You Can Wash Hands Better: Accurate Daily Handwashing Assessment with Smartwatches

Fei Wang, Xilei Wu, Xin Wang, Han Ding, Jingang Shi, Jinsong Han, Dong Huang

Abstract—Hand hygiene is one of the most efficient daily actions to prevent infectious diseases, such as Influenza, Malaria, and skin infections. We have been suggested to wash our hands under professional guidelines to prevent virus infection. However, several surveys show that very few people follow this suggestion. Thus we propose UWash, a wearable solution with smartwatches, to assess handwashing procedures for the purpose of raising users’ awareness and cultivating habits of high-quality handwashing. We address the task of handwashing assessment from readings of motion sensors similar to the action segmentation problem in computer vision, and propose a simple and lightweight two-stream UNet-like network to achieve it effectively. Experiments over 51 subjects show that UWash achieves an accuracy of 92.27% on handwashing gesture recognition, <0.5 seconds error on onset/offset detection, and <5 points error on gesture scoring in the user-dependent setting, and keeps promising in the user-independent evaluation and the user-independent-location-independent evaluation. UWash even performs well on 10 random passersby in a hospital 9 months later. UWash is the first work that scores the handwashing quality by gesture sequences and is instructive to guide users in promoting hand hygiene in daily life. Code and data are available at https://github.com/aiotgroup/UWash

Index Terms—smartwatch, handwashing assessment, gesture recognition, deep neural network

1 INTRODUCTION

Hand hygiene is an efficient and effective approach to preventing various infectious diseases, e.g., colds and flu, enterovirus infections, and skin infections. We conducted a questionnaire on handwashing knowledge and practices over 505 subjects across 26 provinces in China. The questionnaire shows that 96.04% of subjects have heard of World Health Organization (WHO) guidelines or 7-step guidelines but only 34.65% of subjects follow the guidelines, similar to the situation reported in two other surveys conducted in Germany [1] and in Nigeria [2]. Thus, it is critical to raise people’s awareness and cultivate habits of high-quality handwashing in daily life.

Back to the conventional approach in the healthcare scenarios (HCS), hospitals and healthcare centers would like to employ auditors to directly observe and assess the handwashing procedures to promote the healthcare workers’ (HCWs) adherence to the guidelines. However, this approach is time-consuming, time-delayed, and costly. For these concerns, many works propose automatic handwashing monitoring systems to promote HCWs’ adherence and awareness [3, 4, 5, 6, 7, 8, 9, 10, 11, 12]. Given the above practices, we believe the accessibility of an automatic handwashing monitoring solution in people’s daily life is the next step to promoting ordinary people’s awareness of handwashing.

We propose UWash, an automatic solution with smartwatches, to assess handwashing techniques for the purpose of raising people’s awareness and cultivating habits of high-quality handwashing. As shown in Fig. 1, UWash leverages the inertial measurement unit (IMU) of the smartwatch, i.e., accelerometers and gyroscopes, to detect the start/end time of the handwashing procedures, estimate the duration of each gesture, and score the quality of each gesture as well as the entire procedure with WHO guidelines.

Table 1: Gesture scores

• With users, no fixed position. For daily use, we enable UWash to assess handwashing procedures along
with users, whether they are at home, workplaces, restaurants, etc. In contrast, most of the existing approaches can only work at fixed places where systems are deployed. For example, alcohol sensors [6], pressure sensors [3], ultrasonic hot spots [5], and RFID [4] are embedded into dispensers to count handwashing; cameras [7, 8, 9, 13, 14, 15] and mmWave devices [11] are placed on walls to estimate handwashing.

- **Standalone, no extra sensor.** UWash only needs IMU of smartwatches, no extra sensor is required for collaboration. Many existing systems need additional sensors, such as Bluetooth beacons, RFID cards, and Wi-Fi modules on dispensers or on the door, as triggers to detect people’s approaching and start to work [16, 8, 12, 17, 18].

- **Automatic on the start/end detection.** UWash can automatically identify the onset and offset of handwashing procedures. In contrast, the official handwashing APP of the Apple Watch and iWash [12] is designed to be awakened by users’ click or voice commands, largely harming the use will and use frequency. AWash [17] leverages the smart faucet or smart foam soap dispenser to detect the onset and offset of handwashing procedures, limiting the assessment places.

- **Elastic for random gesture sequences.** Fig. 1 shows 9 gestures of WHO guidelines. Some approaches require the users to rigidly follow the sequences [4, 10, 19, 12, 13, 14, 20, 21, 15]. However, people always wash their hands in different gesture sequences. UWash is elastic to assessing handwashing procedures no matter the gesture sequences.

- **Details in the duration of each gesture.** Many existing works simply count the occurrence of handwashing or report the duration of the entire process [4, 12, 19, 22, 14, 20, 18, 21, 15]. However, the different gestures, shown in Fig. 1, focus on cleaning different parts of the hands. Thus, details of the duration of each gesture are a more important metric for assessing handwashing quality. UWash can report this detailed information.

- **Instructive with scoring.** UWash can score the handwashing quality for the purpose of guiding users to improve their handwashing techniques. Since the WHO only provides an overall handwashing recommendation time of 40-60 seconds without specifying the duration for each stage of handwashing, we watched approximately 60 YouTube videos where experts demonstrated handwashing techniques. From these, we carefully selected 12 videos and recorded the duration of each handwashing stage. We then averaged these durations to establish a gold standard for stage durations, which serves as the basis for our scoring, described in Sec. 4.3.

To our best knowledge, our UWash is the first work that provides all these features to meet the requirements of daily handwashing assessment as compared in Table 1.

Though UWash provides a variety of features and multiple functions, our novel methods make it simple. Generally, there are two main schemas for continuous gesture recognition with the time-serial readings. (1) Top-down. This schema first segments the readings into slices then applies gesture recognition on each slice. However, segmenting two contiguous gestures through the readings is challenging and always results in errors as explained in [11]. One strategy to relieve this challenge is to set a pause gesture between two contiguous gestures to make the corresponding readings easy to segment [24]. However, this strategy will raise great inconvenience to users for handwashing assessment. (2) Bottom-up. This schema leverages a sliding window. All samples in the window would be categorized as the same gesture with time-series classification methods such as Hidden Markov Models [10], Dynamic Time Warping [25], Support Vector Machine [26], Recurrent Neural Networks [27], etc. As the window slides, entire readings will be recognized. This schema bypasses the segmenting problem in the top-down schema. However, this schema has an intrinsic false classification when the window spans readings of contiguous gestures.

We apply the bottom-up schema in UWash for it bypasses segmenting problem in the top-down schema. To tackle the intrinsic false of the bottom-up schema, we no longer conduct gesture recognition over the window, but conduct gesture semantic segmentation over the window. Semantic segmentation in the computer vision community is to align every pixel in an image with an object category, aka pixel-wise classification. In UWash, we adapt U-Net [28], a well-known semantic segmentation network for medical images, to align every sample in a sliding window with a gesture category. As the window slides, every sample in the time-serial IMU readings will have gesture alignment for itself, aka sample-wise gesture classification. To facilitate the gesture semantic segmentation results, Pyramid Pooling Module [29] and channel-wise attention [30] are applied to the U-Net. Fig. 1 shows an example of gesture semantic segmentation on a handwashing procedure. With the estimated procedure segmentation, UWash is able to detect the start and end of handwashing, estimate the duration of each gesture, and score each gesture as well as the entire procedure according to the estimated duration without bells and whistles.

The technical novelty of our UWash lies in the synergy achieved by tackling the intrinsic problem in the bottom-up schema with gesture semantic segmentation strategy, picking the right techniques such as U-Net [28], Pyramid Pooling Module [29] and channel-wise attention [30], and proposing a Dual-Branch U-Net framework for the two modal inputs from accelerometers and gyroscopes of smartwatches. In conclusion, the proposed methods provide five main features as follows.

- **Lightweight.** UWash models are lightweight, only 496KB.
- **Simple.** UWash addresses the intrinsic problem in the bottom-up schema with the simple idea, i.e., gesture semantic segmentation. Besides, to make U-Net suitable for time-serial IMU readings, we simply replace its 2D operations, e.g., convolution and pooling, with the 1D versions.
- **Effective.** Extensive evaluation results show UWash
TABLE 1
UWash meet all requirements.

| Work           | no fixed position | no extra sensor | start/end | random sequence | gesture duration | scoring |
|----------------|-------------------|-----------------|-----------|-----------------|------------------|--------|
| RGD camera, 2011 [7] | ×                 | ×               | ×         | ×               | ×                | ×      |
| RFID, 2014 [8]   | ×                 | ×               | ×         | ×               | ×                | ×      |
| Harmony, 2015 [16] | ×                 | ×               | ×         | ×               | ×                | ×      |
| Depth camera, 2016 [9] | ×               | ×               | ×         | ×               | ×                | ×      |
| WristWash, 2018 [10] | ×             | ×               | ×         | ×               | ×                | ×      |
| RFWash, 2020 [11] | ×                 | ×               | ×         | ×               | ×                | ×      |
| HAWAD, 2020 [19]  | ×                 | ×               | ×         | ×               | ×                | ×      |
| Armband, 2020 [22] | ×               | ×               | ×         | ×               | ×                | ×      |
| iWash, 2021 [12]  | ×                 | ×               | ×         | ×               | ×                | ×      |
| AWash, 2021 [17]  | ×                 | ×               | ×         | ×               | ×                | ×      |
| DLASS, 2022 [13]  | ×                 | ×               | ×         | ×               | ×                | ×      |
| Vision-based, 2022 [14] | ×               | ×               | ×         | ×               | ×                | ×      |
| Smartwatch, 2022 [23] | ×             | ×               | ×         | ×               | ×                | ×      |
| ALPHA HW, 2023 [20] | ×             | ×               | ×         | ×               | ×                | ×      |
| CareHAI, 2023 [18] | ×                 | ×               | ×         | ×               | ×                | ×      |
| WashRing, 2024 [21] | ×             | ×               | ×         | ×               | ×                | ×      |
| ResMFuse-Net, 2024 [15] | ×           | ×               | ×         | ×               | ×                | ×      |
| UWash (ours)     | √                 | √               | √         | √               | √                | √      |

performs well in multiple settings, e.g., user-dependent, cross-user, cross-location, and cross-time.

- **Fine-grained.** UWash provides sample-wise classification results, which is fine-grained compared to conventional top-down schema (slice-wise classification) and bottom-up schema (window-wise classification).

- **One model for multiple tasks.** UWash models can automatically detect the start and end of the handwashing procedure, estimate the duration of each gesture, and score each gesture as well as the entire procedure.

The contributions of this paper can be summarized in the following four aspects.

1. We propose UWash to automatically assess handwashing techniques for people’s daily use, which is the first work that provides all features listed in Table 1.

2. We novelly regard the handwashing assessment task as the semantic segmentation task to bypass the intrinsic problem in the bottom-up time-serial classification schema, and design a U-Net variant to achieve it well.

3. We propose a simple approach to obtain a standard of the expected duration of each handwashing gesture following WHO guidelines. With the standard, UWash is the first work that can score the handwashing quality to guide users to improve their handwashing techniques.

4. We collect a dataset with 51 subjects and 5 locations, and conduct an extensive evaluation in settings of user-dependent, cross-user, and cross-location. Besides, we collect a new dataset 9 months later in a hospital to demonstrate the cross-time performance. All datasets and codes have been released for research use.

2 RELATED WORK
Before the COVID-19 pandemic, hand hygiene has already been crucial to preventing healthcare-associated infections in hospitals. Human mandatory audits are applied to improve the healthcare workers’ compliance with the WHO guidelines. However, this approach is labor-intensive, time-consuming, and costly. Thus automatic handwashing monitoring systems are proposed [3], [4], [5], [6], [7], [8], [9], [10], [11], [12] to facilitate healthcare workers’ adherence. Among them, sensors such as alcohol sensors [6], pressure sensors [3], ultrasonic hotspots [5], and RFID [4] are embedded into the dispensers to simply count the handwashing. RGB cameras [7], [13], [14], [20], [18], [15], depth cameras [8], [9], and mmWave devices [11] are placed on the wall to estimate fine-grained handwashing procedures. Since sensors or devices in these works are required to be deployed next to the handwashing sinks in hospitals, they are not suitable for people’s daily use.

Wearable devices such as wristbands [10], [19], armbands [22], smartwatches [16], [23], and smart rings [21] are also proposed to monitor handwashing in recent years. However, wearing wristbands and armbands in daily life is an extra interaction for users, limiting their widespread use. Considering this, smartwatches are ideal platforms for monitoring handwashing procedures. Unfortunately, current smartwatch-based work [16] cannot detect the start/end time of handwashing effectively, requiring to work along with Bluetooth sensors on dispensers [16] or to be awakened manually [12], where the former limits the use places and the latter harms the use frequency. Lattanzi et al. [23] utilized a single smartwatch to detect hand washing quality. However, this method only supports the monitoring of the overall handwashing duration and cannot measure the duration of individual handwashing steps, limiting the effectiveness of the monitoring. WashRing [21] introduced a hand hygiene monitoring system based on smart ring devices. Although smart rings have the advantages of being compact and unobtrusive to wear, they may interfere with the handwashing process when worn on the fingers. Additionally, the components of hand sanitizers may potentially
Fig. 2. UWash can automatically detect the event of handwashing, not requiring to work along with Bluetooth sensors in dispensers [16] or to awaken the monitoring system manually [12]. We attribute this ability partly to the unique characteristics explained in Section 3.1, i.e., successive, periodical, and being with expectable pre-activities and post-activities.

affect the rings. Besides requirements in user experiences, we believe if the handwashing monitoring system can score every individual handwashing gesture and the entire procedure following WHO guidelines, it will help people to improve their handwashing techniques following the reported scores. Thus we propose UWash to achieve this.

In Table 1, we compare UWash with some representative work. The table shows that UWash requires no extra sensor and can work along with users for daily use purposes. In addition, UWash can automatically detect the start/end of the handwashing procedure and can estimate the duration of every gesture regardless of the gesture conducting sequence. Moreover, UWash is the first work with the capability to score the handwashing quality under WHO guidelines.

3 HANDWASHING ANALYSIS

3.1 Features of Handwashing

As mentioned above, UWash can automatically detect the handwashing activity, not requiring to work along with additional sensors [16, 12, 8] or to be activated manually [12]. In addition to the carefully-designed algorithm that we will describe in detail later in Section 4, we also attribute this ability to the unique features of the handwashing activity. With the visualization study in Fig. 2 we conclude three unique features as follows.

(1) Multiple successive gesture stages. When washing hands, people always conduct several successive gestures to clean the palms, back of hands, fingers, wrists, etc., respectively. We visualize one example recorded by the accelerometers in Fig. 2, from which we can find distinguishable signal patterns of multiple successive stages.

(2) Periodic motion under each gesture. When cleaning a part of hands, people always perform periodic back and forth motions. Besides, the periodic records in multiple successive stages are very different, as shown in Fig. 2.

(3) Expectable pre-activities and post-activities. The pre-activities of handwashing procedures always include walking to a sink, wetting hands, applying soap, etc. The post-activities of handwashing procedures always include drying hands with a towel, dropping the towel, walking out of the restroom, etc. These activities are priors that largely promote our start/end time detection.

3.2 Dilemma on Field of View

The handwashing procedures vary from person to person, even from time to time for the same person, leading to diverse handwashing motion sequences. Conventional action recognition approaches use sliding windows with a data-dependent stride to crop clips from sequences. Then gesture classification is conducted clip-by-clip. To facilitate understanding, here we call the size of sliding windows the field of view (FoV), which represents the receptive field that handwashing gesture recognition models can see at one time.

Selecting FoV in the conventional FoV-wise recognition schema is a work of dilemma. As shown in Fig. 3, the left three sub-figures are an example of recorded accelerometer sequences with the FoV of 0.1 seconds, 0.2 seconds, and 1 second, respectively. Let us see the upper-left first,
we can hardly tell the gesture category from one single sequence, for these 10 sequences are quite different. If we take a twice-wider FoV of 0.2 seconds, the tendency of the sequences becomes much clear, e.g., sequences in the 1st and 4th windows are similar; and those in the 2nd and 5th windows are similar. However, the blue/green curves in the 1st/4th window increase, while the blue/green curves in the 2nd/5th window decrease. This leads to an ambiguity in the handwashing gesture recognition. Furthermore, if we take an even wider FoV of 1 second, the unified and periodical patterns in the sequence finally emerge, with which we can easily make an accurate handwashing gesture recognition.

**Pro.** Larger FoV facilitates handwashing gesture recognition.

However, a larger FoV may also cause a larger error. As shown in Fig. 3, the right three sub-figures demonstrate a procedure of gesture switching from gesture 2 (G2) to gesture 3 (G3), where G2 and G3 occupy the duration in 40% and 60% respectively. As G3 occupies the dominant duration, gesture recognition models tend to classify the sequences as G3, resulting in a recognition error of 40%.

**Con.** Larger FoV may lead to larger recognition errors.

To relieve the dilemma on the FoV, one could search for a dataset-specific FoV or propose a dynamic FoV algorithm. This may be over-designed with complex strategies. It is unclear how we can ensure every gesture duration is perfectly divisible by FoVs. Our solution to the dilemma is to borrow the semantic segmentation schema [31] for the handwashing gesture recognition task. Instead of outputting one single gesture category for one entire FoV, the semantic segmentation schema predicts the gesture category for every single sample in an FoV. This schema takes the advantage of a large FoV and makes fine-grained recognition for every moment in the FoV, bypassing the dilemma on FoVs naturally. We will explain our methods in detail in Section 4.

### 4 Methods

Before going into details of the methods, we define our task with symbols. We use $N$ to represent the length of the FoV, which is a pre-defined constant. We use $K$ to represent the size of the training dataset. We use $A$ and $G$ to represent data of the accelerometers and gyroscopes, respectively. We use $Y$ for the sample-wise gesture annotations. With these symbols, the training dataset is $D = \{A^i_j, G^i_j, Y^i_j \mid i \in 1, 2, ..., K; j \in 1, 2, ..., N\}$. Please note that accelerometers and gyroscopes both record data in 3 dimensions, which are not explicitly shown for brevity. We further simplify the notation of the training dataset as $D = \{A, G; Y\}$.

Our goal is to propose a machine learning model $M$ that takes $A$ and $G$ as inputs, and outputs sample-wise gesture recognition results, $Y^*$. We conclude this goal with Equation 1

$$M = \arg \min_M \|M(A, G) \rightarrow Y^*, Y\|$$

where $\|\|_\cdot$ is for the operator to compute distances between the model’s outputs ($Y^*$) and annotations ($Y$).

#### 4.1 Deep Learning Model

U-Net [28] is a pixel-wise classification network architecture widely used in computer vision tasks of visual semantic segmentation. Later, Temporal U-Net [32] replaces 2-dimensional convolutions in U-Net with 1-dimensional convolutions to conduct sample-wise class alignment on 1-dimensional time-serial data. The U-Net clusters can learn features from data in the wider and wider FoVs with the increase of the convolutional layers (please refer to Section 3.2).
for the definition of the FoVs). Further, learned features in large FoVs (at the high-level layers) and small FoVs (at the low-level layers) are combined with skip connections to promote semantic segmentation performance. Considering these good characters on segmentation, we apply Temporal U-Net with several modifications to achieve our task of the sample-wise handwashing gesture recognition. The network architecture is shown in Fig. 4. Next, we explain the reason why we propose these modifications.

(1) Two-stream. Accelerometers and gyroscopes of smartwatches measure linear accelerations and angular accelerations respectively, describing two physical quantities in different scales. To properly leverage data of the two modalities, we have to do data normalization before merging them for the later task. To conduct automatic modality normalization, we feed raw accelerometer data and raw gyroscope data into the two streams of U-Nets, respectively. We also apply Batch Normalization [33] and Leaky Rectified Linear Unit [34] to facilitate the normalization between the two modalities.

(2) Squeeze-and-Excitation Module [30]. Though features learned from the dual-branch U-Nets are considered to be normalized, we still believe their contributions to the final gesture recognition are always not equal. The reason is concluded from the observation that accelerometers and gyroscopes always have different sensitivity when one conducts a specific handwashing gesture. For example, as shown in Fig. 1, accelerometers are more sensitive than gyroscopes for G1, while gyroscopes are more sensitive for G6. To re-weight the contribution of handwashing gesture recognition of the dual-modal sensors, we apply Squeeze-and-Excitation Modules to the learned features. After that, we concatenate the re-weighted features along the channel dimension for gesture recognition.

(3) Pyramid Pooling Module (PPM) [29]. PPM is proven to be efficient to harvest features across different FoVs [29]. Therefore, we apply it in the middle of U-Nets, shown in Fig. 4. Before being fed into PPM, feature maps are with the size of $8 \times 64$, where $8$ and $64$ represent temporal dimension and channel dimension, respectively. We use three average pooling operations with window/stride sizes of $8, 4$, and $2$ on the feature maps, generating three outputs with the size of $1 \times 64, 2 \times 64$, and $4 \times 64$, respectively. Before concatenating three pooling outputs with the input feature maps along the channel dimension, we use convolution layers with the kernel size of $1 \times 1$ to reduce the channel to be of $16$, for the channel information balance between the 3 pooling outputs and the input feature maps. Further, we upsample the pooling outputs and concatenate them with the input feature maps, outputting feature maps with the size of $8 \times 112$.

(4) Input length of 64. We have two reasons to set the input clip length as 64 (FoV of 64). First, as shown in Fig. 3, FoV with the size of 1 second is sufficient to discriminate gestures. For the sampling rate of the smartwatch is 50Hz, the nearest number is 64 (with an integer power of 2). Second, since larger inputs lead to larger models, we set the input length to be 64 instead of 128 or larger for the future deployment on edge devices. Actually, the UWash models are quite lightweight, only 496KB without any model compression, making it possible to deploy UWash in any smartwatches in the future.

We use Pytorch 1.9.0 to implement the network. The initial learning rate is 0.001. The batch size is 16k. We use the cross-entropy function to compute losses and Adam [35] to optimize the network. We train the network for 500 epochs.

### 4.2 Post Smoothing Methods

In testing, given a test time series with the length of $N$, we conduct gesture recognition with the FoV of 64 and the stride of 64. We show a raw recognition output in Fig. 6, which shows some jitter errors due to random false classification. Thus, we further apply two post-smoothing methods to the raw recognition outputs:

(1) Multiple Test Voting (MTV). We conduct gesture recognition over the test time series via the FoV of 64 with the stride of 1, which results in multiple outputs on each sampling point. For each sampling point within the time series, we take the mode of all its outputs as its final recognition result.

(2) The Mode Filter (TMF). For each sample, we use the mode of outputs on its nearest 128 samples as its final recognition result. We call this method the Mode Filter with the window size of 128 and stride of 1.

A post-smoothed example is visualized in Fig. 6, which shows that MTV and TMF can effectively reduce jitter.
4.3 Handwashing Scoring

Scoring the quality of handwashing procedures is subjective, which requires expertise in the type of gestures, the completion of gestures, the duration of gestures, etc. In this paper, we directly evaluate the UWash quality with respect to the WHO guidelines. To obtain the guideline-recommended duration of each gesture, we collected 60+ handwashing videos that describe WHO guidelines and choose 12 of them as references, ignoring those with slow play, fast play, over-detailed explanation, etc. URLs of selected videos are as follows.

(1) https://www.youtube.com/watch?v=qo7Q_wm2Vec
(2) https://www.youtube.com/watch?v=IisgnbMfKvI
(3) https://www.youtube.com/watch?v=0FLQ-EpQ6PM
(4) https://www.youtube.com/watch?v=JvDAtFeUF8g
(5) https://www.youtube.com/watch?v=6JrEeR5OXiE
(6) https://www.youtube.com/watch?v=TClRYmtqClM
(7) https://www.youtube.com/watch?v=YiChdJ
(8) https://www.youtube.com/watch?v=hhKlyoVsbOY
(9) https://www.youtube.com/watch?v=3PmVJQUCm4E
(10) https://www.youtube.com/watch?v=51aTClYmtqClM
(11) https://www.youtube.com/watch?v=4CcGLoYrIPU
(12) https://www.youtube.com/watch?v=qo7Q

Table 2 shows the recommended duration of each gesture in these videos. In addition, we remove the maximum and minimum of each gesture and compute the average as the professional handwashing duration, denoted as $D_{pi}^p$, $i \in [1, 2, ..., 9]$.

![Table 2](image)

We have two empirical assumptions. (1) Since each gesture emphasizes cleaning one part of the hands, we assume each gesture is equally important in handwashing. (2) The quality of cleaning each gesture increases linearly with its duration, and the perfect quality is reached and saturated when the duration is equal to or greater than the professional duration. Given these assumptions, we score handwashing with Equation 2.

$$\text{Score} = \sum_{i=1}^{9} \frac{100}{9} \times \min(1, \frac{D_{pi}^c}{D_{pi}})$$

where $\frac{100}{9}$ is the peak score of each gesture, to match the first assumption; $D_{pi}^c$ represents the estimated duration of the $i$-th gesture; $\min(1, \frac{D_{pi}^c}{D_{pi}})$ matches the second assumption. Finally, the Score of a handwashing procedure is the sum of estimated scores of all gestures.

It is important to highlight that the gold standard for evaluating actual handwashing quality involves professional personnel conducting video observations. This process may consider multiple factors, including the posture of each gesture, the thoroughness of the gestures, and the water flow rate at the sink. Our two assumptions are simplified models for assessing handwashing quality with low cost.

5 Evaluation

5.1 Data Acquisition

This study was approved by the Medical Ethics Committee of the Second Affiliated Hospital of Xi’an Jiaotong University, Xi’an China.

We use the Samsung Gear Sport smartwatches and collect data from motion sensors and corresponding timestamps following [56]. To increase the diversity of external conditions such as the type of hydrants, sinks, dispensers, etc., we collect data at five buildings on campus, i.e., a teaching hall, a laboratory hall, a cafeteria, a dormitory, and a library. At each building, we randomly recruit 10 passersby (11 at the laboratory hall) as participants and train them to wash their hands following WHO guidelines.

To act as the daily handwashing procedure, participants were asked to conduct activities including walking to the sink, washing hands, and walking out of the restroom, while other activities such as wetting hands with water, applying soap, and drying hands with a towel are not mandatory, depending on their behaviors. We denote gestures in WHO guidelines as category 1 to category 9, and all other activities as category 0. Every participant repeats the procedure 5 times, which is a tolerable number and would not cause any hand discomfort. Along with the sensor data, we also use codes from [32] to record videos on the participants’ hands and corresponding timestamps. Five labeling workers view the synchronized video streams to label gestures on motion sensory data collected at each building respectively. Further, we segment motion sensory records with the FoV of 64 and the stride of 1, leading to a simple data augmentation of 63 tamps following [36]. To increase the diversity of external conditions, we collect data at five buildings on campus, i.e., a teaching hall, a laboratory hall, a cafeteria, a dormitory, and a library. At each building, we randomly recruit 10 passersby (11 at the laboratory hall) as participants and train them to wash their hands following WHO guidelines.

5.2 User-Dependent Results

We first evaluate UWash on all participants under the user-dependent setting. For each participant, we use instances corresponding to the first 4 handwashing procedures as the training set, and the last ones as the test set, leading to the training and test set with instances of 643971 and 161020, respectively. In this paper, the training set and the test set have no overlap in all evaluations.

(1) Overall Results. We report overall results including accuracy, precision, recall, and F1 score in Table 3. The accuracy is computed via Equation 3.

$$\text{Accuracy} = \frac{\sum_{p=1}^{51} \sum_{i=1}^{N_p} I(S_{p,i} = S_{p,i})}{\sum_{p=1}^{51} \sum_{i=1}^{N_p}}$$

![Table 3](image)
where \( N_p \) represents the length of the test time-series of the \( p \)-th participant; \( S_{p,i} \) and \( S_{p,i}^* \) represent the ground-truth and the UWash output on the \( i \)-th sample of the \( p \)-th participant, respectively; \( I(S_{p,i}^* = S_{p,i}) \) outputs 1 if UWash recognizes correctly on \( S_{p,i} \), otherwise 0. The table shows that UWash can achieve the sample-wise classification accuracy of 86.31% directly. With simple yet efficient post-smoothing methods, i.e., multiple test voting and the mode filter (see Section 4.2), UWash can eventually achieve an accuracy of 92.27%.

This is a 10-class classification task (9 handwashing gestures + 1 background gesture), so we have 10 precisions, 10 recalls, and 10 F1 scores. We report their means as mPrecision, mRecall, and mF1 in Table 3. Consistent with the accuracy, the results of these three metrics show that UWash performs well, and can be further enhanced with multiple test voting (MTV) and the mode filter (TMF). We also report the ablation study on our adapted methods, i.e., Two-Stream (TS), Squeeze-and-Excitation (SE), and Pyramid Pooling Module (PPM) in Table 3. The table shows that these methods can effectively improve the accuracy of one-stream vanilla UNet.

We further apply representative MobilenetV3-small [38] and ResNet-18-1D [39] on the test clips to conduct clip-wise gesture classification. We take the clip-wise result as the result of all samples in the clip, and compute the sample-wise accuracy via Eq. 3. Table 3 shows that UWash is ~8-10% higher than MobilenetV3-small and ResNet-18-1D. More importantly, MobilenetV3-small and ResNet-18-1D on our task are with 3.056M and 3.851M parameters respectively, while UWash is only with 0.099M parameters, ~2.5% of ResNet-18-1D, much more lightweight.

Table 4 compares our UWash with several recent work in view of number of evaluated subject and granularity. Since the datasets are different, the differences in accuracy are not meaningful for reference.

Next, we are going to show the performance of UWash from other four perspectives, i.e., performance on gestures, performance on participants, start/end detection error, and handwashing scoring results.

(2) Performance on Gestures. We show the confusion matrix of UWash on 10 gestures (9 handwashing gestures + 1 background) in Fig. 7. Though the data of these 10 gestures are not quite balanced (29.2% of background), UWash works well for all gestures, especially for the 2nd, 3rd, 6th, and 7th gestures (zoom in for a better view).

| Method                      | Accuracy ↑ | mPrecision ↑ | mRecall ↑ | mF1 ↑ | Parameters ↓ |
|-----------------------------|------------|--------------|-----------|-------|--------------|
| MobileNetV3-small [38]      | 82.95%     | 80.30%       | 79.28%    | 0.80  | 3.056M (7%)  |
| ResNet-18-1D [39]          | 84.53%     | 82.40%       | 81.87%    | 0.82  | 3.851M (100%)|
| vanilla UNet [28]           | 82.25%     | 80.98%       | 80.23%    | 0.81  | 0.048M (1.2%)|
| UNet+TS                    | 83.36%     | 81.96%       | 81.43%    | 0.82  | 0.099M (2.5%)|
| UNet+TS+SE                 | 84.16%     | 82.76%       | 82.18%    | 0.82  | 0.099M (2.5%)|
| UNet+TS+SE+PPM             | 86.31%     | 84.92%       | 84.48%    | 0.84  | 0.099M (2.5%)|
| UNet+TS+SE+PPM+MTV         | 91.10%     | 90.08%       | 89.68%    | 0.89  | 0.099M (2.5%)|
| UNet+TS+SE+PPM+TMF (UWash) | 92.27%     | 91.26%       | 90.85%    | 0.91  | 0.099M (2.5%)|

Fig. 7. Confusion Matrix of Gesture Prediction. UWash works well for all gestures, especially for the 2nd, 3rd, 6th, and 7th gestures (zoom in for a better view).

TABLE 4

| Work         | Accuracy | #Subject | Granularity | Open-sourced |
|--------------|----------|----------|-------------|--------------|
| WristWatch   | 95%      | 6        | clip-wise   | Not yet      |
| Awash        | 92.94%   | 8        | clip-wise   | Not yet      |
| UWash        | 92~98%   | 14       | clip-wise   | Not yet      |
| RFWash       | 85%      | 10       | sample-wise | Not yet      |
| UWash (Ours) | 92.27%   | 51       | sample-wise | Yes          |

TABLE 3

Results on all participants. The results show that UWash performs well and can be enhanced with post-smoothing methods of multiple test voting (MTV) and the mode filter (TMF). Moreover, UWash is only with ~2.5% parameters of ResNet-18-1D, much more lightweight. TS (two-stream), SE (Squeeze-and-Excitation Module), PPM (Pyramid Pooling Module). ↑ means the larger the better. ↓ means the less the better.

| Work         | Accuracy | #Subject | Granularity | Open-sourced |
|--------------|----------|----------|-------------|--------------|
| WristWatch   | 95%      | 6        | clip-wise   | Not yet      |
| Awash        | 92.94%   | 8        | clip-wise   | Not yet      |
| UWash        | 92~98%   | 14       | clip-wise   | Not yet      |
| RFWash       | 85%      | 10       | sample-wise | Not yet      |
| UWash (Ours) | 92.27%   | 51       | sample-wise | Yes          |
its post-activity (G1) or pre-activity (G9). The other false happens between two successive gestures. As the start/end time of every gesture is annotated manually, the discordance across different labeling workers, participants, and locations may cause false between successive gestures.

(3) Performance on Participants. For the \( p \)-th participant, we use Equation 4 to compute the accuracy:

\[
\text{Accuracy}_p = \frac{\sum_{i=1}^{N_p} I(S_{p,i}^* = S_{p,i})}{N_p}
\]

where symbols share the same meanings with Equation 3.

Fig. 9 shows that 33 of 51 participants achieve an accuracy of over 95%; only 6 of them have an accuracy of less than 85%; the average accuracy is 92.33% (orange bar). The results demonstrate that, for the seen participants, UWash achieves sample-wise handwashing gesture recognition effectively.

(4) Start/End Detection. Desired to reiterate, UWash can automatically detect the start/end time, not requiring to work along with additional sensors [16], [12], [8] or to be awakened manually [12]. We use Equation 5 to compute the start time detection error.

\[
\text{Error}_s = |t_s^* - t_s|
\]

where \( t_s^* \) and \( t_s \) represent the detection and the ground-truth of the start time of a test handwashing procedure, respectively; \(|\cdot|\) is to compute the absolute value. Similarly, we use \(|t_e^* - t_e|\) to compute the detection error at the end time. We compute the start/end detection errors over the test set and report the Mean and standard deviation (SD) in Table 5. The table shows that Means and SDs are all within 1 second, indicating UWash can detect handwashing events correctly and stably.

(5) Scoring Results. UWash is the first work to score handwashing following the WHO guidelines. We use methods described in Section 4.3 to compute handwashing scores on the test set. Further, we compute the Mean and SD of scoring errors against ground truth. As shown in Table 5, the mean and the SD are less than 5 points, indicating UWash can score handwashing well.

We evaluate the cross-domain performance of UWash, which is a critical criterion for a handwashing assessment system for people’s daily use.

(1) Cross-Participant. We train UWash with data of 50 out of 51 participants and test the trained model with data of the remaining participant. We conduct this leave-one-participant-out process over 51 participants respectively to evaluate the cross-participant performance. As shown in Fig. 8, accuracy among some left-out participants is more discrete than those in the user-dependent setting, shown in Fig. 7. For example, the 13th and the 38th participants have expected, the mean accuracy in the cross-participant setting decreases to 83.34%, since the personalized gestures of these individuals are not included in the training set.

Table 7 shows that UWash detects the start/end time of handwashing well even in the cross-participant setting.

|                | Start Detection | End Detection | Handwashing Scoring |
|----------------|----------------|---------------|---------------------|
| Mean           | 0.49s          | 0.23s         | 4.0pts              |
| SD             | 0.58s          | 0.30s         | 4.3pts              |

Table 6 shows that UWash detects the start/end time of handwashing well even in the cross-participant setting.
with errors of $<0.5$ seconds, which means that UWash can effectively distinguish the handwashing gestures and other activities. However, the handwashing scoring performance drops significantly, repeatedly indicating the performance of gesture classification on unseen users highly depends on how well they wash hands following WHO guidelines.

(2) Cross-Participant-Cross-Location. We use data from 4 out of 5 locations to train UWash and test the trained model on the remaining one location. We conduct this leave-one-location-out process over 5 locations where data is collected respectively. Since recruited participants have no overlap between different locations, the leave-one-location-out process also leads to the evaluation in the cross-participant-cross-location setting.

The experimental results are shown results in Fig. 11 and Table 6. In this setting, the performances have similar characteristics to those in the cross-participant setting, e.g., the accuracy is more discrete; the 13th and the 38th participants have the lowest accuracy; the mean accuracy drops to 81.45%; the mean error in the start and end detection of handwashing are 0.39 seconds and 0.14 seconds respectively. The average scoring standard deviation is 14.30 points and 5.23 points respectively. We find that these average values are at the same level as in the Cross-Participant-Cross-Location evaluation listed in Table 6. These results demonstrate that UWash is stable and promising across time. Note that the new dataset is from the new participants, new location, and new date, results of this evaluation provide us strong confidence in performance if UWash is promoted to large-scale real-world use.

6 Conclusion

In this paper, we introduce UWash, a smartwatch-only handwashing assessment system, to raise people’s awareness of handwashing in daily use and adherence to the WHO handwashing guidelines. UWash takes the data of the IMU sensors of smartwatches, i.e., accelerometers and gyroscopes, as inputs, feeds the inputs into a dual-branch U-Nets, and outputs sample-wise gesture recognition results effectively. UWash can detect handwashing start/end time, estimate the duration of every handwashing gesture, and score gestures as well as the entire procedure following WHO guidelines. Experimental results over 51 participants show that UWash works well in the user-dependent, cross-participant, and cross-participant-cross-location settings. In addition, UWash still performs promising on a dataset collected 9 months later in a hospital. Moreover, UWash models are lightweight, only 496KB, with great potential to be deployed on edge devices in the future.
**APPENDIX A**

**THE ONLINE QUESTIONNAIRE**

In the 1st paragraph of Sec.Introduction, we mentioned that we had conducted an online questionnaire on handwashing knowledge and practices over 505 subjects across 26 provinces in China. Fig. 12 lists the number of subjects from these provinces. We report the results of five questions in the questionnaire in Fig. 13, leaving out information on the age, gender, job, etc. The first four pie charts correspond to the questions below respectively.

**Q1. Handwashing is very important in daily life.**

**Q2. Have you heard of the WHO handwashing guidelines or the 7-step guidelines?**

**Q3. How well do you master each step of the WHO handwashing guidelines or the 7-step guidelines?**

**Q4. How often do you follow the WHO handwashing guidelines or the 7-step guidelines when washing hands?**

These charts show that 96.63% of subjects think handwashing is important in daily life. Meanwhile, 96.04% of subjects have heard of standard handwashing guidelines. However, 48.32% of subjects know all steps. What’s worse, only 34.65% subjects wash hands following standard guidelines most of the time. The statistics show that there is a big gap between the knowledge and practices on handwashing in people’s daily life, indicating the urgency to propose an automatic handwashing monitoring system for daily use.

**Q5. Relative to the price of a smartwatch, how much are you willing to pay for an App of handwashing scoring?** The target of Q5 is to investigate the purchase will of potential users. The last chart in Fig. 13 shows that 31.68% of subjects will pay an additional 1% price for the handwashing monitoring services ($3.99 for Apple Watch S6 and Samsung Galaxy Watch3); and 23.37% of subjects will pay an additional 5%. Surprisingly, 15.05% of subjects are willing to pay an additional 10% or more. These statistics show that handwashing monitoring apps like UWash have a considerable market value.
APPENDIX B

HANDWASHING ASSESSMENT EXAMPLES

We show some results of UWash in Fig. 14, Fig. 15, Fig. 16, Fig. 17, Fig. 18, Fig. 19, Fig. 20, Fig. 21.

![Figure 14](image1.png)

**Fig. 14.** Results of the 7th subject in the cafeteria.

![Figure 15](image2.png)

**Fig. 15.** Results of the 10th subject in the cafeteria.
Fig. 16. Results of the 4th subject in the dormitory.

Fig. 17. Results of the 8th subject in the teaching hall.
Fig. 18. Results of the 1st subject in the laboratory hall.

Fig. 19. Results of the 7th subject in the laboratory hall.
Fig. 20. Results of the 1st subject in the library.

Fig. 21. Results of the 2nd subject in the library.