Automatic Identification of Solid-Phase Medication Intake Using Wireless Wearable Accelerometers

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***Abstract*— We have proposed a novel solution to a fundamental problem encountered in implementing non-ingestion based medical adherence monitoring systems, namely, how to reliably identify pill medication intake. We show how wireless wearable devices with tri-axial accelerometer can be used to detect and classify hand gestures of users during solid-phase medication intake. Two devices were worn on the wrists of each user. Users were asked to perform two activities in the way that is natural and most comfortable to them: (1) taking empty gelatin capsules with water, and (2) drinking water and wiping mouth. 25 users participated in this study. The signals obtained from the devices were filtered and the patterns were identified using dynamic time warping algorithm. Using hand gesture signals, we achieved 84.17 percent true positive rate and 13.33 percent false alarm rate, thus demonstrating that the hand gestures could be used to effectively identify pill taking activity.**

I. Introduction

Medication adherence is defined as "the extent to which patients take medication as prescribed by their health care providers" [1]. Non-adherence to medication is a significant problem in the U.S. and results in over $100 billion in additional hospitalization costs each year. According to a report by the New England Healthcare Institute (NEHI), it is estimated that one-third to one-half of all patients in the United States are not adhering to their medications as prescribed by their doctors [2].

Monitoring methods for medication adherence can be divided into *direct* and *indirect*. Examples of direct methods include measuring concentrations of a drug or its metabolite in blood or urine, detecting a biologic marker that is added to the medication, and direct surveillance of the therapy. On the other hand, self-reporting by the patient, questionnaires filled out by the patient, counting the pills or measuring the medications taken by the patient, using electronic medication adherence monitoring systems (MAMS), measuring physiologic markers of the patient, and assessing the medication adherence through a caregiver are considered as indirect methods of measuring medication adherence [1, 3].

Each method has its pros and cons, and no method is considered to be the gold standard. For instance, self-reporting methods are found to overestimate patients' medication adherence, and won't function for people with diminished memory. Those patients who report noncompliance are generally correct, but those who claim adherence, might not be [4]. Interview/questionnaire-based methods lack reliability because they strongly depend on the design of the questions and how the questions are asked [3]. In general, methods that depend on any active patient input, other than taking the medication, are not quite reliable for long-term monitoring [5]. On the bright side, numerous studies have shown that MAMS are more accurate than other techniques at assessing medication adherence [6, 7].

The only MAMS solutions that have been commercially available since the mid 1980's are based on detecting the medication container opening. These types of devices, which detect patients' preliminary action right before taking the medication, are categorized as *non-ingestion monitoring*. These systems act when the patient opens the bottle or breaks the blister by wirelessly sending a message to a central server through the user's mobile phone, thus indicating that a dose has been taken. These devices are safe, simple, low-cost, and easy to operate. However, they can be easily deceived – either deliberately or unintentionally. Moreover, these systems do not indicate how many pills are taken out in each opening, if any; they cannot indicate what has been done with medication.

Shortcomings such as these have led to the advent of a new generation of *ingestion-based* MAMS technologies, which detect the actual ingestion of the medication and its dosage [8]. There are two such recent efforts, both of which are still in clinical trials. The first one from Sequella Inc. (Rockville, MD), uses a fluorophore included in the medication as a tracer, and detects it in the bloodstream through the skin via a wristwatch [9, 10]. Even though fluorophore tracers are used in medical imaging, their potential long-term side-effects on the human body are not well understood. The second ingestion-based MAMS device, from Proteus Biomedical Inc. (Redwood City, CA), is called Raisin. Raisin is a chip attached to every pill with a thin-film battery that is activated upon ingestion as it is exposed to the stomach acid. It sends a high-frequency electrical current through the tissue, which is modulated in a way that it provides a unique marker of the pill when detected by a receiver patch placed on the patient's chest

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or abdomen [11, 12]. Since Raisin uses currents instead of radio-frequency (RF) signals, the patch needs to have relatively large electrodes with good electrical contact with the skin. The major disadvantage of both of these systems is that they require modification to the actual medication, which essentially limits their applicability. Moreover, these technologies may not be acceptable to the consumer because of the stigma associated with ingesting material other than the medication (e.g., markers), even if they are safe for consumption.

Considering the scale of this problem and the rudimentary state of the art technology, novel MAMS solutions seem crucial. We propose an innovative approach to design MAMS, by harnessing a user's natural hand movement gesture to identify the pill taking activity. Our approach has the following salient features: is *reliable* (as demonstrated by our results), *cost-effective* (requires simple hardware), *does not require* patients to ingest potentially harmful markers, and can be readily used with existing medications. For realizing our system, we have used wireless wearable devices with tri-axial accelerometer to detect and identify users' hand gestures during solid-phase medication intake. Experiment results on data collected from 25 users demonstrates the potential of our method.

Rest of our paper is organized as follows. We first describe the devices and the systems used for data collection. Next, we explain the experimental procedure, signal processing, and identification methods. Then we present the results and finally discuss the results and possible future work to improve the methodologies.

II. METHODOLOGY

A. System Overview

Two ez430-Chronos wristwatches (Texas Instruments), which feature a 96-segment LCD display, an integrated pressure sensor, and a three-axis accelerometer, were used in this study. The BMA250 (Bosch Sensortec) [12] sensors that are designed for measuring low-g acceleration are used in ez430-Chronos. The BMA250 has a programmable measurement range of ±2g, ±4g, ±8g, and ±16g. We programmed the watches to have the range of ±2g; hence the resolution was obtained as 3.9 mg. Each axis of the accelerometer was sampled at 20 Hz, and data was wirelessly transmitted to a computer. In order to avoid communication interference, one of the watches transmitted at 915 MHz and the other one at 433 MHz ISM bands. A custom-made program was developed in LabVIEW (National Instrument) that could simultaneously and in real-time obtain, display and restore the transmitted signals from both watches.

B. Experimental Setup

Twenty five subjects, 21 years old or older participated in this study. Subjects were asked to wear the two EZ-Chronos watches on their wrists, one on each hand, and perform two different activities in the way they feel comfortable and natural, while sitting in front of a table. The first activity ("activity-1" hereafter) consists in taking empty gelatin capsules with water. The second activity ("activity-2"), drinking a sip of water and wipe their mouth. Subjects were asked to alternatively perform each activity for ten times. The experimenter provided a cup of water and empty gelatin capsules (size-0) to the subjects on the table. Each segment of the experiment was initiated with the instruction of the experimenter that also began the signal acquisition, simultaneously, and stopped the signal acquisition as soon as the subject confirmed finishing the activity. All procedures were approved by the Institutional Review Board (IRB) Committee at the New York Institute of Technology.

C. Pre-Processing and Dynamic Time Warping (DTW) Algorithm

The restored signals were retrieved for off-line analysis. The following notations were used for this section:

- X_{pw}, Y_{pw}, and Z_{pw} denote the (discrete) time-series representing acceleration, in *x, y,* and *z* directions respectively, of the hand that was used to take a pill or wipe one's mouth. This hand could be either left or right, depending on which hand the user preferred to use for taking pills or wiping mouth.
- X_d, Y_d, and Z_d denote the time-series representing acceleration in *x, y,* and *z* directions respectively, of the hand that was used to drink water. This hand could be either left or right, depending on which hand the user preferred to use for drinking water.
- A *sample* is a collection of six time series: X_{pw}, Y_{pw}, Z_{pw}, X_d, Y_d, and Z_d.

Following steps were used to pre-process the signal:

1. X_{pw}, Y_{pw}, Z_{pw}, X_d, Y_d, and Z_d were detrended by subtracting the mean. This removed the dc component from the signals.
2. Because the total dynamic time warping cost between training and test time series is sensitive to the length of the time series (*i.e.*, the number of data points in the time series), we ensured the time series were of equal length (i.e., we made the number of data points in each time series equal by padding zeroes at the end). The longest action took 360 data points, i.e. equal to 18 seconds.

Training Set: We chose data of 13 random subjects for creating the training dataset. Each subject had 10 samples for activity-1 and another 10 templates for activity-2, with an exception of one subject who had 9 samples for both activities. Therefore, in total, the training dataset had 129 samples to model activity-1 and activity-2.

Test Set: The test set had samples from 12 subjects (who were different from those used in training). Therefore, the test constituted 120 samples for each of the activities.

Identification: We used dynamic time warping (DTW) [13] to classify whether a test sample belongs to activity-1 or to activity-2. DTW is a classical technique for comparing two timeseries, by essentially finding the minimum warp distance, which is the distance between the two time series when they are "optimally" aligned. The alignment allows for measuring the similarity between timeseries that possibly vary in time or

speed. In addition to its suitability to our application, we used DTW because various studies have shown that DTW performs well in activity recognition tasks [14, 15], especially, in tasks involving identification of arm-flex motion [16] and finger movements [17] and other gestures [18].

Identification Procedure: Below, we summarize how we generated the average DTW distance between a test sample and the samples in the training dataset.

- *STEP 1:* The DTW distance between a test sample and each sample of the activity-1 in the training data was computed. Because each sample has 6 time series, this step generated 6 individual DTW distances corresponding to X_{pw}, Y_{pw}, Z_{pw}, X_d, Y_d, and Z_d.
- *STEP 2 (Compute Average DTW Distance with Activity-1 Samples):* STEP 1 was repeated using the test sample and 129 activity-1 samples in the training data. This step resulted in 129 DTW distances for X_{pw}, Y_{pw}, Z_{pw} X_d, Y_d, and Z_d time series. We computed the average DTW distances corresponding to X_{pw}, Y_{pw}, Z_{pw} X_d, Y_d, and Z_d.
- *STEP 3 (Compute Average DTW Distance with Activity-2 Samples):* This step is similar to steps 1 and 2, except we compute the average DTW distance between test sample and 129 activity-2 samples in the training data.
- *STEP 4 (Optional Fusion Step):* We further combined the distances obtained in Step 2 into a fused "DTW distance with activity-1 samples" by averaging the six distances. Similarly, we also compute a fused "DTW distance with activity-2 samples" obtained in Step 3.
- *STEP 5 (Identification):* The following rule was used for classification: If (`Average DTW Distance with activity-1 Samples` > `Average DTW Distance with activity-2 Samples`), classify test sample as activity-1, else classify as activity-2.

III. Results

A. Use of Right and Left Hand to Perform the Activities

The mean and standard deviation of the participants' age was obtained as 26.6 ± 4.1. 23 of the subjects were right-handed and the rest were left-handed. For activity-1, 14 of the subjects took the gelatin capsule with their right hand and the glass of water with left hand. For activity-2, 12 of the subjects wiped their mouth with right hand and drank the glass of water with left hand. In each of the activities, the use of hands for performing the activities was complementary, meaning that no subjects used only one hand to perform activity-1 or -2. Interestingly, the subjects that took the pill with right hand not necessarily wiped the mouth with the same hand.

B. Plotting the Activities

The data obtained from all the axes of accelerometers was retrieved and plotted for individual subjects. Fig. 1 shows one of these plots from the Y-axis, while the subject repeated activity-1 for 5 times. During this activity the subject took the pill with the left hand and water with the right hand. The visual observation of these plots showed that the patterns are activity-specific and subject-specific. Furthermore, the traces

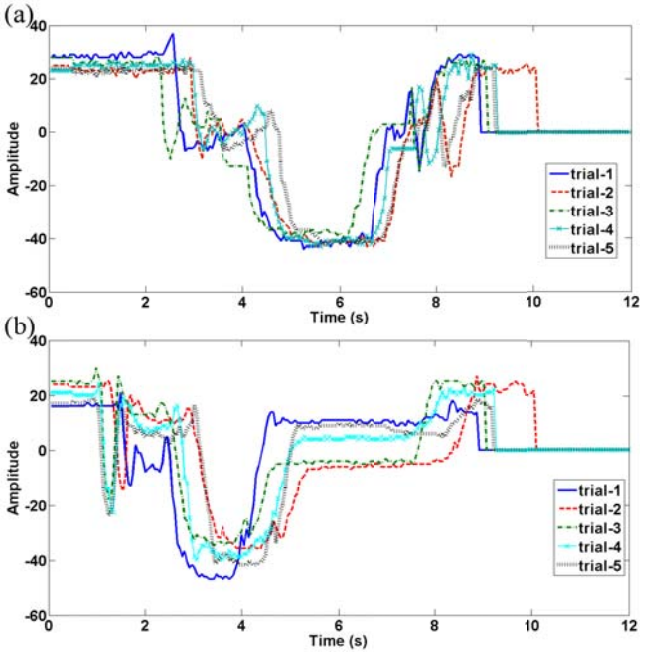

Fig. 1. Typical signals from the Y-axis of the accelerometer while the subject was performing activity-1. The subject took the water with (a) the right hand, and pill with (b) the left hand.

from different trials were manually aligned and the correlation between the traces was obtained. The results showed very good correlation (>0.8) between some of the traces and modest correlation between the other traces (>0.5). However, the overall correlation analysis did not lead to a conclusive result.

C. Identification Results

Error metrics: We assume that activity-1 is "+" class and activity-2 is "–" class. We report two types of errors:

$$True\ Positive\ Rate = \frac{\#\ \text{of "+" samples correctly identified}}{\text{Total \# of+samples presented}}$$

$$False\ Alarm\ Rate = \frac{\#\ \text{of "-" samples incorrectly identified as "+"}}{\text{Total \# of "-"samples presented}}$$

Identification results are shown in Table I. The table shows the true positive rate and false alarm rate of each individual signal (i.e., acceleration in x, y, z directions of the hand used for pill taking/wiping mouth and acceleration in x, y, z directions of the hand used for drinking water). We achieved the best tradeoff between the true positive rate (84.17%) and the false alarm rate (13.33%) by fusing the DTW outputs from both hands. The acceleration data from pill taking hand (Z_{pw}) performed very well (~98.33%) in identifying pill taking/wiping activities but had very high false alarm rate (~37.50%). On the other hand, the acceleration data from the hand used to drink water (X_d, Y_d, Z_d) was not able to identify the pill taking activity. For instance the DTW on X_d signal resulted in an identification performance of 4.17% true positive and 0.83% false alarm rates, indicating that the users

had similar hand movement signals during drinking water in both activities.

TABLE I. IDENTIFICATION RESULTS

Sensor Axis	*True Positive Rate*	*False Alarm Rate*
X_{pw}	0.9583	0.1667
Y_{pw}	0.8833	0.9167
Z_{pw}	0.9833	0.3750
X_d	0.0417	0.0083
Y_d	0.0417	0.0083
Z_d	0	0.0167
All fusion	0.8417	0.1333

IV. DISCUSSION AND CONCLUSION

The study demonstrated that tri-axial accelerometers worn on both wrists could be used to identify solid-phase medication intake using hand movement gestures. The reason for choosing the two activities discussed in Section II was that our preliminary studies showed that the patterns of the hand gestures related to tasks such as scratching/rubbing nose, head and mouth are very different from pill taking patterns – hence, *unrealistically easy* to differentiate. On the other hand, gestures associated with wiping one's mouth are similar to those of medication intake. Other activities, such as bringing food to the mouth may potentially be similar to medication intake. Hence, further investigations and experiments are required to demonstrate that the difference between medication intake activity and other similar activities is sufficient for distinguishing between them.

Although the subjects were asked to take medication in a manner comfortable to them, and were asked to alternatively perform the two activities, all of the subjects performed consistently and did not change hands between the trials. Visual observation and correlation analysis shows that wrist movement patterns did not change from one trial to another. Further observations showed that even if classification of activities over the whole population fails, we can still train the classification system on individual users.

DTW has shown promise in our experiments. However, DTW has three drawbacks: (1) it allows comparison of only two time series; (2) has a high computational cost; and (3) does not allow for sample and feature weighting. In our future work, we will use Generalized Time Warping [20] to circumvent the above drawbacks.

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