for the legs as most activities/postures involving the legs have both legs at a similar displacement with respect to the waist. However, the hands, not required for balance, can be at very different locations making activity recognition difficult. More sensors could be added in future work to remedy this, but at the cost of increased complexity and hardware overhead. Another limitation is the small sample size over which conclusions were made. While we are confident in our findings, the sample size over which the data was taken was small. Although we used individuals with different heights and body types, data from a larger set of individuals could prove that the subset of individuals in our experiments does not represent the norm. In future, we hope to include a larger sample size of individuals.

Further work could be done on experimenting with other transmitter-receiver configurations. There are other configurations that could provide useful information about activity classification. For example, a transmitter/receiver on the bicep/wrist flexors; this would show the degree of extension of the hand around the elbow. While added transmitters and receivers come at the cost of more hardware computational complexity, it should be noted that as wearable devices become more popular, they can be leveraged as part of a body network system rather than having to incorporate new hardware. These could add more advanced classification abilities using PLAR.

VI. CONCLUSION

We have demonstrated that it is theoretically possible to perform activity recognition using only path loss information from radio communication. We proposed the PLAR method which takes advantage of the human body joint structure and showed that with the appropriate transmit power level, communication channels with high packet delivery rates can be established between on-body transmitters and receivers while an individual is performing various activities. The path losses associated with those activities can differ enough to allow for activity recognition.

REFERENCES

[1] Molisch, Andreas F., et al. "IEEE 802.15. 4a channel model-final report." *IEEE P802* 15.04 (2004): 0662.

[2] Fort, Andrew, et al. "Ultra wide-band body area channel model." *Communications, 2005. ICC 2005. 2005 IEEE International Conference on*. Vol. 4. IEEE, 2005.

[3] Albinali, Fahd, et al. "Using wearable activity type detection to improve physical activity energy expenditure estimation." *Proceedings of the 12th ACM international conference on Ubiquitous computing*. ACM, 2010: pp. 311-320.

[4] Yang, Guang-Zhong, and Magdi Yacoub. "Body sensor networks." (2006): 500. pp. 62-76

[5] Hanson, Mark A., et al. "Body area sensor networks: Challenges and opportunities." *Computer* 42.1 (2009): pp. 58-65.

[6] Chipara, Octav, et al. "Reliable clinical monitoring using wireless sensor networks: experiences in a step-down hospital unit." *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*. ACM, 2010:. pp. 155-168.

[7] Tessendorf, Bernd, et al. "Recognition of hearing needs from body and eye movements to improve hearing instruments." *Pervasive Computing*. Springer Berlin Heidelberg, 2011: pp. 314-331.

[8] L. Bao and S. S. Intille. Activity Recognition from User-Annotated Acceleration Data. In A. Ferscha and F. Mattern, editors, Pervasive, volume 3001 of Lecture Notes in Computer *Science*, pp. 1–17. Springer, 2004.

[9] Maurer, Uwe, et al. "Activity recognition and monitoring using multiple sensors on different body positions." *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on*. IEEE, 2006.

[10] Bharatula, Nagendra Bhargava, et al. "Power and size optimized multi-sensor context recognition platform." *Wearable Computers, 2005. Proceedings. Ninth IEEE International Symposium on*. IEEE, 2005: pp. 194-195.

[11] Liang Wang, Tao Gu, Xianping Tao, Jian Lu, A hierarchical approach to real-time activity recognition in body sensor networks, Pervasive and Mobile Computing, Volume 8, Issue 1, February 2012: pp. 115-130.

[12] Keally, Matthew, et al. "Pbn: towards practical activity recognition using smartphone-based body sensor networks." *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*. ACM, 2011: pp. 246-259.

[13] Gordon, Dawud, et al. "A novel micro-vibration sensor for activity recognition: Potential and limitations." *Wearable Computers (ISWC), 2010 International Symposium on*. IEEE, 2010.

[14] Cohn, Gabe, et al. "An ultra-low-power human body motion sensor using static electric field sensing." *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM, 2012: pp. 99-102.

[15] Qi, Xin, et al. "Radiosense: Exploiting wireless communication patterns for body sensor network activity recognition." *Real-Time Systems Symposium (RTSS), 2012 IEEE 33rd*. IEEE, 2012.

[16] Fort, Andrew, et al. "Ultra-wideband channel model for communication around the human body." *Selected Areas in Communications, IEEE Journal on* 24.4 (2006): pp. 927-933.

[17] Reusens, Elisabeth, et al. "On-body measurements and characterization of wireless communication channel for arm and torso of human." *4th international workshop on wearable and implantable body sensor networks (BSN 2007)*. Springer Berlin Heidelberg, 2007.

[18] Nechayev, Yuriy I., et al. "On-body path gain variations with changing body posture and antenna position." *Antennas and Propagation Society International Symposium*. Vol. 1. 2005.

[19] S. Haykin, M. Moher, *Modern Wireless Communications*. New Jersey: Pearson Prentice Hall, 2003: p. 67.

[20] Goyal, Mukul, et al. "Evaluating the impact of signal to noise ratio on IEEE 802.15. 4 PHY-level packet loss rate." Network-Based Information Systems (NBiS), 2010 13th International Conference on. IEEE, 2010.

[21] Pu, Qifan, et al. "Whole-home gesture recognition using wireless signals." Proceedings of the 19th annual international conference on Mobile computing & networking. ACM, 2013: pp. 27-38.

[22] Bjorklund, S., et al. "Millimeter-wave radar micro-Doppler signatures of human motion." Radar Symposium (IRS), 2011 Proceedings International. IEEE, 2011: pp. 167-174.