Detection of Gestures Associated With Medication Adherence Using Smartwatch-Based Inertial Sensors

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***Abstract*—Poor adherence to prescription medication can compromise treatment effectiveness and cost the billions of dollars in unnecessary health care expenses. Though various interventions have been proposed for estimating adherence rates, few have been shown to be effective. Digital systems are capable of estimating adherence without extensive user involvement and can potentially provide higher accuracy with lower user burden than manual methods. In this paper, we propose a smartwatch-based system for detecting several motions that may be predictors of medication adherence, using built-in triaxial accelerometers and gyroscopes. The efficacy of the proposed technique is confirmed through a survey of medication ingestion habits and experimental results on movement classification.**

***Index Terms*—Gesture recognition, pervasive computing, wearable computers, measurement/accelerometers.**

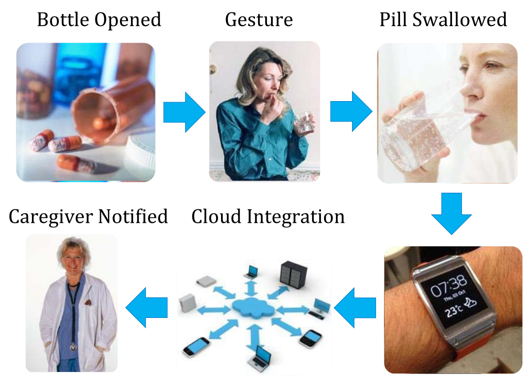

Fig. 1. Various ways in which a SmartWatch or similar wrist-worn device can be employed to detect medication intake and alert clinicians of low adherence.

I. Introduction

IT IS well established that poor adherence to prescription medication can limit the benefits of medical care and compromise assessments of treatment effectiveness [1]. Poor adherence is associated with increased hospital readmissions, medical complications, and even death [2]. It has been estimated that lack of adherence causes approximately 125,000 deaths in the United States, and costs the health care system been $100 and $289 billion pear year [3].

A significant body of research has been conducted to improve adherence to prescription medications through various interventions. These techniques vary tremendously from reminder-based systems, simplified pill packaging, positive reinforcement, financial incentives, and counseling. However, these systems typically suffer from high complexity, user burden, and inaccurate estimations of adherence [4]. One survey of major interventions concluded that less than half of evaluated interventions were associated with statistically significant increases in adherence [5].

In recent years, a greater emphasis has been placed on the role of technology in detecting non-adherence to medications. Because patient behavior can be monitored passively, user burden is potentially less than other methods that rely on patient record keeping, phone calls, and self-reporting. Furthermore, these digital systems have a potential to provide a better adherence assessment than self-reporting. However, these digital system suffer from several substantial limitations. Though they employ sensors to perform activity recognition, it is not always possible to accurately estimate adherence by recognizing a single action such as opening a pill bottle, or removing a capsule. For example, an individual may remove a pill from a medicine bottle, receive a phone call immediately thereafter, and neglect to return to swallow the pill. These factors suggest the need for systems capable of identifying multiple motions or activities associated with medication adherence, rather than relying on a single predictor.

Recently, smartwatches have become widely available on the commercial market. Drom a user-acceptance standpoint, these systems have a clear advantage over other proposed solutions based on custom hardware such as the wrist-worn accelerometry proposed by Chen et al. in [6] or audio-based ingestion monitoring systems proposed by Sazonov et al. and Amft et al. in [7] and [8]. Clearly, the multitude of sensors available on the smartwatch platform, wireless connectivity, as well as the comfort and social acceptance of the form-factor warrant further study into their potential applications in the medical domain. For example, several use cases of the smartwatch platform are shown in Figure 1; the watch can be used as an end-to-end system for characterizing medication adherence by detecting gestures associated with ingestion and capsule removal, relaying this information to caregivers through web services.

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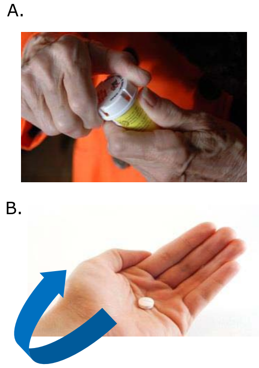

Fig. 2. In (A), the wrist motion necessary to twist the bottle cap open is detected using a tri-axial accelerometer. In (B), the act of turning the palm upward to pour medicine from the bottle is detected using a gyroscope.

In this paper, we propose a system that can detect several motions associated with medication adherence using a custom Android application running on a Samsung smartwatch. The activities that are detected are shown in Figure 2. Using a tri-axial accelerometer and gyroscope, we can determine when a bottle is opened and a pill is retrieved. Furthermore, the proposed system can be used with any standard twist-cap prescription bottle, without requiring that each bottle to be equipped with sensors and wireless connectivity as in the case of the Vitality Glowcap [9].

Many other works describe various approaches to classifying motion using accelerometers and gyroscopes [10], [11]. However, there are several novelties to our particular approach. First, we propose a method for tracking medication adherence using a commercial hardware device, rather than cumbersome custom hardware solutions that have limited applicability in real-world environments. Second, we are able to detect an extremely subtle wrist motion that is significantly more challenging to identify than the fitness-related activities that are emphasized in other works, such as walking, running, and climbing stairs. This is achieved by increasing the recall of the first-stage of the algorithm at the expense of precision, and filtering out the false-positives in the second stage.

Furthermore, we achieve high classification accuracy of the wrist motion associated with opening a pill bottle, using three simple features from each axis of the accelerometer. The majority of other works related to activity recognition extract hundreds of mathematical features from each axis, and perform computationally complex feature selection and classification. These techniques are more burdensome from the perspective of real-time implementation, require more processing power, and can significantly impact battery life as a result of their complexity. Lastly, our classification algorithm runs in real-time on a commercial smartwatch device, while many other works on activity recognition simply use the hardware for signal acquisition, and perform classification offline.

II. Related Work

A. Mobile-Phone Solutions

Several SmartPhone applications such as MyMedSchedule, MyMeds, and RxmindMe, provide advanced functionality for medication reminders. These applications issue reminders, allow users to manually enter their dosage information, and record when they have taken their medication [12]. In [13], Sterns and Mayhorn mounted a pill bottle onto a personal digital assistant running the RxmindMe software, and successfully trained elderly subjects with an average age of 72 to operate the software used to monitor adherence. This work suggests that users from a variety of age groups and backgrounds have the ability and motivation to use electronic monitoring devices if given adequate training.

B. Hardware Approaches

This proposed work is an extension of our prior work described in [14]. However, other hardware approaches have been proposed in recent literature. The work described in [4] describes a portable, wireless-enabled pillbox suitable for elderly and those suffering from dementia. Similar approaches for electronic detection and smart pill boxes have also been proposed [15]. These devices generally suffer from the same shortcoming: they cannot determine if the medication is ingested or simply removed and discarded [16]. In another work, Valin et al. successfully identified medication adherence using a series of images and associated image processing algorithms [17]. Very recent work by Chen et al. in [6] describes a system in which inertial sensors worn on the wrist are used for detection of gestures associated with medical intake, based on a Dynamic Time Warping (DTW) algorithm. In [18] and [19], the WearSens necklace is used to detect different kinds of swallows, including those that may be associated with medication capsules and tablets.

The Vitality Glowcap is a wireless-enabled pill bottle that can report when medication is removed [9] using a cellular network, while a recent product from Amiko [20] is one of the few systems that can monitor the ingestion of medication directly, based on a smart-inhaler technology. Other notable technologies include the Smart Blister from Information Mediary Corporation [21], which can detect when medication is removed from a blister-packet.

III. System Architecture

A. Hardware Description

The SmartWatch application is capable of predicting if a pill has been swallowed using the on-board inertial sensors available on the Android SmartPhone. The application runs as a background service: data is collected and processed even while the user is interacting with other applications on the watch.

The hardware platform used is the Samsung Galaxy Gear SmartWatch running Android 4.2.1. This phone features an 800 MHz ARM-based processor, 512 MB of RAM, and a 320×320 pixel 1.6 inch display. The device also supports transfer of data using the Bluetooth LE protocol, and can be configured to access the Internet using Bluetooth tethering with compatible Smartphones. Once the on-board algorithm detects that the medicine has been ingested, a web-service call is made to store the data in a database for access by caregivers. Though the sample rate of the on-board sensors can be configured, a rate of 16.66 Hz was determined to be sufficient for activity recognition through experimentation. Higher sample rates increase computation power and decrease battery life with no significant effect on accuracy.

B. Android Application

The Android application works as follows. First, samples are acquired from the accelerometer and gyroscope in the X, Y, and Z axis. These values are buffered in a vector-based data structure in memory, which is of a fixed size and operates in a first-in-first-out format. That is, the oldest sample is removed from the structure to make room for each new sample. After every new data point is acquired from the inertial sensors, the DetectMotion function is called. This function implements the feature extraction, processing, and thresholding techniques described in Section IV. This function sets a flag when the accelerometer data suggests that a bottle has been opened, and when the gyroscope data suggests that the hand on which the watch is worn has been turned such that the palm faces upward. A timestamp accompanies each of these flags, which can then be used to detect the time interval between these two motions. If the time interval is less than the set threshold (T=30 seconds), the application reports that the medicine has been taken. Subsequently, a notification email can be transmitted, or a web service call can be made, based on the users individual requirements.

IV. Algorithm Design

In this section, we describe the algorithms running on the Android Service, which predict if medication has been ingested based on the recognition of two activities: (1) The bottle being opened while the SmartWatch is worn on the wrist by detecting the twisting motion of the bottle cap, and (2) the wrist being rotated for the palm to face upwards, in order to pour medicine capsules into the secondary hand. All results are based on data acquired from tri-axial accelerometer and gyroscope samples acquired at 16 MHz. Figure 2 shows the actions the proposed system was designed to identify.

In the following formulas, we refer to the window size as β, and the set of original sensor data as D. $\bar{D}(j)$ refers to the transformed sensor data after being processed in Equation 1, $\acute{D}(k)$ after Equation 2, and $\tilde{D}(n)$ referring to the output after Equation 3. Symbols j, k, and n refer to individual data points in the first, second, and third phases of the algorithm respectively. The constant α refers to a predefined threshold for separating the different peaks.

A. Bottle Opening: Data Transformation

Figure 3 shows the waveforms acquired from the SmartWatch accelerometer for each axis which correspond with a bottle being opened nine times. Each bottle-opening event corresponds with a different peak. Successful identification of the event is dependent on analysis of the features of each peak in all three dimensions. Therefore, the data must be transformed to decouple the perturbations of the signal from the offset, and limit the effects of drift and noise. This new

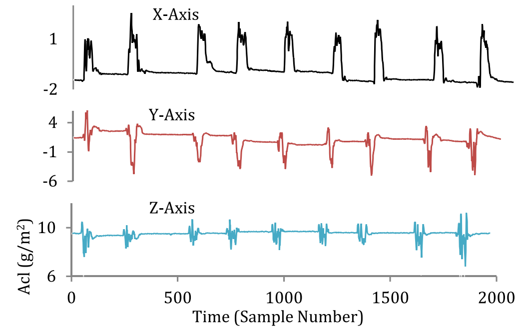

Fig. 3. In Phase (1), data is extracted from the accelerometer. This figure shows the accelerometer data from opening the pill bottle nine times.

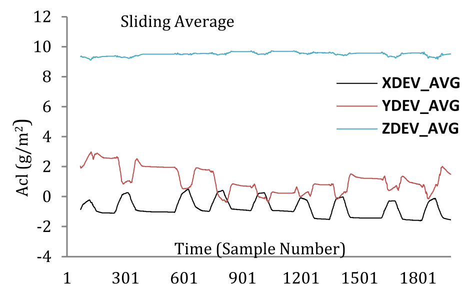

Fig. 4. In Phase (2), the data corresponding with each axis of the accelerometer is converted to a sliding window representation.

waveform, shown in Figure 5, provides a more objective representation of the features of a bottle opening event.

This signal transform is first achieved by generating a new waveform using a sliding-window average of the original data. The relevant equations for each axis are shown in Equation 1. It was determined that 70 is an appropriate value of β, as significantly smaller values are too sensitive to minor fluctuations.

$$\begin{aligned} &\forall D \in \{X, Y, Z\}, \\ &\forall j \in D, \\ &\bar{D}(j) = \frac{1}{\beta} \sum_{i=j-\beta}^{j} D(j) \end{aligned} \tag{1}$$

After the moving-average representation of the data is generated, each point is then assigned a numerical value with respect to the average value in the previous window. This essentially removes the offset from the data and combats the effect of drift, while preserving the critical features of the original waveform. This is shown in Equation 2.

$$\begin{aligned} &\forall k \in D, \\ &\acute{D}(k) = \left| D(k) - \bar{D}(k) \right| \end{aligned} \tag{2}$$

The next transformation simply separates the continuous data into different peaks separated by spans in which the data is zero, based on a simple thresholding technique. This allows different instances to be more easily identified. The relevant equation is shown in Equation 3, and the corresponding waveform (with additional smoothing) is shown in Figure 6. It was experimentally determined that an α value 0.5 g/m^2 of

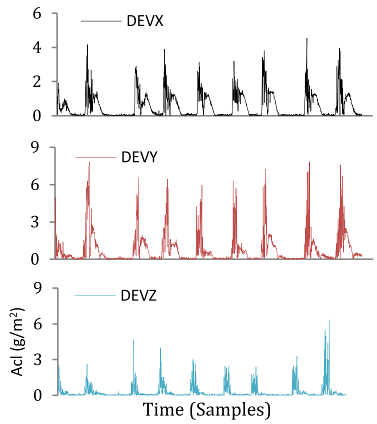

Fig. 5. In Phase (3), the results from Phase (1) and (2) are combined. The new waveforms preserves features from the original while removing the offset.

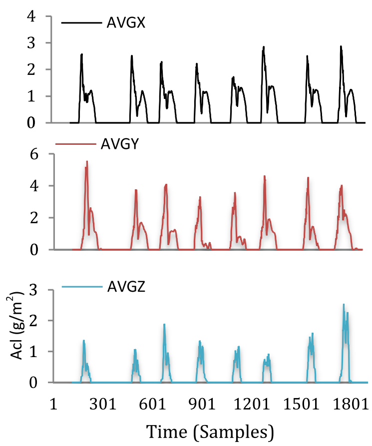

Fig. 6. In Phase (4), data is filtered to remove high frequency noise. Furthermore, values below a certain threshold are zeroed.

visually preserved the critical features of the waveform while removing noise during periods of inactivity.

$$\forall n \in \acute{D},$$
$$\tilde{D}(n) = \begin{cases} 0, & \acute{D}(n) < \alpha \\ \acute{D}(n), & \acute{D}(n) \geq \alpha \end{cases} \tag{3}$$

Subsequently, features from individual 'pulses' can be extracted, which each correspond with a different bottle opening episode. This is shown in Figure 7, which shows one individual pulse in the X axis. By performing a summation of each pulse, which is delimited by a value of zero as described in Equation 3 as a result of the thresholding technique, a distinguishing feature can be extracted from each axis. The width of the pulse, once again delimited by zero, is a secondary feature that can used to improve classification accuracy.

B. Bottle Opening: Detection

Based on the previously collected features, we apply various constraints for the classification of each pulse, as shown in Equations 4. These constraints are formulated on the basis of their efficacy in detecting the twisting motion required to remove the bottle cap. Figure 8 shows the distribution

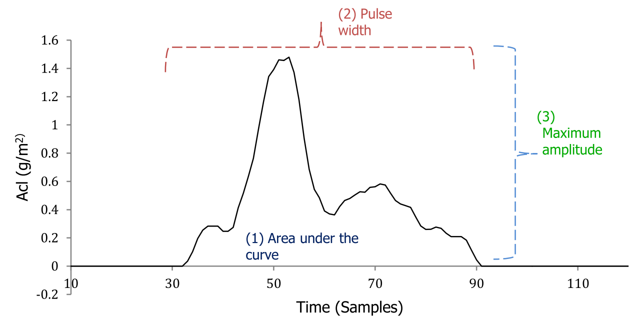

Fig. 7. The output pulses from phase 4 can be analyzed based on several different features for activity recognition and classification.

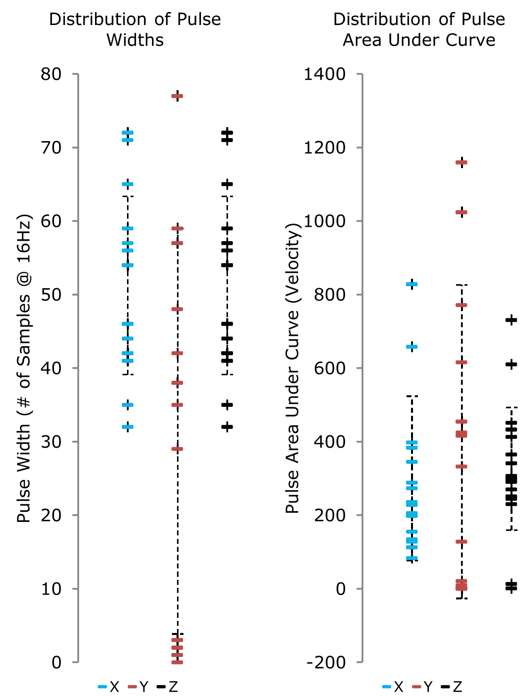

Fig. 8. An analysis of the clustering patterns for different features can be used to assign threshold values for activity recognition. The error bars correspond with one standard deviation.

of feature values such as pulse width for all three axes, and well as the area under the curve of each pulse, as users twisted the bottle cap during the initial phase of data collection. The observations that are made from the feature distribution associated with this activity are used to formulate the constraints for classifying an action as the opening of a bottle cap. Visually, it can be inferred that the data from the Y-axis of the accelerometer is very weakly coupled with the act of twisting the bottle. However, the standard deviation of the X and Z axis data appears to show significantly less variation.

As Equation 4 shows, the first requirement is that the standard deviation of indices of the first nonzero values of the accelerometer data in each axis to be less than three, to reduce the effects of noise and drift. The remaining constraints are the widths of the X, Y, and Z pulses, which correspond with the overall duration of the bottle cap opening event. The bounds on the integral of acceleration (velocity) constrain the intensity of the motion based on what is typical for the action.

This is necessary to prevent motions of similar durations but varying intensity from being misclassified.

$$\begin{aligned} 30 &< WidthX < 75, 0 < WidthY < 80 \\ 10 &< WidthZ < 80, 60 < SumX < 1800 \\ 0 &< SumY < 1200, 20 < SumZ < 1600 \end{aligned} \tag{4}$$

Once it has been determined that the bottle has been opened with a high probability, the system makes a record of this event and begins detection of pill extraction. This is obtained using gyroscope MEMS sensors available on the SmartPhone, which are processed as described in the following section.

C. Medicine Removal: Data Transformation

In the case of most twist-cap medication bottles, it is not possible to reach inside to retrieve the medication. Typically, once the bottle is opened, it is turned upside down and a medication capsule is emptied on the secondary (non-dominant) hand. This requires that the individual turns their hand upside-down with their palm facing upwards for a brief period, as shown in Figure 2(B). If the SmartWatch is worn on the wrist of the secondary hand, this motion can be detected. Data is acquired from the SmartWatch's built-in triaxial gyroscope at a rate of 16 Hz, which represent angular speed around the X, Y, and Z-axis in units of radians/second. The Android API provides output with built-in drift compensation algorithms, though raw data is also available.

The gyroscope data can be integrated along each axis to provide an estimation of rotation in a given unit of time. However, as in the case of the accelerometer processing used to estimate if the bottle cap is removed, the gyroscope data must be transformed for effective activity identification. However, the transformation is much simpler. Equation 5 shows the simple summation of the last β values acquired from the gyroscope. In this equation, x_n corresponds with the n_{th} sample of acquired data, and the same convention is used for the Y and Z axis. The chosen value of β is 12 samples, which corresponds with 750 ms of data at a 16 Hz sample rate. These values are selected based on the observation that most individuals will perform the hand motion in significantly under one second; longer sample rates would distort gyroscope data with extraneous movements and produce false positives.

$$\begin{aligned} &\forall Sample_i \in \{Buffer\}, \\ &x_{sum} = \sum_{k=i-\beta}^{i} x_k \end{aligned} \tag{5}$$

Because the required sample rate for inertial-based activity recognition schemes can be quite low (around 16 Hz in our case), a high computational complexity does not necessarily preclude an algorithm from practical real-time application when the collected data is in the range of several seconds. That being said, the complexity for this particular algorithm is linear. Each acquired data point is another value that must be summed to find the average value of a window. This point must then be subtracted from the window average to find the magnitude difference (Phase III). The number of these operations, along with those associated with the subsequent thresholding and peak detection, do not grow exponentially with the size of the dataset.

D. Removing the Medicine: Detection

Detecting that an individual has poured the medicine into his secondary hand is relatively simple, after the preprocessing shown in Equation 5. The detection of this movement does not imply that any medication was removed- simply that the palm was turned to face upward. Therefore, this is not a primary heuristic for medication adherence, and is used as a supplement to the bottle cap detection mechanism. The constraints on which this movement is detected are shown in Equation 6. First, some time interval ΔT must have elapsed since the last recorded event, to prevent duplicate records of the same event. The absolute value of the movement in the y and z directions must also be less than some arbitrary threshold, to ensure that random hand movements are not considered. Lastly, x_{sum}, the movement around the x axis over the last 12 samples (16 Hz) in radians/second, must be less than the threshold of -28, or greater than 28, depending on which arm the watch is worn. Experimentally, it was determined that lower threshold values could not differentiate relatively minor turns of the wrist to the full action of turning the palm upward that is required to pour medication from the bottle into the hand.

$$\begin{aligned} \Delta T &> 1s \\ |y_{sum}| &< 5, |z_{sum}| < 5 \\ x_{sum} &: \begin{cases} < -28, & LeftHanded \\ > 28, & Right\ Handed \end{cases} \end{aligned} \tag{6}$$

V. Secondary Motions and Other Future Works

Figure 9 shows a illustration of different motions relating to medication ingestion. Starting from an initial condition, the watch being worn on either the primary or secondary hand, the bottle cap is twisted open and poured into either hand. The green markers denote actions that our algorithm is capable of detecting using the previously outlined techniques. The red markers are examples of motions that are not as pronounced. For example, if the watch is being worn on the primary hand, the secondary hand will move very slightly if the primary hand is twisting the cap open. Furthermore, if the watch is worn on the primary hand and the medication is poured into the secondary, the watch-hand is tilted more subtly to allow the medication to slide out of the bottle. As the survey of medication ingestion habits has determined that either hand can be used, detection of these alternative motions warrants a closer look.

Another aspect of inertial sensing associated with medication intake is the act of raising the pill to the mouth, which can be done with either hand. However, the secondary hand will most likely not exhibit any identifying characteristics in this case. The detection of this action can be explored in future work to reduce the false positive rate, but will be less useful for reduction of false negatives as the absense of this motion does not necessarily suggest that the medication has not been taken.

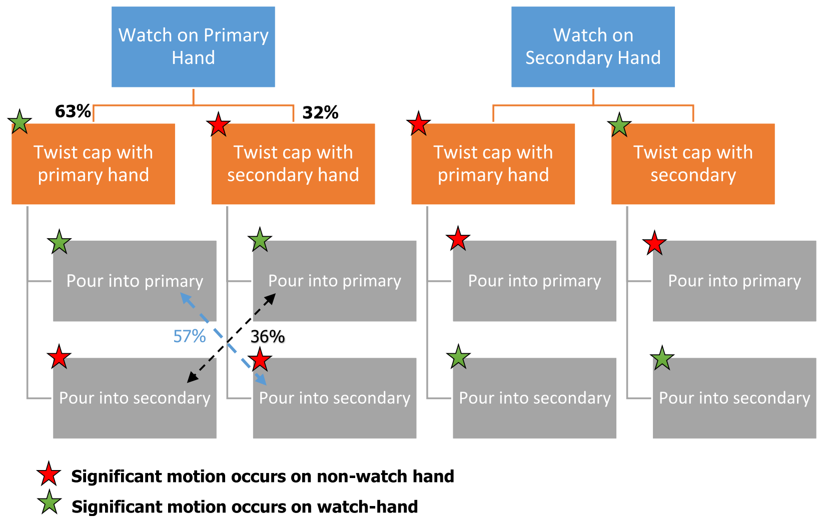

Fig. 9. This figure shows the different motions observed during data collection and reported by users in the survey. Items denoted by a green star are relatively easily detected because the motion is associated with the arm on which the smartwatch is worn.

VI. Experimental Procedure

Training data was collected from five subjects between the ages of 21 and 25, all of which were right-handed. The subjects wore the watch on their left hand in their preferred configuration, and were asked to open the pill bottle using the hand on which the watch is worn. The results were used to formulate the algorithm constraints, which were then tested on the remaining subjects.

A. Gesture Recognition

Twelve subjects were asked to perform several activities while wearing the SmartWatch including walking, opening a medicine bottle, and opening a bottle of water.

The data collection occurred in two separate sessions to increase the diversity in motion patterns. The medicine bottle used was a standard prescription variety containing empty gel capsules (Size 00). As in the case of most standard prescription bottles, opening the lid requires the application of downward pressure while twisting the cap in the counter-clockwise direction. However, the subjects used in the study were not given any instruction on how the bottle was to be opened, in order to avoid influencing activity patterns. After opening the pill cap, the subjects were asked to pause briefly for a period of three seconds, before pouring the medicine out of the bottle.

B. Online Survey of Habits

In order to design an appropriate activity recognition scheme, it is necessary to validate various assumptions about how people take their medication, as well as their opinion on smartwatch devices. An online survey was conducted with a total of 221 responses, in which various questions were posed with respect to how individuals feel about wearing a smartwatch, on what hand they would typically wear it, and how they retrieve and ingest a medication capsule. The participants in the study were anonymous, but represented a diverse set of ages, cultures, and genders. The survey results were used as a basis for algorithm design.

C. Observational Survey

To validate the results of the online survey, twenty subjects were asked to open a pill bottle and consume an empty gel capsule while being observed. No instruction was provided on how the medication should be taken, how the watch should be worn, or how the bottle should be opened. Thus, individuals were allowed to take the medication in a relatively natural environment. This is necessary because anonymous online survey results can be error prone. Online surveys can be particularly challenging because it may be difficult for an individual to ascertain their medication habits without a pill bottle in front of them.

VII. Results

A. Online Survey

From the survey based on responses from 221 individuals, 86% claimed to be right handed. A total of 76% of individuals claimed that they generally would wear a watch on their left hand, with an additional 19% who preferred to wear the watch on their right hand. The remaining 5% of those surveyed expressed no preference.

The next question in the survey asked subjects how they felt about watches in general. 72% of responses were positive, as 38% claimed they always wear a watch, 14% preferred wearing a watch, and 53% stated that they would not mind. Subjects were then asked to estimate what percentage of the time they would remove medicine from the bottle and not consume the pill within the next minute. 12% answered that this would occur occasionally, 6% often, and 1% always. 76% of individuals stated that this would happen very rarely.

Figure 10 shows other relevant survey questions. The first question reveals that though most individuals open a bottle by twisting the bottle with the primary hand, a significant

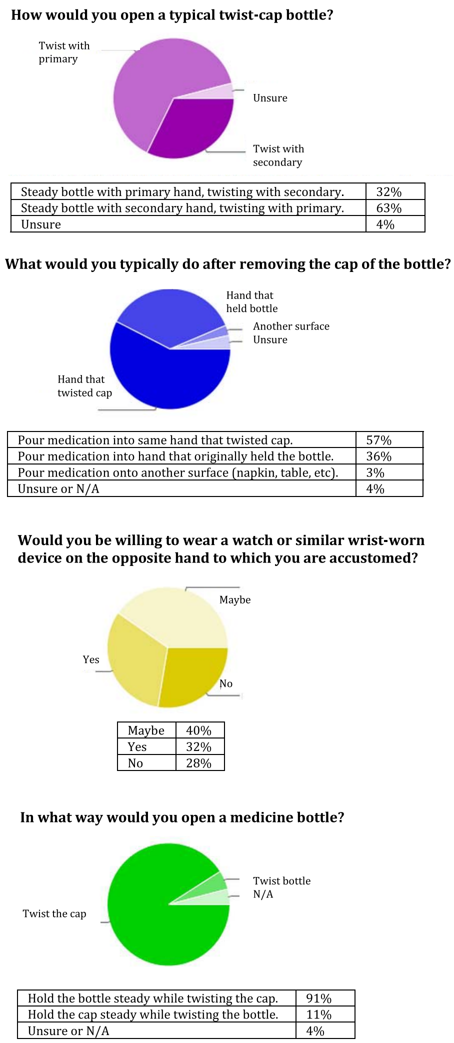

Fig. 10. Partial online survey results are shown above.

TABLE I
OBSERVATIONAL SURVEY OF MEDICATION INGESTION HABITS

Hand used to twist bottle cap	
Dominant	15
Secondary	5
SmartWatch Placement	
Dominant	1
Secondary	19
Pill Extraction Method	
Pour into dominant hand	5
Pour into secondary hand	15
Other	0
$\triangle$T Between Actions	
0-5 seconds	16
5-12 seconds	4
Which End is Twisted	
Cap	17
Bottle	3

TABLE II
CONFUSION MATRIX USING ACCELEROMETER DATA

	Predicted		
Actual	Med. Bottle Opened	Other	*Recall*
Med. bottle	21	3	87.5%
Raise Arm	14	6	30%
Walk	1	23	4.1%
Open door	14	10	41.6%
Water bottle	20	4	16.6%
Precision	30%	6.5%	

TABLE III
CONFUSION MATRIX USING GYROSCOPE DATA

	Predicted		
Actual	Palm Up	Other	*Recall*
Palm Up	24	0	100%
Raise Arm	2	22	91.6%
Walk	1	23	95.8%
Open door	2	22	91.6%
Water bottle	0	24	100%
Precision	82.7%	100%	

percentage (32%) preferred to steady the bottle with their primary hand, and twist with the secondary hand. Therefore, the bottle cap would more frequently be twisted by the opposite hand on which the watch is worn. This is confirmed by another survey question, which established that only 11% of subjects opened the bottle by twisting the bottle base, rather than the cap.

The next question evaluated what happens after individuals open the pill bottle. As hypothesized, most individual's poured the medicine into the palm of their hand, as opposed to another surface such as a napkin or table. However, there was little homogeneity in responses, with 57% who stated that they would pour the medicine into the hand that twisted the cap, and 36% that originally held the bottle.

Generally, the results suggest that some individuals will need to adapt their watch usage in order to recognize the motions suggested in this paper. This can be partially mitigated by developing detection strategies for a broader range of motions and applying template matching, though this is left to a future work. The remaining survey results were promising, as only 28% of subjects claimed that they would not consider wearing a watch on the opposite hand of what they are generally accustomed, compared to 40% who claimed that they would consider it, and 32% who stated that they would be willing.

B. Observational Survey

Observational study results indicated that 75% of subjects used their dominant hand to twist the bottle cap in the observed study, compared to 63% in the online survey. Furthermore, 85% twisted the cap (rather than the bottle) in the observed study, compared to 91% in the online poll. Lastly, 57% of individuals stated that they would pour the medicine into the hand that twisted the cap, compared to 75% who poured into the secondary hand (which is the dominant hand in 95% of cases). Though there are some discrepancies due to limited sample size, the online and observational study results are generally in accord with one another. Full survey results are shown in Table I.

C. Motion Classification Results

The classification results are shown in Table II and III. The results indicate that while accuracy of wrist rotation detection is good, the false-positive rate of pill cap opening detection is very high. This design trade off is necessary to ensure that nearly all real pill opening events are detected; false positives will be filtered out in the second stage of the algorithm. Table II shows that despite very low precision across categories, the recall for the action of 'medicine bottle opened' is very high. The remaining false positives are filtered out in the next stage of the algorithm shown in Table III in which the precision of the 'other' category, which comprises the other four listed actions, is 100%. Note that, because no traditional classifier was used for activity recognition, there is no cross-validation scheme to separate the test and training data. The algorithm was designed and tested on one subject, who later did not participate in the final data collection in order to avoid overfitting the data.

VIII. CONCLUSION

In this paper, a survey was conducted to understand how individuals take their medications from standard-sized twist-cap pill bottles in a normal environment. The results suggest that it is possible to use the Smartwatch as a platform for detection of medication adherence for many individuals. Using the tri-axial accelerometer and gyroscope on the Samsung Smartwatch, we are able to detect (1) the act of twisting the cap of a medicine bottle open, and (2) the removal of a tablet or pill by pouring the pill into the palm of the hand. Though the proposed system imposes some restrictions on how subjects should remove the pill bottle for successful recognition, the system nevertheless has much less human involvement compared to manual record keeping or phone calls from nurses and other forms of adherence detection.

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