Leveraging Wearables for Assisting the Elderly With Dementia in Handwashing

Yetong Cao, *Student Member, IEEE,* Fan Li, *Member, IEEE,* Huijie Chen, Xiaochen Liu, Song Yang, *Member, IEEE,* and Yu Wang, *Fellow, IEEE*

Abstract—Proper handwashing, having a crucial effect on reducing bacteria, serves as the cornerstone of hand hygiene. For elders with dementia, they suffer from a gradual loss of memory and difficulty coordinating handwashing steps. Proper assistance should be provided to them to ensure their hand hygiene adherence. Toward this end, we propose AWash, leveraging inertial measurement unit (IMU) readily available in most wrist-worn devices (e.g., smartwatches) to characterize handwashing actions and provide assistance. To monitor handwashing scenarios round-the-clock while achieving energy efficiency, we design methods that distinguish handwashing from other daily activities and dynamically adjust the sampling duty cycle. Upon detecting handwashing actions, we design several novel techniques to segment different handwashing actions and extract sensor-body inclination angles that handle particular interference of senile dementia patients. Moreover, a user-independent network model is built to recognize the handwashing actions of senile dementia patients without requiring their training data. Furthermore, we propose a transfer learning method that improves system performance. To meet users' diverse needs, we use a state machine to make prompt decisions, supporting 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.

Index Terms—Handwashing monitoring, wrist-worn sensing, LSTM, transfer learning.

1 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. Among ADLs, handwashing serves as a great way for the elderly to reduce bacteria and avoid illnesses or even fatal infections, which is critical in daily life, especially during the outbreak of respiratory viruses such as COVID-19 [2] or H1N1 [3]. Therefore, assisting the elderly with dementia during handwashing is of great importance for their overall well-being.

Recently, Apple introduces new features of a handwashing APP on the Apple Watch [4], which nudges users to wash their hands for a full 20 seconds. This can track how well a user washes his/her hands in terms of duration, but senile dementia patients desire more detailed assistance (e.g., what handwashing action is performed, how well an action is performed, and what action to perform next) to improve their handwashing behavior. Over the last decade, the interest in fully automated handwashing action recognition has been flourishing, utilizing devices ranging from cameras to wrist-worn wearables. Existing works based on cameras [5]–[7] are efficient, but the drawbacks of privacy concerns and high hardware costs often prohibit the installation of cameras in bathrooms. In addition, wearable-based approaches such as [8]–[10] show the initial success of handwashing action monitoring. These approaches mainly extract acceleration and angular velocity features to differentiate handwashing movements. They generally realize promising results for young and healthy people. However, they are always ineffective once adopted to assist in handwashing for older adults with dementia. The reasons comprise of following 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, therefore leading to variable acceleration features for the same handwashing action. Also, motor and muscle weakness and rigidity introduce interferences in inertial measurement unit (IMU) readings (such as more turning points and different positions of peaks and troughs), which always deform the repetitive patterns of hand movements. To emphasize this, we show the accelerometer data of a healthy adult and a senile dementia patient in Fig. 1. 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 more significant individual differences than healthy people [11]. Existing schemes

- *Y. Cao, F. Li, X. Liu and S. Yang are with School of Computer Science, Beijing Institute of Technology, Beijing, 100081, R.P.China. E-mail: {yetongcao, fli, xiaochenliu, S.Yang}@bit.edu.cn*
- *H. Chen is with School of Computer Science, Beijing University of Technology, Beijing, 100124, R.P.China. E-mail: chenhuijie@bjut.edu.cn*
- *Y. Wang is with Department of Computer and Information Sciences, Temple University, Philadelphia, Pennsylvania 19122, USA. E-mail: wangyu@temple.edu*
- *F. Li is the corresponding author.*

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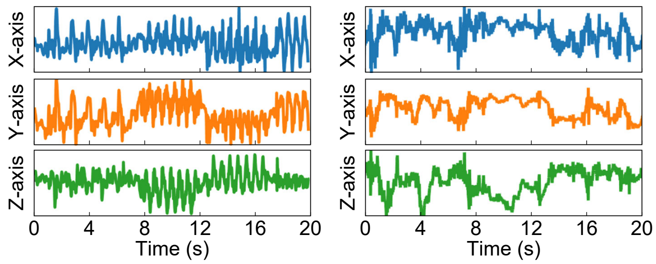


(a) Healthy adult (b) Dementia patient

Fig. 1. Examples of accelerometer data from a healthy adult and a senile dementia patient.

rarely take the great individual differences into consideration; therefore, they have insufficient accuracy for our target users. To recognize various handwashing actions accurately, general characters suitable for every dementia patient should be investigated. (3) *Diverse assistance manner.* Dementia patients suffer from different degrees of cognitive impairment, resulting in diverse executive functioning. They demand different assistance forms, which have 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 and then provide assistance accordingly. 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 retraining or adaptation.

Despite this simple idea, four major challenges underlie the design of AWash:

(1) *How to monitor round-the-clock handwashing while achieving energy-efficiency?* To fully monitor handwashing round-the-clock and avoid running costly algorithms during non-handwashing actions, we need to distinguish between handwashing actions and non-hand washing actions. However, diversities in behavior patterns hinder the modeling of specific activities, making it challenging to profile various actions. To overcome this, we propose a conditional random field (CRF)-based method to determine whether the performed action is handwashing or not. Meanwhile, we design a sampling control method that dynamically adjusts the sampling duty cycle according to the performed activities.

(2) *How to further segment different handwashing actions from the continuous and noisy IMU sensor data?* Visuomotor impairment affects eye-hand coordination for the orderly in some dementias during handwashing [11]. This disturbs IMU sensor data, thereby making it difficult to segment different handwashing actions. Besides, the presence of extra unpredictable movements between handwashing actions is common due to impaired memory and attention span. To address it, upon detecting the handwashing scenario, we use an autocorrelation-based method to further segment different handwashing actions. Then, the start and end point of the handwashing action is determined from linear angular velocity troughs.

(3) *How to extract effective representations of handwashing actions?* 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.

(4) *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 trajectories 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 [11]. To overcome this, we design a hybrid network model to handle user dependence, which makes AWash available to anyone without retraining or adaptation.

In summary, we makes the following contributions:

- We propose AWash, the first 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 detect handwashing scenarios, segment different handwashing actions, 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 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.

The rest of this paper is organized as follows: We first introduce the preliminary in Section 2. Then we present the system design in Section 3. We evaluate the performance of AWash and present the results in Section 4. Section 5 reviews the related work, followed by Section 6 discusses potential directions for further investigation. Finally, Section 7 concludes the paper. A preliminary of this paper appeared in [12].

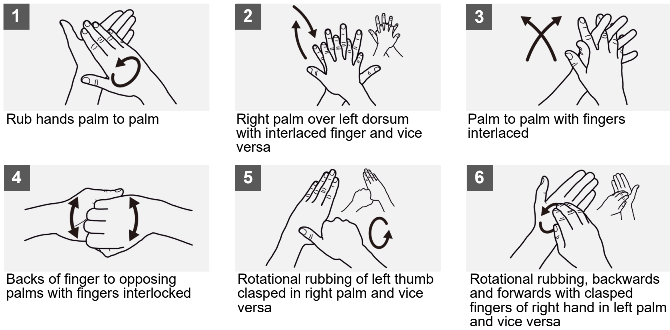
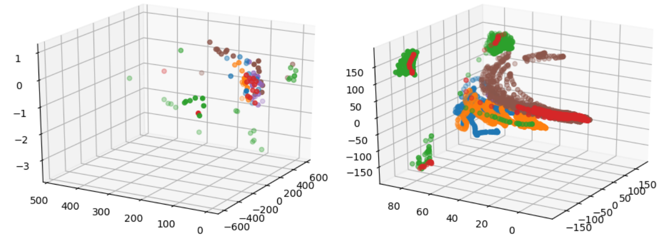


Fig. 2. The handwashing procedure issued by WHO [13].



(a) Conventional acceleration features of handwashing actions (b) Sensor-body angles of handwashing actions

Fig. 3. Distribution of conventional acceleration features and sensor-body angles of six handwashing actions. Different colored points represent different actions.

2 PRELIMINARY

In this section, we first describe the handwashing actions, then introduce the basics of IMU sensors, and finally present the intuition of using wrist posture to characterize handwashing actions which validate the feasibility.

2.1 Handwashing Actions

World Health Organization (WHO) issued guidelines to provide recommendations for the improvement of hand hygiene, shown in Fig. 2. 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.

2.2 Basic of IMU Sensor

The inertial measurement unit (IMU) sensors usually include a 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer, which can be used to calculate the posture of objects in three-dimensional space. Due to its portability, high accuracy, and ease of use, IMU is widely embedded in smartwatches and bracelets, mainly used to record steps or perform exercise tracking. In recent years, the development of wearable systems has brought very important improvements to human activity detection. Some work has shown that IMU is promising to support fine-grained activity monitoring, such as tooth brushing [14], fitness tracking [15], and has great potential in handwashing detection [10].

2.3 Intuition of Handwashing Action Recognition Using Wrist Posture

Previous hand action recognition approaches mainly extract unique acceleration and angular velocity features such as *empirical cumulative distribution function representation* [16], *mean*, *standard deviation*, *kurtosis*, and *skew* from each scrub for classification. We ask an elder dementia volunteer to collect handwashing data, and we extract the above five features to form a five-dimensional feature vector. To illustrate the feature distribution, we use t-distributed stochastic neighbor embedding (t-SNE) to reduce the feature vector to the three-dimensional space. Fig. 3(a) shows the t-SNE projection of feature distribution of a senile dementia patient performing six handwashing actions. We can observe that points of the same handwashing actions do not show significant narrow distribution, while some points of different handwashing actions have near positions. Moreover, only a limited feature sequence is extracted during handwashing, which might lead to unreliable modeling of handwashing actions. This indicates that such feature extracting approach is inefficient to distinguish handwashing actions of older adults with dementia.

Fig. 3(b) shows the scatter plot of sensor-body angles, which describes the wrist posture. The six handwashing actions are drawn in points with different colors. We can observe that points of each action are mainly clustered in a narrow belt, and points of different actions have distinguishable distribution positions. This demonstrates that sensor-body angles catch the nuance and unique information of handwashing actions, thereby being used in this paper.

3 SYSTEM DESIGN

This section first presents the system overview, then introduces the design of our proposed system, AWash, which recognizes handwashing actions through sensing the user's wrist posture, and fosters the independence of the elderly with dementia by providing appropriate guidance during handwashing.

3.1 System Overview

The basic idea of AWash is to calculate wrist posture measurement from the IMU data collected by wrist-worn devices, then distinguish handwashing actions, and finally deliver effective interventions for the elderly with dementia. The system overview of AWash is shown in Fig. 4. The smartwatch continuously collects IMU sensor data and sends them to an edge device through wireless connections such as Bluetooth and Wi-Fi. The edge device receives the real-time IMU data and deploys data processing algorithms. There are five components of our system: *Handwashing Scenario Detection*, *Handwashing Action Segmentation*, *Handwashing Information Derivation*, *Handwashing Action Recognition*, and *Handwashing Assisting*.

In *Handwashing Scenario Detection*, *Conditional Random Field (CRF)-based Activity Recognition* is performed to determine whether the user is washing his/her hands through

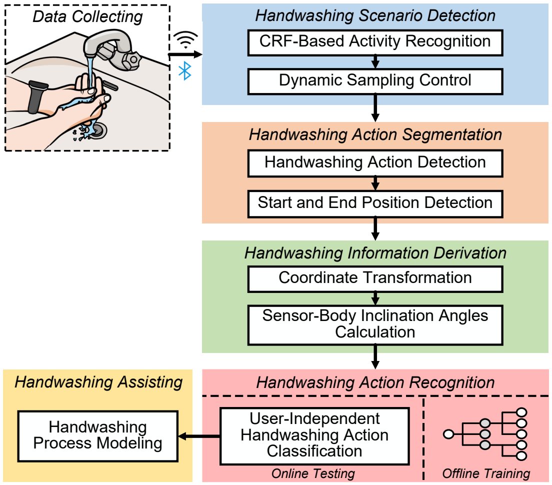


Fig. 4. The overall framework of AWash.

a calculation of handwashing probability. Meanwhile, *Dynamic Sampling Control* dynamically determines the sampling duty cycle to achieve energy efficiency.

In the *Handwashing Action Segmentation* phase, we first perform *Handwashing action detection*, which leverages the autocorrelation-based method to distinguish handwashing movements from non-handwashing movements and extra movements. Then, 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 AWash is *Handwashing Action Recognition*, which builds a hybrid neural network in the edge server to extract hidden user-independent features from the time series sensor-body inclination angles and realize promising recognition of handwashing actions. Moreover, we develop a transfer learning method to improve learning of the neural network of senile dementia patients utilizing general knowledge learned from healthy adults, which relieves the pain of collecting sufficient training data from senile dementia patients.

Upon recognizing handwashing actions, the *Handwashing Assisting* provides different assistance to diverse users according to their diverse needs. Senile users 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 demand to be prompted by obsessive behaviors. We use a state machine to model the handwashing process of senile users. By customizing the output functions, we support users with customized assistance.

3.2 Handwashing Scenario Detection

As the first step, handwashing scenario detection is crucial to avoid running costly classification algorithms during non-handwashing activities. We design a lightweight conditional random field (CRF) based classifier to recognize various daily activities. Furthermore, we design a sampling control strategy, which uses high sampling during handwashing and uses low sampling during other activities.

3.2.1 *CRF-Based Activity Recognition*

Recently, automatic detection of handwashing scenarios has gained particular interest. For example, Apple Watch [4] listens for the sound of soap and water running to determine the start of handwashing. However, having the microphone continuously sense the environment brings privacy concerns and high computational costs. In this paper, we seek to use only IMU sensors to distinguish between handwashing scenarios and non-handwashing scenarios. The non-handwashing scenarios involve a large number of activities, such as dining, walking, and toileting. These activities can affect the IMU sensors very diversely due to multiple factors such as the user's height, age, and habits. Conventional machine learning techniques that model each activity category usually receive insufficient accuracy, especially in the limited sampling frequency. To address intra-class variations and inter-class similarities, an intuitive way is to apply the Hidden Markov Model (HMM) method. However, we find that the HMM-based method can not achieve the desired accuracy because the real-life data violate the independence assumptions of the HMM [17].

To this end, we adopt the CRF, which eliminates the unreasonable hypotheses in HMM. CRF is initially designed for labeling sequential images. It can directly incorporate many observed features and conditionally model the probability of a labeled sequence. Specifically, we first apply a 0.5s sliding window with 50% overlap to the time series IMU data. Then we calculate the mean-crossing rate (indicates the changes in the body state) of all six sensor axes (three for accelerometer and three for gyroscope) to build feature vector x_k at window k. Given the feature vector sequence from successive windows $\mathbf{X} = \{x_1, x_2, ..., x_K\}$, our goal is to estimate an activity label sequence $\mathbf{Y} = \{y_1, y_2, ..., y_T\}$ where y_i represents handwashing or non-handwashing actions. The likelihood of the labeled data is calculated as:

$$P(\mathbf{Y}|\mathbf{X}) = \frac{\prod_{t=1}^{T} \Psi(y_{t-1}, y_t, \mathbf{X})}{\sum \prod_{t=1}^{T} \Psi(y_{t-1}, y_t, \mathbf{X})}, \tag{1}$$

where Ψ is the potential function. The model is trained to maximize $P(\mathbf{Y}|\mathbf{X})$. The main difference between CRF and HMM is that HMM models the joint probability of both the labels and input features $P(\mathbf{Y}, \mathbf{X})$, while CRF models $P(\mathbf{Y}|\mathbf{X})$. This allows CRFs to incorporate complex features of the feature sequence $\mathbf{X}$ in real-life environments.

To estimate parameters as well as capture the interdependency of the label, we introduce the state to the model. A state is defined as $s_i = (y_i, b_i, e_i)$, where y_i is the label, b_i and e_i represent the begin time and end time respectively. The likelihood of state sequence $\mathbf{S} = \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_T\}$ given $\mathbf{X}$ is defined as:

$$P(\mathbf{S}|\mathbf{X}) = \frac{\prod_{t=1}^{T} \Psi(s_{t-1}, s_t, \mathbf{X})}{\sum \prod_{t=1}^{T} \Psi(s_{t-1}, s_t, \mathbf{X})}. \tag{2}$$

The potential function Ψ is defined as

$$\Psi(y_{t-1}, y_t, \mathbf{X}) = \exp(\sum \theta_k f_k(s_{i-1}, s_i, \mathbf{X})), \tag{3}$$

where f_k is a boolean function, and θ_k is the weight of f_k.

During the training phase, f_k and θ_k are learned by finding the maximum of $L(\theta) = \sum logP(s_i|x_i)$. We implement the optimization algorithm by L-BFGS based on the following equations:

$$P(S|X, \theta) = \frac{\prod M_t(s_{i-1}, s_i|X)}{\sum \prod M_t(s_{i-1}, s_i|X)}, \tag{4}$$

$$M_t(s_{i-1}, s_i|X) = [m_t(y_{t-1}, y_t|X)], \tag{5}$$

$$\begin{aligned} m_t(y_{t-1}, y_t|X) = exp(&\sum \lambda_k f_k(y_{t-1}, X, t) \\ &+ \sum u_k f_k(y_t, X, t)), \ \lambda_k, u_k, \in \theta. \end{aligned} \tag{6}$$

After training, we estimate the activity label sequence by maximizing $P(\mathbf{Y}|\mathbf{X}, \theta)$, which is solved by finding the optimal path of the graphical model, which yields new equation as follows:

$$\max \sum \theta G_i(s_{i-1}, s_i, X), \tag{7}$$

where $G_i(s_{i-1}, s_i, X) = (f_1(s_{i-1}, s_i, X), f_2(s_{i-1}, s_i, X), ..., f_N(s_{i-1}, s_i, X))^T$. Although CRF eliminates the independence assumptions, it maintains the same first-order Markov assumptions as the HMM model makes. The time complexity of inferring the active label sequence in CRF is the same as that of HMM, except that it requires more computation than HMM when training CRF. Therefore, the proposed method achieves time-efficient and can react immediately once the handwashing scenario is detected.

Note that different handwashing actions are seen as a whole at this stage. Upon detecting the handwashing scenario, we analyze the handwashing data to further recognize the performed handwashing activities. We ensure the analyzed data are longer than 20 seconds to avoid interrupting the analysis when those poorly performed handwashing actions are incorrectly classified as non-washing scenarios. The 20-second timer provides a reasonable trade-off between timely assistance and computational efficiency. Experiment validates the effectiveness of our proposed method, which is shown in Section 4.5.2.

3.2.2 Energy-Efficient Sampling

A sampling control strategy is necessary to minimize the battery consumption while ensuring capture handwashing actions. Luo *et al.* propose a duty cycle control algorithm [18] that changes the sampling duty cycle based on the percentage of battery left and current activity. However, when a user wash hands when the battery runs low, direct application of such method will result in very low sampling. This can lead to inaccurate recognition of fine-grained handwashing actions. Therefore, we modify the method proposed in [18] to be battery-irrelevant.

The model is specified by the elements of $\{S, A, O, \Phi, \Omega, R\}$, which represent state, action, observation, state transition function, observation function, and reward function respectively. The state at time t is specified to be $S_t = (\eta_t, t)$, where η_t is the percentage time the user is washing hand during an observation window, which is set to be one minute. We define the actions to be $A_t = \{0, 1, 2\}$ that represents sampling duty cycle, where 0 is no sampling, 1 is the minimal sampling for the device,

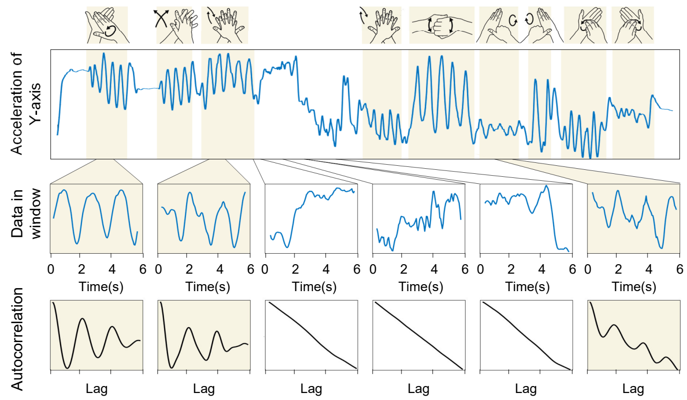


Fig. 5. Example of processing accelerometer data of Y-axis using autocoloration-based method.

and 2 is the sampling duty cycle required by AWash (not to confused by sampling rate). The observation $O_t = 0, 1, 2$ indicates the percentage time the user is washing hand during an observation window, where 0 is 0%, 1 is between 0% to 100%, and 2 is 100%. The state transition function $\Phi(\eta_{t+1}|\eta_t, t)$ indicates the handwashing probability during different times of a day, which can be learned from the user traces. The observation function is defined as:

$$\Omega(O_t|S_t, A_t) = \Omega(O_t|\eta_t, A_t) = \frac{\binom{A_t}{O_t}\binom{3-A_t}{\eta_t - O_t}}{\binom{3}{n_t}}, \tag{8}$$

and the reward function is defined as $R(S_t, A_t) = A_t \cdot \eta_t$.

The dynamic control of sampling duty cycle is solved by maximizing $E \sum \gamma^t R(S_t, A_t)$, where $\gamma \in (0, 1)$ is the factor to ensure convergence of the model. With this sampling control strategy, the sampling duty cycle is high during handwashing scenarios and decreases to a low sampling duty cycle during non-handwashing scenarios. The experiment validates the effectiveness of the sampling control method. Details of the experiment result are shown in Section 4.5.3.

3.3 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/non-handwashing actions between predefined handwashing actions are common in real-life, which disturbs handwashing action monitoring. To avoid unnecessary computational cost and misclassification, we design algorithms to detect and segment handwashing actions.

3.3.1 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. To enable effective data processing, AWash first applies the moving average filter to reduce the random noises from the IMU sensor readings roughly.

We observe that 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, which can detect periodicity robustly with significant data variations.

We first apply a 6 s sliding window to the time series accelerometer data to ensure capturing of 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 rate. If the data in the window are from the same kind of handwashing action, the autocorrelation-lag trajectory will show more than two peaks. The lag associated with the first peak is determined as the repetition period P. If the data in the window are from extra movement or non-handwashing movement, no autocorrelation peak can be observed.

Fig. 5 shows an example of processing accelerometer data of the Y-axis. Handwashing movements are marked with the yellow background, and 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.

3.3.2 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, and Z-axis data of accelerometers and gyroscopes. To address this, we turn to use the linear angular velocity (LAV):

$$LAV = \sqrt{(w_x)^2 + (w_y)^2 + (w_z)^2}, \tag{9}$$

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 P are considered the positions where a handwashing action begins and ends. Then, by searching

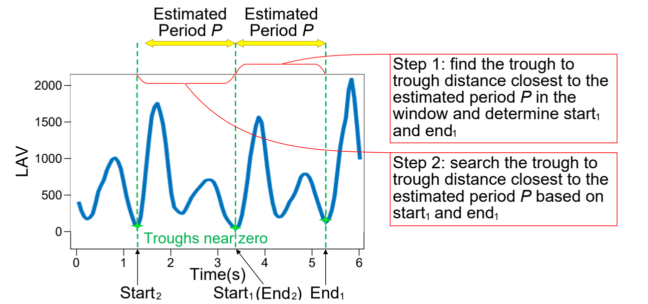


Fig. 6. Example of searching the start and end positions of handwashing actions based on LAV data.

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. 6 shows an example of searching start and end points based on LAV results.

3.4 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.

3.4.1 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. 7 shows the three coordinate systems and Euler rotation angles. 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:

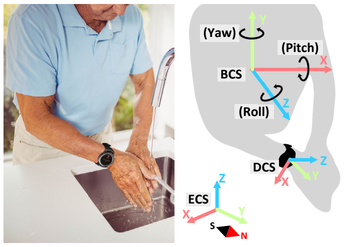
$$P_e = \mathbf{q_{de}} P_d \mathbf{q_{de}^{-1}}, \tag{10}$$

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:

$$P_b = \mathbf{q_{eb}} P_e \mathbf{q_{eb}^{-1}}, \tag{11}$$

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,



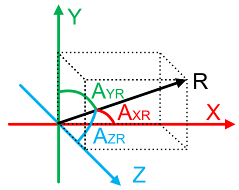


Fig. 7. The involved coordinate systems. Fig. 8. Inclination angles.

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:

$$\mathbf{q_{eb}} = \begin{bmatrix} sin\frac{\phi}{2}cos\frac{\theta}{2}cos\frac{\psi}{2} - cos\frac{\phi}{2}sin\frac{\theta}{2}sin\frac{\psi}{2} \\ cos\frac{\phi}{2}sin\frac{\theta}{2}cos\frac{\psi}{2} + sin\frac{\phi}{2}cos\frac{\theta}{2}sin\frac{\psi}{2} \\ cos\frac{\phi}{2}cos\frac{\theta}{2}sin\frac{\psi}{2} - sin\frac{\phi}{2}sin\frac{\theta}{2}cos\frac{\psi}{2} \\ cos\frac{\phi}{2}cos\frac{\theta}{2}cos\frac{\psi}{2} + sin\frac{\phi}{2}sin\frac{\theta}{2}sin\frac{\psi}{2} \end{bmatrix}. \quad (12)$$

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:

$$\alpha = |arctan(\frac{Accumulated\ Distance\ in\ Y\text{-}axis}{Accumulated\ Distance\ in\ X\text{-}axis})|. \quad (13)$$

Note that the range of α calculated using Equ. 13 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 [19]:

$$\psi = \begin{cases} \frac{3\pi}{2} + \alpha; & if\ Q = 1 \\ \frac{\pi}{2} - \alpha; & if\ Q = 2 \\ \frac{\pi}{2} + \alpha; & if\ Q = 3 \\ \frac{3\pi}{2} - \alpha; & if\ Q = 4 \end{cases}, \quad (14)$$

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

3.4.2 Sensor-Body Inclination Angles Calculation

Fig. 8 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:

$$\begin{bmatrix} A_{XR} \\ A_{YR} \\ A_{ZR} \end{bmatrix} = \begin{bmatrix} arctan(\frac{\sqrt{a_y^2+a_z^2}}{a_x}) \\ arctan(\frac{\sqrt{a_x^2+a_z^2}}{a_y}) \\ arctan(\frac{\sqrt{a_x^2+a_y^2}}{a_z}) \end{bmatrix}, \quad (15)$$

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

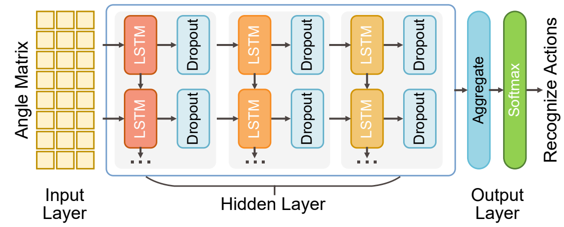


Fig. 9. Architecture of the hybrid model.

An intuitive way to recognize different handwashing actions is to compare the collected data with known templates (e.g., dynamic time warping). 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 build an efficient neural network to learn the relationship between sensor-body inclination angles and handwashing actions.

3.5 Action Recognition

In this section, we first sketch the hybrid network model to identify handwashing actions. Then, we introduce the detailed user-independent handwashing action recognition method. Finally, we present the transfer learning strategy to improve the recognition performance.

3.5.1 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. 9 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. The output layer consists of an aggregate layer and a softmax layer, which recognizes handwashing actions.

3.5.2 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. 10 by using t-SNE to reduce feature dimensionality. The same handwashing actions of three volunteers have a narrow distribution, while

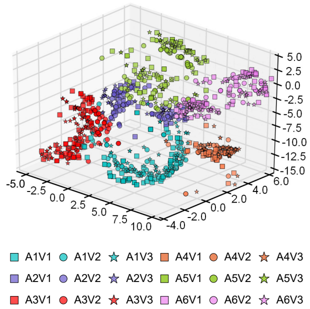


Fig. 10. t-SNE projection of the time-series user-independent features of handwashing actions performed by three volunteers. *A* represents the handwashing action ID, and *V* represents the volunteer ID. For example, *A*1*V*1 represents the volunteer 1 performing action 1.

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. In addition to the six predefined handwashing actions, we added an additional *NULL* class to prevent misclassification of non-handwashing actions and poorly performed actions as predefined handwashing actions. 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 4.4.

3.5.3 Transfer Learning

Train a well-performed model requires to collect data from a large number of senile dementai patients to include sufficient diversities. However, there is no public data set of senile dementia patients that contains detailed handwashing activities acquired from wrist-worn devices. It is troublesome to collect sufficient training data because we need the consent of relevant personnel for long-term sampling and need the cooperation of the elderly with dementia, which is very costly.

The scarcity of labeled time-series data can hinder the proper training of deep learning models. To alleviate the data scarcity problem, we propose a transfer learning method. The idea of transfer learning is to extract knowledge from a different but related source domain and use it to improve the learning of a model on our target domain. Data from the source domain can compensate for the scarcity of data on the target domain. We obtain the source domain from healthy adults, which is defined as $D_s = \{X_s, Y_s\}$, where X is the input data to the hybrid network and Y is the associated action labels. And the target domain is defined as $D_t = \{X_t, Y_t\}$. We perform transfer learning by first learn a predictive function f_s to associate Y_s with X_s, then solve the predictive function f_t that associates Y_t with X_t based on f_s. Specifically, the proposed transfer learning involves five steps:

1) Acquiring D_s: original IMU sensor data is firstly processed as introduced in Section 3.3 and Section 3.4. The sensor-body inclination angles are calculated, normalized, and form X_s. To address the heterogeneity of the source data, we normalize X_s using min-max normalization. Besides, the associated action labels are aggregated to form Y_s.
2) Learning of f_s: X_s is inputted to the hybrid network. By minimizing the differences between Y_s and the predicted results, the parameters of f_s at each layer are learned.
3) Initializing a network in the target domain: initializing the hidden layer of the hybrid network uses the weights and bias of f_s. Then, we build a new output lay on the hybrid network.
4) Acquiring D_t: we process the data from dementia patients as described in the first step to obtain D_t.
5) Learning of f_t: we solve f_t by frizzing the hidden layer and fine-tuning the weights of the output layer using $D_t = \{X_t, Y_t\}$.

Using this method, we can achieve accurate handwashing action recognition by collecting a small amount of data from senile dementia patients. We show the results in Section 4.5.1.

3.6 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 [20]. 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 assistance needs. For example, seniles 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 essential part of nursing interventions for them [21]. 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 [22]. For those who have severe dementia, the problem is more complicated. Accordingly, seniles with different cognitive abilities require different assistance to improve hand hygiene.

3.6.1 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 historical 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).

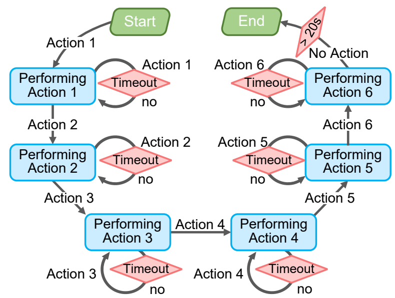


Fig. 11. State transition diagram.

- *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}.

Caregivers, physicians, and family members can 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.

Fig. 11 shows an example of a state transition diagram for prompting users when they do not follow the recommended step order during the task. 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. The state transition diagram can be modified flexibly according to the user's needs.

3.6.2 Design of Audio Prompt

AWash provides users with audio prompts. The reasons include: (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 [23], and (iii) video 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 the female voice [24], 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.

4 Evaluation

This section evaluates the performance of AWash with eight participants in various scenarios.

4.1 Experimental Setup

To validate the feasibility of AWash, we build a prototype equipped with a 9-axis IMU sensor, MPU9250 [25]. The prototype includes a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer, which is an alternative to a smartwatch. During handwashing, our prototype collects the IMU sensor data with the sampling rate of 100Hz and sends them to a laptop through Wi-Fi. The laptop acts as the edge server, which processes time-series IMU sensor data then recognizes the handwashing actions using a deep learning network. Given the detected actions, the edge server assists the user in the proper execution of the handwashing process. 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 being implemented in commodity smartwatches.

TABLE 1
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

We recruit 8 participants from an elderly community to record handwashing data. 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) [26] is used to test the presence of cognitive impairment in participants. Table 1 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 record handwashing data 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. Data collection of each session is currently 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.

4.2 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.

4.3 Overall Performance

To understand AWash's performance to recognize handwashing actions in the user-independent scenario, we con-

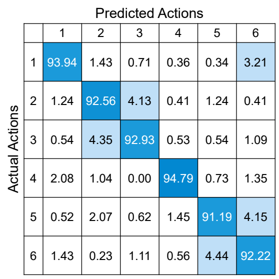


Fig. 12. Overall performance.

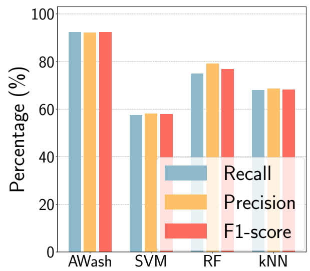


Fig. 13. AWash v.s. traditional.

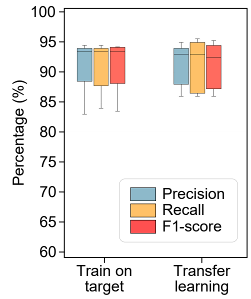


Fig. 14. Performance of transfer learning.

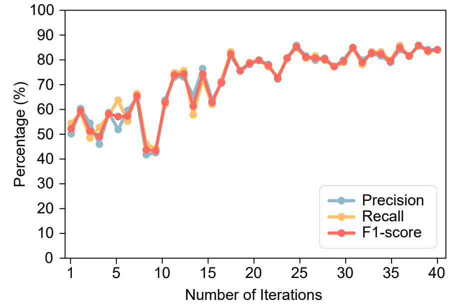


Fig. 15. Performance of handwashing scenario detection.

duct 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. 12 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 for the imbalance errors is the imbalance in the number of collected instances.

4.4 Comparative Study

AWash designs a set of novel algorithms to accurately recognize handwashing actions for senile dementia patients. We first compare AWash with several highly used prediction methods, then we test typically related works with our dataset and report the comparison between AWash and them.

4.4.1 Comparison With Highly Used Prediction Methods

A wide variety of prediction methods have been used for recognizing human activities. The choice of prediction method in our domain is difficult since it must be accurate in differentiating handwashing actions and robust against natural behavior variations. Similar to [27], we chose three additional highly used classifiers, including Ploy kernel Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (kNN), each with different advantages and limitations. All classifiers are implemented with the default setting by `Sklearn`. We extract significant features as input to these classifiers including *empirical cumulative distribution function representation* [16], *mean*, *standard deviation*, *kurtosis*, and *skew* from sensor-body inclination angle data, which have been proven effective by existing studies for activity recognition [28]. We conduct five-fold cross-validation for each prediction method and report the recall, precision, and F1-score in Fig. 13. It shows that AWash outperforms all tested methods, followed by RF and kNN. This again emphasizes the challenges of accurately and robustly recognizing handwashing actions in senile dementia patients, and demonstrates that the algorithms proposed by AWash are critical and effective.

TABLE 2
Comparisons of AWash with typical works on handwasing monitoring via wrist-worn wearables.

Work	Method	Additional Tools	User Dependence	Recall (%)	Precision (%)	F1-score (%)
Harmony	HMM	✓	✓	73.36	74.49	74.07
WristWash	HMM	×	✓	70.60	72.60	71.59
AWash	Deep Learning	×	×	92.94	92.60	92.76

4.4.2 Comparison With Typical Related Works

There are several approaches exploiting the IMU sensor on wrist-worn wearables to monitor handwashing actions, namely, WristWatch [10] and Harmony [9]. They are initially designed for healthy adults, but we are interested in how well they perform when used on senile dementia patients. Therefore, we implement WristWatch and Harmony with our dataset, using the same experimental setup as they described. We compare AWash with them in terms of method, the requirement of additional tools, user-dependence, recall, precision, and F1-score in Table 2. Both WristWatch and Harmony incorporate the HMM-based analysis method. As we discussed in Section 3.2.1, the HMM-based method can not achieve desired accuracy because handwashing actions from senile dementia patients usually violate the independence assumptions of the HMM. In contrast, AWash designs a deep learning model, which is effective in learning the nuance of handwashing actions. Moreover, Harmony requires additional components, including Bluetooth beacons, Bluetooth-enabled liquid dispensers, relays, and a server, which renders it difficult to be widely deployed. Besides, WristWatch and Harmony are user-dependent; that is to say, they do not work well when generalizing to new users. In contrast, AWash only uses IMU on the wrist-worn wearables, and it is user-independent to save the effort of collecting training data from new dementia users.

Meanwhile, in terms of handwashing action recognition performance, WristWatch and Harmony achieve recall, precision, and F1-score all below 70%. This emphasizes the earlier point in Section 1 that they are intended to be used by healthy adults and are not suitable for senile dementia patients. And AWash is accurate and overcomes most of the limitations of existing approaches.

4.5 Key Algorithm Study

4.5.1 Performance of Transfer Learning

To evaluate the effectiveness of our proposed transfer learning algorithm, we collect data from 35 healthy adults to form the source domain and take data collected from eight participants as the target domain. We conduct leave-one-participant-out-validation on the data of eight older adults. Fig. 14 compares the results of train on target only and transfer learning. We can observe that the performance of the system is slightly improved when using transfer learning, with average recall, precision, and F1 improved 0.19%, 0.33%, 0.26% respectively. This shows that our transfer learning strategy has the potential to make up for the problem of insufficient label data and realize the accurate detection of handwashing in senile dementia patients.

4.5.2 Performance of Handwashing Scenario Detection

To study how accurate our proposed method can distinguish the handwashing activity from non-handwashing activities, we ask participants to wear our prototype and record their non-handwashing daily activities, including sleeping, dining, walking, sitting, washing hands, standing, toileting, taking a shower, reading, going upstairs/downstairs, and watering plants (labeled as non-handwashing). We conduct five-fold cross-validation to evaluate the performance of distinguishing the handwashing activity from non-handwashing activities. To understand the detailed performance, we report the algorithm performance with different numbers of training iterations in Fig. 15. We can observe alternating peaks and troughs and increases in precision, recall, and F1-score from 1 iteration to 40 iterations. As 25 iterations is a good trade-off between computation complex and performance (achieve precision, recall, and F1-score above 80%), we adopt 25 iterations in the training phase. Moreover, the results demonstrate that our proposed method can achieve reasonable performance in real-life environments, thereby providing the basis for the system. Note that once handwashing actions are detected, we use a timer to ensure the analyzed handwashing data are longer than 20 s. Therefore, those poorly performed handwashing actions and extra actions between handwashing actions would not interrupt the analysis of the whole handwashing procedure. Furthermore, in the future, we will combine modern smart home appliances such as smart faucets and smart foam soap dispensers to further ensure the accuracy of handwashing scenario detection.

4.5.3 Performance of Dynamic Sampling Control

Accurate recognition of handwashing actions requires more samples to be collected, i.e., a high sample rate. However, it certainly leads to higher energy consumption and computational costs. Therefore, we propose to dynamically adjust the sampling duty cycle based on whether the user performs handwashing activities. To evaluate the performance of the sampling control strategy, we randomly simulate the handwashing activities during 24-hour. As shown in Fig. 16, when users do not wash their hands, the sampling duty cycle is kept low to avoid wasting energy. When a handwashing activity is detected, the duty cycle will increase to ensure the sampling result. Different combinations of high and low duty cycles can be used by our proposed method on a case-by-case basis. Here we give an example: if we use 75% duty cycle during handwashing and 25% during other ADLs, AWash can save 50% energy compared with a fixed duty cycle of 75%. Overall this control strategy is effective in saving energy consumption.

4.6 Impacts of Various Issues on Handwashing Action Recognition

4.6.1 Impact of Hybrid Model Structure

In the hybrid model, the number of LSTM network layers and 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%.

4.6.2 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. 17 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.

4.6.3 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 using data collected at participants' homes for training and data collected at the children sinks 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.

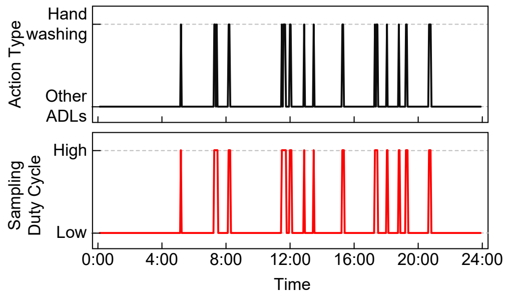


Fig. 16. Performance of Dynamic Sampling Control.

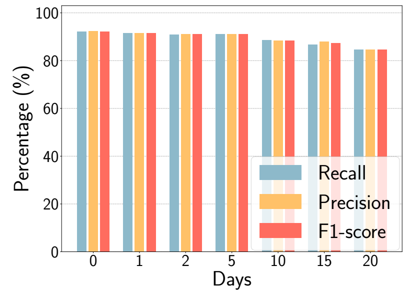


Fig. 17. Recognition over 20 days.

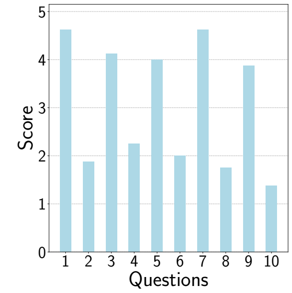


Fig. 18. User rating.

4.6.4 *Impact of Hardware Difference*

To evaluate the robustness and adaptiveness of AWash against diverse hardware, we implement it with another two types of wrist-worn prototype, MPU9150 (refereed as to device B), and ADXL356 (refereed as to device C). They have different features and prototype size compared to the default MPU9250-based prototype (refereed as to device A). We ask the participants to wear the new prototypes and perform each handwashing activity 30 times. Specifically, we evaluate AWash in five cases differentiated by the training dataset and testing dataset: (i) the data collected using device B are split into 75% training data and 25% testing data, (ii) the data collected using device C are split into 75% training data and 25% testing data,(iii) the training data are from device A, and the testing data are from device B, (iv) the training data are from device A, and the testing data are from device C, (v) the data from all devices are mixed to build a new dataset, 75% are used for training, and the remaining 25% are used for testing. Table 3 reports the result for the five cases. Good performance is achieved in case (i) and case (ii), confirming that our algorithm is robust to hardware differences and is expected to be implemented in various commodity devices. Besides, the relatively poor performance of case (iii) and case (iv) suggest that the training set from one hardware is not enough to build a device-independence system. This is mainly due to the size difference between the two types of hardware. However, we find that case (v) achieves relatively high performance compared to case (iii) and case (iv). This motivates us to regularly update the training dataset to include more device models so as to improve AWash's performance.

TABLE 3
Impact of hardware difference.

Case Index	Recall (%)	Precision (%)	F1-score (%)
Case (i)	91.18	90.15	90.66
Case (ii)	88.79	86.81	88.79
Case (iii)	73.16	72.49	72.98
Case (iv)	75.02	74.90	74.96
Case (v)	84.45	83.99	94.22

4.7 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 4 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.

TABLE 4
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

4.8 User Experience

After the participants experienced the assistance of AWash, a System Usability Scale (SUS) [29] 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. 18 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.

5 Related Work

Monitoring and promoting systems are founded to be effective solutions to assist elderly dementia patients with bathroom routines [30], [31], table-setting [32], tea-making [33], dressing [34] and toothbrushing [24], [35].

As for handwashing assistance technologies for the elderly with dementia, vision-based methods have been employed. Mihailidis et al. [36] 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 [37]. The COACH system [7] tracks hands using flocks of features, leverages a partially observable Markov decision process method to model different handwashing actions, and assists 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 with handwashing. The emergence of smartwatches and fitness bands provides new solutions for handwashing monitoring. Uddin et al. [8] 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 [9] 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 [10] 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 younger adults. Also, existing techniques can not address the significant diversity in user behavior caused 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. Therefore, there is a need to design a new wearable-based handwashing monitoring method system for senile dementia patients.

Approaches based on Wi-Fi [38], [39], RFID [40], acoustic signals [27], [41]–[43], lights [44], [45], and thermal infrared signals [46] have been widely developed to detect human activities. However, being sensitive to water, soap foam, and environmental temperature makes them unsuitable for handwashing action recognition. Some rings like magnetic sensors can accurately recognize gestures [47], but they should be taken off when washing hands for better overall cleanliness. Also, Electromyogram (EMG) acquired from arm muscles contributes to identifying actions [48]. However, senile 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 and thus can be deployed on the most affordable wrist-worn devices, which can be more widely accepted by senile dementia patients.

6 Discussion

The results from the controlled lab study and outside-the-lab study (conducted at the participants' homes) show that AWash is effective in handwashing assisting. AWash can detect the handwashing scenarios automatically, recognize six handwashing activities accurately, and model the overall handwashing performance flexibly. As the first wearable-based handwashing assisting system for senile dementia patients, AWash certainly leaves some directions to be further explored. First of all, we only demonstrate that AWash is energy-effective yet do not seriously evaluate the energy consumption. However, the prototype has an average power consumption of below 40 mA under a 100 Hz sampling rate, which can support long-term use even on energy-limited smartwatches. We are planning to implement AWash with commodity devices to fully study the energy consumption.

Second, the experimental results show that AWash mostly requires about less than 0.9 seconds to recognize the handwashing activities. This fast information exchange allows AWash to assist senile dementia patients in getting real-time assistance Moreover, the low delay may create an opportunity for AWash to incorporate speech recognition, Natural Language Processing (NLP), and new modalities, which are seen as the future direction for implementing more effective handwashing assistance.

Third, we have focused on detecting handwashing activities so far. There are many other daily activities (e.g., eating and climbing stairs) that might affect the IMU on smartwatches in a similar way to handwashing, as they can be modeled as several unique sub-activities and are periodic or quasi-periodic. We believe that AWash has the potential to be extended to assist many more activities, and we are planning to investigate the diverse pattern of other daily activities to extend the coverage of AWash.

Fourth, we only report the comparison between AWash and existing handwashing recognition approaches and commonly used classifiers. There exist some approaches that successfully exploit the IMU sensors on wearables to enrich the everyday lived experiences in dementia care [49]. They mostly focus on searching the significant features from sensory data to realize high-accuracy movement recognition. It is worth investigating how these feature selection strategies can be exploited to improve the performance of AWash.

Last but not least, we have only tested AWash with a proof-of-concept prototype, whose role is to collect and send the IMU data to a paired laptop via Wi-Fi so far. The data processing algorithms, deep learning network, and the assistance component are deployed in the edge server (i.e., a laptop in our proof-of-concept study). The design requires minimal computational capability, thus can be applied by most existing smartwatches. As a serious push is evident on the battery life and application development support, implementing data processing algorithms in the smartwatches becomes possible. For example, WearOS gives access to the smartwatch's sensors and the GPU [50]. We are planning to gradually deploy the algorithms to the smartwatch, eventually realizing handwashing action recognition and hand washing assistance using only smartwatches in the future.

7 Conclusion

In this paper, we present AWash, a cognitive assistant 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, a hybrid network model, and a transfer learning technique, 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 would recruit more participants and conduct studies on diagnosed patients with different dementia levels via collaborations with medical institutes. 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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Yetong Cao received the BEng degree in computer science and technology from Shandong University, Shandong, China, in 2017. She is now working toward the PhD degree in Computer Science from Beijing Institute of Technology, Beijing, China. Her research interests include mobile computing and ubiquitous computing.

Fan Li received the PhD degree in computer science from the University of North Carolina at Charlotte in 2008, MEng degree in electrical engineering from the University of Delaware in 2004, MEng and BEng degrees in communications and information system from Huazhong University of Science and Technology, China in 2001 and 1998, respectively. She is currently a professor at School of Computer Science in Beijing Institute of Technology, China. Her current research focuses on wireless networks, ad hoc and sensor networks, and mobile computing. Her papers won Best Paper Awards from IEEE MASS (2013), IEEE IPCCC (2013), ACM MobiHoc (2014), and Tsinghua Science and Technology (2015). She is a member of ACM and IEEE.

Huijie Chen received the B.Eng degree from the School of Computer Science, Henan University of Economics and Law, Zhengzhou, China in 2010, the M.Seng degree from the School of Computer Science, Taiyuan University of Science and Technology, Taiyuan, China in 2013, and Ph.D. degree in computer sience from the Beijing Institute of Technology, Beijing, China in 2020. He currently works in the school of computer science, Beijing University of Technology, Beijing, China. His research interests include Smart Sesning, crowdsensing, and mobile computing.

Xiaochen Liu received the BEng degree in Internet of Things from China University of Petroleum, Shandong, China, in 2020. She is now working toward the MEng degree in the School of Computer Science and Technology, Beijing Institute of Technology. Her research interests include computer networks and the IoT.

Song Yang received the Ph.D. degree from Delft University of Technology, The Netherlands, in 2015. From August 2015 to July 2017, he worked as postdoc researcher for the EU FP7 Marie Curie Actions CleanSky Project in Gesellschaft für wissenschaftliche Datenverarbeitung mbH Göttingen (GWDG), Göttingen, Germany. He is currently an associate professor at School of Computer Science in Beijing Institute of Technology, China. His research interests focus on data communication networks, cloud/edge computing and network function virtualization.

Yu Wang is currently a Professor in the Department of Computer and Information Sciences at Temple University. He holds a Ph.D. from Illinois Institute of Technology, an MEng and a BEng from Tsinghua University, all in Computer Science. His research interest includes wireless networks, smart sensing, and mobile computing. He has published over 200 papers in peer reviewed journals and conferences. He has served as general chair, program chair, program committee member, etc. for many international conferences (such as IEEE IPCCC, ACM MobiHoc, IEEE INFOCOM, IEEE GLOBECOM, IEEE ICC), and served as Editorial Board Member for several international journals, including IEEE Transactions on Parallel and Distributed Systems. He is a recipient of Ralph E. Powe Junior Faculty Enhancement Awards from Oak Ridge Associated Universities (2006), Outstanding Faculty Research Award from College of Computing and Informatics at the University of North Carolina at Charlotte (2008), Fellow of IEEE (2018), and ACM Distinguished Member (2020).