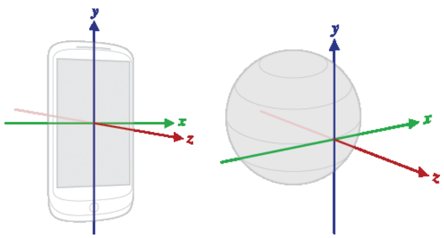

Figure 1: Phone and Earth Coordinate System [8]

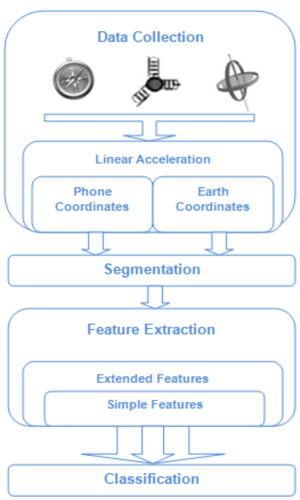

Figure 2: Activity Recognition Block

any other acceleration (the device is stationary or moves with constant speed), the accelerometer measures the gravity acceleration that points toward the center of the Earth, so with this information the tilt angles pitch and roll can be determined. Also, the magnetic field sensor provides the magnetic vector in the three axes of the device's coordinate system in orthogonal directions. This sensor could be utilized to derive the device's azimuth angle. With the fusion of the data from the accelerometer and the magnetic field sensor, it is possible to detect the orientation of device. But this combination has some drawbacks like noisy output from accelerometer or low response time and inaccurate readings from the magnetic field sensor. In order to overcome these limitations, the gyroscope was integrated into the system. The gyroscope has high response time and provides smooth outputs but its frailness comes from the fact that it drifts over time. The gyroscope provides rotation speeds relative to the phone's own coordinate system and this data can be used to correct errors caused by the accelerometer and the magnetic field sensor. With the fusion of these sensors, using the rotation vector which contains the rotation angles along each axis, it is possible to calculate the orientation of the phone. So, the gravitational force affecting on each axis of the accelerometer can be excluded and pure accelerometer values (linear acceleration) can be obtained.

The magnetic field sensor can also be utilized as the compass to convert the acceleration output of the smart phone from its body frame of reference to the earth frame of reference. If all acceleration outputs are generated according to a single reference point, similar measurements can be observed for the same set of activities regardless of the orientation of the phone. As illustrated in Figure 1, using the magnetic field vector, the coordinate system of the phone could be converted to the earth magnetic coordinate system [8]. So fused sensor system generates the same acceleration output independent of orientation of the phone during the motion.

Figure 2 shows the block diagram of activity recognition steps. In the data collection step, embedded sensors are used to compute gravity component in order to obtain dynamic acceleration value. This value can either be read in phone coordinate system or converted into earth coordinate system with the help of magnetic field sensor. Afterwards, time and frequency domain features are calculated for each segment of the data. In the final step, the classifier algorithm is used for the recognition of activities.

III. Performance Evaluation

In this section, we explain the performance of the activity recognition process explained in Section II. First, we present the experiment set up and the system parameters, and next, we will present the results and improvements in each section.

a. Android Application

Before starting the experiments, in order to collect the movement data from the subjects, an Android application is developed which gathers data from the embedded accelerometer, gyroscope and magnetic field sensors of the smart phone. Since it is a user-friendly application and it does not require any expertise to use, before performing the activity, user selects the ground truth label from the list, and then puts the phone into the pocket and performs the activity.

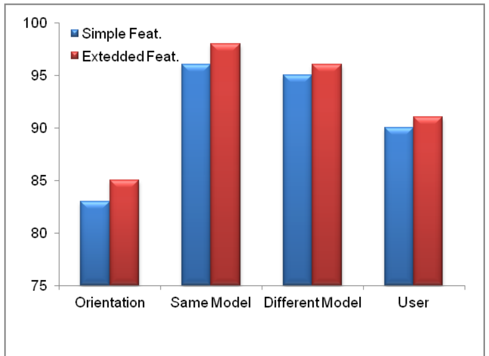

Figure 3: Recognition rates using simple and extended feature sets.

b. Experiment Scenarios

The experiments were performed in two batches. In the first stage, recognition accuracy of the system was measured by different dependency conditions, such as orientation, device and user dependency, using only the accelerometer sensor. In the second stage, acceleration readings are isolated from the gravitational force and the linear acceleration data was obtained by enabling the use of the gyroscope and the magnetic field sensor which made it possible to convert the phone coordinate system to the earth coordinate system. Hence, the same tests were performed again with the same set of subjects to collect linear acceleration readings both in the phone and earth coordinate systems together. In order to detect the body movements of a subject, pockets of the trousers are selected as the most suitable place to carry the phone, as in most of the previous work [1-3, 7]. In the experiments, tests were performed to measure the orientation, device and user dependency of the activity recognition system. Hence, we had 4 different test cases performed by each individual:

- **Orientation tests:** carry the same phone in vertical/horizontal orientations to investigate orientation dependency
- **Device tests:** carry the same model phones (Device A/B) in the same pocket to find the effect of the device difference, i.e. calibration, on recognition accuracy
- **Device-model tests:** carry different model phones (Model X/Y) in the same pocket to measure the effect of the phone model
- **User tests:** all participants carry the same device to evaluate the user dependency.

In the data collection stage, 16 male and 4 female, total of 20 healthy participants between the ages 18 and 59 were asked to perform five locomotion activities. All participants were wearing trousers and phones were placed into their pockets before performing each activity. All activities were performed for 3 minutes and a total 15 minutes of movement data was collected from every participant in each step of the experiments. Two Samsung Galaxy W and one Samsung Galaxy S3 model smart phones were used. In the orientation experiments, first, participants were asked to perform the given activities while the phone was placed vertically in their pockets whereas in the second step phone was placed horizontally. In the device dependency experiments, first, subjects were asked to carry the same model devices in the same pocket and then different models while they were performing the related activities again. Finally in the user dependency experiments, the data was collected from different participants by carrying the same device.

In the classification phase, collected data from all individuals was evaluated separately and classification results were calculated on a subject basis. In the orientation dependency tests, while the data collected in one orientation was given as the training set, the data coming in the other orientation was used as the test data in the classifier. Again in the device dependency test, the data collected in one device was used as the test set and the data collected with the other device as the training set. In the user dependency tests, the leave-one-out approach was used. The collected data was processed offline: first,

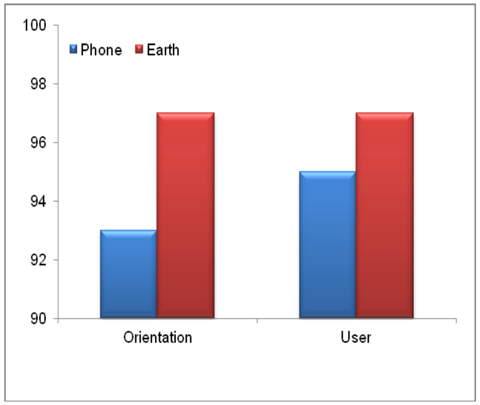

Figure 4: Recognition rates using linear acceleration according to different coordinate systems

the features are extracted from the raw data and then the classification was applied using the KNN classifier available in the Matlab statistics toolbox.

c. Activity Recognition with Simple Features

In the first attempt, the recognition accuracy of the system was measured using the simple time domain features. The mean, the variance and the standard deviation of each window were calculated using the magnitude of the accelerometer axes and also each of the axes separately. As a result, a feature vector with a length of 12 was obtained. This feature vector was reduced to 3 features that are the variance, the standard deviation of the magnitude and the mean of Z-axis. This reduction was performed by selecting the features which improve the recognition rates most using the sequential-forward selection. In Figure 3, we see that when the same model phones are carried in the same pocket, 96% accuracy can be achieved while it is 95% if the phone model is different. Also in the user dependency tests 91% accuracy was achieved. However, the accuracy in the orientation test was lower compared to the other tests, resulting in a 83% recognition rate.

d. Activity Recognition with Extended Features

In order to improve the overall performance of the system, we expanded the feature set with the frequency domain features described in Section II-a. In Figure 3, we observe that using more sophisticated frequency domain features improves the classification by 1-2% in all cases. As these results suggest, we can achieve acceptable accuracy results with different devices, models and users. However, when the orientation of the phone changes, the accuracies decrease. Hence, in the next step, we focused on how to improve the accuracy for the cases with different orientations of the phones. Also Table 1 shows that mostly there is a misclassification between periodic activities such as walking, biking and running and stationary activities such as sitting and standing.

		Classification				
		Running	**Standing**	**Biking**	**Sitting**	**Walking**
Truth	**Running**	82.9%	1.3%	8.5%	2.6%	4.7%
	Standing	0.5%	87.2%	1.5%	9.3%	1.5%
	Biking	4.5%	2.1%	83.3%	1.2%	8.9%
	Sitting	0.6%	8.9%	0.5%	89.1%	0.9%
	Walking	5.6%	1.2%	8.6%	0.5%	84.1%

Table 1: Confusion matrix of orientation tests using only accelerometer with extended feature set

e. Activity Recognition with Linear Acceleration

After expanding the feature set with frequency domain features, we still encountered results with low accuracy in the orientation tests. The orientation of a phone can be recognized by fusing sensor data from the accelerometer, the gyroscope and the magnetic field sensor, hence, the gravity component on each axis can be isolated to obtain the linear acceleration values. In order to measure the effect of the linear acceleration on the recognition rates, new tests are performed with 20 different participants again. In these tests, the linear acceleration data referenced by the phone and earth coordinate systems were collected at the same time. Only the extended feature set is used in the classification since it provided better results in the previous tests.

		Classification				
		Running	Standing	Biking	Sitting	Walking
Truth	Running	93.5%	0.1%	4.5%	0.2%	1.7%
	Standing	0.1%	97.2%	0.1%	2.3%	0.3%
	Biking	5.4%	0.3%	87.3%	0.1%	6.9%
	Sitting	0.2%	3.4%	0.1%	96.1%	0.2%
	Walking	1.2%	0.1%	5.4%	0.2%	93.1%

Table 2: Confusion matrix of orientation tests using linear acceleration with phone coordinate system

As illustrated in Figure 4, in the orientation tests the recognition accuracy increased to 93% with the new dataset using the linear acceleration values when the phone coordinate system was selected as the reference. Also in the user-dependency tests, the recognition accuracy increased to 95%. Confusion matrix in Table 2 shows that the recognition rate of biking activity is still below the acceptable values. It is mostly confused with walking and running according to speed of pedaling.

		Classification				
		Running	Standing	Biking	Sitting	Walking
Truth	Running	97.5%	0.1%	1.4%	0.2%	0.8%
	Standing	0.1%	97.4%	0.3%	2.1%	0.1%
	Biking	2.9%	0.1%	95.2%	0.2%	1.6%
	Sitting	0.3%	2.3%	0.1%	97.1%	0.2%
	Walking	0.9%	0.1%	1.9%	0.2%	96.9%

Table 3: Confusion matrix of orientation tests using linear acceleration with earth coordinate system

Before the design decision of fusing the accelerometer, the gyroscope and the magnetic field sensors, we expected that if the movement of the smart phone could be measured according to a single reference system, the orientation in the pocket would lose its meaning. So we converted the linear acceleration readings from the phone coordinate system to the earth coordinate system. Figure 4 confirms our assumption that results of the orientation dependent tests boosted up to 97%. Also similar increase is visible in the user dependency tests with 97% accuracy. Also Table 3 shows that, there is a significant increase in the recognition accuracy of biking activity compared to results obtained using phone coordinate system.

IV. Discussion and Conclusion

In this paper, we focused on the challenges of practical activity recognition on smart phones. We specifically focused on the challenges arising from the differences in user behaviors and device, model differences as well as the burden of the training phase when using statistical machine learning algorithms in the classification of activities. Using the accelerometer, the magnetic field sensor and the gyroscope on the phones, we explored the recognition of simple locomotion activities in a device, user and orientation-independent way. With the experiments, performed with 20 users, we showed that although the accuracies are quite high in user and device dependency test, the difference in the orientation of the phone decreases the accuracy. To improve this, we proposed to use the linear acceleration, excluding the effect of gravitational force using the earth coordinates with the help of the gyroscope and the magnetic sensor. With this modification, we showed that the accuracy results increased remarkably. As a future work, we will investigate the impact of the device position, i.e., where the phone is carried, such as in the pocket or in the bag, on the performance. Also, we will investigate the effect of using multiple sensors on the energy consumption of the mobile phones.

Acknowledgements

This work is supported partially by the Bogazici University Research Fund under the grant numbers 11A01P7 and 11A01D4, and by the Galatasaray University Research Fund under the grant number 13.401.002.

References

[1] Incel, O.D., Kose, M., Ersoy, C, A Review and Taxonomy of Activity Recognition on Mobile Phones, Springer BioNanoScience Journal, Volume 3, Issue 2 (2013), Page 145-171, 2013.

[2] Reddy, S., Mun, M., Burke, J., Estrin, D., Hansen, M., Srivastava, M.: Using mobile phones to determine transportation modes. ACM Trans. Sen. Netw. 6(2), 1–27 (2010)

[3] Siirtola, P., Roning, J.: Recognizing human activities user-independently on smartphones based on accelerometer data. International Journal of Interactive Multimedia and Artificial Intelligence 1(5), 38{45} (2012)

[4] Lane, N.D., Xu, Y., Lu, H., Hu, S., Choudhury, T., Campbell, A.T., Zhao, F.: Enabling large-scale human activity inference on smartphones using community similarity networks (csn). In: Proceedings of UbiComp '11, pp. 355–364. ACM, USA (2011)

[5] Jun-geun Park Ami Patel, D.C.J.L.S.T.: Online pose classification and walking speed estimation using handheld devices. In: Proceedings of UbiComp 2012, pp. 113–122 (2012)

[6] Lane, N., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., Campbell, A.: A survey of mobile phone sensing. Communications Magazine, IEEE 48(9), 140 –150 (2010)

[7] Kose, M., Incel, O.D., Ersoy, C.: Online human activity recognition on smart phones. In: Workshop on Mobile Sensing: From Smartphones and Wearables to Big Data, pp. 11-15., (2012).

[8] Sensor Manager Tutorial, http://developer.android.com, 2013.

[9] Blanke, U., & Schiele, B.: Sensing location in the pocket. Ubicomp Poster Session, 2008.

[10] Yang, Jun.: Toward physical activity diary: motion recognition using simple acceleration features with mobile phones. Proceedings of the 1st international workshop on Interactive multimedia for consumer electronics. ACM, 2009.