AIR: Recognizing Activity through IR-Based Distance Sensing on Feet

Xinlong Jiang
Institute of Computing Technology, CAS, Beijing, China;
University of Chinese Academy of Sciences, Beijing, China;
University of California Irvine
Irvine, CA 92697, USA;
Beijing Key Laboratory of Mobile Computing and Pervasive Device, Beijing, China
jiangxinlong@ict.ac.cn

Yiqiang Chen
Institute of Computing Technology, CAS, Beijing, China
yqchen@ict.ac.cn

Junfa Liu
Institute of Computing Technology, CAS, Beijing, China
liujunfa@ict.ac.cn

Gillian R. Hayes
University of California Irvine
Irvine, CA 92697, USA
gillianrh@ics.uci.edu

Lisha Hu
Institute of Computing Technology, CAS, Beijing, China
hulisha@ict.ac.cn

Jianfei Shen
Institute of Computing Technology, CAS, Beijing, China
shenjianfei@ict.ac.cn

Ubicomp/ISWC'16 Adjunct, September 12-16, 2016, Heidelberg, Germany
ACM 978-1-4503-4462-3/16/09.
http://dx.doi.org/10.1145/2968219.2971447

Abstract
In this paper, we describe the results of a controlled experiment measuring everyday movement activity through a novel recognition prototype named AIR. AIR measures distance from the feet using infrared (IR) sensors. We tested this approach for recognizing six prevalent activities: standing stationary, walking, running, walking in place, going upstairs, and going downstairs and compared results to other commonly used approaches. Our results show that AIR obtains much higher accuracy in recognizing activity than approaches that rely primarily on accelerometers. Moreover, AIR has good generalization ability when applying recognition model to new users.

Author Keywords
Activity Recognition; Infrared Sensor; Wearable System

ACM Classification Keywords
H.5.m. Information Systems: Information Interfaces and Presentation—Miscellaneous

Introduction
Activity recognition can be used for a variety of applications in the ubicomp space and beyond [1,2]. Applications in this space include transportation [3], smart homes [4,5], assisted living [6,7,8], fitness [9]

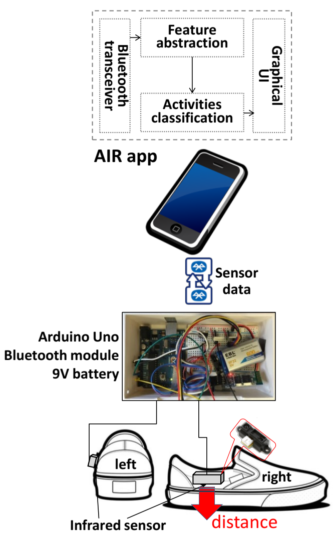

Figure 1. System architecture of AIR.

and more. A variety of approaches have been used, each with their own challenges [10].

Increasingly, wearable devices (smartphone, band, etc.) equipped with a rich set of sensors have enabled simple mobile activity recognition [11,12]. However, these approaches still suffer from limited reliability for certain activities. To address these challenges, we developed AIR, an Activity recognition system that relies on IR sensors attached to the outer side of shoes. IR sensor measures the distance from the feet to its nearest object (most often the floor) and can achieve higher accuracy than approaches that rely primarily on accelerometers and gyroscopes. In this paper, we describe the results of experiments to measure the accuracy of AIR compared to these other methods, noting that for applications for which very high accuracy is required, AIR may be an appropriate alternative to existing off the shelf products.

AIR System

The AIR system records and classifies user activities through IR sensors on the shoes and a mobile phone based classifier (see Figure 1). Specifically, AIR uses infrared sensors (SHARP GP2Y0A41SK0F) connected to an Arduino Uno board. These sensors measure distances 50 times per second and transfer data to the mobile device via Bluetooth nearly continuously. The recognizer, on the smartphone, includes: a feature abstraction module, a daily activities classification module, and a graphical user interface.

The AIR system segments the data using a two-second sliding window with 50% overlap, producing a data vector $\boldsymbol{d}_t = \{d_1, \dots, d_L\}$ at time t, L is the window length. Then eight time-domain features and eleven frequency-domain features are extracted and normalized for training and classification. The time domain features include the mean value, standard deviation, the maximum, the minimum, the first quartile, the second quartile, the third quartile and the number of mean crosses. The frequency domain features include the first ten Fast Fourier Transform (FFT) coefficients and spectral energy. Based on a specific classification algorithm, a classification model is trained. In testing process, unlabeled feature vectors are sent to the model, and the classification results are obtained.

Experimental Validation

To verify the feasibility of our approach, we conducted experiments to compare it with existing motion sensors based methods. Four participants (one woman and three men) were involved in our experiments. Each of them wore AIR on the outer side of shoes, wore a Microsoft Band on the wrist, wore another Microsoft Band on foot, and carried a smartphone in the front pocket while performing six pre-defined activities (see Figure 2). Using both the smartphone and band, we collected the accelerometer and gyroscope data, and then we segment the data using a two-second sliding window with 50% overlap. In each window, we first get composed value of 3 axis $\left\{c_i = \sqrt{x_i^2 + y_i^2 + z_i^2} \,\middle|\, i = 1,2,\dots,L\right\}$, L is the window length, and then use equation (1) to get the calibrated values. After that, the same eight time-domain and eleven frequency-domain features as for AIR are extracted.

$$c_i' = c_i - \frac{1}{L}\sum_{i=1}^{L} c_i \qquad (1)$$

Classified as -->	a	b	c	d	e	f	Recall
a=walking	781	2	2	0	0	0	.995
b=downstair	45	376	5	0	0	1	.881
c=upstair	33	6	415	1	0	1	.910
d=running	1	0	6	522	0	0	.987
e=stationary	0	0	0	0	621	1	.998
f=walk in place	1	0	1	0	0	551	.996
Precision	.907	.979	.967	.998	1	.995	

(a)

Classified as -->	a	b	c	d	e	f	Recall
a=walking	780	4	1	0	0	0	.994
b=downstair	70	342	4	0	0	11	.801
c=upstair	42	4	399	3	1	7	.875
d=running	0	0	10	519	0	0	.981
e=stationary	0	0	0	0	622	0	1
f=walk in place	7	0	5	0	0	541	.978
Precision	.868	.977	.952	.994	.998	.968	

(b)

Classified as -->	a	b	c	d	e	f	Recall
a=walking	565	32	23	1	0	2	.907
b=downstair	167	222	19	1	0	6	.535
c=upstair	69	10	351	0	0	30	.763
d=running	4	3	0	521	0	3	.981
e=stationary	0	0	0	0	631	2	.997
f=walk in place	0	2	20	0	0	585	.964
Precision	.702	.825	.850	.996	1	.932	

(c)

Classified as -->	a	b	c	d	e	f	Recall
a=walking	744	5	11	0	0	15	.960
b=downstair	36	354	6	5	0	16	.849
c=upstair	135	5	271	0	0	33	.610
d=running	0	1	0	510	0	0	.998
e=stationary	1	0	2	1	557	0	.993
f=walk in place	37	2	15	7	2	481	.884
Precision	.781	.965	.889	.975	.996	.883	

(d)

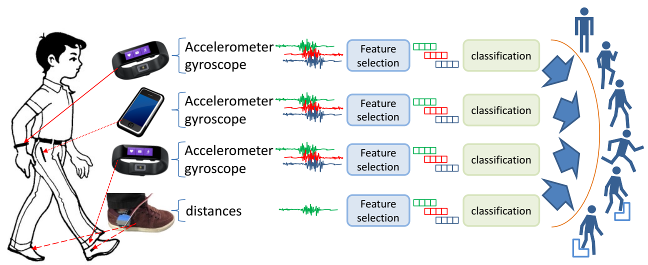

Figure 2. Comparison experiments of AIR and three motion sensors based activity recognition methods.

We used 10-folds Cross Validation Tests (CVT) to evaluate the performance of AIR system and three motion sensors based methods. We compared five classification algorithms using the Weka tookit [13], including Bayes Network (BN), Decision Tree (DT), Nearest Neighbor (NN), Multi-Layer Perceptron (MLP), Lib-Support Vector Machine (SVM) using the default parameters (see Table 1).

	Precision / Recall (%)				
	AIR		Motion Sensors (MS)		
	2 Feet	1 Foot	Foot	Wrist	Pocket
BN	92.2 91.8	91.0 90.6	89.4 89.4	82.2 82.4	88.8 88.7
DT	94.4 94.4	93.5 93.5	88.7 88.7	85.3 85.3	88.7 88.8
NN	95.9 95.8	95.6 95.5	83.1 83.2	83.1 83.1	91.2 91.1
MLP	96.3 96.2	94.9 94.8	85.7 85.6	87.0 86.9	91.7 91.5
SVM	96.2 95.9	95.3 95.0	88.7 87.9	90.4 89.7	89.6 89.0

Table 1. CVT classification results of five classifiers

Results from Table 1 indicate that all the five classifiers can achieve higher precision and recall with AIR than with traditional motion sensors based approaches, which can be explained as distance features are more reliable than motion features. Additionally, we find if we deployed AIR on both two feet, we can further improve the classification accuracy than AIR on one foot. And these results are consistent across most of the classifiers with SVM performing best on average.

In details, the confusion matrices for our experiments (see Figure 3) indicate that motion sensor approaches on both the foot and wrist struggle to classify stairs separately from walking (see Figure 3c and 3d). On the other hand, the pocket-held motion sensors tend to over classify activities as running, and also cannot classify going up and downstairs well (see Figure 3e). However, AIR 1 Foot can effectively reduce the misclassification of walking and stairs (see Figure 3b). And AIR 2 Feet further improved the classification ability of model (see Figure 3a).

To test AIR's generalization ability when using it without training on a specific person, we also tested the same empirical data using a Leave-One-Out (LOO) test with SVM (see Figure 4). The results of this test indicate that AIR performs much better without specific training than methods based on motion sensors in both precision and recall. AIR 2 Feet can achieve 95.0%~97.3% precision and 94.5%~97.1% recall for all four users. In addition, for three motion sensors based methods, data obtaining from foot performs the best, further indicating that the foot may be the best body position for this type of activity recognition.

Conclusion

In this paper, we described a novel IR-based activity recognition system named AIR, which can accurately

Classified as -->	a	b	c	d	e	f	Recall
a=walking	702	19	29	29	0	5	.895
b=downstair	64	295	12	52	0	2	.694
c=upstair	37	8	297	24	1	10	.788
d=running	3	2	0	530	0	0	.991
e=stationary	0	0	0	9	590	0	.985
f=walk in place	10	2	8	34	0	498	.902
Precision	.860	.905	.858	.782	.998	.967	

(e)

Figure 3. Confusion matrix of (a) AIR 2 feet; (b) AIR 1 foot; (c) MS on foot; (d) MS on wrist and (e) MS in pocket with SVM algorithm.

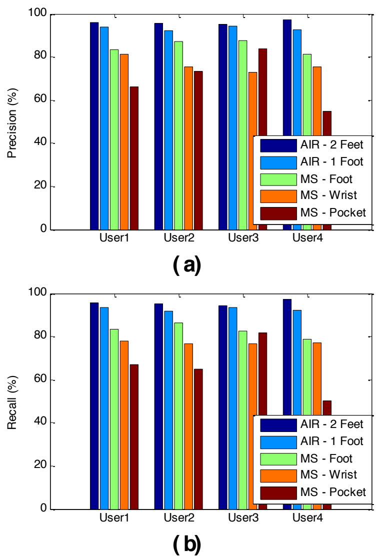

Figure 4. LOO test results of four participants with SVM algorithm.

classify six prevalent daily activities using two infrared sensors attached on the outer side of shoes. The results of experiments with four users indicate that AIR may be more accurate in detecting these types of activities than commonly used approaches that rely on motion sensing. And AIR has good generalization ability when applying to new users. Additional work is needed to understand which situations and applications might require this level of precision. Additionally, we must repeat this experiment with a larger set of test subjects to verify that these differences are significant and reliable across a large population.

Acknowledgements
This work is supported in part by Natural Science Foundation of China (NSFC) under Grant No.61572471, Beijing Municipal Science & Technology Commission No.Z161100000216140, Science and Technology Planning Project of Guangdong Province, China, under Grant No.2015B010105001, and Research Foundation of Ministry of Education and China Mobile No.MCM20150401.

References
1. Bao L, Intille SS. Activity recognition from user-annotated acceleration data. In Pervasive computing 2004 Apr 21 (pp. 1-17). Springer Berlin Heidelberg.
2. Chen Z., et al. Inferring social contextual behavior from bluetooth traces, UbiComp2013: 267-270
3. Liao Lin, et al. "Learning and inferring transportation routines." Artificial Intelligence 171.5 (2007): 311-331.
4. Tapia EM, Intille SS, Larson K. Activity recognition in the home using simple and ubiquitous sensors. Springer Berlin Heidelberg; 2004 Apr 21.
5. Van Kasteren, Tim, et al. "Accurate activity recognition in a home setting." Proceedings of the 10th international conference on Ubiquitous computing. ACM, 2008.
6. Fogarty J, et al. Sensing from the basement: a feasibility study of unobtrusive and low-cost home activity recognition. In Proceedings of the 19th annual ACM symposium on User interface software and technology 2006 Oct 15 (pp. 91-100). ACM.
7. Philipose, Matthai, et al. "Inferring activities from interactions with objects." Pervasive Computing, IEEE 3.4 (2004): 50-57.
8. Chen Z., et al. Unobtrusive sleep monitoring using smartphones, PervasiveHealth 2013: 145-152
9. Kranz, Matthias, et al. "The mobile fitness coach: Towards individualized skill assessment using personalized mobile devices." Pervasive and Mobile Computing 9.2 (2013): 203-215.
10. Brush, A., et al. "Activity recognition research: The good, the bad, and the future." Proceedings of the Pervasive 2010 Workshop on How to do Good Research in Activity Recognition, Helsinki, Finland. Vol. 1720.
11. Choudhury, et al. "The mobile sensing platform: An embedded activity recognition system." Pervasive Computing, IEEE 7.2 (2008): 32-41.
12. Incel, O. D., Kose, M., & Ersoy, C. (2013). A review and taxonomy of activity recognition on mobile phones. BioNanoScience, 3(2), 145-171.
13. Weka toolkit, http://www.cs.waikato.ac.nz/ml/weka