Actitracker: A Smartphone-based Activity Recognition System for Improving Health and Well-Being

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Abstract—**Actitracker is a smartphone-based activity-monitoring service to help people ensure they receive sufficient activity to maintain proper health. This free service allowed people to set personal activity goals and monitor their progress toward these goals. Actitracker uses machine learning methods to recognize a user's activities. It initially employs a "universal" model generated from labeled activity data from a panel of users, but will automatically shift to a much more accurate personalized model once a user completes a simple training phase. Detailed activity reports and statistics are maintained and provided to the user. Actitracker is a research-based system that began in 2011, before fitness trackers like Fitbit were popular, and was deployed for public use from 2012 until 2015, during which period it had 1,000 registered users. This paper describes the Actitracker system, its use of machine learning, and user experiences. While activity recognition has now entered the mainstream, this paper provides insights into applied activity recognition, something that commercial companies rarely share.**

Keywords— Activity recognition, sensors, smartphones, data mining, health, mobile health, fitness.

I. INTRODUCTION

A lack of adequate physical activity is an enormous problem in our society, because physical inactivity dramatically increases the health risks for many diseases, including cardiovascular disease [3, 11, 14], colon cancer [4], diabetes mellitus, hypertension, and osteoporosis [16]. According to the World Health Organization, inactivity is responsible for approximately two million deaths per year [13], while a healthy amount of physical activity has been shown to significantly reduce the risk of all-cause mortality [1, 12]. Inactivity is also associated with health-related societal problems like childhood obesity [6] and impacts the ability of the elderly to live independently. The good news is that according to a report from the US Surgeon General, even moderate amounts of exercise can substantially improve one's health [17]. Activity recognition technology can address the problems associated with inactivity by providing people with accurate information about their activities. In this paper we describe Actitracker, a smartphone-based activity monitoring service, which learns highly accurate personalized activity models. Actitracker was deployed for public use from 2012 to 2015.

The fitness market currently offers many activity tracking products, such as the Fitbit (www.fitbit.com), but such products require the purchase of specialized hardware and were not very popular at the time our smartphone-based service was first deployed. Commercial activity recognition apps now are available for smartphones, but these are often not very accurate, the applications are proprietary, and the data, algorithms, and results are not publically released. Hence, these applications are of limited usefulness to researchers. Smartwatches have recently entered the market and also support activity recognition, but these additional devices are also expensive, are far from ubiquitous, and also rely on proprietary apps. Actitracker's algorithms and performance results, on the other hand, are described in detail in our prior work [7,10] and the activity data is also published [20] so that it can be used by the research community. These algorithms are also used to generate highly accurate personalized models [10], which far outperform the default universal models. Currently most commercial products want to retain control over their data and even limit the ability of users to access their own data; such products typically only allow the exporting of high level results. Activity data, if made public, can provide useful health information, by helping us to understand and measure activity levels over time, by season, by region, and by demographic factors such as age, profession, and weight.

Prior work describing Actitracker's algorithms and activity recognition performance [7, 10] focused entirely on highly structured settings, where users were directed to perform specific tasks at specific times. This prior work also did not describe the overall system or the user interface component, including the activity reports. This is also the first paper to describe user experiences with the complete system in a fully naturalistic setting. Although Actitracker was developed in a university research lab, it was designed to mimic a commercial service. This was to remedy criticism with prior research on activity recognition, which noted that such systems are not evaluated in natural settings and are usually terminated before they gain real users. To help ensure that Actitracker gained some real users, thousands of hours were spent to implement a system that was easy to use. Actitracker was only promoted by research articles and word of mouth, which explains why the service only attracted a modest user base of about 1,000 registered users. But this user base was sufficient to provide an assessment of the strengths and weaknesses of the tool.
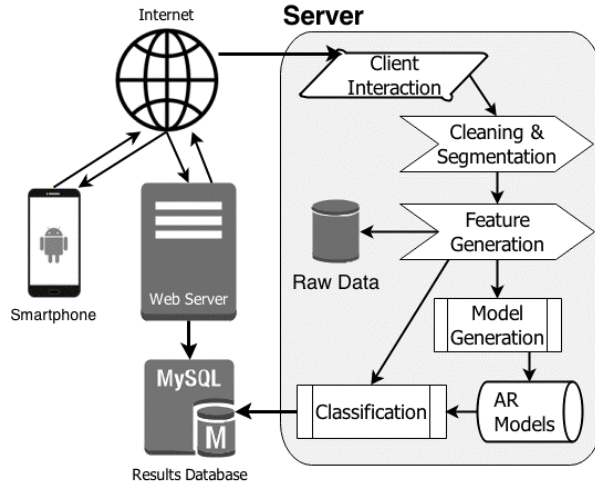
Fig. 1. Actitracker System Architecture

II. System Architecture

Actitracker utilizes a client-server model to perform activity monitoring. A high level view of the basic Actitracker system architecture is provided in Fig. 1, which shows the major system components. The client runs on the smartphone and transmits sensor data to the Acitracker server for processing. The server performs data cleaning and preprocessing steps and then transforms the low level time-series accelerometer data into examples, where each example contains high level features that describe 10-seconds of activity [7, 10]. The transformed data is then passed to a classification model that assigns an activity for each 10 seconds of data. Actitracker identifies five activities: *walking*, *jogging*, *stairs* (up or down), *standing*, and *sitting/lying down*. Sitting and lying down are combined because it is difficult to distinguish these two activities from a smartphone positioned in one's pocket.

If the user has provided sufficient training data through the Actitracker self-training process, then a personalized activity recognition model is applied; otherwise a universal (impersonal) classification model is applied. The results are stored in a database, and detailed reports can subsequently be displayed either on the user's phone or via a secure Actitracker web account. The details of the system components are described in the next few sections: the smartphone client is described in Section III, the user interface is described in Section IV, and the machine learning components that implement activity recognition are described in Section V.

The high level system architecture shown in Fig. 1 involves several important design decisions and tradeoffs. First, virtually all functionality is offloaded from the phone to the server. This simplifies the design of the client but increases the load on the server and hence impacts the scalability of the system. The primary reason for doing things this way is that it enables the server to receive and store all raw sensor data. This is useful because the raw data can then be shared with other researchers [20] and alternate feature encodings can be applied at a later date. Nonetheless, because these advantages are primarily for researchers, a commercial system would migrate at least the preprocessing and data transformation code to the client app. This will save phone battery life because even though the phone's processing demands will increase, the amount of data that will need to be transmitted will be reduced to 2.9% of the current size [9]. It would also be practical to implement all of the functionality on the phone, leading to a perfectly scalable system—but with no access by researchers to user data. These alternative design and engineering decision, along with their advantages and disadvantages, are discussed in one of our other papers [18].

III. Smartphone Client Application

Actitracker supports Android smartphones and the client app is available for free from the Google Play store. The smartphone client polls the accelerometer sensor data every 50ms and periodically transmits it to the Actitracker server. The client's user interface is simple and enables the user to toggle the service on and off, modify the settings, view the activity results, and enter training mode. First time users are prompted to create a secure account on the Actitracker server; this account is used by the phone to submit data and also by the web server to authenticate users attempting to view their data via the web interface.

The settings screen allows users to change data transmission and storage settings. Users can choose to transmit their data using "Wi-Fi Transmission," "Mobile Network Transmission," or both (Wi-Fi only saves battery life). Users can also choose to upload data at frequencies ranging from once a minute to once an hour. The activity reports available via the phone app are similar to those available from the web interface and are described in Section IV. The training mode screen enables a user to provide labeled activity data so the system can automatically generate and use a personalized activity recognition model. The training mode is recommended since research shows that personal models greatly outperform the universal (impersonal) ones [10]. The training mode guides the user to progress though the set of activities. As long as a minimum amount of data is available for each of the required activities a personal model will be created and enabled. We require only a few minutes of data per activity because research has shown that good results are possible with small amounts of personal training data [10].

IV. User Interface

The user interface provides each user with access to the Actitracker results. These results are available from within the app or via a secure web account. Users can also obtain documentation and information about Actitracker, provide feedback about the service via several online surveys, and provide information to Actitracker via a user profile, although some of these capabilities are currently only available via the web interface. The most important function of the user interface is to provide access to the activity recognition results from Actitracker's database through a personal dashboard.

A. User Documentation, Surveys, and Profile

Actitracker documentation assists the user in learning about the service. Under the "About" menu for the web interface, there is a short description of the service, a "quick start" guide, and a user manual that provides some additional details. A privacy policy and document that explains the terms of use are also provided. Although most of the data is not particularly sensitive, privacy issues nonetheless are a concern to some users. Finally, we provide a frequently asked question list with detailed answers.

Two online surveys are provided in order to improve the Actitracker service and evaluate it effectiveness. The short daily survey is intended to capture feedback about the service for a single day of use, and most of its questions are concrete and relate to the accuracy of the various activity predictions. That survey also asks about battery drain and provides a space for free-form comments. The comprehensive survey is meant to be filled out only occasionally, and asks about twice as many questions, including some higher level questions about the usefulness of the service. The survey results help us to describe and quantify user experiences in Section VI.

Users are prompted upon registration to fill out a profile that includes their gender, age, height, and weight. Some of the profile information is used to determine the user's peer group so that we can compare that user's activity results with those in the same peer groups (based on age, gender, and body mass index). In the future, user profile information may also be used to improve activity recognition performance, since this information could be incorporated into the universal activity recognition models. The demographic information collected in the user profile can also be used to advance research on inferring personal traits like gender, height, and weight from accelerometer data [19].

B. Activity Results

The user interface provides convenient access to summary and detailed activity information. Summary information includes calories burned and FitDex (a single numerical value that summarizes a user's total level of activity). The system allows the user to specify goals for each of these measures and displays progress toward these goals. Achievements and lifetime achievements are also available (currently only via the web account). For example, the system will track the total time (lifetime) spent walking. An
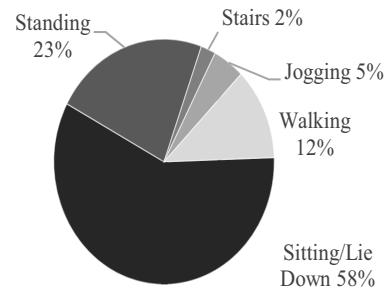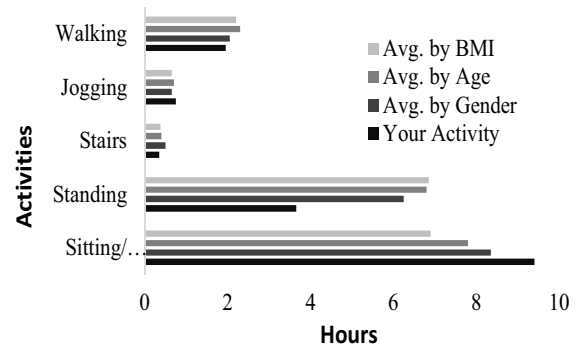

Fig. 2.   Activity breakdown for one day

Fig. 3.   Activity Comparison

"activity breakdown" report is displayed in Fig. 2 and an "activity comparison" report is displayed in Fig. 3. These particular reports are taken from the web interface and correspond to a single day of activity, although the user is free to select any desired time frame. Note that the activity comparison report relies on the profile information provided by the user in order to establish the various groups for comparison (BMI is calculated from the height and weight information).

Fig. 4 shows an example of the timeline report. This report shows the results at the most granular level—at 10 second increments. Because of the highly granular nature of the data, it may appear that a user is performing multiple activities at any time, but in this chart only one activity is identified at each 10-second interval, which is clear upon zooming in to any specific time span.
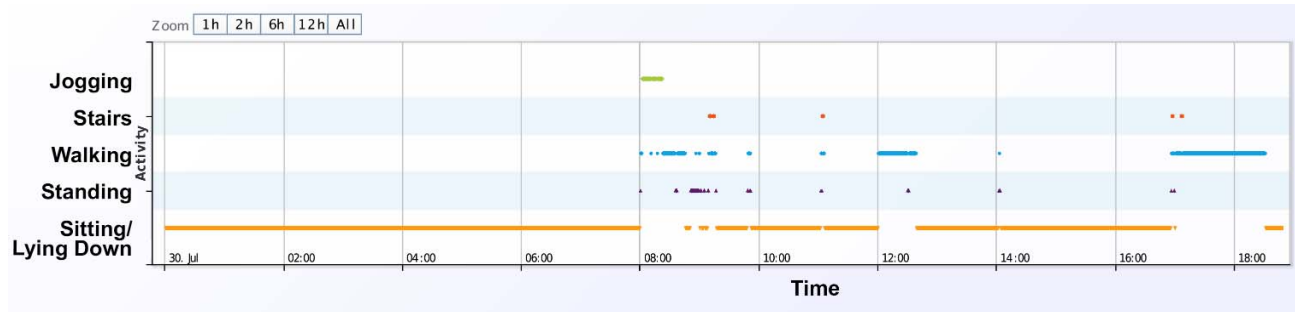

Fig. 4.   Activity Timeline

V. Machine Learning Component

The Actitracker server implements and automates the entire machine learning component. Every step, from data cleaning and preprocessing to model induction and activity prediction, is automatically performed by the server as it receives data from client phones, without human intervention.

A. Data Segmentation and Quality Control

Each data connection from a client leaves the server with an ordered list of accelerometer records (a timestamp and x, y, and z acceleration readings) collected over a period of several minutes or hours. These lists of data are first divided into 10-second, non-overlapping segments. This has several advantages. First, it allows us to use standard classification techniques which require discrete examples. Second, this allows us to handle each example independently, which facilitates parallelization. Finally, the use of discrete examples enables clients to connect and submit data periodically without requiring data from separate connections to be matched up during processing.

Due to the way android smartphones collect accelerometer data, repeat and null values may occur if the operating system or hardware is too busy to provide new sensor readings at the requested rate. In order to ensure the quality of the data, we utilize the sensor readings for a 10-second window of data only if at least 90% of the readings are good (i.e., not null or a repeated value). In practice this preprocessing code discards very few examples.

B. Feature Generation

The raw accelerometer records in each example are transformed into a set of 43 summary features that have been empirically shown to perform well [7]. These features are simple statistics, including the means and standard deviations of acceleration per axis, the binned distribution of values, and a heuristic measure of wave periodicity. These features are computationally easy to generate, ensuring that the system remains scalable and that it can provide results to the end user in near real time.

C. Model induction

Prior work has demonstrated that models built using training data from one user are excellent at predicting that user's activity from unlabeled data, with accuracies in the high 90's [10]. However, unlike this prior work and almost all other similar work, Actitracker's data is not collected in the lab, but in real time and "in the wild." If the incoming data has an activity class label attached to it (i.e., via the app's training mode), it is considered training data. New training data is combined with all previously received training data from the same user and then is automatically used to generate a personal activity classification model for the user. The model is then stored for later use in classifying unlabeled data from the user. Actitracker currently maintains personal models and a single universal/impersonal model for use when a user has not provided personal training data. The Actitracker system uses models generated by using the Random Forest classification algorithm, since this algorithm was shown to perform very well in our prior activity recognition

research [10], and because the algorithm is fast at generating models and classifying new data. Each model is represented as a Java object, and is cached in RAM for speed of access and serialized to long term storage for persistence.

Because training data is user-submitted, it may be the case that the user has not submitted training data for all activities, or that they have submitted insufficient training data for some activities. Thus, before inducing a personal model, Actitracker checks to make sure that it has at least one minute of accelerometer data for each of the walking, sitting, and standing activities. If the user later submits training data for additional activities, the model is rebuilt using the new and old training data. In the future we may implement hybrid models, where data for missing activities is taken (i.e., transferred) from other users or from users with similar physical characteristics.

Users have a high degree of control over what training data they submit, so it is possible that they will submit training data with severe class imbalance (e.g. one hour of sitting data and only a few minutes for other activities). To prevent this from unduly biasing the predictions of the induced activity recognition models, we down-sample any activity for which there are more than three times that user's mean number of examples per activity. We assume that the most recent examples will be the most useful in classification, since a user's gait may change over time due to injury or age. However, old examples may still contain useful and diverse information about their gait. Thus we designed our sub-sampling process as an exponential function that selects a few old examples and many recent ones.

D. Prediction

Unlabeled examples are classified using the personal Random Forest model for the user, if one is available, or else with the default impersonal/universal Random Forest model. This universal model was generated by researchers on high quality data gathered under lab conditions. This model is known to perform modestly well on unseen users, with an average accuracy of 75%, which is competitive with impersonal models generated by other researchers working with similar activities [10]. Our results indicate that personal models are far superior, however, and generally achieve an accuracy over 95% for each activity. Prediction results are stored as a set of probabilities. For each 10-second example, the probabilities that during that time the user is walking, jogging, sitting, standing, or climbing stairs are all stored. This allows displays and summaries of activity to take into account the classifier's uncertainty.

VI. User Experiences

User experiences have been collected via a formal on-line survey, which also allows free-form comments, and by more informal feedback from our own researchers and early adopters. The surveys include a short daily survey and a more comprehensive survey meant to be filled out only once. Strategies for addressing many of the weaknesses are briefly mentioned in this section or in Section VII under future work.

A. Usability

Usability relates to the ease of use and learnability of a human-made object. Actitracker was designed to be easy to use—ideally you just "set it and forget it." Overall, responses indicate that Actitracker is an easy tool to learn. However, there were two key issues related to ease of use, which involve the positioning of the device on the body and battery drain.

Our prior smartphone-based activity recognition research asks the test subjects to carry the phone in their front pants pocket [7, 10]. We adopt this recommendation but users are free to carry the phone any way they want. This may compromise the accuracy of their activity recognition results, but if the user utilizes the training mode to generate a personal model, the system should be able to function normally, as long as the location is consistent and the sensor signals are sufficient to differentiate the various activities. The question of where and how people carry their smartphones has been studied and quantitative statistics have been captured [2, 5]. While many factors can come into play (e.g., gender, age, nationality) our user experiences are quite simple: the recommended phone location is not an issue for men but is an enormous issue for women. Both prior research and our user experiences show that women carry their phones in a variety of locations, namely: purse, back pocket, front pocket, hand, and jacket pocket. Women typically do not use the front pants pocket because the phone will not fit in that pocket. But although the back pocket would probably provide an adequate sensor signature for activity recognition, women transfer the phone to their hand or a table prior to sitting down. These issues are significant enough that women are very likely to avoid this service or stop using it. This is backed up by our user statistics, which show that women make up only 20% of our registered users but generate only 13% of the activity data.

Actitracker's impact on battery life is another key usability issue. The results of the user survey, provided in Fig. 5, are consistent with our team's experience—Actitracker seems to have a modest but significant impact on battery life, often reducing the battery life by 20%-30%. Although the survey does not explicitly ask what impact this reduction in battery life has on their phone usage, it is clear based on our personal experiences that this additional drain sometimes prevents the phone from lasting a complete day. A closer analysis of the data further confirms our own experience, which is that the impact of Actitracker usage on battery life seems to fluctuate dramatically on different days—with no immediately apparent explanation.
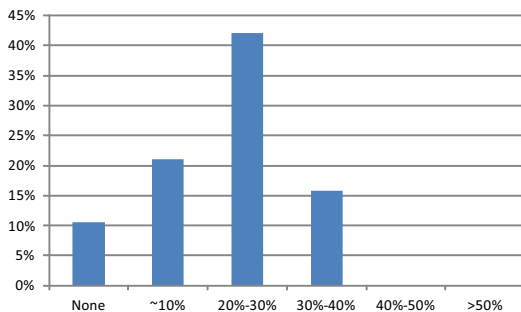
Fig. 5. Perceived reduction in battery life due to app

B. Accuracy and Efficacy

In this section we discuss the accuracy and efficacy of the system, mainly through the perceptions of the users. This may be more important than actual accuracy since perceptions determine whether the system is used. Our surveys ask about the perceived accuracy of the service, both at an overall level and for specific activities. The results for the overall accuracy are summarized in Fig. 6 and Fig. 7. Fig. 6 shows the responses to the assertion "Overall the app is accurate at measuring my activities." The scale for this statement is the same as for most of the accuracy-based questions, where "1" means that they disagree with the statement and "5" indicates that they agree with the statement. A "3" is interpreted as meaning that the app results are often correct but do not fully meet expectations. Fig. 7 shows the responses to the assertion "Do you think that the app accurately measures the overall amount of physical activity that you do?" In this case, the scale is set so that "3" corresponds to the ideal value (balanced), whereas "1" corresponds to under predicting the total amount of activity and "5" corresponds to over predicting it. Note that one can misclassify some activities while providing an accurate assessment of the overall amount of physical activity.
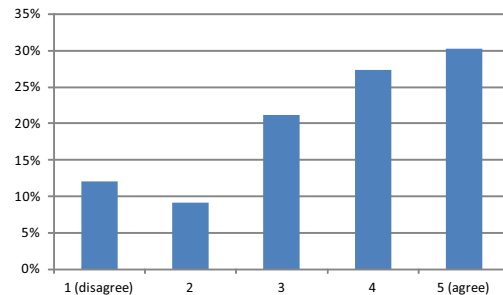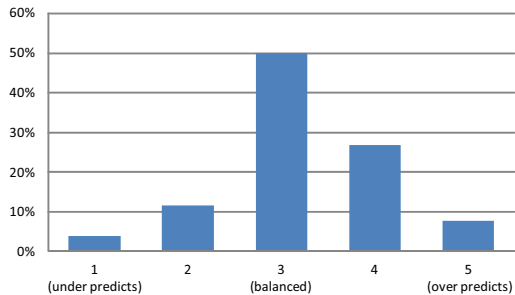
Fig. 6. Response to "App provides accurate predictions"

Fig. 7. Response to "App predicts proper amount of activity"

The results in Fig. 6 and Fig. 7 are quite positive, but show that there are errors and that there is room for improvement. The results concerning the accuracy of the specific activities are summarized in Fig. 8. The assertion was "I feel that my ___ results were accurate," where the blank was filled in with the appropriate activity. The scale was the same used for Fig. 6, where 1 corresponds to "disagree" and 5 to "agree." Only the averaged values are shown. The survey results show that the service generally provides good results, but with room for improvement. Specific comments from users indicate that often the results are highly accurate—for example, the timeline perfectly indicates when there is a long walk, with

virtually no misclassifications during the walking period. Similarly, one may walk up and down between levels in one's home and the short episodes of stair climbing are correctly reflected in the timeline chart. However, there are other times when basic activities are mistaken and these results are glaring. We believe that a major source of such errors is due to changing orientations of the phone within the pocket, which are not adequately taken into account by our current system. Solutions to this problem are discussed in Section VII.
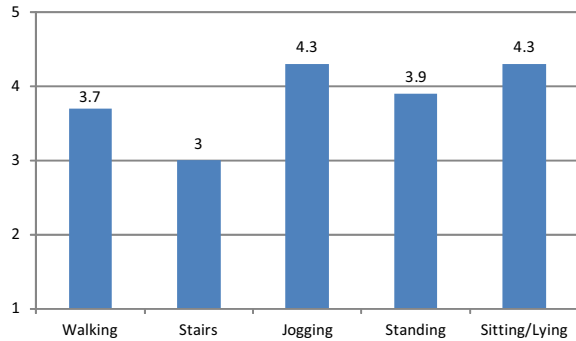

Fig. 8.   Response to "App accurately predicts specific activity"

Some of the specific comments that we received also show that the system is able to properly reflect a mixture of activities. For example, the activity of "snow shoveling" appears as a mixture of "walking" and "standing." Most users also agree that training yields much improved results and that the results are quite poor without training. We do not have much information on the performance using the universal models "in the wild" because we recommended that all users utilize the training mode as soon as possible. But prior results in a controlled environment show that the personal models greatly outperform the universal models [10].

One of the metrics we created was the FitDex, which, as described in Section IV, summarizes a user's total level of activity with a single number. When asked whether this single number appropriately summarized their total amount of activity, the mean response using our 5-point scale (1=disagree and 5=agree) was 3.5. Overall, we have found that the FitDex does tend to correlate with how active one is each day, but the values are poor when one runs Actitracker for only part of the day. This is a consequence of our current assumption, which is that a user is active only when the tool is running and confirms that they are active. We could address this by setting the FitDex relative to the number of hours it is collecting data, but the current scheme encourages usage of the app. One solution is to modify the service to only display a Fitdex value when the app has run for a threshold number of hours.

C. Objective Assessment of Performance

Other research is able to measure the accuracy of activity recognition models with relative ease because the experimental setup is very precise—subjects are told to perform specific activities for specific amounts of time, in specific locations [7,10]. It is extremely difficult and time-consuming to generate such objective performance metrics "in the wild" (i.e., in a fully natural setting). Nonetheless, such

objective metrics are important, even given the user satisfaction metrics from the survey results. In this section we discuss the performance results for three Actitracker subjects, who kept a detailed diary of their activities for a 12-hour period. These subjects had sufficient training data so that they each had personal activity recognition models. A sample of one of these diaries is provided in Table 1.

TABLE I.   PARTIAL ACTIVITY DIARY ENTRY FOR SUBJECT 1

Duration	Activity
18:24 - 18:34	Standing
18:35 - 19:27	Sitting
19:27 - 19:33	Wander about house (walk/stand)
19:33 - 19:40	Sit down to eat chili
19:40 - 19:42	Get water to drink (thirsty)
19:42 - 19:55	Eat while sitting down
19:55 - 19:58	Walk to work desk
19:58 - 21:27	Sit at work desk

The times are noted to the nearest minute and the activities are described briefly, but are not always mapped precisely to a single basic Actitracker activity. For example, "wander about house" really means walking about, but also includes time spent chatting while standing. In cases like these it is not simple to identify individual activities, and any real attempt to do so would require tracking activities at the second-level rather than minute-level. Tracking at this fine level of granularity would tend to interfere with the subject, thus invalidating the purpose of the evaluation. A less intrusive mechanism, such as video tracking, could be used, but this would be costly and time consuming and might still interfere with the behavior of the test subjects. Furthermore, some activities are a mixture of two or more basic activities and such a system would still not enable one to break them down precisely into their component parts.

The evaluation process involves querying the Actitracker database for the activity results for the appropriate user over the specified times, and comparing those results so the actual activity (or activities) noted by the user. Because Actitracker issues predictions at 10 second intervals but the users track times at the minute level, if the evaluator noticed a small time shift in the transition to a new activity, the transitions were aligned to remove any errors due to minor inaccuracies in time. In cases like the "wander about house" activity mentioned earlier, where the user notes that it is a mixture of two activities, our evaluation process counts either activity as correct. The results for the three test subjects are provided in Table 2.

TABLE II.   ACTITRACKER ACTIVITY FOR 3 USERS OVER A DAY

Subject #	Accuracy
1	91.2%
2	79.5%
3	98.1%
Ave	89.6%

The evaluation process used to measure Actitracker accuracy for the three subjects also identified where most of the errors occur. Subject 1 had the "walking" and "standing" activities occasionally classified as "sitting/lying down." These errors were sporadic and were generally within long periods of correct classifications, so a user would most likely ignore or barely notice these errors in the timeline view. Subject 2 sometimes had "walking" mislabeled as "stairs," which is the most common misclassification for the "walking" activity [10], but also had many instances of "sitting" misclassified as "standing." Further analysis showed that these errors came from the end of the day when the subject sat in a chair that is different from his normal chair. This other chair accounted for 3 hours and 23 minutes of "sitting" and this activity was mislabeled for 1 hour and 32 minutes of that time; this one error explains most of subject 2's errors. Subject 3 had a very high accuracy and most of the errors came from misclassifying short periods of "walking" as "lying down/sitting."

VII. CONCLUSION AND FUTURE WORK

This paper describes a deployed smartphone-based activity monitoring application called Actitracker, which provides the user with an accurate assessment of their activities and allows them to monitor the impact of any behavioral changes. This is the first high level view of the entire activity recognition system, although particular aspects of the system, and research results in controlled settings, have been reported elsewhere [7, 9, 10, 18]. The collected data, including some labeled data, has been made available to researchers [20].

We faced many challenges while developing and deploying this tool, and learned several lessons. One key lesson that we learned was that some people, mainly women, rarely carry their phone in their pocket. This impacts the utility of our service. This could be addressed by making the activity recognition models more flexible, so that they can dynamically recognize different body locations, or by having features that are somewhat location independent. Much of this work began, and was deployed, before fitness trackers became popular and before smartphone-based activity recognition entered the mainstream. Some of the features, such as self-training, were demonstrated to be very effective, while such capabilities are still not standard. Our research group is now focused on smartwatch-based activity recognition, which is capable of recognizing many more activities than smartphone-based activity recognition (our most recent study included 18 different activities). We believe many of the lessons learned in smartphone-based activity recognition will carry over to activity recognition using other devices and sensors.

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