Finger-writing with Smartwatch: A Case for Finger and Hand Gesture Recognition using Smartwatch

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ABSTRACT

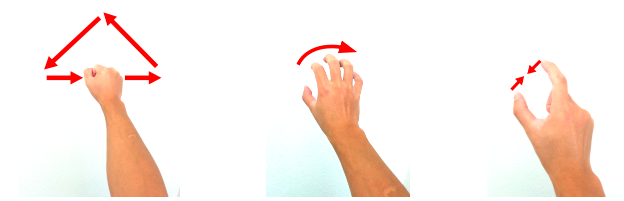
Smartwatch is becoming one of the most popular wearable device with many major smartphone manufacturers such as Samsung and Apple releasing their smartwatches recently. Apart from the fitness applications, the smartwatch provides a rich user interface that has enabled many applications like instant messaging and email. Since the smartwatch is worn on the wrist, it introduces a unique opportunity to understand user's arm, hand and possibly finger movements using its accelerometer and gyroscope sensors. Although user's arm and hand gestures are likely to be identified with ease using the smartwatch sensors, it is not clear how much of user's finger gestures can be recognized. In this paper, we show that motion energy measured at the smartwatch is sufficient to uniquely identify user's hand and finger gestures. We identify essential features of accelerometer and gyroscope data that reflect the movements of tendons (passing through the wrist) when performing a finger or a hand gesture. With these features, we build a classifier that can uniquely identify 37 (13 finger, 14 hand and 10 arm) gestures with an accuracy of 98%. We further extend our gesture recognition to identify the characters written by the user with her index finger on a surface, and show that such finger-writing can also be accurately recognized with nearly 95% accuracy. Our presented results will enable many novel applications like remote control and finger-writing-based input to devices using smartwatch.

Categories and Subject Descriptors: C.5.3 [Computer System Implementation]: Microcomputers – portable devices

Keywords: Wearables; Gesture Recognition; Mobile Computing.

1. INTRODUCTION

There has been a sharp increase in the popularity of smartwatches in last one year. With recent release of smartwatches from Apple [1], LG [2], Motorola [3] and Samsung [4], it is expected that they will be at the forefront in adaptation of wearable devices. Apart from the fitness applications (which are also available in wrist-bands such as Fitbit [5]), the smartwatches provide a rich user interface to interact via voice or touch. Current smartwatches support applications like email, instant messaging, calendar, navigation by connecting to user's smartphone over Bluetooth.



(a) Arm gesture - drawing a triangle with arm (b) Hand gesture - rotate hand right to increase volume (c) Finger gesture - zoom out with fingers

Figure 1: Examples of arm, hand and finger gestures

This increasing popularity of smartwatch presents a unique opportunity. Because the smartwatch is worn on the wrist, it is possible to understand user's hand and arm movement better than ever before. Most of today's smartwatch have accelerometer and gyroscope sensors built in them. If we can capture and analyze these sensors' data, we can understand user's arm, hand and finger gestures. It is expected that smartwatch sensors would be able to identify user's arm gestures (when the gesture involves the movement of shoulder or elbow joint) with ease, however, it is not clear if it can recognize user's hand and finger gestures. The finger gestures are especially challenging to be detected using smartwatch since the movement in the wrist when doing a finger gesture is very small and it is not clear whether it can be recognized uniquely. If this is feasible, there can be a plethora of applications. A user wearing a smartwatch can remotely control nearby television, computer, smartphone or any smart device using the finger gestures. If the finger movements are captured by the smartwatch, user can write with her finger (in the air or on a surface) to input text on smartwatch or any other connected device.

In this paper, we investigate the following questions: Can accelerometer and gyroscope sensors in smartwatch be used for identifying user's arm, hand and finger gestures? Although it is likely that arm and hand gestures can be recognized using smartwatch sensors, how accurately can we determine user's *finger gestures* e.g. zoom-in, zoom-out etc. (Fig. 1)? Even further, can we identify the characters when user writes with her index finger in air or on the surface by

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simply monitoring smartwatch sensors? Our study provides affirmative answers to all these questions. The contributions of our work are as follows:

(1) We first show that measured motion energy in accelerometer and gyroscope of smartwatch can be used to distinguish the *type of a gesture* - arm, hand or finger. We then show that even low-intensity finger gestures such as moving index finger up and down is captured with corresponding motion energy in the smartwatch sensors. This motivates us to design a hand and finger gesture recognition technique using smartwatch.

(2) We show that due to the tendons passing through human's wrist, it is possible to *uniquely* identify a finger gesture using the smartwatch. We provide essential features derived from accelerometer and gyroscope data that can be used to identify the gestures. Our machine learning classifier can identify 37 (13 finger, 14 hand and 10 arm) gestures with an accuracy of 98%.

(3) We then extend our gesture recognition technique to identify the characters when user writes with her index finger on a surface while wearing the watch. Our classifier can identify the characters from 26 alphabets with an accuracy of nearly 95%.

The rest of the paper is organized as follows. In Section 2, we provide the details of our experiment settings and describe how motion energy can be used to distinguish the type of gestures. Section 3 provides the details of our gesture recognition technique and Section 4 shows how finger-writing characters can be detected when wearing the smartwatch. Additional challenges and our ongoing work are described in Section 5. Section 6 discusses the related work and Section 7 concludes the paper.

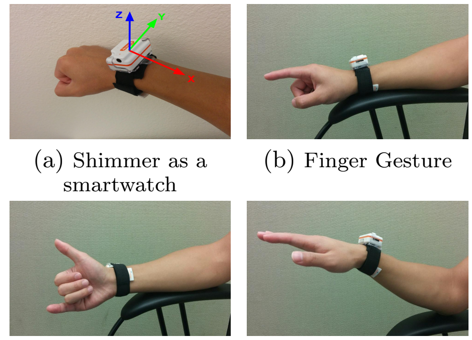
2. MOTION ENERGY AND GESTURE TYPE

In this section, we describe our experiment settings and show how we can determine the gesture type using the measured motion energy from the smartwatch.

2.1 Experiment Settings

Sensor Data Collection: We use a Shimmer [6] device attached to a wristband as the smartwatch as shown in Fig. 2a. The Shimmer contains an accelerometer sensor and a gyroscope sensor. The sensor data is collected at 128 Hz on Shimmer and transferred to a smartphone via Bluetooth. We use the Shimmer instead of any commercially available smartwatch because most smartwatch available in market provide only a limited API support for collecting accelerometer and gyroscope data. The sampling frequency of 128 Hz for Shimmer is not too high since the typical sampling frequency for accelerometer on current smartphones and smartwatches is 200 Hz [10] and 100 Hz [7] respectively. This means that a Shimmer closely resembles a smartwatch in terms of the motion sensors.

Gesture Experiments: Although our primary focus in this work is to identify finger and hand gestures using smartwatch, we also consider arm gestures for comparison. This way, we classify all the gestures in three types: arm, hand and finger. The list of all gestures we tested in our experiments is provided in Table 1. A total of 37 gestures are considered in our work which consists of 13 finger gestures, 14 hand gestures and 10 arm gestures. The data is collected for each gesture by repeating it for 10 times. Apart from the gestures, we also recognize characters when user writes on



(a) Shimmer as a smartwatch (b) Finger Gesture (c) Hand Gesture (d) Arm Gesture

Figure 2: Experiment settings showing how we perform different types of gestures

the surface while wearing the Shimmer. These experiments are described in Section 4.

Type	Gestures
Arm	ThumbsDown, Push, Left, Right, Up, ClockwiseCircle, Cross, AntiClockwiseCircle, LeftTwice, RightTwice
Hand	AntiClockwiseCircle, ClockwiseCircle, DownOnce, DownTwice, GunShoot, LeftOnce, LeftTwice, Phone Call, RightOnce, RightTwice, RotateLeftVolumeDown, RotateRightVolumeUp, UpOnce, UpTwice
Finger	IndexFingerClick, ZoomIn, ZoomOut, One, Two, Three, Four, Five, OneTwice, ThumbsUp, Singleclick, DoubleClick, TwoTwice

Table 1: List of gestures used in our experiments

In order to maintain consistency across the gestures of each type, we adhere to the following guidelines. As shown in Fig. 2b, while doing the finger gestures, the wrist and the arm are affixed to the chair arm. For the hand gestures, the arm is affixed, however, the wrist is free to move and/or rotate (Fig. 2c). The arm gestures have the highest freedom of movement where only user's elbow is assumed to be touching the chair arm (Fig. 2d). Note that other arm gestures with movement of shoulder joint can also be recognized using our approach without requiring any major modifications.

2.2 Classifying Gesture Type - Finger, Hand or Arm

In this section, we answer the following question: can we determine if a given gesture is a finger, hand or arm gesture based on the smartwatch sensor data?

The motion energy behind the movement in different types of gesture is likely to be different. We can expect that motion energy observed during the arm gesture to be the highest, followed by hand gestures and then the finger gestures. The motion energy (or simply energy) can be measured for smartwatch's accelerometer and gyroscope as shown in [11]. The energy is computed as

$$\text{Energy} = \sum_{i=1}^{\text{window\_length}/2} \text{magnitude}_i^2 \qquad (1)$$

where magnitude values are the Fast Fourier Transform (FFT) coefficients calculated over the time window. Because all gestures considered in this work last for very small duration, we set the window size to be the time of the complete gesture. The energy is only calculated for half the window since the remaining magnitude values are redundant which follows from the symmetry of FFT. Also, we only choose to

Figure 3: 3 Shimmers used to measure finger, wrist and forearm motion

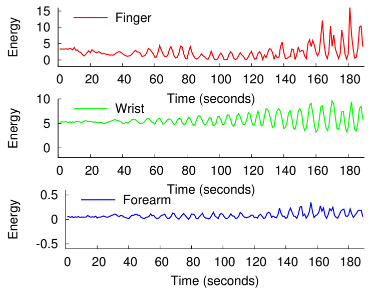


Figure 4: Motion energy in finger, wrist and forearm when doing a finger gesture

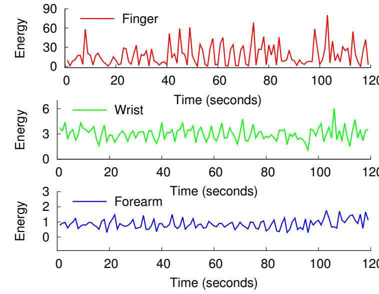


Figure 5: Motion energy in finger, wrist and forearm when doing a hand gesture

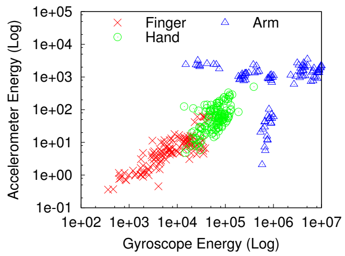


Figure 6: Accelerometer and gyroscope motion energy can be used to differentiate the type of gesture: arm, hand or finger

Classified as –>	Finger	Hand	Arm
Finger	129	1	0
Hand	3	136	1
Arm	0	0	100

Table 3: Confusion matrix for logistic regression classifier

calculate the energy within the lower frequency range of 0 to 1 Hz which is known to indicate low intensity activities and minor changes in posture [11].

Fig. 6 shows the energy of accelerometer and gyroscope for different gestures. We calculate the energy for all three axis and show the highest among the three axis in Fig. 6. It can be seen that the energy values can clearly distinguish the type of gesture. The finger and arm gestures have the lowest and the highest accelerometer and gyroscope energy respectively, while the energy values of hand gestures fall between the two. Arm gestures that involve more wrist rotation (such as ThumbsDown) will result in higher gyroscope energy. On the other hand, the arm gestures with more motion but less rotation (e.g. up or down) have more accelerometer energy and less gyroscope energy.

Using these attributes, we build machine learning classifiers to classify gestures in the three types. We use three different machine learning methods - Naive Bayes, Logistic Regression and Decision Tree - for comparison. We will use these three methods along with 10-fold cross-validation to present our evaluation throughout the paper. The results of the classifications are presented in Table 2. It can be observed that the True Positive Rate (TP Rate) for arm gesture classification is 100% while the classification accuracy is slightly lower in finger and hand gestures. Logistic regression-based classifier achieves the highest overall accuracy (maximum weighed TP rate) among all three methods. Table 3 provides the confusion matrix for the logistic regression-based classifier. It shows that hand and finger gestures are often misclassified among each other especially when some hand gestures such as UpOnce or DownOnce have similar motion energy as the finger gestures.

Classifier	TP Rate		
	Finger	Hand	Arm
Naive Bayes	91.50%	81.40%	100.00%
Logistic Regression	99.20%	97.10%	100.00%
Decision Tree	99.20%	93.60%	100.00%

Table 2: Gesture type classification accuracy

2.3 Motion Energy in Wrist from Finger and Hand Gesture

We now investigate the resultant motion energy in wrist when performing a finger or a hand gesture. Higher resultant energy would mean that wrist motion is a good representation of the finger/hand gesture and it might be possible to *uniquely identify* the gesture itself.

For analyzing this, we use three separate Shimmer sensors - one on the index finger, the second on wrist (like the smartwatch as before) and the third one on the forearm. The setup is shown in Fig. 3. When the user performs a finger or a hand gesture, measured motion energy in index finger Shimmer sensor would be the highest. However, it is not clear how much of this motion is reflected by the motion energy measured at the wrist and the forearm Shimmer sensors. We study the forearm case because it was shown by [8] that forearm muscles are good representatives of the hand movements.

With this setup of three sensors, the user performs a finger gesture and data is collected from all the three sensors. The user moves her index finger up and down with increasing the frequency of up-down with time. This is shown in Fig. 4. We can observe that motion energy measured in index finger sensor is very high, and it increases with time as user increases the frequency of motion. The motion energy at the wrist and the forearm sensors are also shown in Fig. 4. It is observed that forearm has lesser motion energy compared to the wrist sensor. We also see that the motion energy measured in the wrist sensor is a good indication of finger movements. Since the finger motion energy is the highest while doing a finger gesture, we can use a wearable ring (such as [9]) to identify the gestures, however, its limitation is that it can only be used to understand gestures of one specific finger on which the ring is worn. While with smartwatch, it is possible to recognize gestures of all fingers as we will show in Section 3.

We repeat the experiment with a hand gesture where user continuously makes a fist and releases the fist. The results of measured motion energy are presented in Fig. 5. Compared to the finger gesture, more motion energy is observed in the index finger sensor. We conclude the same phenomenon as Fig. 4 that motion energy in wrist is more compared to the forearm and it is also a good representative of the hand movement.

3. GESTURE RECOGNITION

We know from the previous section that there is a noticeable motion energy observed in the wrist when performing a finger or a hand gesture. In this section, we leverage this to build a gesture recognition technique. We first provide a brief description of anatomy of human hand and wrist to describe how tendons are responsible for creating a unique signature of different gestures.

3.1 Anatomy of Hand and Wrist

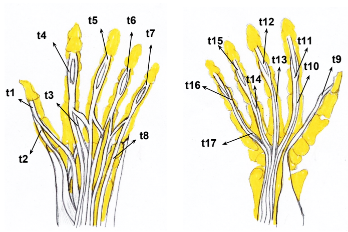


Figure 7: Tendons in posterior (left) and anterior (right) view of human hand and wrist

There are a total of seven different muscles in the forearm which are responsible for extension (releasing a fist) and flexion (making a fist) motions. These muscles include five extensor muscles and two flexor muscles. Each of these muscles are responsible for movements of different sets of fingers. The movement itself, however, is carried out using the tendons which are tissues that connect the muscles with the finger bones (refer Fig. 7). There are seventeen tendons on the front and back of the wrist. When user moves a finger or the hand, these tendons get pushed or pulled, resulting in some movement around the wrist area. As we show next, this movement is sufficiently rich to recognize different finger and hand gestures.

3.2 Primitive Gestures

To demonstrate that movement of tendons can be used to distinguish different gestures, we first take examples of primitive gestures and show how smartwatch accelerometer and gyroscope data is different for each of them. Fig. 8 shows the accelerometer data for Y-axis when the four fingers and the thumb individually perform a simple up-down gesture once. Simple visual inspection reveals that each finger (or the thumb) has clearly distinct pattern when performing the same gesture. This is because different tendons are involved in the movement of different fingers and the thumb. For example, for the index finger, extensor tendons t3 and t4 (Fig. 7) enable the up movement, while for the little finger, extensor tendons t7 and t8 create the up movement.

We also test how the accelerometer pattern is different when performing different gestures using the same finger. For this, user performs three different gestures - up-down, circular motion and left-right - using her index finger. Fig. 9 shows that the accelerometer data from smartwatch is sufficiently different for each gesture even when performed using the same finger.

3.3 Gesture Recognition

After our preliminary study with primitive gestures, we now attempt to identify each gesture (finger, hand or arm) uniquely given the accelerometer and gyroscope data from smartwatch. In order to perform this gesture recognition, we collect the data of all gestures listed in Table 1 (each gesture

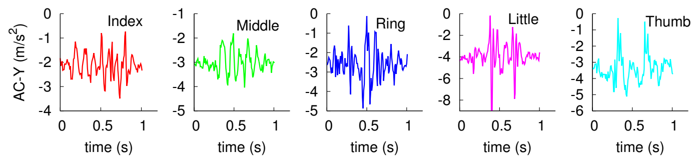


Figure 8: Accelerometer Y-axis when performing the same up-down gesture with four fingers and the thumb

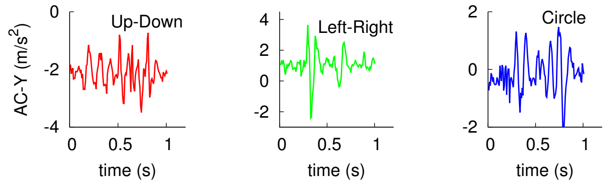


Figure 9: Accelerometer Y-axis when doing three different primitive gestures with index finger

repeated 10 times). Since each gesture has a different time duration, we use a time interval between two gestures where user's hand is stationary to delimit the gesture boundaries for both training and testing.

Feature Extraction and Evaluation: After collecting the data for all gesture instances, we calculate various features using the data. The complete list of features is provided in Table 4. This forms a subset of features extracted from [11]. In [11], it was shown that these features closely correlate to human activity (e.g. walking, running etc) and various postures (e.g. sleeping, sitting etc.). Because these features were initially proposed for smartphone to evaluate human body movement, it is not clear that their direct application to smartwatch gesture recognition would be useful or not. To calculate the worth of these features, we use Information Gain-based feature evaluation.

Type	Features
Motion Energy	ACEnergy, ACLowEnergy
Posture	DCMean, DCTotalMean, DCArea, DCPostureDist
Motion Shape	ACAbsMean, ACAbsArea, ACTotalAbsArea
Motion Variation	ACVar, ACAbsCV, ACIQR, ACRange

Table 4: Features selected from [11]; refer [11] for complete definitions and full names; all features are calculated for both accelerometer and gyroscope; some features calculated across all three axis while the others for all three axis individually

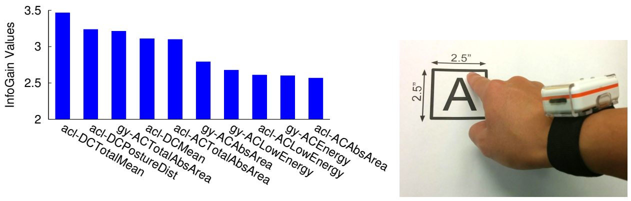
Information gain [13] measures the number of bits of information obtained in predicting a gesture in presence of a feature compared to the feature being absent. It is measured by calculating the entropy. Let F be a feature and G be the set of gestures then Equ. 2 and Equ. 3 calculate the entropy of G in absence and presence of feature F respectively.

$$E(G) = -\sum_{g \in G} p(g) \log_2 p(g) \tag{2}$$

$$E(G|F) = -\sum_{f \in F} p(f) \sum_{g \in G} p(g|f) \log_2 p(g|f) \tag{3}$$

Here, $p(g)$ is the fraction of instances for gesture $g \in G$, $p(f)$ is the probability that feature F has the value f and $p(g|f)$ is the fraction of instances of g given $F = f$. The information gain of F is then calculated as $E(G) - E(G|F)$.

We calculate the information gain for all features in Table 4 and order them in decreasing order of their information gain. Fig. 10a shows the information gain of top 10 features. It is observed that features of motion energy, posture and shape have high information gain in distinguishing the gestures, while motion variation features are of little use in classification. This is expected given that motion shape and posture related features are likely to be useful in distinguishing among the gestures of one type - arm, hand or finger, and as we saw in Section 2, motion energy is useful in classifying the gesture type itself. Hence, we only use motion energy, posture and shape related features in our identification.



(a) (b)

Figure 10: (a) Top 10 features with highest information gain; *acl-* and *gy-* indicate features calculated for acclerometer and gyroscope respectively (b) Experiment settings of how user writes alphabets on a surface while wearing the smartwatch

Identification Performance: Using the features selected from previous section, we build three classifiers as before - Naive Bayes (NB), Logistic Regression (LR) and Decision Tree (DT). The results of the gesture identification are presented in Tables 5 and 6. Table 5 shows the maximum, minimum and average TP rate for all gestures, and top three most misidentified gestures for each classifier. We observe that Naive Bayes outperforms the other two classifiers with an overall accuracy of 98%. The top 3 misidentified gestures of NB and DT suggest that finger gestures recognition is comparatively more difficult than hand and arm gestures. For the LR classifier, the model performs well to classify finger and hand gestures but the accuracy of arm gestures recognition is relatively lower (top 3 misidentified are arm gestures). Since in this paper, we are interested in understanding the feasibility of gesture recognition, we only use the data collected from a single person. However, the method can be extended for more than one user where a separate classifier is trained for each user based on how she performs the given gesture. We leave the accuracy evaluation of such user-specific classifier to future work.

Table 6 shows the confusion matrix for each gesture type for the NB classifier. The arm gestures have high TP rate of identification and they are only misidentified as other arm gestures. This is in line with our results in Table 3 where arm gestures were not misclassified as other types of gestures. The hand gestures have the highest TP rate in Table 6 although they had the lowest classification accuracy in Table 3. This means that they were often misclassified but with additional set of features, they are rarely misidentified. The finger gestures, on the other hand, have the lowest classification and identification accuracy.

4. FINGER WRITING WITH SMARTWATCH

We saw in the previous section that even finger gestures can be identified with a very high accuracy. Motivated by this, we now take a look at detecting finger writing using the smartwatch. Writing with the index finger (on a surface or in the air) is one of the most intuitive way of human-computer interaction. If we can detect what a user is writing with her index finger using her smartwatch, it can be used to input text to smartwatch itself or other connected nearby devices such as a smartphone. For example, a user can finger-write an instant message to her smartwatch or an email to her smartphone. In this section, we investigate the question: can we detect the characters written by the user with her index finger using the smartwatch accelerometer and gyroscope sensors?

Classifier	**TP Rate**			**Top 3**
	Max.	**Min.**	**Avg.**	**Misidentified**
NB	100%	80.00%	98.11%	Finger-One, Arm-Left, Finger-Two
LR	100%	60.00%	94.60%	Arm-Up, Arm-ClockwiseCircle, Arm-Cross
DT	100%	80.00%	95.41%	Finger-One, Arm-Left, Finger-TwoTwice

Table 5: Gesture recognition accuracy and top three misclassified gestures

Gesture Type	**TP Rate**	**Misidentified as**		
		Finger	**Hand**	**Arm**
Finger	93.85%	2	1	0
Hand	98.57%	0	1	0
Arm	96.00%	0	0	2

Table 6: TP rate of each type of gestures in NB classifier; finger gestures have the lowest TP rate among the three types

Finger-writing on Surface: A user can write with her index finger on a surface or in the air. Writing on the surface (on a desk, on a wall or on one's thigh) is often preferred as it provides a touch-based feedback to the user, allowing her to be more accurate in writing. In this work, we have focused on detecting writing on the surface and we are currently extending this to air-writing as discussed in Section 5. The touch-based feedback received by the user when writing on the surface generates a counter-acting force, pushing and pulling the index finger tendons in different ways. This movement of tendons is reflected in the smartwatch accelerometer and gyroscope, and it allows us to detect the characters.

To collect the sensor data, we use the settings shown in Fig. 10b where user writes a character on any surface. The size of the alphabet written by the user is approximately 2.5” in width and height, however, user writes on a surface without any printed characters or box. The accelerometer and gyroscope data is collected when user writes all 26 alphabets 10 times. We calculate the same set of features as in the gesture recognition and put them to test for classification.

Classification Performance: Table 7 shows the results for character classification using the three machine learning methods. It is observed that logistic regression outperforms the other two classifiers in overall accuracy. It shows that characters in finger-writing can be uniquely identified with an accuracy of 94.6%. Table 7 also shows that “D” and “U” are the most often misclassified alphabets in all three classifiers. In our classification, “D” and “U” are most often misclassified as “B” and “V” respectively. This is because these alphabets have similar primitive strokes. Some of the other misclassified instances include “W” as “N” and “R” as “A”. In general, the classification accuracy of approximately 95% means that finger-writing on a surface while wearing a smartwatch can be an accurate way of inputting text to

Classifier	TP Rate Max.	Min.	Avg.	Top 3 Misclassified
NB	100%	70.00%	90.00%	"D", "U", "W"
SL	100%	80.00%	94.62%	"D", "U", "R"
DT	100%	70.00%	88.08%	"D", "U", "A"

Table 7: Classification accuracy of recognizing finger-written alphabets and top three misclassified alphabets

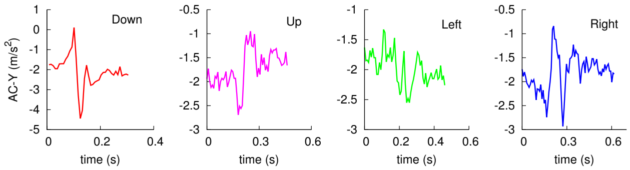


Figure 11: Accelerometer Y-axis data for four primitive strokes when writing in the air using the index finger

smartwatch itself (e.g. instant messaging) or other devices connected to the smartwatch (e.g. smartphone).

5. POTENTIAL AND CHALLENGES

During this research, we discovered that smartwatch has a great potential in enabling gesture recognition and finger-writing. Our findings suggest that the smartwatch can also be used to detect fine-grained movements of user's fingers. This opens a new avenue for research where the smartwatch can be used for many novel applications such as virtual touch screen and interaction with smart-environment.

There are numerous challenges in realizing the true potential of smartwatch. First, in this paper, we have only explored finger gesture recognition when user's wrist and arm are affixed to the chair arm. Recognizing finger gestures while the arm and wrist are allowed to move freely is challenging as it requires a method that can cancel the noise due to arm/wrist movement to distill the signals of finger movement. Another challenge is that different people write and perform different gestures in different ways. Such user-specific characteristics (e.g. right vs. left handed user etc.) require a separate user-specific classifier to be trained. Reducing the computational complexity, memory requirements and energy consumption of training and testing such a classifier is an important direction of future work. Additional challenges are introduced when extending our finger-writing on surface to finger-writing in the air due to unconstrained movement of user's finger. In our ongoing work, we are pursuing to design such air-writing system. Fig. 11 shows some preliminary results where we can see how different primitive strokes in the air are different in terms of smartwatch's accelerometer data. We are also addressing additional challenges such as detecting continuous writing to form words and sentences. The same framework will be further extended to create a virtual touch-screen where user can interact with remote devices by simply moving her fingers in the air.

6. RELATED WORK

Gesture recognition related research has gained a lot of interest in recent years. The research can be classified in two types: motion sensor-based approaches and RF-based approaches. Similar to our work, in the motion sensor-based gesture recognition, accelerometer and gyroscope sensors embedded in various devices are used for gesture recognition. In [9], authors presented a wearable ring platform which can be used to understand user's finger gestures and writing. However, this limits the gestures to a specific finger, and gestures using other fingers like little finger or thumb can not be identified. In this work, we showed that smartwatch-based gesture recognition is more general as it allows us to recognize gestures from all fingers and hand. Similarly, [8] introduced an arm-band which is worn on the forearm to be able to recognize many arm and hand gestures. As we showed in Section 2.2, more motion energy is observed in the wrist compared to the forearm, making smartwatch a more accurate way of gesture recognition. Also, due to limited motion energy in forearm, it can not be used for detecting finger gestures or writing. In RF-based gesture recognition, [12] showed how Doppler shift can be used to detect user's arm gestures even when user is not equipped with any device. In our previous work [14], we showed how an access point can detect user's arm gestures performed while holding the smartphone. Such device-free gesture recognition is difficult to be applied to identify low-intensity finger gestures and writing.

7. CONCLUSIONS

In this work, we explored how smartwatch can be used for gesture recognition and finger-writing. We showed that smartwatch sensors can accurately detect arm, hand and even finger gestures. It was also demonstrated that smartwatch can detect the characters when user writes on a surface using her index finger. Gesture recognition and finger-writing using smartwatch can be used to create novel applications for interacting with nearby devices and remotely controlling them. As part of our ongoing work, we are designing a virtual touch-screen and techniques to detect user's finger-writing in the air based on smartwatch sensors.

Acknowledgements

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