A Smartwatch-Based Medication Adherence System

Haik Kalantarian, Nabil Alshurafa, Ebrahim Nemati, Tuan Le, Majid Sarrafzadeh
University of California Los Angeles, Deptartment of Computer Science
Email: {kalantarian, nabil, tuanle, majid}@cs.ucla.edu, ebrahim@g.ucla.edu

***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 adherence to prescription medication based the identification of several motions using the built-in tri-axial accelerometers and gyroscopes. The efficacy of the proposed technique is confirmed through a survey of medication ingestion habits and experimental results on movement classification.**

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. 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 [1].

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 [2]. One survey of major interventions concluded that less than half of evaluated interventions were associated with statistically significant increases in adherence [3].

In recent years, a greater emphasis has been placed on the role of technology in detecting non-adherence to medications. 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.

Recently, smartwatches have become widely available on the commercial market. These devices contain a multitude of sensors including but not limited to: a microphone, camera, accelerometer, and gyroscope. Due to the ubiquity of watches, this technology can be used for various wireless health-monitoring applications discretely, with low user burden. Furthermore, from 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 [4] or audio-based ingestion monitoring systems proposed by Sazonov et al. and Amft et al. in [5][6]. In this paper, we propose a system that estimates adherence of a user to gel-capsule-based medication using a custom Android application running on a Samsung smartwatch. The activities that are detected are shown in Figure 2. Using on-board sensors, we can determine when a bottle is opened and a pill is retrieved. This is achieved through a combination of on-board peripherals including the tri-axial accelerometer and gyroscope. By employing several sensors to detect different actions, such as a system has the potential for higher accuracy than existing schemes, with no compromises on comfort and practicality. 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 [7].

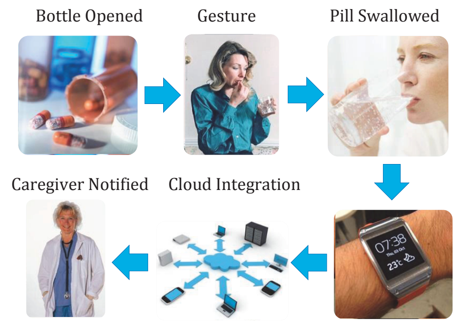

Fig. 1. This figure shows the various ways in which a SmartWatch or similar wrist-worn device can be employed to detect medication intake and alert clinicians of low adherence.

This paper is organized as follows. Section II outlines related work in electronic detection of adherence. Section III describes the major components of our proposed system. Section IV describes the proposed algorithms. Section V presents the experimental setup, followed by results in Section VI and concluding remarks in Section VII.

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[8]. Other works propose cell phone reminders and in-home technology to transmit reminder messages, but results are mixed [9].

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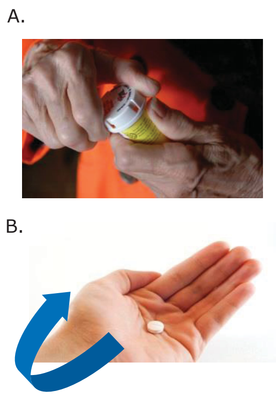

Fig. 2. This figure shows the two motions associated with medication intake that are detected using the proposed SmartWatch-based system. In (A), the wrist motion necessary to twist the bottle cap open is detected using a tri-axial accelerometer. In (B), the act of turning the palm upward to pour medicine from the bottle is detected using a gyroscope.

B. Hardware Approaches

The work described in [2] 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 [10][11][12]. These devices generally suffer from the same shortcoming: they cannot determine if the medication is ingested or simply removed and discarded. In another work, Valin et al. successfully identified medication adherence using a series of images and associated image processing algorithms [13]. Other works such as that by Huynh et al. [14] as well as Bilodeau et al. [15] propose camera-based systems for detecting medication adherence, with strong results. Very recent work by Chen et al. in [4] 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.

The Vitality Glowcap is a wireless-enabled pill bottle that can report when medication is removed [7] using a cellular network, while a recent product from Amiko [16] 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 [17], which can detect when medication is removed from a blister-packet. Lastly, our prior work in [18] explored the possibility of using inertial sensors on a necklace platform to detect medication swallows based on the movement in the lower throat during a swallow.

III. System Architecture

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.

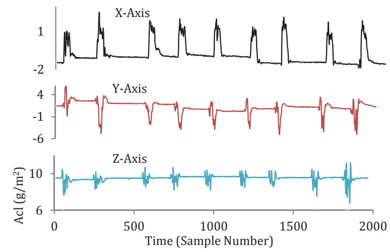

Fig. 3. In Phase (1), the X, Y, and Z axis data is extracted from the accelerometer. This figure shows the accelerometer data that corresponds with an individual opening the pill bottle nine times, smoothed with a window size of 3 samples.

The hardware platform used is the Samsung Galaxy Gear SmartWatch running Android 4.2.1. 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.

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 from the bottle into the secondary hand. Unless both of these actions are not detected within several seconds of each other, the system considers that the medication has not been ingested. 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.

A. Bottle Opening: Data Transformation

Figure 3 shows the waveforms acquired from the SmartWatch accelerometer for the X, Y, and Z-axis, which correspond with a bottle being opened nine times. Each bottle-opening event corresponds with a different peak, as shown in the figure. 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 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, in which β is defined as the window size. It was determined that 70 is an appropriate value of β, as significantly smaller values are too sensitive to minor fluctuations.

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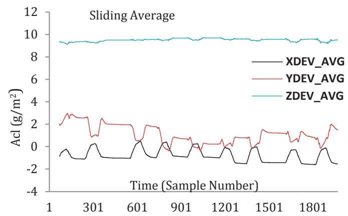

Fig. 4. In Phase (2), the data corresponding with each axis of the accelerometer is converted to a sliding window representation, in which each point is the average of the 35 points that came before and after it. This step is necessary to remove the offset from the data and show relative changes in sensor data.

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

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. The constant α refers to a predefined threshold for separating the different peaks. It was experimentally determined that an α value 0.5 g/m^2 of visually preserved the critical features of the waveform while removing noise during periods of inactivity.

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

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.

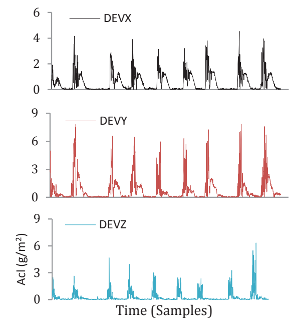

Fig. 5. In Phase (3), the results from Phase (1) and Phase (2) are combined. The new waveforms show the variance of each data point relative to the sliding-window average obtained in Phase (2). This preserves the key features from the original waveform while removing the offset.

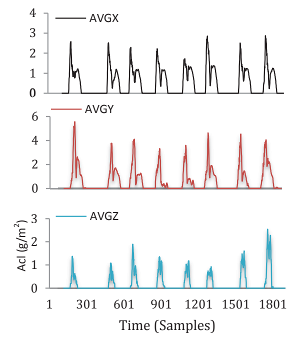

Fig. 6. In Phase (4), data from Phase (3) is filtered to remove high frequency noise. Furthermore, values below a certain threshold are zeroed. This allows each bottle opening action to be a separate 'pulse', the width of which is a key feature indicative of the action being performed.

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. Figure 8 shows the distribution 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 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.

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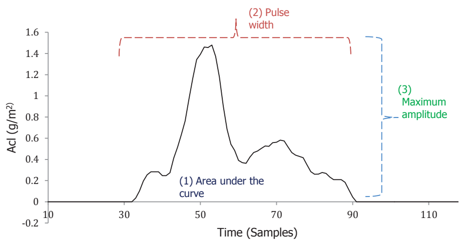


Fig. 7. The output pulses from phase 4 can be analyzed based on several different features for activity recognition and classification.

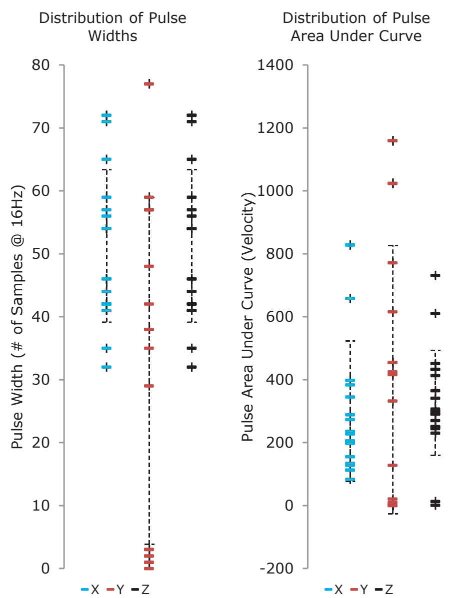


Fig. 8. This figure shows the distribution of the collected features (pulse widths and area under the curve), based on collected data (twisting the bottle cap). An analysis of the clustering patterns for different features can be used to assign threshold values, in order to identify the action in question. The error bars correspond with one standard deviation. Larger standard deviations are typically associated with weaker features.

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

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.

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 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.

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. 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 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.

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

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. The constraints on which this movement is detected are shown in Equation 6. First, some delta of time 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. Experimental Procedure

Training data was collected from five subjects between the ages of 21 and 25, all of which were left 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. 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.

VI. Results

A. Gesture Recognition Results

The classification results are shown in Table I and II. The results indicate that while accuracy of wrist rotation detection is very high as a result of the algorithm simplicity of the data processing, 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 I 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 II in which the precision of the 'other' category, which comprises the other four listed actions, is 100%.

TABLE I
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 II
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%	

B. Patterns in Medication Ingestion: Survey Results

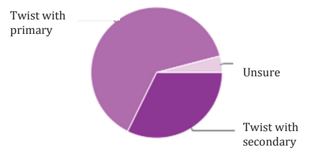
From the survey based on responses from 221 individuals, 86% claimed to be right handed. A total of 76% of individuals claimed that they generally would wear a watch on their left hand, with an additional 19% who preferred to wear the watch on their right hand. The remaining 5% of those surveyed expressed 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 9 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 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.

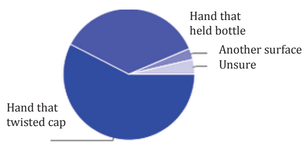
The next question evaluated what happens after individuals open the pill bottle. As hypothesized, most individual's poured the medicine into the palm of their hand, as opposed to another surface such as a napkin or table. However, there was little homogeneity in responses, with 57% who stated that they

How would you open a typical twist-cap bottle?



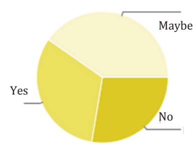
Steady bottle with primary hand, twisting with secondary.	32%
Steady bottle with secondary hand, twisting with primary.	63%
Unsure	4%

What would you typically do after removing the cap of the bottle?



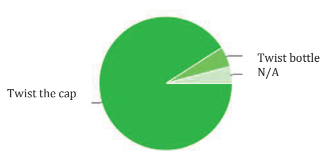
Pour medication into same hand that twisted cap.	57%
Pour medication into hand that originally held the bottle.	36%
Pour medication onto another surface (napkin, table, etc).	3%
Unsure or N/A	4%

Would you be willing to wear a watch or similar wrist-worn device on the opposite hand to which you are accustomed?



Maybe	40%
Yes	32%
No	28%

In what way would you open a medicine bottle?



Hold the bottle steady while twisting the cap.	91%
Hold the cap steady while twisting the bottle.	11%
Unsure or N/A	4%

Fig. 9. Partial survey results are shown above.

would pour the medicine into the hand that twisted the cap, and 36% that originally held the bottle.

Generally speaking, 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.

VII. 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. Future research will explore the integration fo the Smartwatch with existing smart-health systems, as well as detection of medication adherence with other forms of medication packaging.

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