A Wearable Sensing Framework for Improving Personal and Oral Hygiene for People with Developmental Disabilities

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Abstract— **People with developmental disabilities often face difficulties in coping with daily activities and many require constant support. One of the major health issues for people with developmental disabilities is personal hygiene. Many lack the ability, poor memory or lack of attention to carry out normal daily activities like brushing teeth and washing hands. Poor personal hygiene may result in increased susceptibility to infection and other health issues. To enable independent living and improve the quality of care for people with developmental abilities, this paper proposes a new wearable sensing framework to monitoring personal hygiene. Based on a smartwatch, this framework is designed as a pervasive monitoring and learning tool to provide detailed evaluation and feedback to the user on hand washing and tooth brushing. A preliminary study was conducted to assess the performance of the approach, and the results showed the reliability and robustness of the framework in quantifying and assessing hand washing and tooth brushing activities.**

I. INTRODUCTION

Development disabilities can affect a child's physical, learning, language and behavioural abilities. These conditions start developing while the child is still in the developing stage. It can affect their day-to-day activities significantly and has the potential to last throughout their lives. A person with developmental disability can have difficulties in communication, interpreting information, conveying feelings, and making requests. Thus, it can be difficult for him/her to live independently [1]. Some people with developmental disabilities could also suffer from other cognitive issues such as problems in perception, memorisation or attention [2]. In the UK, around 1.5 million people have at least one such disability. Among them, about 350,000 people have severe developmental disabilities. People with mild developmental disabilities are no different from other people and can be very capable, but they may have difficulties or take longer for them to learn new skills. Others with more severe conditions might have difficulties to express themselves. Although some children with developmental disabilities might grow up to be independent, many of them need constant care with regard to activities of everyday living such as washing and getting dressed [1].

Developmental disabilities is a general term which covers different neurobehavioral disorders which impede learning. Autism Spectrum Disorder (ASD) is one type of developmental disabilities and characterised with impaired social and communication skills, understanding others, restricted and repetitive patterns of behaviours. They can also have difficulties in processing sensory information, poor motor skill, abnormal gait and posture and exhibit odd facial expressions. Anxiety and Attention deficit hyperactivity disorder (ADHD) are the most common neurobehavioral disorders among children. Children with ADHD have difficulties in maintaining attention and social interactions [3]. Behavioural and psychological syndromes of dementia (BPSD) is a condition commonly present in people with developmental disabilities which can affect mood, perception, thought, motor activity diurnal rhythm and personal changes which can increase mortality rate and reduction of cognitive abilities. Wandering and agitation are the most common types of BPSD [3]. Profound and multiple disabilities (PMD) is another related condition where an individual loses intellectual abilities along with hearing and/or visual impairment, significant health issues and motor impairments. Children with PMD generally cannot speak and can only rely on gestures or facial expressions to communicate [4].

It is common for people with developmental disabilities to exhibit challenging behaviours. These behaviours may provide stimulations to the individual, such as attracting attention and avoid demanding tasks. However, these behaviours can hinder their learning, induce stress and tension on themselves and their carer, and impede their ability to become independent. Some common examples of challenging behaviours are aggression, destructive behaviour, self-injury, violence, etc. [5]. To care for people with developmental disabilities and enable them to live a healthy and independent lives, their activities needs to be monitored focusing mainly on detecting challenging behaviours and quickly attending to them. It should be noted that these behaviours can change from the person to person and various in different environments [5]. By capturing the activities and behaviours, the underlying reasons/causes for the behaviours can be deduced and preventative steps can be taken to avoid the challenging behaviours. Programmes can be designed to help these children to get into the society and live healthy and independently.

In tackling challenging behaviours and caring for people with developmental difficulties, carers and teachers mainly rely on logging an individual's behaviours trying to understand the individual needs, and deduce the causes of the behaviours over time. Given the increasing cost of care, such labour intensive and individualised care has become impractical in the current healthcare services. To address this issue, healthcare services have sought for technological solutions. The recent advances in wearable technologies could provide the needed monitoring functions for the care of people with learning disabilities. All the new wearable devices are already equipped with inertial and other sensors, and studies have shown the reliability and accuracy in using such devices for monitoring daily activities and quantifying behaviours.

This paper presents a novel approach of using a wearable smartwatch for the care of people with developmental disabilities. In particular, this paper presents a framework for pervasive monitoring of oral and personal hygiene, which are the major health problems for people with developmental disabilities. By detecting and quantifying hand washing and tooth brushing activities, the framework could provide the needed information to help children to learn and understand how well they brush their teeth and wash their hands. Research have shown that promoting habits like washing hands can improve wellbeing of children [6]. Also habits like washing hands and brushing teeth can prevent infections. As an example, washing hands regularly can prevent diarrhoea and acute lower respiratory infections [7]. The aim of this research to improve wellbeing and independent living of these children.

To achieve this, an off-the-shelf smartwatch is used as the hardware platform to capture users' hand movements and audio signals. In the coming sections we will discuss the method, the results from our preliminary study and future directions.

II. Previous work

Accelerometers have been proposed for detecting challenging behaviours of people with developmental disabilities. Three axes accelerometers on wrists and ankles have been proposed for detecting challenging behaviours of children with developmental disorders [8]. It could detect aggression, disruption and self-injury with a precision of 70%. For classification, Naïve Bayes, decision tree and SVM are used and it is observed that SVM produced the best results [8]. In another study, a wrist band with an accelerometer and a gyroscope was proposed to quantify activities of daily life, such as drinking and hand washing [9]. The wristband can also be used to detect walking, jogging and smoking. Light weighted pre-processing routines were proposed to remove noise and perform segmentation in the wristband before sending result data to the mobile phone. Hand washing was characterised by turning on tap, rubbing or flipping motion of hand and turning off the tap. Drinking was characterised by hand motion when drinking with a cup or a bottle or another container. In order to classify the different movements, a rule base is used in [9]. [10] analysed accelerometer data sampled at 50 Hz, and detected hand flapping and body rocking of children with ASD. It also suggests the use of audio data to improve the accuracy.

Lee *et al.* [11] proposed a smart toothbrush equipped with a three axes accelerometer and magnetometer to detect inappropriate tooth brushing of individuals. This research divides teeth into several regions and detect the area being brushed and determine if brushing of each area is appropriate or not. Apart from assessing the tooth brushing technique, accelerometer data collected from a toothbrush can be used to identify the individual user, as shown in [12]. Eleven features were extracted from two axes of the accelerometer including mean, standard deviation and cycle length. Support vector machine was used for the classification.

With the advent of smartwatches, growing number of people are choosing to use them in place of their traditional wrist watches. These smart devices come with inbuilt sensors like accelerometers and gyroscopes. Therefore, most smartwatches are designed with functions for monitoring users' activities and fitness. Thomaz *et al.* proposed the use of a smartwatch to detect eating episodes as a step towards monitoring food intake [13]. Random forest was proposed to classify the eating episodes based on features, such as mean, variance, skewness, kurtosis and RMS extracted from the 3 axes accelerometer.

Apart from wearable devices, smartphone has also been proposed for evaluating tooth brushing where audio data are used to assess the brushing performance [14]. The audio data alone could detect which region is being brushed and could classify the brushing stroke into 2 classes. The system could give scores for each section being brushed based on stroke quality and time spent. To accurately evaluate the performance, the scoring system was designed jointly with a dentist. Hidden Markov Model (HMM) was used in the system to classify the performance based on features, such as 12-order MFCC, log energy, 13-order delta, 13-order acceleration coefficients for MFCC and log energy coefficients.

III. Materials and methods

The main purpose of this study is to detect and quantify hand washing and tooth brushing activities.

In assessing hand washing, several hand motions are required for a proper hand wash. The guidelines of hand washing by World Health Organisation is used in this study [15]. Wetting hands, applying soap, rinsing with water and drying are not considered for simplicity. The concerned hand motions are divided into 9 sections in this research. These motions are named from W01 to W09 as shown in Figure 1. One of the aims of this research is to detect the different hand washing movements using a smartwatch, and the detected results can be used as a metric to quantify the performance or quality of the hand washing activity.

The other aim of this research is to assess the tooth brushing activities. Similar to previous research, we aim to detect which area of teeth the user is brushing, but instead of using a sensor enabled toothbrush, we propose to use smartwatch to assess brushing movements. Teeth can be divided into separate sections for the purpose of studying as shown in Figure 2. These sections are named from B01 to B18.

In the real world situation, a person wearing a smartwatch will be performing normal day-to-day activities such as dressing up, having a shower, eating and etc. To provide a detailed analysis on hand washing and tooth brushing activities, a hierarchical approach is designed in the framework. As shown in Figure 3, the framework first distinguishes hand washing or tooth brushing activities from other normal activities. Once it detects hand washing, it will then classify which hand washing motion is performed. Likewise, once it detects a tooth brushing episode, it will then classify which region of the teeth the user is currently brushing. As described, this is a multiple stage process as shown in Figure 3.

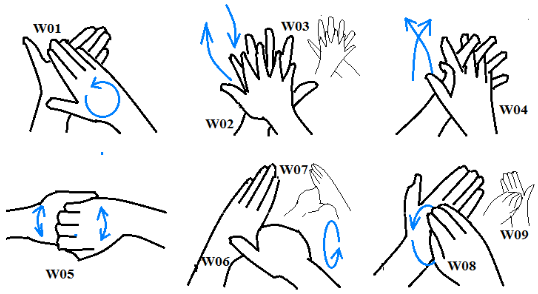

Figure 1. Hand washing motions [15]

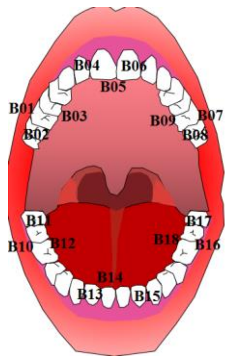

Figure 2. Regions in the mouth

The smartwatch LG G Watch W 100 is used in this research. This watch has a 3-axis accelerometer, gyroscope and a compass. For the intents of this paper, both accelerometer and gyroscope data are used. Also, audio data is recorded from the watch while participants are conducting the relevant activities. Linear acceleration and gyroscope sensors transfer data at a varying rate around 150Hz. Using the built-in microphone of the watch, audio data was recorded with a sampling rate of 8 kHz on a mono channel. The sensor coordinate system for the smart watch device is shown in Figure 4. An android app was developed based on [16] to collect data from the watch with a mobile phone, as shown in Figure 5. The data were later transferred to a computer for analysis.

To validate the framework, 7 healthy volunteers were required and participated in the study, 3 females and 4 males. Their ages ranged from 23 years to 33 years. All participants are right handed and worn the watch on their right wrists during the study. In the study, the participants were asked to perform a set of activities, which includes brushing their teeth, washing hands and other normal daily activities, while data was collected. The data collected from the smartwatch was transferred to a mobile phone via its Bluetooth Smart link. Data was marked by the researcher while observing the participants during the study, and marks were then used to segment the data for validation. Segmenting the audio data for validation is relatively trivial since the researcher gave verbal instructions to the participants during the study and such instructions could be clearly identified from the audio track later. After the data was collected, data were processed and analysed by using the data mining software Weka [17].

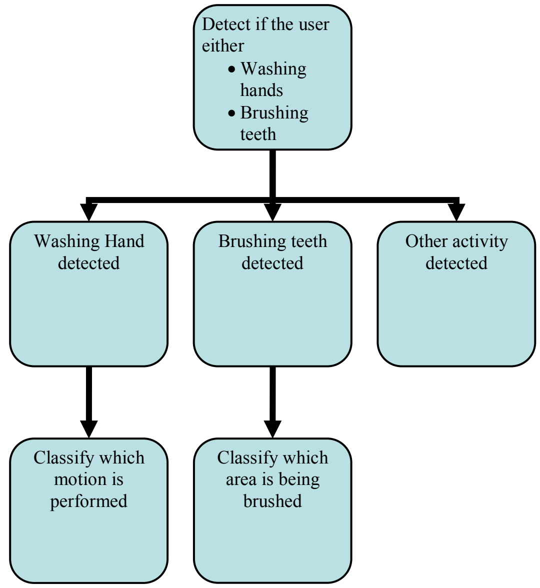

Figure 3. A Hierarchical Classification Framework

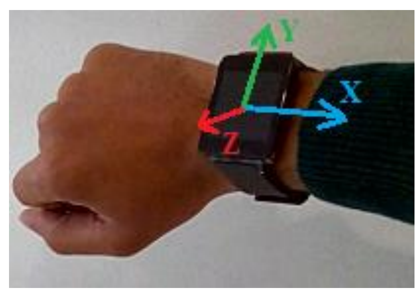

Figure 4. Coordinate System for Android devices [18]

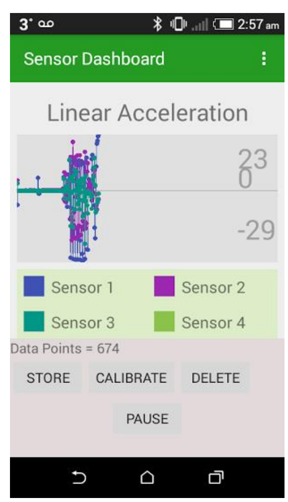

Figure 5. Mobile application used to collect data

TABLE I. GROUPING OF CLASSES

Stage	Classes														
2	B								W						R
3	B1				B2				W1				W2	W3	
	B01, B02, B04, B06, B07, B08, B09, B10, B11, B13, B15, B16, B17, B18				B03, B05, B12, B14				W01,W02, W03, W04, W08, W09				W05	W06	
4	B1	B2	B3	B4	B03	B05	B12	B14	W1	W2	W3	W4	W05	W06	
	B01 B04 B10 B13	B02 B08 B11 B17	B06 B07 B15 B16	B09 B18					W01 W04	W02 W09	W03	W08			

For inertial measurements, although the sampling rate was set to 200 Hz, this cannot be guaranteed by the android operating system and the actual rate can vary [19]. Linear interpolation was used to approximate any missing data and maintain a constant sampling rate.

This research classifies data in four stages. The first stage is a binary classifier which is designed to discriminate the activities into two classes. Tooth brushing and hand washing are grouped together into a single class (called "activity" class) and all other activities are grouped into the other class. If this stage detects teeth brushing or hand washing, then it moves to stage 2. In this stage, it tries to classify the activity into either hand washing or teeth brushing activities. After identifying what activity the user is performing, the algorithm moves to stage 3. In this stage, it classifies which hand motion is performed. Several hand washing classes had to be grouped together to form new classes due to their similarities. Likewise, stage 3 classifies which area is brushed. Similar to the hand washing classes, teeth brushing classes had to be grouped together in stage 3. After deciding which class the data is belong to in the stage 3 the algorithm moves to stage 4 where the data are classified into more specific classes. The summary of the grouping of classes can be seen in Table I.

The first stage of the classification aims to detect episodes of activities (either hand washing or tooth brushing). Using all the sensors to monitor the user at all-time could drain the battery and severely impede the usability of the wearable device. Therefore, it is preferred that only one of the sensors is used to monitor the user all the time. From the initial study, it was found that the first level classification (i.e. classifying if the user is performing an activity or not) can be achieved only with accelerometer data. Also, only very simple features are needed to perform this as shown in Table II. Therefore, when monitoring the user all the time, only accelerometer data should be monitored and relatively small processing power is required for this task. However, using only IMU data has a drawback. When the user imitates the motion of an activity without actually performing it; e.g. doing the motion of hand washing without touching water, the algorithm classifies it as hand washing. To overcome this, audio data can be used. This is because activities such as hand washing with water and tooth brushing has distinct audio characteristics. Furthermore, studies suggested that audio can be used to discriminate between three classes namely, brushing, washing and other with high accuracy level.

TABLE II. LEVEL 1 CLASSIFICATION SUMMARY

Classes	**True positive %**	**Selected features**	**Overall accuracy**	**Classifier**
A	97.7	xMeanAcc yMeanAcc zMeanAcc xSdAcc ySdAcc zSdAcc	98.1%	Naïve Bayes
R	100.0			

When analysing data from IMU, various features had to be calculated. Then, data are labelled and analysed with Weka. Features obtained from the 3-axis accelerometer and the 3-axis gyros cope includes: Mean values, xMeanAcc, xMeanGry, Stdevs, xSdGyr, Energy and cor1 to cor15.

- Mean values for the time window were calculated for each axis.
- The mean value for x axis of the accelerometer is named "xMeanAcc" and that of the gyroscope is named "xMeanGyr".
- Stdevs - standard deviation values were calculated from all axis.
- xSdGyr - Standard deviation value for x axis of the gyroscope.
- Energy values were calculated to capture the frequency components of the data. Energy is defined as sum of the absolute values of the discrete Fourier transform components divided by the number of components. Please refer to equation 1 where w is the number of FFT components.

$$Energy = \frac{\sum_{i=1}^{w}|x_i|}{w} \qquad (1)$$

- Correlation features were calculated. Data values were arranged as accX, accY, accZ, gyrX, gyrY, gyrZ where acc represents accelerometer and gyr represents gyroscope. Correlation between each value of these were calculated. Therefore, 15 correlation features were obtained for each time window (${}^{6}_{2}C$). These features were named from cor1 to cor15 where cor1 representing the correlation between accelerometer x axis and accelerometer y axis.

For classification, Naïve Bays Classifier is used. Naïve Bays is a simple classifier which is fast and efficient. Also, this classifier is selected since it can be implemented in wearable devices which have limited processing and memory capacities.

Let C_i is the i^{th} class and f is a feature vector calculated from data. Therefore, $f_1, f_2 \ldots f_n$ are individual features. The Naïve Bays estimator is as follows.

$$P(C_i|f_1 .. f_n) = P(f_1|C_i)P(f_2|C_i) \ldots\ldots\ldots\ldots P(f_n|C_i)P(C_i)$$

In order to apply this, the individual features are assumed to be conditional independent. Also, because of the $P(C_i)$

term, the number of instances of the class C_i influence the calculation. Therefore, number of instances of each class is kept approximately equal.

The first level classification is performed with accelerometer data alone. Brushing and hand washing are grouped into the class “A” and all other activities are grouped into class “R”. First, data were collected, labelled and analysed with Weka. A feature selection step was performed with “classifier subset evaluator” with “rank search” as the search method. 6 simple features were selected and calculated for the classification. Please refer Table I for information about the classification.

For classification of level 1, the following Naïve bays classifier is used, where A represents the activity (i.e. hand washing or tooth brushing)

$$P(A|f_1,f_2,f_3,f_4,f_5f_6) = P(f_1|A)P(f_2|A)P(f_3|A)P(f_4|A)P(f_5|A)P(f_6|A)P(A)$$

f_1 to f_6 are, xMeanAcc, yMeanAcc, zMeanAcc, xSdAcc, ySdAcc and zSdAcc in order. This can be shown in the form of a Bayesian Network graph as shown in Figure 6.

In level 1 classification, the algorithm tries to classify if the user is performing a target activity (i.e. hand washing or tooth brushing) or other activities. If a target activity is detected, the algorithm moves to level 2. In the study, all the audio data acquired during data collection was divided into 3 categories; brushing, hand washing and others. A number of features were calculated from this data using the software jAudio [20]. 0.5 seconds window lengths were used with 50% overlapping to calculate features.

Afterwards, the features were labelled with class names B (brushing), W (hand washing) and R (other). Next, they are analysed with Weka. A Naïve Bayes classifier was used to classify the data and a 10 fold cross validation for testing. Also feature selection step is carried out with chi squared statistic and gain ratio. The results obtained is shown in Table II along with the selected features.

The next step is to perform the classification in the stage 3. For this stage, instead of audio data, it was found that inertial measurement data is sufficient for classifying different movements. Various features were extracted from the data.

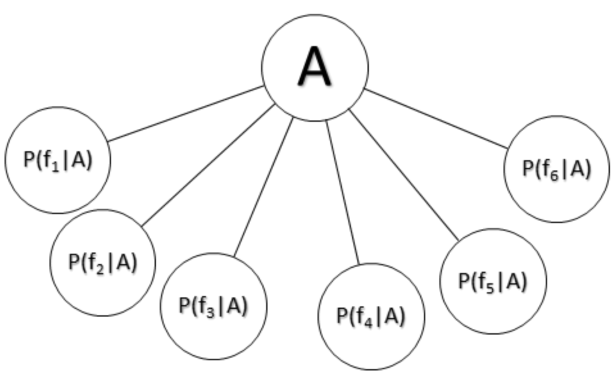

Figure 6. A Naïve Bays Classifier for detecting the target activity A (i.e. hand washing or tooth brushing)

In detecting hand washing movements, the motions depicted in Figure 1 can be divided into 3 main classes. The first class which contained movements H01, H02, H03, H04, H08 and H09 were grouped together to form class H1. Movements H05 and H06 could be taken as two separate classes. Table 1 summarises these divisions. After labelling the data appropriately, the dataset was fed to Weka and it was found that Naïve Bays classifier can classify the data accurately. Chi squared statistic and gain ratio was used to carry out a feature selection step. The results are shown in Table III.

Secondly, tooth brushing is considered. The regions of teeth are divided into two main classes called B1 and B2. B1 contains B01, B02, B04, B06, B07, B08, B09, B10, B11, B13, B15, B16, B17 and B18 regions. B2 class encompasses B03, B05, B12 and B14 regions. A feature selection process was performed and the results are shown in the Table III. To select the features, chi squared statistic and gain ratio was used.

After the classification in stage 3, stage 4 classification is then be performed. Please refer to Table I to see how the tooth brushing regions and hand washing movements are being grouped into different classes. Hand washing are divided into 6 different movements. Tooth brushing are divided into 8 different regions. Table IV shows the results of level 4 classifications.

TABLE III. LEVEL3 CLASSIFICATION SUMMARY

Classes	True positive %	Selected features	Overall accuracy	Classifier
B	96.2	Spectral flux Spectral variability Root mean square Zero crossings Strongest beat Beat sum Strength of strongest beat Strongest frequency via zero crossings MFCC0 MFCC3	95.4%	Naïve Bayes
W	97.9			
R	93.4			

TABLE IV. LEVEL 2 CLASSIFICATION SUMMARY

Classes	True positive %	Selected features	Overall accuracy %	classifier
B1	77.8	yMeanAcc, xSdAcc, ySdAcc, zSdAcc, xSdGyr, ySdGyr, zSdGyr, cor2, cor4, cor6, cor8, cor9, cor14, cor15	72.7	Naïve Bayes
B2	53.4			
W1	99.4	xSdAcc, xSdGyr, energy1, energy2, cor1, cor2	96.7	Naïve Bayes
W2	100.0			
W3	86.0			

TABLE V. LEVEL 3 CLASSIFICATION SUMMARY

Classes	True positive %	Selected features	Overall accuracy %	classifier
B03	91.8	yMeanAcc, yMeanAcc, zMeanAcc, xSdAcc, ySdAcc, zSdAcc, xSdGyr ySdGyr, zSdGyr, energy1, energy2, energy3, energy4, energy5, energy6, cor1, cor2,cor3, cor4, cor5, cor6, cor7, cor8, cor9, cor10, cor11, cor12, cor14, cor15	83.7	Naïve Bayes
B05	98.4			
B12	74.1			
B14	69.1			
B1	48.5	yMeanAcc, zMeanAcc, xSdAcc, ySdAcc, zSdAcc, xSdGyr, ySdGyr, zSdGyr, energy2, energy4, cor1, cor2,cor4, cor5, cor6, cor8, cor9, cor11, cor12, cor14, cor15	54.2	Naïve Bayes
B2	52.3			
B3	68.8			
B4	40.6			
H1	95.2	xMeanAcc, yMeanAcc, zMeanAcc, xSdAcc, ySdAcc, zSdAcc, xSdGyr, ySdGyr, zSdGyr, energy1,energy2, energy3, energy4, energy5, energy6, cor1, cor2, cor4, cor5, cor6, cor8, cor9	85.1	Naïve Bayes
H2	82.3			
H3	88.3			
H4	70.2			

IV. DISCUSSION

In this study, simple features calculated with only accelerometer data is used for initial classification step. These simple features and a simple classifier like Naïve Bays combine to provide a processing and memory efficient classification system. This is designed to minimise the power consumption of the smartwatch. In the following classification stages, gyroscope and audio data is also used.

In this study, to demonstrate and assess the proposed framework, participants were continually monitored and instructed by an observer on which motion to be performed and when to start/stopped. Also, in the tooth brushing case, mouth was divided into discrete regions and brushed them separately. These may be unnatural and can alter the participants' natural behaviour. It can be a source of error in this study. Also, the study was performed in a controlled environment with minimal ambient noise. In real scenarios, noise can influence the results obtained. Clearly, learning disabilities affect people of all ages. This preliminary study was conducted with 7 healthy people aging from 23 to 33 years. Although this is a preliminary study, this study has demonstrated the feasibility of a novel concept of using a wearable smartwatch for evaluating hand washing and tooth brushing activities providing a new insight into using wearable device for personal and oral hygiene applications.

V. CONCLUSION AND FUTURE WORKS

A novel approach is presented for pervasive monitoring of personal and oral hygiene using a smartwatch. A hierarchical classification framework is proposed for detecting hand washing and tooth brushing episodes, and classifying hand washing motion or tooth brushing regions in the subsequent stages of classification. To validate the proposed approach, a preliminary study was conducted with 7 participants and they were asked to perform a series of activities while wearing a smartwatch. The data were obtained from the embedded three axes accelerometer, three axes gyroscope and microphone of the smartwatch. Significant features are extracted and selected using chi squared statistic and gain ratio and the data were classified which Naïve Bayes classifier in Weka data mining tool. Accuracy rate above 95% was obtained in detecting the hand washing and tooth brushing episodes, and accuracy of 96% and 72 % were obtained in distinguishing the 3 main hand washing movements, and 2 main regions of tooth brushing respectively from the sensory data. In detecting the sub-regions in tooth brushing, the accuracy was 67.9±20.4% and in detecting detailed hand washing movements, the averaged accuracy was 84.0±10.6%.

This study will be extended with more subjects to assess the reliability of the proposed framework. Also, all participants were right handed. Therefore, the effect of right or left handedness needs to be determined. This research focuses on developing a system to assist people with learning disabilities to live more independent life and later study will recruit people with learning disabilities. In addition, comparative analysis should be performed to identify optimal machine learning algorithms.

This study focuses mainly on detecting if a person is washing hands, brushing teeth or other activities. The detection results can be further analysed to evaluate the performance or quality of their hand washing or tooth brushing activities providing the needed feedbacks to the users and their carer. As an example, the user can be notified if he/she needs to improve brushing her lower right teeth through a message on the mobile phone. In addition, interactive gaming can be customised and individualised to improve the necessary hand washing or tooth brushing skills. Although the proposed framework was designed for people with developmental disabilities, the proposed hand washing episode and movement detection can also be applied for maintaining hand hygiene in hospitals, which is a major concern in patient safety. In addition, the tooth brushing detection approach can also be applied to help any children to learn how to brush their teeth properly.

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