AWash: Handwashing Assistance for the Elderly with Dementia via Wearables

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***Abstract*—Hand hygiene has a significant impact on human health. Proper handwashing, having a crucial effect on reducing bacteria, serves as the cornerstone of hand hygiene. For the elder with dementia, they suffer from a gradual loss of memory and difficulty in coordinating steps in the execution of handwashing. Proper assistance should be provided to them to ensure their hand hygiene adherence. Toward this end, we propose AWash, leveraging only commodity IMU sensor mounted on most wrist-worn devices (e.g., smartwatches) to characterize hand motions and provide assistance accordingly. To handle particular interference of senile dementia patients in IMU sensor readings, we design a number of effective techniques to segment handwashing actions, transform sensor readings to body coordinate system, and extract sensor-body inclination angles. A hybrid neural network model is used to enable AWash to generalize to new users without retraining or adaptation, avoiding the trouble of collecting behavior information of every user. To meet the diverse needs of users with various executive functioning, we use a state machine to make prompt decisions, which supports customized assistance. Extensive experiments on a prototype with eight older participants demonstrate that AWash can increase the user's independence in the execution of handwashing.**

I. Introduction

The world is aging rather rapidly, and the proportion of the elderly with dementia is growing at a phenomenal rate. For example, a recent report demonstrates that an estimated 8 million Americans age 65 and older are living with Alzheimer's or other dementias [1]. The elderly with dementia experience a gradual loss of memory and steady deterioration of executive functioning to perform necessary activities of daily living (ADLs) such as eating, grooming, and dressing. In addition, handwashing serving as a great way for the elderly to reduce bacteria, avoid illnesses or even fatal infections, is very critical in daily life, especially during the outbreak of respiratory viruses such as COVID-19 [2] or H1N1 [3]. Therefore, providing assistance to the elderly with dementia during handwashing is of great importance for their overall well-being.

Existing works based on vision technology [4]–[6] are efficient, but the drawbacks of privacy concerns and high hardware costs often prohibit the installation of cameras in bathrooms. In addition, several systems based on wrist-worn devices [7]–[9] have been proposed in recent years, mainly extracting acceleration and angular velocity features to differentiate handwashing movements. These methods generally realize promising results for young and healthy people. However, they are always ineffective once adopted to assist handwashing for older adults with dementia. The reasons comprise of follows three aspects: (1) *Different behavior patterns.* The handwashing behavior patterns of senile dementia patients are quite different from those of young and healthy adults. For example, the hand movement trajectory of older adults with dementia is more tortuous than healthy adults. Also, motor and muscle weakness and rigidity introduce interferences in IMU sensor readings (such as more turning points and different positions of peaks and troughs), which always deform the repetitive patterns of hand movements. Thus, recognition of handwashing action for senile dementia patients demands advanced data processing techniques. (2) *More distinct individual differences in handwashing movement patterns.* Due to the difference in cognitive impairment, the elderly with dementia show the spatial and temporal variance in handwashing task execution. Thus, their handwashing motion patterns have more significant individual differences than healthy people [10]. (3) *Diverse assistance manner.* Dementia patients suffer from different degrees of cognitive impairment, resulting in diverse executive functioning. They demand different forms of assistance, which has not yet been addressed by existing systems. So far, the wearable-based handwashing assistance system for the elderly with dementia is still a relatively new field, which requires further exploration, and this situation is getting more urgent with the aging population's global trend.

Motivated by the above reasons, we propose AWash, a handwashing assistance system for the elderly with dementia leveraging only commodity IMU sensors so that it can be implemented on most wrist-worn devices (e.g., smartwatches). Through observation, we find that during handwashing, the wrist posture of senile dementia patients is distinct among different handwashing actions and robust to various interferences. This inspires us to investigate wrist posture measurements to characterize handwashing actions then provide assistance according to the performed actions. Our goal is to build a handwashing assistance system for the elderly with dementia, which can accurately recognize handwashing actions, provide different handwashing assistance solutions to diverse and heterogeneous users, and can generalize to new users without

Fan Li is the corresponding author. The work of Fan Li is partially supported by the National Natural Science Foundation of China (NSFC) under Grant No.62072040, 61772077 and Beijing Natural Science Foundation under Grant No. 4192051. The work of Song Yang is partially supported by NSFC under Grant No. 61802018.

retraining or adaptation.

Despite its simple idea, three major challenges underlie the design of AWash:

(1) *How to obtain each type of handwashing movement fragment from the continuous and noisy IMU sensor data?* Visuomotor impairment affects eye-hand coordination for the orderly in some dementias during handwashing [10]. It causes the noise of peaks and troughs in IMU sensor data and disturbs the actual handwashing fragment detection. In addition, handwashing movement segmentation will also be interfered by other types of movements. For example, the movement switches between different handwashing actions and unpredictable movements due to impaired memory and attention span. To address it, we use an autocorrelation-based method to detect the handwashing movement fragment. Then, the start and end point of the handwashing movement fragment is determined from the troughs of linear angular velocity.

(2) *How to derive the representative wrist movement information to distinguish the various handwashing movements of the elderly with dementia?* Sensory readings collected from wrist-worn devices are coarse and noisy due to the uncoordinated nature of movements of the elderly with dementia. Therefore, motion speed and displacement information directly estimated from the accelerometer and gyroscope readings are insufficient when adopted in handwashing motion recognition for senile dementia patients. To overcome this issue, we investigate the relative inclination angles between the IMU sensor and user body (sensor-body inclination angles) to facilitate accurate and robust handwashing action recognition.

(3) *How to design a user-independent handwashing motion recognition system for senile dementia patients with diverse cognitive impairment?* There has been some evidence that senile dementia patients have very diverse handwashing patterns due to the different cognitive impairment levels. For example, users with the same cognitive ability level may have different motion trajectory during handwashing, while dementia patients with different cognitive abilities have not only different hand motion trajectories but also different path tortuosities of the motion trajectory [10]. To overcome this, we use a hybrid network model to handle differences in user behaviors, which makes AWash available to anyone without retraining or adaptation.

In summary, this work makes the following contributions:

- We propose AWash, a wearable-based handwashing assistance system for older people living with dementia. It can characterize the unique handwashing pattern of the elderly, recognize handwashing actions, and support customized guidance to diverse users.
- We design a set of data processing algorithms to segment handwashing movements and decode the relative position between the IMU sensor and the user body from sensor readings. A hybrid network model is used to deal with the significant variance between individuals and achieve user-independent handwashing action recognition. Moreover, we use a state machine to allow customize assistance for users with diverse cognitive impairments.
- We implement a prototype system and conduct experiments with various parameters and scenarios. The experimental results from eight older adults demonstrate that AWash effectively recognizes the handwashing actions of the elderly with dementia and can increase their independence in washing their hands.

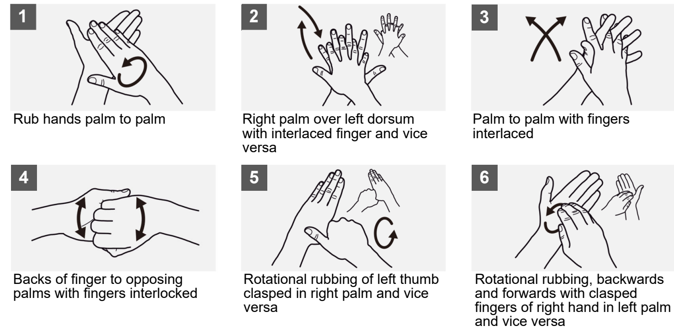

Fig. 1. The handwashing procedure issued by WHO [28].

The remainder of this paper expands on the above contributions. We begin with a brief introduction to handwashing actions and the system overview.

II. System Design

A. Handwashing Actions

World Health Organization (WHO) issued guidelines to provide recommendations for the improvement of hand hygiene, which is shown in Fig. 1. The handwashing procedure comprises six actions, namely, rub hands palm to palm (*action* 1), right palm over left dorsum with interlaced fingers and vice versa (*action* 2), palm to palm with fingers interlaced (*action* 3), backs of fingers to opposing palms with fingers interlocked (*action* 4), rotational rubbing of left thumb clasped in right palm and vice versa (*action* 5), and rotational rubbing, backwards and forwards with clasped fingers of right hand in left palm and vice versa (*action* 6). In this paper, we focus on the recognition of these six handwashing actions. In addition, the general methods proposed in this work can be extended to other handwashing actions easily.

B. System Overview

The basic idea of AWash is to analyze the IMU data collected by wrist-worn devices and distinguish handwashing actions. Triggering handwashing data collection and detecting whether users use the soap have been addressed through some techniques. For example, leverage Bluetooth or Wi-Fi modules to locate a user and determine whether the user is close to the bathroom sink, and use smart faucet and smart foam soap dispenser to detect a user turning on the faucet and using soap. We currently focus on recognizing handwashing actions of the elderly with dementia and providing assistance according to the performed actions.

As data providers, the elderly wear wrist-worn devices to record their hand movements while washing their hands. The system overview of AWash is shown in Fig. 2. There are

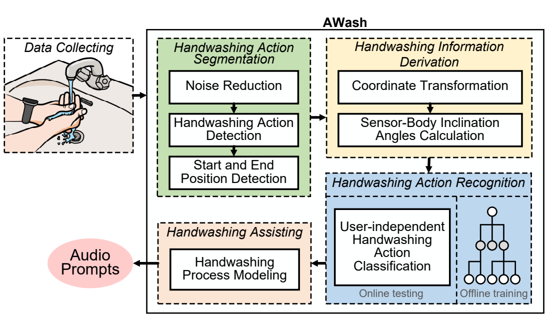

Fig. 2. The overall framework of AWash.

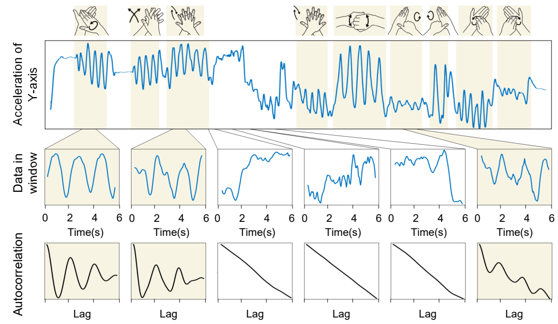

Fig. 3. Example of processing accelerometer data of Y-axis using autocoloration-based method.

four components of our system: *Handwashing Action Segmentation*, *Handwashing Information Derivation*, *Handwashing Action Recognition*, and *Handwashing Assisting*.

In the *Handwashing Action Segmentation* phase, we first perform *Noise Reduction* that removes IMU sensor data noise by the moving average filter. Then, we perform *Handwashing action detection*, leveraging autocorrelation-based method to distinguish handwashing movements from non-handwashing movements and extra movements. Last, we segment each handwashing action based on the fact that the start and end of an action result in troughs of linear angular velocity.

In the *Handwashing Information Derivation* phase, *Coordinate Transformation* is performed to align sensor readings to the body coordinate system. Relative inclination angles between the IMU sensor and user body are then calculated to characterize handwashing actions.

The core of *Handwashing Action Recognition* is a hybrid network model. Time series sensor-body inclination angles server as input. The hidden layer of the model contains a multi-layer LSTMs model, and the output layer contains an aggregate layer and a softmax layer. With the great power of neural network techniques, the proposed hybrid network can extract user-independent features. After training, the model can realize promising recognition of handwashing actions.

The *Handwashing Assisting* aims to provide different assistance to diverse users according to their diverse needs. Seniors with different levels of cognitive abilities will encounter different problems during handwashing. Accordingly, they require different assistance to improve hand hygiene. For example, some users need instructions on a specific step, some users need to be prompted when they miss a step, and some users demanded to be prompted of obsessive behaviors. We use a state machine to model the handwashing process of senior users. By customizing the output functions, we support users with customized assistance.

C. Handwashing Actions Segmentation

Intuitively, we can apply the sliding window method to segment the collected data into continuous segments, and then extract features for classification. However, extra movements of hands are required to switch between different types of handwashing actions. For example, *action* 4 is performed by rubbing the back of fingers against the palm with finger interlocked, and *action* 5 is performed by rotational rubbing the left thumb and right thumb. If the user performs *action* 4 and *action* 5 in succession, an extra movement, from finger interlocked to clasp the thumb, will be introduced. Also, the IMU sensor data contains non-handwashing movements (e.g., scratching) due to impaired memory and attention span. To avoid unnecessary computational cost and misclassification, we design algorithms to detect and segment handwashing actions.

1) Noise Reduction: To enable effective data processing, AWash first applies the moving average filter to reduce the random noises from the IMU sensor readings roughly.

2) Handwashing Action Detection: A key observation is that the elderly with dementia always perform each kind of handwashing action repeatedly during handwashing. Such repetitive movements lead to repetitive patterns in accelerometer data. While extra movement and non-handwashing movement usually do not have repetitive patterns. Thus, our basic idea is to check whether the accelerometer data in a sliding window have repetitive patterns, then detect the handwashing actions. However, due to the impaired eye-hand coordination ability of senile dementia patients, accelerometer data of each execution of handwashing action are noisy and coarse. The data from repeated handwashing movements differ in amplitude, the number of peaks, and peak positions. Intuitive ways such as comparing peak to peak distance and Fourier transform can not solve our problem. Therefore, we adopt autocorrelation to process the acceleration of handwashing actions. The autocorrelation sequence of a periodic signal has the same cyclic characteristics as the signal itself. Thus, autocorrelation can help determine the presence of cycles and estimate cycle period.

We first apply a sliding window to the time series accelerometer data. By observing that most handwashing actions are performed within 2.5s, we set the window size to 6s to ensure that the window can capture repeated handwashing actions. Then, we calculate the autocorrelation of the data in the window by varying lag from 1 to window size $\times$ fs -1, where fs is the sampling frequency. Suppose the data in the window are from the same kind of handwashing action. In that case, at least two lags will result in autocorrelation peaks, one is the possible repetition period P, and the other is twice times of the possible repetition period $2P$. If the data in the window

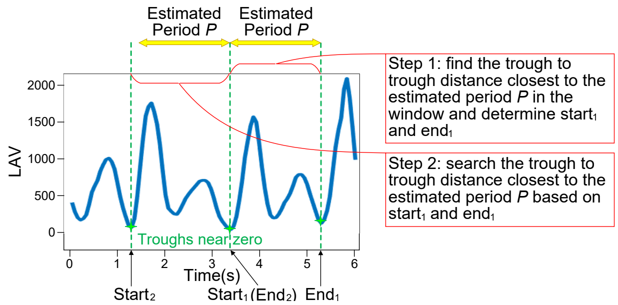

Fig. 4. Example of searching the start and end positions of handwashing actions based on LAV data.

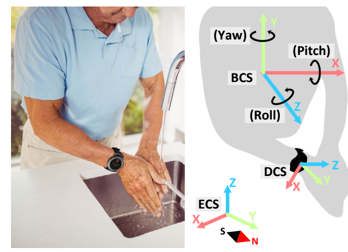

Fig. 5. 3 involved coordinate systems.

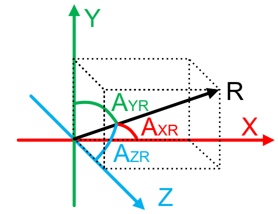

Fig. 6. inclination angles.

are from extra movement or non-handwashing movement, no autocorrelation peak can be observed.

Fig. 3 shows an example of processing accelerometer data of the Y-axis. Handwashing movements are marked with yellow background, non-handwashing movements and extra movements are marked with white background. We can observe that although accelerations of the same kind of handwashing action have diverse waveforms (e.g., different number of peaks), the auto autocorrelation-based method can distinguish handwashing actions with non-handwashing movements and extra movements effectively. Since X, Y, and Z-axis reflect the characteristics of handwashing actions from different angles, we take a movement as handwashing actions if the time series data from any axis are classified as handwashing actions. Note that we do not process the gyroscope data in this stage because accelerometer data have better performance and are sufficient to realize promising detection.

3) Start and End Position Detection: By observing that the amplitude of IMU sensor data is directly proportional to movement intensity, we check the IMU sensor data values to locate each action's start and end position. Since the device coordinate system rotates with the wrist when performing different handwashing actions, the start and end of each handwashing action might be peaks or troughs of X, Y, Z-axis data of accelerometers and gyroscopes. To address this, we turn to use the linear angular velocity (LAV):

$$LAV = \sqrt{(w_x)^2 + (w_y)^2 + (w_z)^2} \tag{1}$$

where w_x, w_y, w_z are the gyroscope readings in the X, Y, Z axis, respectively. The use of LAV relieves us of the bother of determining whether the start and end of action correspond to a peak or a trough. In the LAV data of a handwashing action, the start and end positions must correspond to the trough near zero. To accurately segment the action without being interfered by the extra troughs, we first compare the distance between troughs and the estimated period P in the sliding window. The indexes of two troughs with a distance closest to the estimated period P are considered the positions where a handwashing action begins and ends. Then, by searching forward and backward, the start and end positions of the other handwashing actions in the sliding window are located by finding troughs that have distance most similar to the estimated period P. Fig. 4 shows an example of searching start and end points based on LAV results.

D. Handwashing Information Derivation

We first transform sensor readings to the body coordinate system and then calculate sensor-body inclination angles. **The advantages of using sensor-body inclination angles include (i) interferences affect sensor-body inclination angles to some extent, but not seriously. (ii) diversity in motion trajectory and path tortuosity only have a marginal effect on the sensor-body inclination angles. (iii) different users can have consistent patterns of sensor-body inclination angles.¿¿¿¿¿¿¿¿¿**

1) Coordinate Transformation: During handwashing scenarios, three coordinate systems are involved, namely, *Device Coordinate System* (DCS), *Earth Coordinate System* (ECS), and *Body Coordinate System* (BCS). Fig. 5 illustrates the three coordinate systems and Euler rotation angles: pitch, roll, and yaw. We first transform IMU sensor data from DCS to ECS, then transform data from ECS to BCS, and finally calculate the sensor-body inclination angles.

DCS to ECS: AWash first uses a quaternion-based method to align data from DCS to ECS. Quaternion is a complex number of the form $\mathbf{q} = q_i\mathbf{i} + q_j\mathbf{j} + q_k\mathbf{k} + q_r$, where $\mathbf{i}$, $\mathbf{j}$, and $\mathbf{k}$ are the fundamental quaternion units, q_i, q_j, q_k, and q_r are real numbers. To simplify the calculation processs, we perform normalization based on $q_i^2 + q_j^2 + q_k^2 + q_r^2 = 1$. We convert sensor readings from DCS to ECS using quaternion-based rotation:

$$P_e = \mathbf{q_{de}} P_d \mathbf{q_{de}^{-1}}, \tag{2}$$

where P_d is the data collected in DCS, P_e is the rotated data in ECS. The quaternion from DCS to ECS $\mathbf{q_{de}}$ can be obtained directly from IMU sensors. Also, $\mathbf{q_{de}^{-1}}$ is the conjugate quaternion of $\mathbf{q_{de}}$.

ECS to BCS: We found that participants would face different directions when washing their hands. Just converting data from DCS to ECS cannot provide stable posture patterns to achieve accurate sensing. Thus, we transform the converted data in ECS to BCS to normalize the sensor readings, computed as:

$$P_b = \mathbf{q_{eb}} P_e \mathbf{q_{eb}^{-1}}, \tag{3}$$

where P_e is the converted data in ECS, P_d is the rotated data in BCS. The $\mathbf{q_{eb}}$ is the quaternion from ECS to BCS, and $\mathbf{q_{eb}^{-1}}$ is the conjugate quaternion of $\mathbf{q_{eb}}$. Given that quaternions from ECS to BCS cannot be directly obtained from the sensors, we use the Euler angle-based method to calculate the wanted quaternions $\mathbf{q_{eb}}$. We transform the data in the order of yaw (ψ), pitch (θ), and roll (ϕ), which is defined as:

$$\mathbf{q_{eb}} = \begin{bmatrix} sin\frac{\phi}{2}cos\frac{\theta}{2}cos\frac{\psi}{2} - cos\frac{\phi}{2}sin\frac{\theta}{2}sin\frac{\psi}{2} \\ cos\frac{\phi}{2}sin\frac{\theta}{2}cos\frac{\psi}{2} + sin\frac{\phi}{2}cos\frac{\theta}{2}sin\frac{\psi}{2} \\ cos\frac{\phi}{2}cos\frac{\theta}{2}sin\frac{\psi}{2} - sin\frac{\phi}{2}sin\frac{\theta}{2}cos\frac{\psi}{2} \\ cos\frac{\phi}{2}cos\frac{\theta}{2}cos\frac{\psi}{2} + sin\frac{\phi}{2}sin\frac{\theta}{2}sin\frac{\psi}{2} \end{bmatrix}. \quad (4)$$

We noticed that during handwashing, users always extend their hands in the same direction as they face. We are inspired to use users' hand movements to infer the direction they are facing, or guide users to swing their arms forward a few times to help determine their body directions. We assume that users are standing on the horizontal ground. Thus, θ and ϕ are zero. And, ψ can be defined as the counterclockwise rotation angle around the North direction. First, we calculate the double integral of the Cartesian plane of the acceleration on the X-axis and the Y-axis in ECS, which are the accumulated distance from the acceleration along the X and Y-axis. Second, we calculate the angle α between the X-axis and the Y-axis displacement caused by arm movements as follows:

$$\alpha = |arctan(\frac{Accumulated\ Distance\ in\ Y\text{-}axis}{Accumulated\ Distance\ in\ X\text{-}axis})|. \quad (5)$$

Note that the range of α calculated using Equ. 5 is between 0 and $\frac{\pi}{2}$. We need to convert it from 0 to 2π to get the yaw angle ψ. We adopt a quadrant-based method to convert α to ψ, which is defined as [30]:

$$\psi = \begin{cases} \frac{3\pi}{2} + \alpha; & if\ Q = 1, \\ \frac{\pi}{2} - \alpha; & if\ Q = 2, \\ \frac{\pi}{2} + \alpha; & if\ Q = 3, \\ \frac{3\pi}{2} - \alpha; & if\ Q = 4, \end{cases} \quad (6)$$

where Q is the quadrant of arm movement that can be estimated based on the order of peaks and trough on accelerations on the X and Y-axis.

2) Sensor-Body Inclination Angles Calculation: Fig. 6 shows the sensor-body inclination angles, A_{YR}, A_{ZR}, and A_{XR}, where R is the acceleration of BCS. The sensor-body inclination angles can be calculated as follows:

$$\begin{bmatrix} A_{XR} \\ A_{YR} \\ A_{ZR} \end{bmatrix} = \begin{bmatrix} arctan(\frac{\sqrt{a_y^2+a_z^2}}{a_x}) \\ arctan(\frac{\sqrt{a_x^2+a_z^2}}{a_y}) \\ arctan(\frac{\sqrt{a_x^2+a_y^2}}{a_z}) \end{bmatrix}. \quad (7)$$

where a_x, a_y, a_z are the transformed acceleration in BCS.

Traditionally, action recognition can be realized by comparing the collected data with known templates (e.g., dynamic time warping) or learning information from the collected data (e.g., machine learning-based techniques and neural network-based techniques). However, it is challenging to generate a user-independent standard template for each handwashing action. Therefore, we first extract sensor-body inclination angles and then use the efficient neural network to generate user-independent features and identify different handwashing actions using the statistical-based method. Prior work has demonstrated that such three-step approaches can achieve high-accuracy user-independent classification [31].

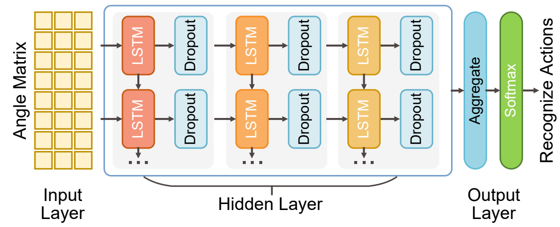

Fig. 7. Architecture of the hybrid model.

E. Action Recognition

In this section, we first sketch the hybrid network model to identify handwashing actions, then introduce the detailed user-independent handwashing action recognition method.

1) Hybrid Model: After extracting the time series sensor-body inclination angles, a new challenge arises: how to extract the user-independent features quickly and ensure the real-time ability and accurate classification of handwashing actions? To address this problem, we leverage the power of Long Short Term Memory (LSTM) to learn meaningful information hidden in wrist posture sequences, and develop a hybrid model to achieve accurate classification.

Fig. 7 shows the architecture of the hybrid model, which consists of three layers, the input layer, the hidden layer, and the output layer. The input layer takes the sensor-body inclination angles as input. Then, the information of the wrist posture and movements of hands are fed into the hidden layer. The hidden layer extracts user-independent features. Specifically, we leverage the power of LSTM. Since the single-layer LSTM cannot provide sufficient fine-grained features, we use the multi-layer LSTM network to obtain user-independent features. Each LSTM layer has the form of a chain of repeating modules, and each module has similar structures composed of a cell, an input gate, an output gate, and a forget gate [32]. These gates play different roles. Through the iterative process, they can unitedly pick relevant information through an unsupervised manner. The output layer consists of an aggregate layer and a softmax layer, which recognizes handwashing actions. The network is trained to minimize the differences between collected ground truth and the predicted results.

2) User-independent Handwashing Action Recognition: Given the sensor-body inclination angles, we normalize them and stretch them to the same length in time scale. We then use the hybrid network to generate user-independent features based on the input angle matrix $M = \{A'_{XR}, A'_{YR}, A'_{ZR}\}$ and recognize each handwashing action. For an input vector $m_{i,t}$ of the i^{th} LSTM layer, we can obtain an output $h_{i,t}$. The accumulated output of the last LSTM layer over time is a compressed representation of handwashing action. We show examples of the extracted features from three volunteers in

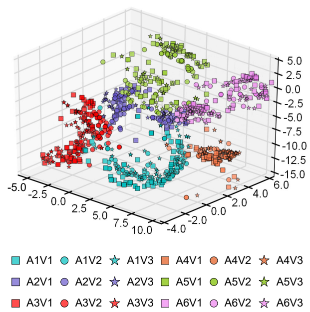

Fig. 8. t-SNE projection of the time-series user-independent features of handwashing actions performed by three volunteers. *A* represents the handwashing action ID, and *V* represents the volunteer ID. For example, $A1V1$ represents the volunteer 1 performing action 1.

Fig. 8 by using t-distributed stochastic neighbor embedding (t-SNE) to reduce feature dimensionality. The same handwashing actions of three volunteers have a narrow distribution, while different handwashing actions have a diverse distribution. The results show that the extracted features enable discriminating handwashing actions and handling the differences in user behaviors. Finally, the output layer obtains a prediction probability for each handwashing action. We take prediction with the highest probability as the recognized action.

Sensor-body inclination angles are robust to interferences, and the hybrid network derives cross-user patterns of handwashing movements. Compared with the traditional methods based on training the acceleration and angular velocity features for detection, we significantly improve the recognition recall, precision, and F1-score. Experiment details are presented in Section III-D.

F. Handwashing Assisting

We aim to deliver effective interventions, foster the independence of the elderly with dementia by providing appropriate guidance for handwashing. Handwashing assistance for the elderly with dementia based on common-sense knowledge is not sufficient. Dementia is a progressive impairment of cognitive function, often accompanied by a decline in motor ability [33]. After consulting with potential users, their family members, caregivers, and physicians, we found that the elderly with different cognitive abilities always encounter various problems when washing hands and have different needs for assistance. For example, seniors with mild cognitive decline might forget the handwashing process and miss a few steps in the overall task. Practicing handwashing actions in the same procedure is an important part of nursing interventions for them [11]. The situation of the elderly with moderate dementia is worse. They might forget how to perform a specific action, have obsessive behaviors, fail to focus on the task, then lose track of the overall progress. The patients are nevertheless able to cope, provided with some verbal guidance [34]. For those who have severe dementia, the problem is more complicated. Accordingly, seniors with different cognitive abilities require different assistance to improve hand hygiene.

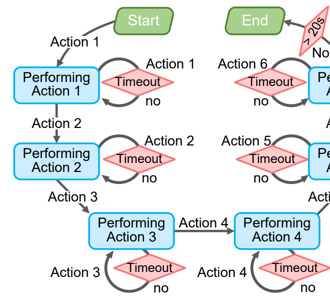

Fig. 9. State transition diagram.

1) Handwashing Process Modeling: To support customized assistance, we adopt the state machine to model the process of user's handwashing and provide assistance. The use of state machine technology is because its outputs depend on the entire history inputs, not just on the most recent input. Five variables are included, namely *input*, *output*, *state*, *next-state function*, and *output function*:

- *Input*, I_t, can be six handwahsing actions.
- *Output*, O_t, is the prompt decision.
- *State*, S_t, means the current state of the user (e.g., performing *action* 1).
- *Next-state function*, $n(I_t, S_t) \mapsto S_{t+1}$, maps the input I_t and the state S_t to the next state S_{t+1}.
- *Output function* $o(I_t, S_t) \mapsto O_t$, maps the input I_t and the state S_t to the output O_{t+1}.

Before using AWash, caregivers, physicians, and family members help users set up customized prompts. When continuous handwashing actions are recognized and inputted to the state machine, the system continually updates the status and prompts according to user-defined output functions.

We present an example of prompt to users when they do not follow the recommend step order during the task, which can help the users to practice handwashing procedures. Fig. 9 shows the state transition diagram. The start and end state are marked in green. The remaining states are marked in blue. An arrow from state S_t to state S_{t+1} describes that transformation happens with input I (next-state function). We add time constraints to monitor obsessive behaviors and make sure the time length of handwashing is sufficient. The user-defined outputs are hidden in the diagram. Here we give an example: if state *performing action 2* gets an input of *action* 6, AWash will guide the user to perform *action* 3.

2) Design of Audio Prompt: AWash provides users with audio prompts. The reasons are from three aspects: (i) they are familiar with audio prompts because their family members and caregivers always use verbal instructions, (ii) prompting in the verbal medium rather than the visual medium provides a more direct augmentation of executive function [35], and (iii) video prompts may distract them and interrupt the execution of handwashing tasks.

The audio prompts provided by AWash are carefully designed to be understood by the elderly with limited cognitive ability: (1) Whether the voice is known does not affect the assistance performance, and the male voice is preferred to

TABLE I
PARTICIPANTS' INFORMATION.

ID	1	2	3	4	5	6	7	8
Age	81	75	74	71	71	68	65	65
Gender	F	M	M	F	M	M	F	M
MoCA	21	20	18	21	25	27	23	28

the female voice [17], we chose to use a smooth and gentle male voice. (2) More straightforward commands require less cognitive ability. We use " *Rub palm to palm*" instead of "*You missed a step. Please rub your palm with another palm now.*" (3) The target users usually suffer from hearing loss. We send a test prompt to make sure all prompts are loud enough to be heard clearly during the initialization.

III. EVALUATION

A. Experimental Setup

To validate the feasibility of AWash, we build a prototype equipped with a 9-axis IMU sensor (including a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer), which is an alternative to a smartwatch. A laptop is paired with the prototype via Wi-Fi, which acts as the edge server. During handwashing, the sensor readings are recorded with the sampling rate of 100Hz. A camera is placed above the sink to record participants' handwashing actions to provide ground truth. Audio prompts are recorded in a male's smooth and gentle voice. In the experiment, we use an external speaker to play the audio prompt, which can be played by a built-in speaker after implemented in commodity smartwatches.

We recruit 8 participants aging between 65-81 to perform handwashing. They are selected among residents of an elderly community. This study was conducted with the approval of the ethics committee of the facility and the consent of the participants' families. Before data collection, the Montreal Cognitive Assessment (MoCA) [36] is used to test the presence of cognitive impairment in participants. Table I presents the demographic information about participants and their evaluation results. Scores on the MoCA range from 0 to 30, with a score of 26 and higher generally considered normal.

After a short training, participants are asked to wash their hands repeatedly for 5 times in sinks (30-35 inches) at their homes and a children sink (26 inches) in our lab. Also, all participants are asked to collect their handwashing data with the AWash prototype at least once a day for a 20 day experiment. To accommodate differences in position to wear the device, they are encouraged to wear the prototype according to their habits. Currently, data collection of each session is triggered manually, which can be triggered automatically in future work through smart sensing or smart home products. In total, we collected over $6,000$ action segments.

B. Evaluation Matrices

Recall. The ratio of the instances that are correctly captured as label A among all instances that should have a label A. High recall means that the classifier is returning a majority of all positive results.

Precision. The ratio of the instances that are correctly recognized as label A among all the instances predicted as label A. High precision means that the classifier is returning accurate results.

F1-score. The harmonic mean of precision and recall, which is defined as $2(recall{\cdot}precision)/(recall{+}precesion)$, where an F1-score reaches its best value at 1 (perfect precision and recall) and worst at 0.

C. Overall Performance of Handwashing Action Recognition

To understand AWash's performance to recognize handwashing actions in the user-independent scenario, we conduct leave-one-participant-out-validation, where data from one participant are used for testing and the remaining participants for training. We use data collected at participants' homes since the heights of the sink in their home are comfortable to use, and the extracted sensor-body inclination angles are usually consistent and unique. Overall, AWash achieves 92.94% average recall, 92.60% average precision, and 92.76% average F1-score among eight participants. Moreover, 80% of the recognition time delay is less than 0.9 seconds. This indicates that AWash can achieve accurate handwashing action recognition in a timely manner, and the elderly with dementia can benefit from AWash without providing their training data.

Fig. 10 shows the detailed confusion matrix of the cumulative results. Each entry $C_{i,j}$ is defined as the ratio of the number of the i^{th} action predicted as the j^{th} action to the total number of the i^{th} action. We find that false identification occurs between *actions* 2 and 3, and between *actions* 5 and 6. This is because each pair of handwashing actions share very similar movement patterns and wrist postures. We also can observe that instances belonging to *action* 1 are more likely to be misclassified as *action* 6 than *action* 5. A possible reason of the imbalance errors is the imbalance in the number of collected instances.

D. Comparison Between AWash and Traditional Methods in Handwashing Action Recognition

Traditional methods of recognizing handwashing actions mainly extract features including *empirical cumulative distribution function representation* [37], *mean*, *standard deviation*, *kurtosis*, and *skew* from acceleration and classifying actions based on machine learning methods. To compare the performance of traditional methods and AWash in recognizing handwashing actions of the elderly with dementia, we implement traditional methods to the collected IMU sensor data. Three mostly used classifiers, Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (kNN) are tested. Fig. 11 shows the recognition results. Three tested classifiers received recall, precision, and F1-score less than 80%. AWash outperforms the traditional methods in handwashing recognition of the elderly with dementia.

E. Impacts of Various issues on Handwashing Action Recognition

1) Impact of Hybrid Model Structure: In the hybrid model, the number of LSTM network layers and the number of

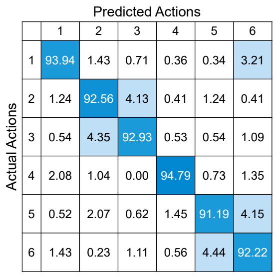

Fig. 10. Overall performance.

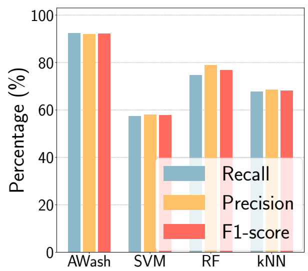

Fig. 11. AWash v.s. traditional.

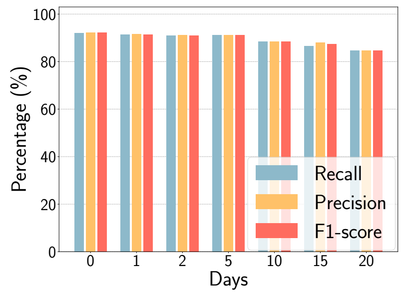

Fig. 12. Recognition over 20 days.

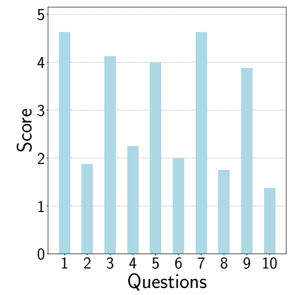

Fig. 13. User rating.

memory cells at each layer have an important impact on the performance of user-independent feature extraction and handwashing action recognition. After configuring more than 20 different combinations of model parameters, we found that system performance can be improved when the number of layers and memory cells increases. However, more LSTM layers and memory cells reveal a higher level of movement information but also lead to higher computational costs. In order to reduce costs and ensure fine-grained recognition, we configure the hybrid model with 128 cells, and three LSTM layers, which enable AWash to receive recall, precision, and F1-score higher than 92%.

2) Long-Term Recognition Performance: Long-term performance is a critical aspect of recognition performance since the elderly with dementia have unstable motor abilities, and dementia progresses at different speeds for a different person. Fig. 12 shows the handwashing action recognition performance of AWash of all participants over 20 days. After training, the testing data are collected on the same day, 1 day later, 2 days later, 5 days later, 10 days later, 15 days later, and 20 days later. When using the data collected on the 20^{th} day for testing, recall, precision, and F1-score are all above 84%, which is acceptable in real environments. Moreover, we plan to update the training data regularly for better performance.

3) Impact of Sink Height: Sensor-body inclination angles are sensitive to sink heights. Therefore, we evaluate AWash with data collected in a children pedestal sink. When use data collected at participants' homes for training and data collected at the children sink for testing, the leave-one-participant-out-validation reaches 81.74% recall, 83.50% precision, and 82.10% F1-score. When we expanded the training data set to include data collected from children sink, the recall increases to 87.86%, precision increases to 88.16%, and the F1-score increases to 88.07%. Since AWash supports user-independent handwashing action recognition, we can collect training data from healthy older adults in various usage environments to improve system performance.

F. Effectiveness of Handwashing Assistance

We ask participants to wash hands three times when only provided a poster illustrated with washing steps to set up their handwashing ability baseline. Due to the cognitive differences of the recruited participants and limited sample size, it is not feasible to conduct an overall analysis of the effectiveness of AWash. Therefore, we conduct a within-subject user study. Participants 1, 2, 3, and 4 with lower MoCA scores are prompted when they miss handwashing steps in the overall task. The remaining participants are prompted when they do not follow the recommended step order. We validate the effectiveness of the handwashing assistance provided by AWash by comparing the number of handwashing actions that participants could perform (for participants 1-4) and the number of handwashing actions that participants could perform in the correct order (for participants 5-8).

TABLE II
PERFORMANCE OF PARTICIPANTS IN HANDWASHING TASKS IN THREE CONDITIONS.

	Prompt when miss steps in the overall task				Prompt when perform steps in wrong order			
ID	1	2	3	4	5	6	7	8
Baseline	3.67	3.67	3.00	4.00	4.67	5.00	4.67	5.33
AWash 1st day	5.40	5.40	5.40	5.60	5.80	6.00	5.80	6.00
AWash 20th day	6	5	5	6	6	6	6	6

Table II shows the detailed results of eight participants. Comparing to baseline, the number of handwashing actions participants are able to complete increases when using AWash. Specifically, for participants 1, 2, 3, and 4, they have the problem of being unable to perform the proper handwashing actions, organizing handwashing steps, and repeating obsessive actions. With the help of AWash, they can follow the audio guidance to wash their hands, perform missed actions, and stop obsessive behaviors. For participants 5, 6, 7 and 8, when performing handwashing tasks, they occasionally make mistakes in planning the handwashing steps and forget one or two actions. When using AWash, they can reorganize the order of handwashing actions and execute the missed actions in time. During the 20 days experiment, there is no significant difference in the number of actions that participants can perform correctly. The results indicate that AWash has promising prospects to help the elderly with dementia complete handwashing tasks.

G. User Experience

After the participants experienced the assistance of AWash, a System Usability Scale (SUS) [38] questionnaire gathers feedback from each participant, which ranks from 1 (strongly disagree) to 5 (strongly agree). SUS consists of 10 items and is suitable for small sample sizes with reliable results:

1) I think that I would like to use this system frequently.
2) I find the system unnecessarily complex.
3) I think the system is easy to use.
4) I think that I would need the support of a technical person to be able to use this system.
5) I find the various functions in this system are well integrated.
6) I think there is too much inconsistency in this system.
7) I would imagine that most people would learn to use this system very quickly.
8) I find the system very cumbersome to use.
9) I feel very confident using the system.
10) I need to learn a lot of things before I could get going with this system.

Fig. 13 summarizes the responses of eight participants. Five positive statements (question 1, 3, 5, 7, and 9) receive high scores, and five negative statements (question 2, 4, 6, 8, and 10) receive low scores. The high evaluation of participants shows that AWash offers a good user experience.

IV. Related Work

Monitoring and promoting systems are founded to be effective solutions to assist elderly dementia patients with bathroom routines [12], [13], table-setting [14], tea-making [15], dressing [16] and toothbrushing [17], [18].

As for handwashing assistance technologies for the elderly with dementia, vision-based methods have been employed. Mihailidis et al. [19] employ cameras to determine the spatial coordinates of the user's body and hands and determine the user's action and its quality accordingly. Based on this system, a planning system that uses Markov decision processes to decide when and how to provide prompts is presented in [20]. The COACH system [6] tracks hands using flocks of features, leverages a partially observable Markov decision process method to model different handwashing actions, and assist users with verbal or visual prompts. However, the deployment cost of these vision-based methods is high, which is difficult to get in large-scale promotion applications, especially in developing countries and areas. Moreover, the use of cameras in bathrooms brings many privacy concerns.

Another aspect of relevant work focuses on using wrist-worn devices, an alternative to the vision-based method, to monitor or assist handwashing. The emergence of smartwatches and fitness bands provides new solutions for handwashing monitoring. Uddin et al. [7] propose a wearable sensing framework that provides flexible API to the activity monitoring applications. They show the case of handwashing as proof of concept but do not identify the detailed handwashing actions. Harmony [8] takes the data of the accelerometer and gyroscope of a smartwatch as input. It detects the presence of the different gestures based on the decision tree method and uses the washing duration to indicate the quality of each handwashing episode. WristWatch [9] uses a 6-axis Inertial Measurement Unit (IMU) mounted on a wrist-worn device to record hand movements and a hidden Markov model-based method to monitor handwashing routines. WristWash is more practical than mere action classification because it allows for continuous recognition. However, both Harmony and WristWash are primarily designed for younger and healthy adults. They cannot be directly applied to the handwashing assistance of the elderly with dementia because the behavior patterns of senile dementia patients are different from those of the younger adults. Also, existing techniques can not address the significant diversity in user behavior that causes by cognitive ability diversity. Moreover, previous efforts have the weakness of only providing a single prompt solution, which can not meet the needs of senile dementia patients with various cognitive abilities and executive functioning.

Approaches based on Wi-Fi [21], RFID [22], acoustic signals [23], lights [24], and thermal infrared signals [25] have been widely developed to detect human activities. However, being sensitive to water, soap foam, environmental temperature makes them not suitable for handwashing action recognition. Some rings like magnetic sensors can accurately recognize gestures [26], but they should be taken off when washing hands for better overall cleanliness. Also, Electromyogram (EMG) acquired from arm muscles also contributes to identifying actions [27]. However, senior dementia patients experience difficulties in adjusting to changes and accepting new things.

Compared with previous solutions, AWash has the following advantages. AWash can address the unique interference of the elderly, extract user-independent features, and achieve continuous fine-grained handwashing action recognition. Besides, it provides different assistance to heterogeneous users. Moreover, Awash only relies on commodity IMU sensors thus can be deployed on most affordable wrist-worn devices, which can be more widely accepted by senior dementia patients.

V. Conclusion

In this paper, we present AWash, a cognitive assistive technology that takes a new step in helping the elderly with dementia washing their hands. AWash uses only the IMU sensor on off-the-shelf wrist-worn devices (e.g., smartwatches) to collect handwashing data. By using a set of novel data processing technologies and a hybrid network model, AWash is capable of recognizing handwashing actions in user-independent scenarios. The goal of AWash is to provide timely prompts and guidance on handwashing routines for older adults with varying degrees of dementia. For this purpose, we adopt the state machine that allows users to customize the appropriate guidance. Experiments are conducted to demonstrate that AWash can be a potential solution to assist the elderly with dementia in the handwashing routine.

In the future, we plan to recruit more participants and conduct user studies on diagnosed patients with different dementia levels via further collaborations with medical institutes. We will also investigate automatic data collection method and energy-saving method to make AWash more suitable for practical application. We strongly believe that wrist-worn-based handwashing assistance has the great potential to significantly improve the health and life quality of patients with dementia.

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