

Medicine Intake Detection Using a Wearable Wrist Device Accelerometer

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Abstract. Medicine intake detection and feature selection algorithm are proposed in this paper. A precise medicine intake detection method is crucial in medicine intake monitoring system; it is an important factor in order to prevent the harm in the case of medicine non adherence for elderly patients or any people with chronic diseases and need to take medicine regularly. Wrist movement is the main function of intake gesture detection using a wearable 3-axis accelerometer. Activities of interest for medicine taking monitoring are drinking gesture, picking and taking medicine by hand and palm. This paper applied the eigenvalues and covariance for change detection and features selection. Eigenvalues are considered to solve the improper data truncation issue caused by a fixed window size, because respective time during those activities is very varying. Its results are satisfactory. The gestures were classified by feature characteristics with an accuracy as high as 96.7% in the case of medicine taking by palm.

Keywords: Medicine Intake Detection, Features Characteristic, Eigenvalues, 3-axis Accelerometer.

1. Introduction

Medical sensor networks and Healthcare systems are diverse and pervasive for homes, nursing homes and hospitals. They have been considered as improvement to quality of life, because of the increasing number of aging population [1]. According to World Health Organization (WHO), chronic diseases are the leading cause of mortality for 63% of all death [2]. Medicine adherence is important to prevent the serious harm due to medicine non-adherence or do not taking prescribed medication. Moreover, the system helps to reduce long-term cost for assistance payment and reminding people who need to take medicine regularly. The most important, the curative will be in keeping with the medical treatment [1].

Generally, medicine intake detection for medicine intake monitoring systems lacks mobility. Patients should take the medicine at the specified area that system is supported. For example, a system that employs a medicine dispenser or pill box to assist drug adherence, which will send the information when patients receive their medicines or the box is opened by the time specified. Consequently, patients are forced to change intake behaviour tailor to system requirements and limited work area [3, 4].

Beside those systems, medicine intake detection from image processing methods [5, 6] is also popular and wildly adopted but the system is not suitable for daily life or daily tasks, because the system supported only at the specified area and it might not be raised privacy issue to users when the system is used. Moreover, camera or video surveillance should not have any occlusions and it has the problem when two interested objects are touching together in the direction parallel with the camera. Occlusion can be resolved by using

stereo camera [7] to compute the position of objects in 3D, but patients still have to take the medicine in the region of the stereo camera. Those methods can detect gesture of picking medicine by hand but cannot detect medicine taking by palm.

Arm gestures detection using two-stage recognition system with 4 accelerometers approach for eating detection is not suitable for the elderly patients and regular use [8]. Intake gestures detection that uses a wearable 3-axis accelerometer with RF transmitting is more appropriate for daily life and elderly patients, which is proposed in this paper. The device is worn at patient’s wrist. Patients do not have to change their behaviour to be consistent the system according to the specific conditions or limited work area. It is more convenient for a regularly use. Gestures of interest are drinking gesture, picking and taking medicine by hand and palm. Those activities are performed spontaneously with standing and sitting postures.

This paper proposes in data change detection, feature selection and gestures classification directly related to medicine intake. Data change detection while raising hand up and down uses eigenvalues consideration instead the method of fixed truncation window, because a spontaneously moving hand causes the very varying time during interest activities. Eigenvalues consideration from covariance matrix, which is resulted from applying sliding window to the smoothed data, solves the improper data truncation issue caused by a fixed window size. Type of gestures can be classified by specific characteristics [9] and provides accuracy as high as 96.7% in the case of take medicine by palm.

2. Method and Methodology

This section composes of two main parts describing features selection and classification. Eigenvalues is applied for features selection to solve the improper data truncation issue caused by a fixed window size. This work uses 3-axis accelerometer included in eZ430-Chronos watch and transmits sensor data through USB RF access point with 33 packets per second. Each packet consists of three bytes sensor data in 2’s complement format. The sensor has 2g range sensitivities with 56 counts/g ($1/56=18\text{mg}$) [10, 11].

2.1. Features Selection

Hand activities cause the change of data in 3- axis while raise hand up or down. Data change detection is important to detect a range of interest features. First, we smoothen raw data using moving average with window size equal 15 samples. Second, we calculate the eigenvectors and eigenvalues from covariance matrix which is resulted from applying sliding window to the smoothed data with window size equal 35 samples. From Fig.1, moving average decreases variation of data and the local maximum eigenvalues in the range of unimportant data. It is useful for change detection for using eigenvalues consideration.

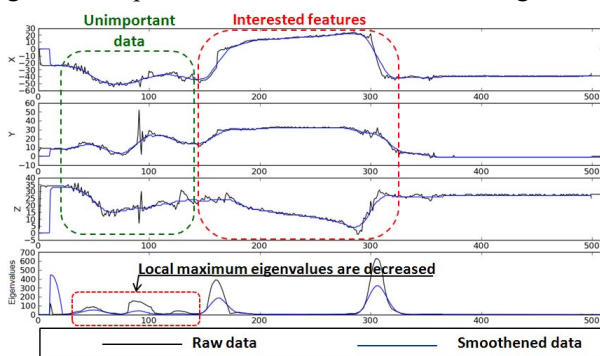


Fig. 1: Smoothen signal by moving average

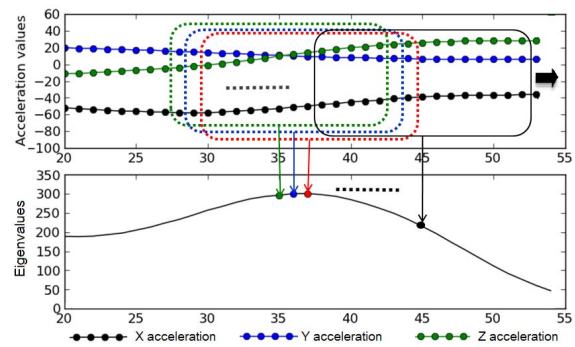


Fig. 2: Eigenvalues from sliding window

From Fig.2, if we assume sliding window size equal 15 samples and black frame is heading of sliding window. Each sliding window was calculated the covariance and eigenvectors. Covariance is statistical parameter that tells the relative between the dimensions of data set in any axes. Eigenvalues from covariance matrix imply the variation of data in any axes [12, 13]. In each window, eigenvectors represents the direction of data variation and eigenvalues explains the variance of data in the direction of its eigenvectors. Eigenvalues get small when low data variance and large when high data variance in the window having high variation in 3-axis. Consequently, ranges of changed data have high eigenvalues, because data in 3-axis are changed rapidly when raise hand up and down. Each window has three eigenvectors and three eigenvalues

according to the number of dimension. Then, rearrange eigenvalues and keep only the extreme value for considering the data change that show at eigenvalues. From Fig. 3, those positive half waves of eigenvalues are considered for data change detection.

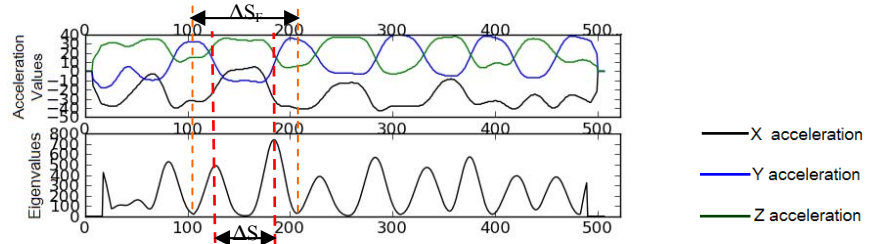


Fig. 3: Smoothen data and its eigenvalues form sliding window

From Fig. 3, ΔS is time between any two-consecutive peaks of eigenvalues (peak-to-peak). ΔS_F is time between any two-consecutive half waves concerned with ΔS and their unit is samples. At peaks of eigenvalues represent the highest variance of data with its neighbour, this point is the middle of changed data. Thus, a half wave of eigenvalues represents the range of changed data at a time.

For features selection, ΔS should be more than 100 samples but not over 600 samples because of [8]. Eigenvalues at both two-consecutive peaks should be more than 100 for acceptable because unimportant data were smoothened. Data in the range of ΔS_F , which concerned to those conditions, will be selected for classification. Therefore, data of general movements are truncated because eigenvalues are small. For classification, selected features will be classified by specific characteristics explained in the next part.

2.2. Classification

For classification, gestures can be classified by features characteristic [9]. Each hand gesture has the signal shape difference in pattern and time during gestures is distinguishable. Sensor signal in any axes has their own characteristic for acceptable and feature criteria for classification. Information for classification are signal shape (ϵ), range of data (X, Y, Z), its amplitude (\square) and ΔS_F . Acceleration signal shape represents hand's movement direction along its axis. Interested shapes for classification are positive half wave (convex or \cap) and negative half wave (concave or \cup) that occurs with 3-axis of selected feature. Signal shapes in any axis represents the hand direction according to the position while hand move. Range of data represents hand's position and its amplitude represents the velocity of hand movement. Moreover, time is a factor for gestures separation between drink gesture and the group of medicine taking by hand and palm. Mean duration of drink gesture is 9.7 second [8]. Time length of selected feature is equal ΔS_F . Where $140 < \Delta S_F < 600$ for drink gesture and $45 < \Delta S_F < 140$ for medicine intake gestures by hand and palm. TABLE 1 summarized the criteria of each gesture for classification. Each box informs the criteria information of any axis for gestures classification composed of the signal shape (ϵ), range of data according to the axis and amplitude (\square).

TABLE 1 GESTURE CHARACTERISTIC

Axis	Criteria of Gesture Characteristic (Signal Shape ϵ , Amplitude \square , Range of data (X, Y, Z))					
	Drink ($140 < \Delta S_F < 600$)		Hand ($45 < \Delta S_F < 140$)		Palm ($45 < \Delta S_F < 140$)	
	right	left	right	left	right	left
X	$\epsilon = \cap, \square > 40$ $-80 < X < 40$	$\epsilon = \cap, \square > 40$ $-80 < X < 40$	$\epsilon = \cup, \square > 30$ $-70 < X < 10$	$\epsilon = \cup, \square > 30$ $-70 < X < 10$	$\epsilon = \cap, \square > 10$ $-75 < X < 0$	$\epsilon = \cap, \square > 10$ $-75 < X < 0$
Y	$\epsilon = \cap, \square > 30$ $-60 < Y < 50$	$\epsilon = \cup, \square > 30$ $-60 < Y < 50$	$\epsilon = \cap, \square > 20$ $-50 < Y < 50$	$\epsilon = \cup, \square > 20$ $-50 < Y < 50$	$\epsilon = \cap, \square > 10$ $-15 < Y < 40$	$\epsilon = \cup, \square > 10$ $-50 < Y < 10$
Z	$\epsilon = \cap, \square > 10$ $-20 < Z < 20$	$\epsilon = \cap, \square > 10$ $-20 < Z < 20$	$\epsilon = \cup, \square > 10$ $-40 < Z < 50$	$\epsilon = \cup, \square > 10$ $-40 < Z < 50$	$\epsilon = \cup, \square > 60$ $-80 < Z < 50$	$\epsilon = \cup, \square > 60$ $-80 < Z < 50$

3. Results and Discussion

3.1. Experimental Results

Training data consists of the both left and right of 47 drink gestures, 107 hand gestures, 92 palm gestures and 354 other gestures. Each participant wore a watch and ate some placebo pills (fake pill). Participants' position while experiment is both of standing and sitting. Ages of the participants are between 22 to 58 years old. The movement of gestures follows gesture categories.

- Drink: Drinking some water from a glass then moved to mouth and put the glass back to table.
- Hand: Pick some pills by a hand (left of right) then take to mouth with standing and sitting posture.
- Palm: Hold some pills in a palm (left and right), take them to mouth with standing and sitting posture.

Smoothened data in the range of ΔS_F are considered for classification. After selected feature, minimum and maximum values of smoothen data will be found firstly to check that they was in the desire range or not. Interested points to considering the signal shape are both peak of any two consecutive eigenvalues half wave and the middle point between two them. Smoothen data in X, Y and Z axis at those three points will be considered the shape of each axis that is concave or convex shape. Signal shape, range of data and its amplitude of each axis were classified according to criteria of gesture characteristics at TABLE I and interpreting. Then, data in the range of next two-consecutive Eigen wave will be processed and repeats until the end of signal.

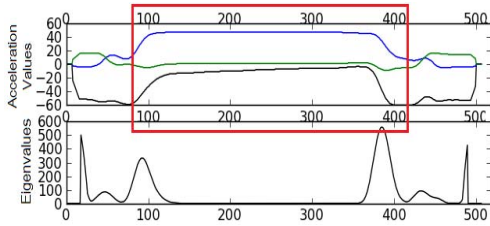


Fig. 4: Example signal of Drink gesture

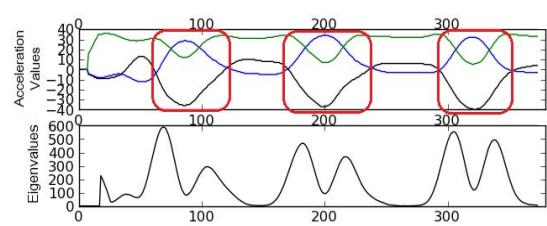


Fig. 5: Example signal of picking medicine by hand

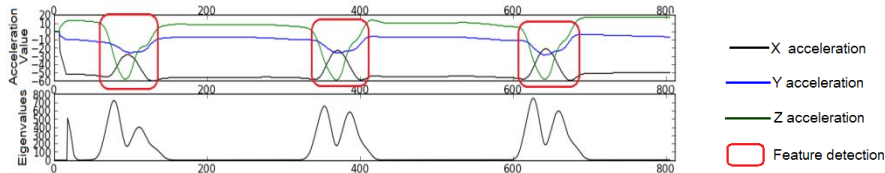


Fig. 6: Example signal of taking medicine by palm

From Fig. 4-6, smoothened data in the range of two first peaks are unimportant data and inconsistent with the criteria of gesture characteristics, which were discarded. Data in the next two peaks are according to the characteristic criterion of drink gesture, picking and taking medicine by hand and palm respectively. From Fig. 4, shape of X, Y and Z are convex. At Fig. 5, shape of X and Z are concave but shape of Y is convex. At Fig. 6, shape of X is convex but shape of Y and Z are concave. The system searches the feature by peak-to-peak automatically until the end of signal. Results of classification are shown at the TABLE 2.

TABLE 2 RESULT OF GESTURES CLASSIFICATION

Gesture (action)	Interpreting			
	<i>drink</i>	<i>hand</i>	<i>palm</i>	<i>other</i>
<i>drink</i>	74.5%	15.5%	0%	10%
<i>hand</i>	0%	88%	3%	9%
<i>palm</i>	0%	2%	96.7%	1.3%
<i>other</i>	3.6%	4.3%	0.3%	91.8%

From TABLE 2, palm gesture has the highest accuracy and drink gesture has the lowest accuracy because palm gesture signal has more specific characteristic but drink gesture signal has more ambiguously and varying when it moves naturally and user just sip water. Other gesture is general movement which cannot leach out of signal at feature selection process. It will be picked out at classification process while using feature characteristic criterion.

3.2. Discussion

Features selection by eigenvalues consideration provides high performance to detect all range of events and specific characteristic also provides the satisfactory result. Since the device is not mounted or fixed at a position but it can be move freely, position of device at the wrist and wearing it loosely are affected directly with raw data quality for classification and the accuracy will be decreased. Moving average solves that problem which eliminates local maximum eigenvalues. Consequently, unimportant data will be discarded when the device is worn loosely. Specific characteristic cannot classify the overlap features or distort signal

that cause from device wearing and occur the interpreting errors. For example, when users just sip of water, ΔS_F is shorter than normal then the interpreting will be hand gesture.

4. Conclusion

As a problem of aging population increase and chronic diseases are the leading cause of mortality, medicine adherence is important and major factor for those who need to take medicine regularly to adhere to medical treatment. Medicine intake monitoring by using a wearable 3-axis accelerometer provide more suitability for daily life and privacy for patients who uses the system. Smoothened data using moving average is first screening process to eliminate unimportant data by decrease data variation and local maximum of eigenvalues. Feature selection using consideration of eigenvalues from covariance given high accuracy for detects the interest feature and some of unimportant data were rejected as well. Feature classification using feature characteristics provides satisfactory accuracy at 96.7% and 88% in the case of medicine taking by

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