Ready, Steady, Touch! — Sensing Physical Contact with a Finger-Mounted IMU

YILEI SHI, Augmented Human Lab, The University of Auckland, New Zealand
HAIMO ZHANG, Augmented Human Lab, The University of Auckland, New Zealand
KAIXING ZHAO, IRIT, University of Toulouse, France
JIASHUO CAO, Augmented Human Lab, The University of Auckland, New Zealand
MENGMENG SUN, Northwestern Polytechnical University, China
SURANGA NANAYAKKARA, Augmented Human Lab, The University of Auckland, New Zealand

A finger held in the air exhibits microvibrations, which are reduced when it touches a static object. When a finger moves along a surface, the friction between them produces vibrations, which can not be produced with a free-moving finger in the air. With an inertial measurement unit (IMU) capturing such motion characteristics, we demonstrate the feasibility to detect contact between the finger and static objects. We call our technique ActualTouch. Studies show that a single nail-mounted IMU on the index finger provides sufficient data to train a binary touch status classifier (i.e., *touch* vs. *no-touch*), with an accuracy above 95%, generalised across users. This model, trained on a rigid tabletop surface, was found to retain an average accuracy of 96% for 7 other types of everyday surfaces with varying rigidity, and in walking and sitting scenarios where no touch occurred. ActualTouch can be combined with other interaction techniques, such as in a uni-stroke gesture recogniser on arbitrary surfaces, where touch status from ActualTouch is used to delimit the motion gesture data that feed into the recogniser. We demonstrate the potential of ActualTouch in a range of scenarios, such as interaction for augmented reality applications, and leveraging daily surfaces and objects for ad-hoc interactions.

CCS Concepts: • **Human-centered computing → Interaction devices**; *Ubiquitous and mobile computing systems and tools.*

Additional Key Words and Phrases: Finger Touch, Touch Interaction, Everyday Surface

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1 INTRODUCTION

Touch interaction has become a widely adopted, natural, and ubiquitous input modality. The development of various technologies has aimed at extending touch interaction beyond electronics of limited sizes onto various everyday objects, such as human bodies, walls, and clothes. One approach is to overlay sensors onto the target surface [65–67]. However, instrumenting specific surfaces is hard to scale, often requiring non-trivial setup

Authors' addresses: Yilei Shi, yilei@ahlab.org, Augmented Human Lab, The University of Auckland, New Zealand; Haimo Zhang, haimo@ahlab.org, Augmented Human Lab, The University of Auckland, New Zealand; Kaixing Zhao, kaixing.zhao@irit.fr, IRIT, University of Toulouse, France; Jiashuo Cao, Augmented Human Lab, The University of Auckland, New Zealand; Mengmeng Sun, Northwestern Polytechnical University, China; Suranga Nanayakkara, suranga@ahlab.org, Augmented Human Lab, The University of Auckland, New Zealand.

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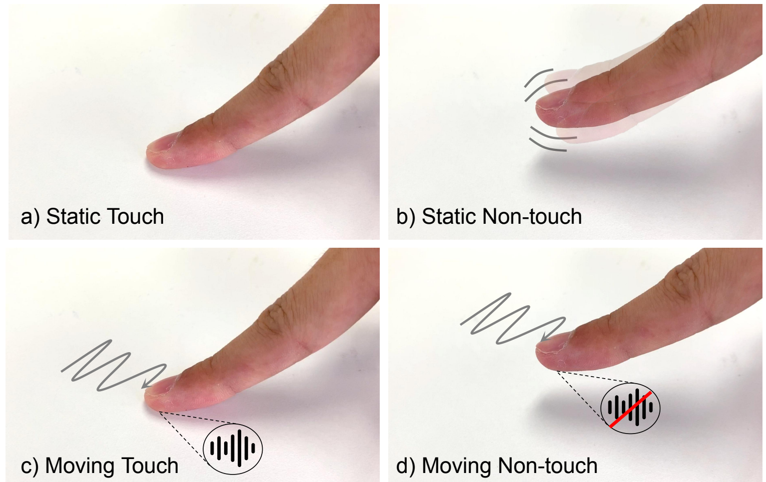

Fig. 1. Human fingers exhibit distinctive movement patterns and acoustic signals while touching a surface or moving in the air. Compared to static touch on an object (a), keeping a finger still in the air (b) show stronger involuntary tremor; compared to a finger sliding on a surface (c), moving a finger in the air (d) lacks the acoustic signal due to the friction between the finger and the underlying object.

overhead in terms of sensor and material cost, and human time and effort. Optical sensing is an alternative approach. Unfortunately, it suffers from occlusion and requires high computing power. Research has also shown that they are subject to a relatively high error rate [57] for touch sensing. Recently, IMU-based wearable devices were explored for touch sensing. However, solutions so far have been only applicable in specific scenarios, such as on bumpy surfaces [14], when interacting with vibrating objects [24], detecting tapping gestures [11, 22] or requiring extra sensing modalities [63] to register touch. In this work, we explored the use of IMU as a general-purpose touch sensor without some of these limitation.

Our sensing technique, ActualTouch, continuously reports whether the finger is in contact with any object, regardless of the finger movements, with a single finger-mounted IMU. We observed that the finger exhibits distinctive characteristics when it touches a physical surface. For example, resting a finger on a static surface (Figure 1a) could be more stable than holding it still in the air (Figure 1b); sliding a finger on a surface (Figure 1c) would generate some acoustic signals that are absent when the finger moves in the air (Figure 1d). These differences could be captured by a finger-mounted IMU, which identifies the occurrence of finger touch.

ActualTouch has three key additions to previous work that sensed finger touch with IMU [11, 22]. First, it continuously senses finger touch status, making it possible to derive the touch up event, apart from the touch down event enabled in previous work. We believe this is essential for supporting richer touch interaction experiences. Second, it works on a wide variety of surfaces without specific training. We trained a model for a normal rigid surface, and tested it on 7 other surfaces with varying rigidity and 2 scenarios without touch. The model worked well with an average accuracy of 96%. Third, the combination of touch status sensing and other IMU sensing capabilities, such as finger movement tracking, supports a variety of use cases that otherwise require disparate sensing mechanisms.

The specific contributions of our paper include:

(1) Proposing a novel and robust sensing technique to detect ubiquitous finger touch, regardless of objects or surfaces being touched, with a single finger-mounted IMU.

(2) Benchmarking the sensing capability in terms of mounting positions, fingers, gestures and different types of objects.
(3) Evaluating ActualTouch's applicability as a middleware for other touch sensing techniques, such as uni-stroke touch gesture recognition.
(4) Demonstration of potential applications that could be supported by ActualTouch.

2 RELATED WORK

Our technique measured finger motion characteristics as an indicator of touch on everyday passive objects. These characteristics are representative of finger tremor and acoustics signals arising from the friction between the finger and the object. Thus, this section reviews previous research in five areas relevant to touch sensing: tremor sensing and its applications in human-computer interaction (HCI), electrical-based sensing, optical-based sensing, acoustic sensing and IMU-based sensing.

2.1 Tremor Sensing and HCI

Tremor is a physiological phenomenon widely existing in any human body. While physiologic and essential tremors are common to healthy human subjects, abnormal tremor is an important indicator in early diagnosis and assessment of neurodegenerative diseases and dyskinesia [9]. Various methods have been proposed to detect abnormal tremor. Zeng et al. [61] asked a user to hold and point a light source towards a reference plane, and captured and analysed the movement pattern of the reflection with a stereo imaging system. Kaji et al. [18] used Leap Motion, a contactless motion tracking device, to measure tremor without requiring the user to hold anything in the hand. Wang et al. [53] measured pathological tremors by tracking the hand with ultrasonic-based acoustic localisation using the smartphone. Zhang et al. [62] used wrist-worn accelerometer data to detect tremor in Parkinson's Disease patients, and found that the CNN model outperformed other conventional machine learning approaches with handcrafted features.

One topic of research on tremor in HCI is to compensate for pathological tremor to improve user experience of elderly and affected users. Plaumann et al. [43] measured hand tremor with a smartphone and a wrist-worn motion sensor, which is used to compensate for inaccurate touch interactions. Wacharamanotham et al. [52] demonstrated that sliding-based target selection is more stable for elderly users with hand tremor, based on the evidence that tremor is reduced when the finger touches and slides across a surface.

Another topic is to leverage normal tremor as an input modality. Strachan et al. [51] measured muscle tremors with the accelerometer attached to a phone to support squeeze input and to detect whether it is being held in the hand. Williamson [54] exploited the synchronisation of tremor signal between different fingers on a same hand, to group fingers hovering above a capacitive 3D touch screen. To our knowledge, little research has been conducted on leveraging normal physiological tremor to support touch interaction.

2.2 Electrical-based Sensing

Electrical-based methods have been widely used to sense touch on everyday objects. For example, Touché [46] developed a novel swept frequency capacitive sensing technique to detect hand touch, as well as specific gestures, by attaching a wire or electrode to objects. Cohn et al. [7] leveraged the electromagnetic noise in home environments to sense human touch near or on electrical infrastructure without extra deployed sensors. For non-conductive objects, an extra conductive layer attached onto objects could also support finger touch or hand operation detection. Researchers have used this method to sense touch interactions on various everyday objects, such as walls [67], papers [65], desks [44], keyboards [48, 49] and DIY objects of arbitrary shapes [10, 66].

Electrical-based sensing has also been embedded into wearable devices. For example, Em-Sense [25], a wrist worn device, leveraged the electromagnetic signals emitted by everyday electrical and electromechanical objects to detect touch. Skintrack [68] embedded four electrodes into off-the-shelf smartwatches to localise finger touches by calculating the difference of phases of active electrical signals that a finger wearable emitted. Extremely small nail-mounted devices was also developed to sensing merely force while interacting with rigid objects [17]. Electrical based sensing techniques usually work on conductive objects. Otherwise, an extra layer is required, increasing the cost of systems when extended to other everyday surfaces or objects.

2.3 Optical-based Sensing

Another solution is to use various cameras. Computer vision technologies have been developed in the past few decades to recognise human fingers. Assisted by other sensing techniques, such as acoustic sensors [16] or an IR laser [32], they can easily turn a surface into an interactive interface. The development of the depth camera, which can sense the distance the sensor from objects, greatly simplified such systems and enabled diverse interactions on everyday surfaces or objects with combinations of cameras [55, 56]. Other cameras, such as thermal cameras [26], could also be used to track finger touch on arbitrary surfaces. The main limitation of above optical solutions was that the finger touch actions might be occluded by other objects, such as the body parts.

Researchers have also explored embedding cameras or other optical sensors into wearable devices to support always-available touch interactions with everyday objects. For example, Anywhere Surface Touch [38] embedded a microphone and a camera into a wrist wearable device to sense interactions on any surface. However, to sense finger touch, the system required resting the wrist on the surface, pressing the mic against the object. More miniaturised finger wearable devices have also been developed to support always-available interaction whenever the finger touches a surface. Magic Finger [59] integrated an optical mouse sensor and an RGB camera into a device worn on the fingertip. Similarly, 3DTouch [36] coupled an optical laser sensor with a 9-DOF inertial measurement unit to support 3D interaction techniques, such as selection, translation and rotation. 3DTouch is closely related to ActualTouch. Above two works compromise the natural haptic feedback of the fingertip that is quite important for their everyday native functions [6].

2.4 Acoustic Sensing

Acoustic sensing has also been extensively investigated to enable interactions on everyday surfaces. The most direct method was to attach acoustic sensors onto a surface. For example, Scratch Input [15] used a contact microphone to listen to the sound generated from finger scratches on a surface, such as a wall, and then recognised several simple gestures with machine learning algorithms. With multiple contact microphones set up on a rigid surface, researchers were also able to accurately localise discrete knocks [41, 42] or even continuous finger touch on passive objects [58]. Ono et al. [39] used an active acoustic signal sensing technique to enable hand interactions on objects of any surfaces. Specifically, they trained machine learning models to classify discrete touch locations based on the change of the acoustic resonance. In addition to sensing the acoustic signals propagating through the objects, sonar could also be applied to sense near surface interactions [35].

The research most relevant to ActualTouch were those integrating acoustic sensing into wearable devices. For example, Fingersound [63] used a contact microphone to segment uni-stroke thumb gestures on other fingers, which focused on on-hand always-available interaction. Off-the-shelf smartwatches could also be used to sense hand gestures, activities, as well as objects that generate acoustic signals [23, 24]. Most of these works mainly illustrated the capability of classifying hand gestures, general hand activities, and objects that actively emit acoustic signals. However, ActualTouch focuses on sensing whether the finger is touching or operating on any rigid object without requiring any instrumentation.

2.5 IMU-based Sensing

Due to their rich sensing capability, IMU has been used to sense various human activities, such as lower lims behavior [1, 30, 40], repetitive exercises [33], various sports [5, 37], as well as various everyday activities [23].

The small sizes of IMU also made it the ideal sensor to sense hand activities. For example, Airwriting [2–4] leveraged pure IMU data to segment intentional hand gesture input. It requires the user to wear a glove, which eliminates the natural touch feedback the finger receives. Asterisk and Obelisk [12] designed specific in-the-air motion schemes to encode identification information. Users can retrieve information by easily following the moving pattern. FingerOrbit [64] captured the thumb's movement with an IMU to provide synchronised moving interaction.

Researchers also used IMU to build contact sensing wearables. For instance, Viband [24] overclocked the IMU of an off-the-shelf smartwatch to detect hand contact with objects that vibrate. FingerSound [63] used a finger-worn IMU to sense finger gestures, which supports eyes-free text input. With a hybrid acoustic-motion sensing configuration, it segmented thumb-to-index touch events with a contact microphone, and used the IMU data to classify gestures. Finger-mounted IMU has also been used to sense finger tapping gestures on everyday surfaces [11, 22]. Specifically, similar to our observation, Gu et al. [11] leveraged finger motion characteristics to differentiate between tapping on an actual table and that simulated in the air. One of the limitations stated in their work is the lack of touch up event detection. Our work solves this limitation, by analysing the microvibration characteristics to track touch status, instead of analysing the motion characteristics to detect the landing of the tapping gesture, as in the previous work. In addition, we mounted the IMU on the fingernail, which can more accurately track the fingertip movements on a surface. Another work that closely related to ActualTouch is by Han et.al. [14]. They used a finger-mounted IMU to sense directional touch gestures on bumpy surfaces. Although wearable touch sensing systems built with IMU has been extensively investigated, there exists one significant bottleneck for touch sensing capability - requirement of extra methods to confirm touch status. Some used bumpy surfaces [14] or vibrating objects [24] to register touch. Others only focused on tapping gestures [11, 22], or touch movements [63] that created sounds. Some research just investigated finger tracking [21] without being able to sense touch. This largely limited the interaction techniques that were supported by IMU as well as the applicable use cases for IMU. ActualTouch aims to fill this gap by enabling continuous touch status sensing on any surfaces with a single IMU for any gestures.

3 ACTUALTOUCH

3.1 Theory of Operation

Our touch sensing technique is based on two basic physical phenomenon. First, a finger may exhibit distinctive moving patterns when touching a physical surface, which is difficult to duplicate without touch surfaces. For example, when a finger tries to remain static in the air, the finger still exhibits microvibrations [45]. Such movements might result from physiologic tremor [9], a permanent presence in the human body. In contrast, when touching a static object, it is easier for a finger to remain static with less micro-movement, given the finger is restricted by the surface. This difference may also exist when the finger is moving around. When the finger moves in the air, it is more likely the finger will also move little bit up and down. However, when touching a surface, the up-and-down movements of the finger is restricted by the surface. Second, finger touch movements usually generate acoustic signals, which sometimes are even audible. However, moving the finger around in the air does not emit any sound. Both differences reveal an opportunity to sense finger touch on everyday surfaces with a single IMU sensor.

We verify our assumption by capturing the motion data of fingers movement in the real world. We attached a 9 DoF IMU sensor, the SparkFun MPU9250[1], to the fingernail of the index finger and performed touch actions with and without moving around, for both in the air and touching a table. We recorded the accelerometer data and plot the data in the time domain, as shown in Figure 2. The data confirms our assumption. When the finger is kept

[1] https://learn.sparkfun.com/tutorials/mpu-9250-hookup-guide/all

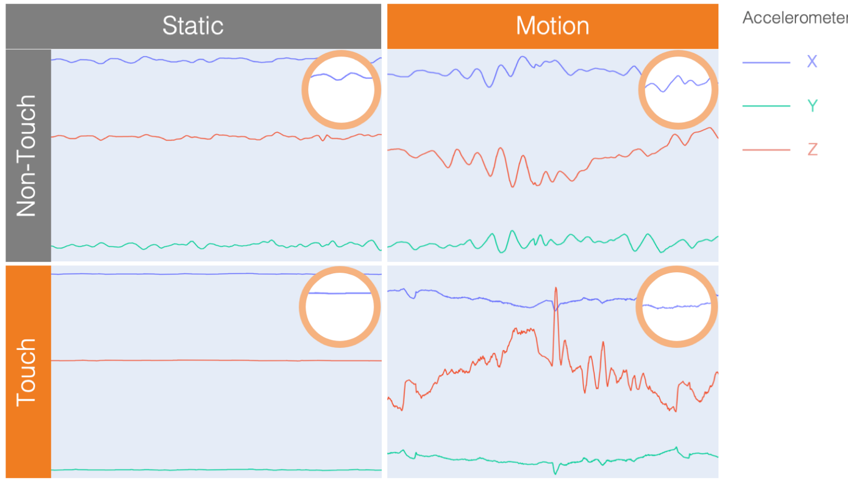

Fig. 2. Raw accelerometer signal captured from a fingernail-mounted IMU for 4 different conditions: touch/non-touch and moving/static on a table. Data for X, Y and Z axes is plotted separately here.

static without moving, touching on a surface generates more stable signals compared to in the air. When the finger is under a moving condition, all x, y, and z-axis exhibit similar patterns if the finger is in the air. However, when touching a surface, the specific direction where the finger moves presents larger data fluctuation. FFT-analysis also presented an obvious difference among different conditions (Figure 3). Especially when the finger moves around, the IMU captures some bio-acoustic signal [24] while moving on a surface. We saw potential in leveraging all these features to detect whether a finger is touching an object, independent of its actions. Our "eyeballing" is not meant to exhaustively discover its extent, but to suggest the promising potential of this observation. If we can differentiate between touch and non-touch by "eyeballing", it is quite likely that a neural-network-based machine

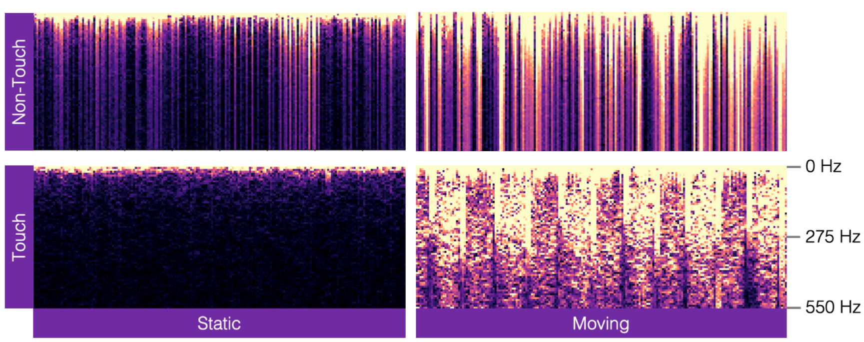

Fig. 3. FFT spectra of the x-axis accelerometer signal from a fingernail-mounted IMU for 4 different conditions: touch/non-touch and moving/static on a table. The vertical axis is the frequency, which increases downwards. The horizontal axis is the time that increases to the right. The frequency range in the plots is 0~550Hz, as labelled in the bottom-right subplot.

learning approach, as we later used, would employ many other more subtle features than a human could possibly identify.

3.2 Implementation

3.2.1 Hardware. We redesigned the SparkFun MPU9250 IMU breakout board in a more compact form factor, i.e., 7mm×9mm (Figure 4), suitable to be attached to the fingernail and minimising the influence on the finger movement. We selected the fingernail as the most appropriate sensor position based on our study, which would be described later. Luckily, this also brings some unexpected benefits. Firstly, since the nail-mounted IMU always moves together with the fingertip, our technique is able to capture the moving information of the finger, including rotating movement. Combined with its touch delimiting capability, our system can support uni-stroke touch gestures. Secondly, mounting an IMU onto fingernails does not interfere with the finger's natural tactile sensation, which is an important feedback when interacting with objects. We used an Arduino DUE [2] to read the IMU data, including data of accelerometer, gyroscope and magnetometer, through its I2C port and sent the data to a MacBook Pro via native programming port. The sampling rate of our device was about 1100Hz without overclocking the Arduino. In our pilot test, we found that 1100Hz was high enough to capture finger movements, as some consecutive data started to repeat when the finger is moving around. In our study, we also show that there is a potential to lower the sampling rate to around 220Hz to reduce power consumption and computation workload, which still maintaining an acceptable performance, although lower accuracy.

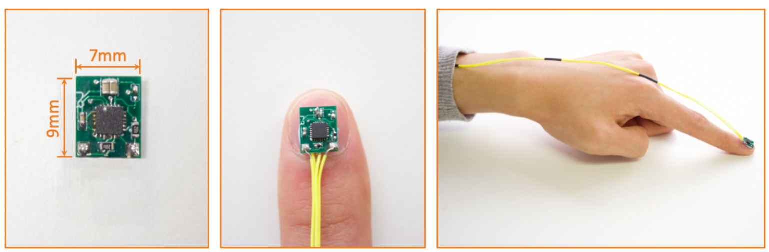

Fig. 4. Customised IMU PCB that could be attached to a fingernail.

3.2.2 Sensing Model. Instead of using traditional machine learning, we used neural network (NN) to train our touch sensing classifier due to some considerations. First, various features may exist in the data, some of which might not be distinguishable with our eyeballing. Accuracy of traditional machine learning alrogithom is largely affected by the feature generation process. As NN automatically extracts as much potential information from the data as possible, it better serves the purpose of this paper: bench-marking the sensing capability of ActualTouch. Second, as we can see from the signal (Figure 2 and 3), when the finger is performing different gestures, i.e., moving around or remaining static, the signals exhibit different features. We aim to use a single model to detect touch for both gestures, which might be difficult with traditional machine learning algorithm.

According to previous research [60], the interaction among sensor measurements usually includes all dimensions. Thus, we also used a 2D convolutional neural network (CNN) architecture, implemented with the PyTorch[3] framework to train our classifier. This model was a variant of LeNet [29] with customised convolutional units and fully connected layers (Figure 5). Specifically, each convolutional unit in our CNN model is comprised of a convolutional operator, a rectified linear unit (ReLU) activation layer [34] and a pooling layer [47]. Figure 5 illustrates our network architecture.

[2] https://store.arduino.cc/usa/due
[3] https://pytorch.org/

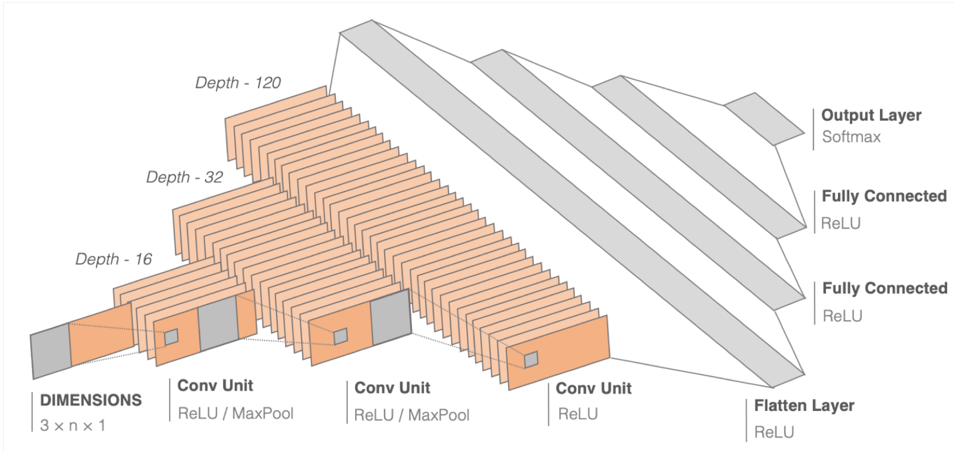

Fig. 5. The LeNet convolutional neural network (CNN) architecture used to recognise touch events. There are 3 convolutional units, two fully connected layers and a softmax activation function.

It should be noted that the IMU orientation highly influenced the accelerometer data due to gravity, which would cause an over-fitting according to our test. To eliminate this effect, we used the derivatives of accelerometer data instead of the raw data. We stack all 3 types of data (along x, y and z axis) into a data matrix of 3 rows, n columns and 1 channel, where n is the length of the input data (window length effect would be discussed in studies). To show the sensing potential of ActualTouch, we used predefined hyper parameters without further fine-tuning during training (except for the input data length). The model was trained on a dedicated workstation with two GTX1080Ti graphics cards with 11GB of video RAM each.

4 STUDY 1: FINGER & POSITION

4.1 Study Design

For this study, we evaluate the performance of our sensing technique on fingers and different positions. Specifically, we tested all fingers except the thumb due to that thumbs were rarely used for touch interaction in real world. For each finger, we tested 3 different places for placing the IMU (Figure 6), i.e., the Fingernail (FN), the Middle Phalanx (MP) and Proximal Phalanx (PP). We attached three IMUs respectively to the fingernail and two phalanges of one finger. For fingernail, we used Blu-Tack to affix the sensor. For phalanges, we used soft elastic bands to bind the sensor on the skin. The elastic bands were tight enough so that the IMUs do not slip against the skin. We collected data with 3 Aruidno-DUE micro-controllers simultaneously at a sampling frequency of 1100Hz.

As described in the previous section, we do see signal difference between keeping static and moving around. Thus, we tested touch sensing for both of them. For moving around, the "∞" shape was used. Participants were required to perform these two gestures for both touching the table and in the air at a comfortable speed. Our system started to collect finger motion data after participants started performing the gestures, making sure all the data we collected were correctly labelled. During each trial, participants continuously performed the gestures for 30 seconds non-stop, with their dominant hand. For each gesture, participants needed to perform two repetitions. The testing order of fingers as well as the gestures were randomised. In total, there were 4 gestures $\times$ 2 repetitions $\times$ 4 fingers = 32 trials for each participant, which would take around 20 minutes. Participants were allowed to take a rest whenever they felt tired with they hands or arms. We recruited 12 participants (2 females and 10 males) aged between 21 and 31 (M = 26.4, SD = 3.5). None of them reported any problems with their hands. All

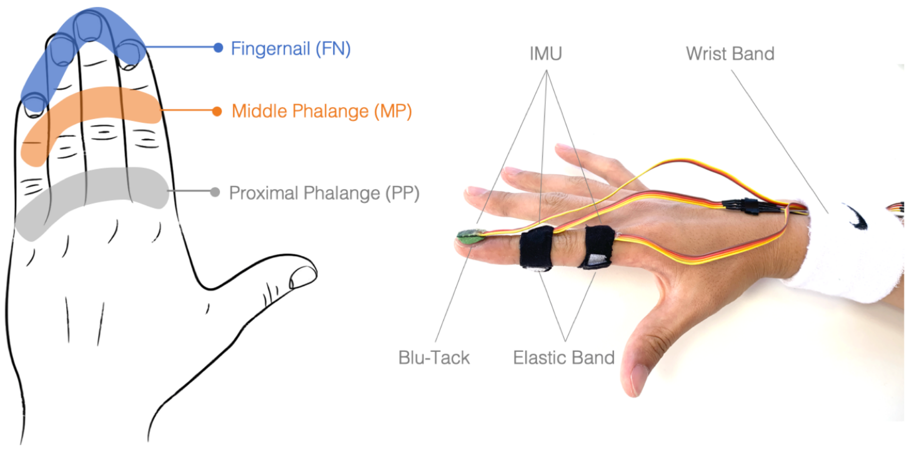

Fig. 6. In the study, we tested 4 fingers (except the thumb) at three locations: fingernail, middle phalanx and proximal phalanx. The setup of the apparatus, as shown on the right side of the figure, allows for the simultaneous collection of data at three locations on a finger.

were right-handed. The study was conducted on an ordinary High-Density Fibreboard (HDF) table with plastic vinyl.

4.2 Result

We analysed the accuracy with respect to different fingers, augmentation locations and motion status, i.e., moving or keeping static. We fixed the window length at 120 data points (effects of window length and sampling rate will be reported in the next study). We performed two types of cross-validation: within-group and leave-one-user-out. For within-group cross-validation, we trained a model on 80% of data from every participant, and tested it on the remaining 20% of data from them. For leave-one-user-out cross-validation, we trained a model on all data from 11 participants, and tested it on the data from the remaining participant.

Table 1. Within-group and leave-one-user-out touch classification accuracy for different fingers and augmentation locations. The average accuracies and standard deviations (in parentheses) are reported.

		Index Finger	Middle Finger	Ring Finger	Little Finger
Within Group	FN	97.12% (SD = 0.75%)	92.92% (1.73%)	94.78% (1.16%)	96.80% (0.93%)
	MP	92.37% (1.08%)	85.33% (1.37%)	88.39% (2.07%)	89.19% (1.35%)
	PP	85.10% (1.47%)	78.09% (1.37%)	79.47% (2.14%)	82.70% (1.22%)
Leave-one-user-out	FN	96.64% (2.94%)	92.51% (8.94%)	94.01% (5.25%)	95.42% (3.93%)
	MP	90.36% (5.01%)	84.21% (7.88%)	86.66% (8.03%)	87.50% (8.92%)
	PP	82.56% (5.45%)	75.49% (7.53%)	76.34% (10.30%)	79.87% (11.37%)

4.2.1 Finger & Position. The results for each finger and augmentation location was shown in Table 1. For within-group cross-validation, attaching IMU to fingernails had the highest average accuracy, which is 95.40% (SD = 1.95%) for all four fingers. Middle phalanges and proximal phalanges had a lower average accuracy for four fingers, which were 88.82% (SD = 2.89%) and 81.34% (SD = 3.17%) respectively. The overall accuracy of both finger and augmentation locations showed a trend of decreasing with the increasing of the distance between the IMU and the fingertip. Thus, we concluded that fingernail is the place where provides the highest accuracy. In terms of fingers, we found that index finger has the highest sensing accuracy for all three locations, which is predictable, as it is most commonly used for touch interaction. However, the second highest is little finger, for both three place. The middle finger has the lowest sensing accuracy among all four fingers. For leave-one-user-out cross-validation, the accuracies are 94.64%, 87.18% and 78.57% for fingernails, middle phalanges and proximal phalanges respectively. The overall result was close to the within-group accuracy, showing evidence of generalisability across users. Finally, we also saw a possibility of training a single model to sense both moving gestures and static gestures. We will further discuss this in the next study, which compares a larger set of gestures to validate the sensing robustness.

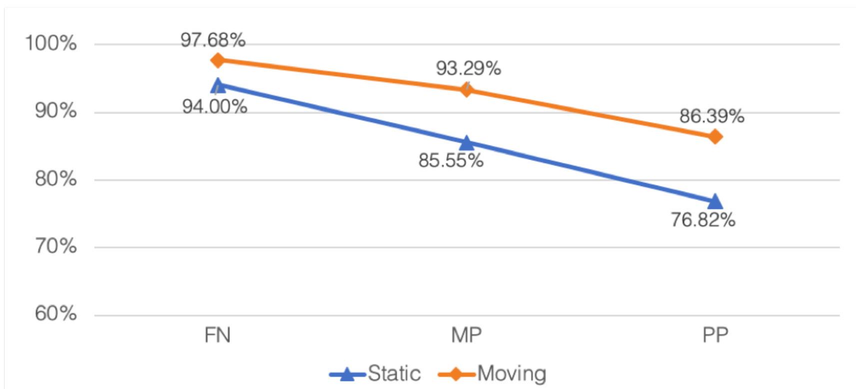

Fig. 7. Touch sensing accuracy for different motion status (moving & static) and augmentation locations.

4.2.2 Gesture Difference. We also evaluated the sensing accuracy of two motion status with respect to different augmentation locations, as shown in Figure 7. We found that the overall accuracy of "moving" is higher than "static". Moreover, the accuracy of "static" drops faster than "moving" when the augmentation location moves away from the fingernail. The accuracy difference at fingernails is less than 4% but increased to almost 10% at proximal phalanges. Although the system still has an acceptable accuracy at middle phalanges for "moving" status, which is 93.29%, the accuracy of sensing "static" gesture dropped to 85.55%. Considering that static touch also plays an important role in touch interaction, we will use fingernail as the position for augmentation both for the following studies and our demos. Nonetheless, there are motivations for designing ActualTouch into a ring form factor depending on specific use cases.

5 STUDY 2: TOUCH GESTURES

This study aims to verify the feasibility of ActualTouch and to benchmark the parameters for our sensing algorithm. Specifically, we tested its sensing accuracy on index finger in terms of gestures, sensing frequency, window length of data, arm effect and user effect.

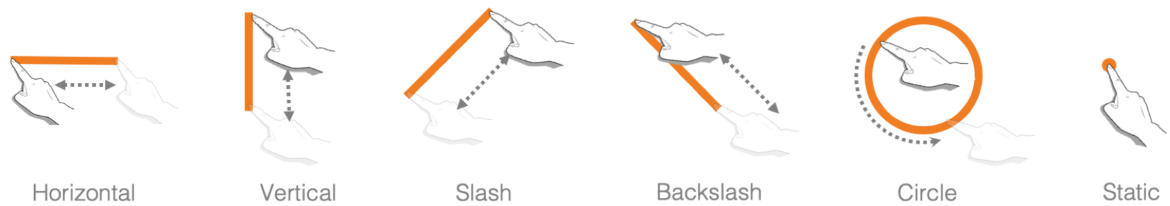

Fig. 8. Gesture set for study 2.

5.1 Study Design

The tasks in this study involved performing 6 types of basic finger movements (Figure 8), including straight lines ("*Horizontal*", "*Vertical*", "*Slash*" and "*Backslash*"), curved trajectory ("*Circle*") and keeping the finger stationary (*"Static"*). They included the most common finger touch movements situations on an ordinary surface. Participants were required to perform all gestures under two conditions, "*Touch*" (touching the table) and "*Non-touch*" (performing the same gesture in the air). In addition, to better understand the influence of the elbow, we designed 2 different arm postures, "*Elbow-down*" and "*Elbow-free*", which represented the elbow resting on the table or staying in the air while performing the tasks.

For each trial, the participant was first introduced to the gestures and elbow statuses. Then, they started to perform the gestures following the experimenter's instructions without stopping. After the participant started performing a gesture, the system collected data from IMU for 30 seconds. During each trial, participants were required to repeatedly perform the same requested gesture back and forth at a comfortable speed without lifting the finger until the data reading finished. Participants were allowed to have a rest between any two trials whenever they felt tired, ensuring that fatigue would not influence the data. For each participant, there were 24 different trials (2 touch status $\times$ 2 elbow status $\times$ 6 gestures) in total. It took around 20 minutes to finish the study.

As index finger is the most frequent finger we used for touch interaction, this study was conducted on index finger of the dominant hand. An single IMU was attached to the index fingernail of each participant for collecting data with a sampling frequency of 1100Hz. We recruited 12 participants (2 females and 10 males) aged between 20 and 30 (M = 25.3, SD = 2.5). None of them reported any problems with their hands. All were right-handed. The study was conducted on the same table for study 1.

5.2 Results

We conducted a simple preprocessing on the data before training the model and analysis. First, to eliminate the orientation influence, we calculated the derivative of the accelerometer data and did not use the raw data for training. We then restructured the data into small time-series segments, which could be directly fed into our network as introduced in the "Implementation" subsection. We investigated 4 different window lengths - 60, 120, 180 and 240 data points, which respectively represented a time period of 54ms, 109ms, 163ms and 218ms. We also re-sampled the data to investigate the effect of sampling frequency. Specifically, we downsampled the data to 1/2, 1/3, 1/4 and 1/5 of the original frequency, which respectively correspond to sampling rates of 550Hz, 367Hz, 275Hz and 225Hz. All data was split into a training set and a testing set for cross-validation. Same as previous study, we trained a general model for all participants (i.e., within-group). As we did not apply a hyper-parameter tuning process, we did not reserve data for further validation which would usually be conducted in a typical AI paper.

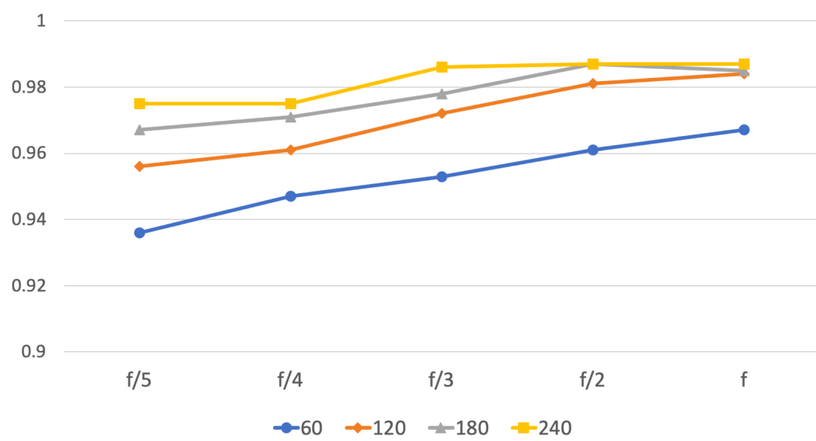

Fig. 9. Touch sensing accuracy of CNN model using different window lengths and sampling rates. f is the raw sampling rate of the apparatus, which is 1100Hz.

5.2.1 Sampling Frequency and Window Length. We first analysed the influence of sampling rate and window length on accuracy, which could decide on a model to be used in the following studies and analyses. As we described above, we resampled the data with 5 sampling rates and 4 window lengths. For each combination of these two factors, we trained a CNN model and evaluated the accuracy. Results showed that with increasing window length, the accuracy of touch detection also increased (Figure 9). The accuracy was highest with the window length of 240 (98.3%). A Shapiro-Wilk test showed that the classification accuracy did not follow normal distribution ($p <$ .001), so we performed a Friedman test and found a significant effect of window length ($\chi^2 = 1393.5, p < .001$). A pairwise Wilcoxon Signed-Rank test with Bonferroni correction showed that a window length of 60 was significantly worse than others (p < .001), but no significant difference between 120, 180 and 240. For different window lengths, higher sampling rates always perform significantly better than lower sampling rates (p < .001). Although most consumer electronic devices nowadays do not support such high sampling frequencies, we believe this to be practical for future devices. Therefore, in our following studies, we use the apparatus at its original sampling frequency, i.e., 1100Hz, and with a window length of 120 data points, which is around 109ms, to perform our data analysis.

5.2.2 Gesture Difference. We analysed the accuracy for all different gestures, which has been shown in Figure 10. The overall touch sensing accuracy for all gestures is 98.6% (SD = 1.9%). As the data did not follow normal distribution, we performed a Friedman test, which showed no significant difference between different gestures ($\chi^2 = 1.3, p = .931$). To better understand the performance of the technique, we also analysed the true-positive rate and true-negative rate, which were respectively 98.6% (SD = 1.9%) and 98.5% (SD = 2.9%). A Friedman test showed no significant difference between gestures in terms of true-positive rate ($\chi^2 = 9.3, p = .098$) and true-negative rate ($\chi^2 = 7.6, p = .182$). Therefore, we conclude that for our technique, the sensing accuracy is consistent among different finger movements.

5.2.3 Elbow Effect. We also investigated the influence of resting the elbow on the table. The result showed that the average accuracy was 97.7% (SD = 0.5%) for elbow resting on the table and 98.8% (SD = 0.3%) for elbow in the air. Since there are only two groups, we performed a Wilcoxon Signed-Rank test and found that the sensing

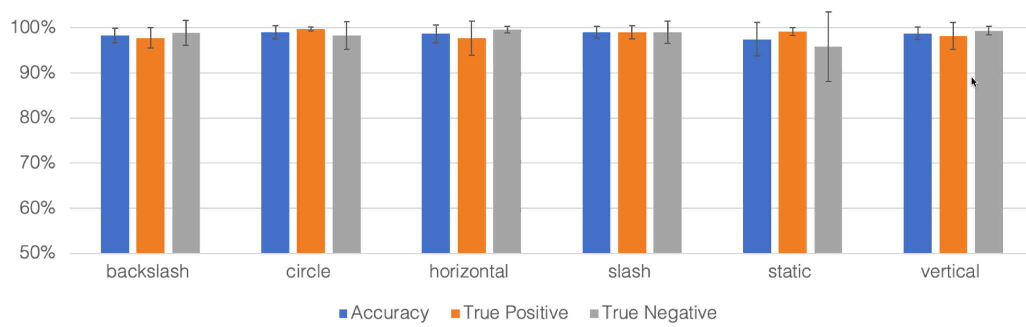

Fig. 10. Touch sensing accuracy of different gestures with the window length of 120.

accuracy was significantly higher when elbow in the air ($\chi^2 = 1.8, p = .113$). A possible reason that results this might be that when the elbow is resting on the table, it is easier for the finger to keep static, which created some ambiguity for the algorithm. This is actually a supportive result for including this technique in interactions on-the-go, under which the elbow is usually in the air. In general, our system has high performance for both scenarios, which make it possible to work for both use cases.

5.2.4 Cross-user Accuracy. To investigate the robustness of our sensing technique, we did a cross-user validation with the data. Specifically, with the data we collected from 12 participants, we performed leave-one-out and leave-eleven-out cross-user validation. We trained a model with the data from 1 (and 11) participants and tested the accuracy on the data of the remaining participant(s). We performed this test for all the participants and obtained the overall accuracy. Surprisingly, the results showed very close accuracies of 95.9% (SD = 2.6%) for leave-one-out and 95.9% (SD = 6.4%) for leave-eleven-out cross-user validation. A further Wilcoxon Signed-Rank test ($\chi^2 = 29.0, p = .433$) found no significant difference between the accuracy of these two models. Difference did exist between individuals. For example, our leave-one-out analysis result was highly influenced by a specific user, which was only 77%. 7 other participants had an accuracy higher than 98%. Similar situation happened to our leave-eleven-out analysis. Thus we conclude that a cross-user model would generally work well for most users, with few exceptions. We anticipate that our technique would accommodate walk-up usage scenarios for most new users, without retraining the model, whereas extra data collection and training of the model might be needed only for few users.

5.2.5 Including Gyroscope Data. In previous analysis, we only used the accelerometer data. Gyroscope data can also provide information about the motion of the finger. Therefore, we also validate the sensing accuracy of including gyroscope data for our sensing capability. Similar as accelerometer data, we also calculate the derivative of gyroscope data. We also used the raw gyroscope data since it was not affected by the finger orientation. We stack all the data together, forming a 2D data matrix, to train a new model. The accuracy of this model was around 95%, which was lower than using merely accelerometer data. In addition, it also took longer time for the algorithm to converge. Thus, we concluded that gyroscope data had too much noise for touch sensing and should not be used for our technique.

6 STUDY 3: SURFACE EFFECTS

ActualTouch was developed mainly for touch interaction on-the-go. In this study, we further investigated if the performance model we developed in study 1 was robust enough to work with typical everyday surfaces. We believe that it is impractical to train one model for every surface. Thus, in this study, we intentionally tested our models trained in study 1 without training any new models for these surfaces.

Fig. 11. Nine usage scenarios tested in our study.

6.1 Study Design

We tested the accuracy of our trained CNN model in study 1 (without any further training) on 9 different usage scenarios that we may encounter in our everyday life (Figure 11). These surfaces could be roughly categorised into three different types, including everyday passive objects of different orientations and softness: *Wall*, *Sofa*, *Hand Bag*, *Chair*; human bodies: *Thigh*, *Arm*, *Back of hand*; and two non-touch situation: *Sitting*, *Walking*. For the 7 surfaces that we tested touch, participants were required to perform continuous touch actions at a comfortable speed, similar to study 2. However, due to different orientations and sizes, we did not specify the gestures to be performed. Participants could do whatever they want, such as drawing circles and keeping still, as long as keeping on performing touch status during each trial. *Sitting* and *Walking* were used to test the true-negative rate. For *Sitting*, participants were required to sit on an object, not just limited to chairs, and do whatever they want to do, keeping the finger in the air without touch anything during the data collection part. For *Walking*, participants would walk like normal. We think these scenarios represented data with a large variance for testing our model for the initial exploration.

We recruited 12 participants (1 female) aged between 20 and 29 (M = 26.2, SD = 1.5), all right-handed. The device was mounted on the index finger of their dominant hand. The same system setup in study 2 was used to conduct this study. In this study, we did not specify the elbow condition. For each participant, there were 18 trials and took around 10 minutes to finish all the trials.

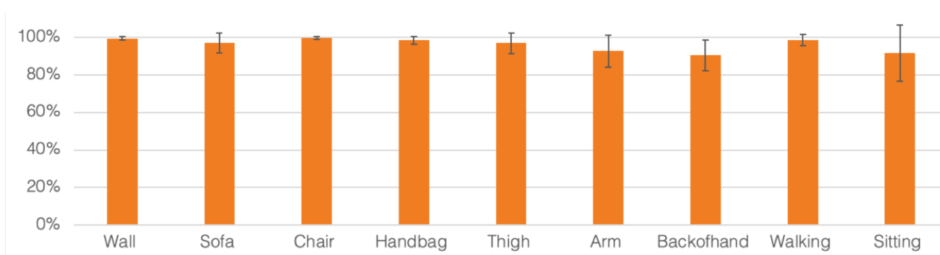

Fig. 12. Touch sensing accuracy of the nine usage scenarios.

6.2 Results

Sensing Accuracy. The touch detection accuracy is shown in Figure 12, with an average accuracy of 96.06% (SD = 5.45%). Overall, our algorithm could reliably detect the finger touch event on most surfaces (*Chair*, *Sofa*, *Wall*, *Hand Bag*) with different finger orientations and different parts of human body (*Thigh*, *Back of Hand* and *Arm*), all of which are over 90% accuracy. The touch sensing on arm (M = 92.76%, SD = 8.52%) and back of hand (M = 90.43%, SD = 8.10%) is a little lower than touching on other objects. Specifically, we found that accuracy of touching on the arm was affected a few inaccurate trials. On most trials, our model had an accuracy of over 95%. ActualTouch also had a good performance of over 90% for sensing the non-touch status of the fingers under two different cases, i.e., walking and sitting.

False Rate Pattern. As our sensing technique is not 100% accurate, false positive or false negative do happen. For post-hoc interactions, such as touch gesture detection, these wrong predictions could be eliminated by using a filter. Thus, we analyse the false predictions, for both false-positive and false-negative, to provide some basic information. We look at the length of consecutive false predictions and plot the result in Figure 13. For most use cases, only 10% of the consecutive false predictions had a length of more than 35 data points. All use cases have less than 5% of consecutive false predictions whose length is longer than 100 data points. Therefore, in our next study on uni-stoke touch interaction, we used 100 data points as our filter.

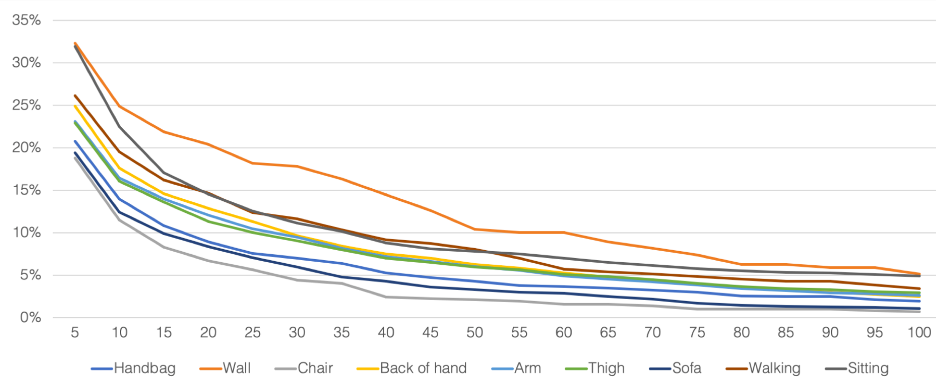

Fig. 13. The length of consecutive false prediction for each use case.

7 STUDY 4: UNI-STROKE TOUCH INPUT

In this study, we validated ActualTouch's capability to serve as a "middleware" for supporting other interaction techniques, using uni-stroke touch gestures as an example. When a finger touches a surface and performs a gesture, our technique could be used to extract the gesture data by detecting the start and end of the finger touch on the surface. Finally, both accelerometer data and gyroscope during this touch period was used to classify a gesture. This study evaluates our technique from an application perspective, revealing its potential to support downstream services and applications.

7.1 Study Design

We used Graffiti uni-stroke gestures (Figure 14), a commonly used gesture set for shorthand text entry, as our study stimuli. Similar to FingerSound [63], we also extended the gesture set to 28 gestures by adding one more gesture, "delete", which is frequently needed in text editing. At the beginning of the study, participants were

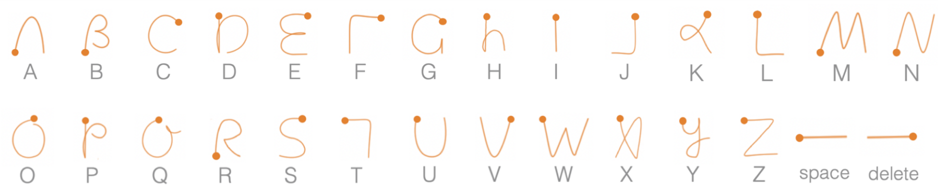

Fig. 14. The Graffiti uni-stroke gestures used for the study. We extended the gesture set with two more gestures, which could be used as the spacebar and the delete key during text entry. The dot on each gesture represents the starting points.

given some time to familiarise with all the gestures. Before a trial started, they were asked to keep their finger in the air. Then, the experimenter started the trial with a keypress. Our system started to record both touch and non-touch data generated during the trial. The participants then needed to place their finger on the table and perform the gesture at a comfortable speed. They were instructed to input the extended Graffiti alphabet gesture set with the "elbow free" gesture. Finally, the experimenter would complete the trial and stop reading data with a keypress. Then another trial could be started again. Participants had access to a document that showed all the gestures they were supposed to perform. Each gesture was performed 10 times by each participant, resulting in 280 trials. All these 280 trials were presented in a random order. Participants were allowed to rest when they felt tired. It took around 25 minutes for each participant to finish the study. We recruited 12 participants (3 female) aged between 20 and 29 (M = 25.3, SD = 2.4), all right-handed. The same system setup as previous studies was used. As before, we used a window length of 120 with the previously trained CNN model for touch detection.

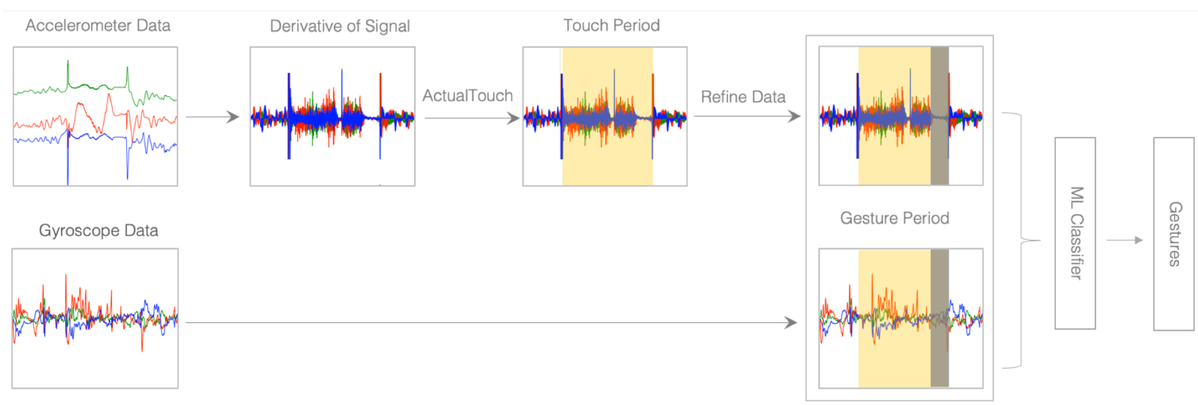

Fig. 15. The data processing pipeline for the Graffiti uni-stroke gesture recogniser based on ActualTouch.

7.2 Results

7.2.1 Touch Gesture Extraction. A moving window of the length of 120 data points with a step size of 1 was fed into the classifier trained in study 2 to segment the uni-stroke touch gesture from other finger motions not touching the surface (Figure 15). By visualising the data, we found most gestures had more than 400 data points. Thus, we set 400 as the minimum length of a touch gesture. A single touch gesture ends whenever there are 100 successive non-touch data points appearing. To compensate for false negatives, i.e., actual touch being classified as non-touch, we merged two gesture segments if the "non-touch period" between them were shorter than 300

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	Delete	Space
A	98%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%
B	2%	95%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
C	0%	0%	95%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%
D	0%	0%	0%	67%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	28%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%
E	0%	2%	0%	0%	95%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%
F	0%	0%	0%	0%	0%	91%	2%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	0%	0%	0%
G	0%	0%	0%	0%	0%	0%	85%	0%	0%	0%	0%	0%	5%	0%	0%	0%	5%	0%	0%	0%	2%	2%	0%	0%	0%	0%	0%	0%
H	0%	0%	0%	0%	0%	0%	0%	91%	0%	0%	2%	2%	0%	0%	2%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
I	0%	0%	0%	2%	0%	0%	0%	0%	86%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	2%	2%
J	0%	0%	0%	0%	0%	0%	0%	0%	0%	88%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	7%	0%	2%	0%	0%	0%	0%
K	0%	0%	0%	0%	0%	2%	2%	0%	2%	0%	91%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%
L	0%	0%	2%	0%	0%	0%	0%	2%	0%	0%	5%	90%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
M	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	0%	93%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%
N	7%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	2%	88%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
O	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	88%	0%	0%	0%	7%	0%	2%	0%	0%	0%	0%	0%	0%	0%
P	0%	2%	0%	17%	0%	0%	0%	5%	0%	0%	0%	0%	0%	0%	0%	74%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Q	0%	2%	2%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	2%	0%	88%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%
R	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	90%	0%	0%	0%	0%	0%	0%	2%	2%	0%	0%
S	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	91%	0%	0%	0%	0%	2%	0%	0%	0%	0%
T	2%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	95%	0%	0%	0%	0%	0%	0%	0%	0%
U	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	93%	2%	0%	2%	0%	0%	0%	0%
V	0%	0%	0%	0%	0%	5%	0%	0%	0%	7%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	84%	0%	2%	0%	0%	0%	0%
W	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	95%	0%	0%	0%	0%	0%
X	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	95%	0%	0%	0%	0%
Y	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	95%	2%	0%	0%
Z	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%
Delete	0%	0%	0%	0%	0%	5%	0%	0%	2%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	91%	0%
Space	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	95%

Fig. 16. Confusion matrix for Graffiti uni-stroke Gestures recognition

data points (normal finger moves at a frequency of 3Hz [13]). After this processing, 43 trials (around 1.28% of all data) contained no or multiple touch gestures. They may result from participants' finger accidentally leaving the table while performing the gestures. We removed this data from further processing. After looking into the data, we also noticed that participants may keep their fingers on the table for a while after finishing the gestures. However, the time participant's finger remained on the table may differ between them, potentially affecting the classification accuracy of the gestures. Specifically, we found when most users kept their finger still on the table, the root mean square of all accelerometer derivative data would be smaller than 2. We filtered out all these data chunks in a gesture their length exceeded 100 data points. Finally, we connect the left data trunks as the refined gesture data.

7.2.2 Gesture Classification. We used the logistic regression of scikit-learn[4] to train a classifier using the extracted gesture data. Similar to the preprocessing in our earlier studies, we used the derivative of the accelerometer data to eliminate the influence of gravity. We also calculated the derivative of the gyroscope data. We calculated the following features from the data: *maximum* and *minimum* of derivative of accelerometer data; *mean* and *standard*

[4] https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

deviation of gyroscope data and its derivative; *root mean square* of all the data; *sum* of *std* of x-axis and z-axis derivative of accelerometer data; difference between sum of *root mean square* of x and z accelerometer data and y accelerometer data.

Note that we especially chose features that combined x-axis and z-axis accelerometer data. This is because we noticed that when participants performed touch gestures, the "pitch" angles of their finger could differ from person to person, influencing the data of the x-axis and z-axis. Therefore, we extracted some features by combining the data of the x-axis and z-axis. To reflect the data change in the time domain, we evenly divided the data of each gesture into 20 chunks and calculated all the above features for each chunk. To eliminate the influence of large outlier data in each chunk, we removed the top 10% large values. We put all these features together as our final features. We randomly selected two thirds of all the data as training samples and used the rest as a test set. We used a single model for all participants. The overall accuracy was 90.25%.

7.3 Discussion.

The confusion matrix (Figure 16) showed that most gestures had an accuracy of more than 90%. Only 2 gestures had an accuracy below 80%, which were letter "P" and "D". They had the lowest accuracy, 67% and 74%. This was because these two gestures were similar to each other and the only difference was where the gesture ends. This result was consistent with previous work, FingerSound [63]. One possible solution could be redesigning the gesture for these two letters to reduce the ambiguity. In General, we believe that our technique's accuracy was sufficient to support uni-stroke touch inputs. Especially when the gesture set is shrink to s smaller gesture set, ActualTouch has the potential to have a better performance.

8 APPLICATIONS

In this section, we introduce the user cases supported by ActualTouch. All these application scenarios were supported by the NN models trained in previous study without further training. It should be noted that although we did not focus on fabricating a standalone hardware which communicates with the computer wirelessly, we have enough confidence that developing such system is not a big challenge according to existing research[19, 20].

8.1 Facilitating Touch Interaction for AR/VR

Our sensing technology could be used to improve the touch interaction experience with AR/vR head-mounted device. Research showed that the state-of-the-art touch sensing with depth cameras of Hololens[57] suffers from a high error rate, especially when the finger is hovering closely (<1cm) above the surface. Existing research[11] showed that IMU can substantially improve the accuracy of tapping gestures. ActualTouch has the similar system configuration and can robustly sense continuous finger touch and could be used as an complementary technology to further improve continuous touch sensing for mixed-reality head-mounted devices. We built a AR demo with a webcam to show the use case (Figure 17). With ActualTouch, the system can reliably sense touch on an ordinary

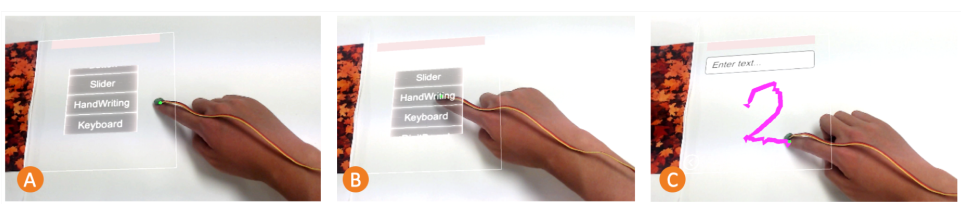

Fig. 17. We created a MR demo with ActualTouch and a single camera. ActualTouch can support: A) scrolling, B) click and C) continuous touch gesture input.

table, even without using the depth camera. This enables the system to detect continuous touch interaction techniques, such as scrolling a list or performing a uni-stroke gesture.

8.2 Pointing Device on Any Surface

Although this paper focused on the use of IMU for touch sensing, it provides much more other useful information. The 9 degrees of freedom (9DoF) IMU that we used, i.e., MPU9250, had accelerometer, gyroscope and magnetometer, and thus can estimate the 3D orientation of the fingertip. As finger rotation naturally happens when the finger moves around, it is possible to combine finger orientation sensing and touch sensing to build a miniaturised finger-mounted pointing device. We built a fully functional prototype to emulate a computer mouse.

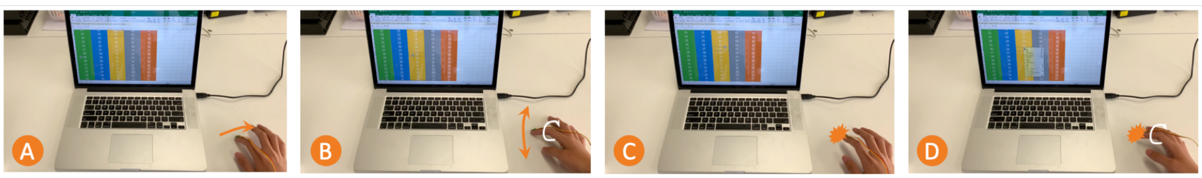

Fig. 18. Combined with IMU's capability to track coarse finger orientation, ActualTouch can be used as a miniaturised 2D pointing device on everyday surfaces. In addition to clicking and dragging as on a trackpad, users can also use the side of the finger to scroll or perform right-clicks.

As shown in Figure 18, using the system is as natural as moving a finger around. Compared to traditional mouse, we surprisingly found one benefit of our new system. As the IMU can detect the orientation of the finger, we can assign different functions to a gesture with different finger orientations. For instance, we set a normal tapping as a mouse left click (Figure 18C). To trigger right click, user can just perform a tapping with right side of their fingers (Figure 18D). Similar design technique could also be used to differentiate normal cursor movement gestures (Figure 18A) and scrolling (B). As there are more various finger orientations, such as tapping with left side of fingertip, knuckle and so on, It might have a larger design space than traditional mouse.

8.3 Extending Smartwatch Input

ActualTouch also enables users to leverage human bodies as input interfaces. For example, ActualTouch can extend the interaction with a smartwatch to the back of the hand (Figure 19) as a potential solution to the fat finger problem [50]. Here, we show that users can touch the backside of the hand and then perform gestures to scroll through items in a menu. A swipe gesture to the left could be used to select the highlighted item.

Fig. 19. ActualTouch can extend the input area of the smartwatch to the back of hand.

8.4 Always-available Thumb-to-finger Input

Although we did not evaluate ActualTouch on the thumb, we surprisingly found our sensing technology also works on the thumb for thumb-to-finger interaction, which is an always-available micro gesture input technique [31] that has been extensively investigated in the past several years. With a nail-mounted IMU on the thumb, ActualTouch enables the thumb to perform click or sliding gestures on other fingers (Figure 20). As the IMU we used can also detect absolute orientation of the finger, performing sliding gestures on different positions which usually results in rotation along different axes, can be assigned different functions. It is also possible to use ActualTouch as a pointing device on the fingers for future wearable devices, such as smart-glasses, which usually does not have a large dedicated touchpad to interact with.

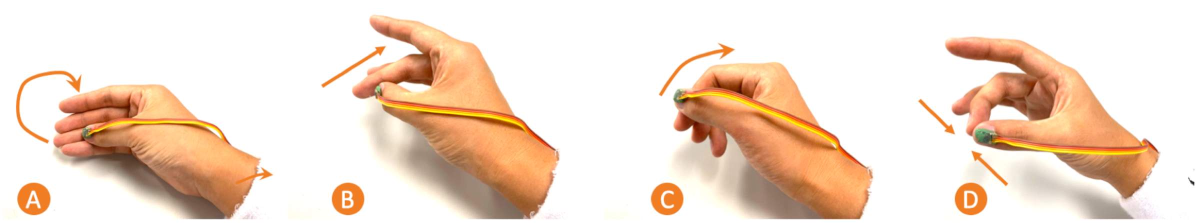

Fig. 20. ActualTouch enables thumb-to-finger interactions without training new models. It supports various interactions techniques, such as drawing, various sliders and clicks.

8.5 Back-of-Device Interaction

Leveraging the surfaces beyond the touchscreen on smart devices, such as the backside of the device, for touch interaction has also been investigated by many researchers. A popular solution is to augment these surfaces with sensors[8, 27, 28] to capture touch interaction. ActualTouch can provide another alternative for sensing, without augmenting every single devices. In Figure 21, we show that users can use the back side of a smartphone to perform for interaction without instrumenting the surfaces. It enables diverse interactions using the back of device, including navigate on the touchscreen by touching at the back of a smartphone and performing touch gestures.

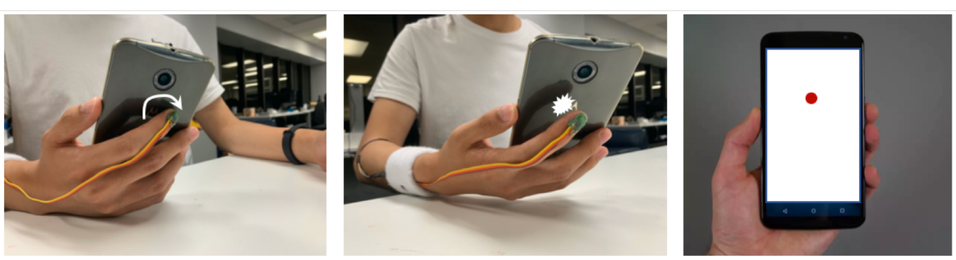

Fig. 21. Our sensing technique also supports back-of-device interaction.

9 DISCUSSION AND FUTURE WORK

9.1 Hardware Limitation

Our current system was tethered to a computer through a physical wire, which means that the device is not fully portable. Nonetheless, we would like to highlight that this is relatively easy to overcome, given the IMU is the only component to be worn on the body. In fact, prior work such as NailO [20] has successfully demonstrated the possibility of a self-contained wireless nail-mounted solution. Alternatively, self-contained on-skin PCB [19] could also be used to fabricate wearable solutions.

9.2 Potential Noise

Several sources of noises affect the performance of ActualTouch. As indicated in our second study, when the arm is resting on a table, the sensing accuracy would drop down by around 1.1%. Intuitively, when the palm, wrist, or elbow rests on a surface, the finger is indirectly connected to the surface, and the IMU data might be similar to and inseparable from those due to the direct touch of the finger. In addition, some users might by affected by pathological tremor, making it more challenging to detect touch. Although we did not focus on this type of tremor, we have demonstrated that our touch detection works well with various types of motion, which might work well in the presence of pathological tremor. Currently ActualTouch is susceptible to sources of vibration other than hand tremor and motion, such as on moving, vibrating or shape-changing objects. Future work is required to further investigate the influence of these noises.

9.3 User Experience Evaluation

In this paper, we mainly focus on benchmarking the basic sensing capabilities of ActualTouch. In the future, we will conduct specific studies to understand the user experience of our technology used as a pointing device. Considering the new form-factor of our device, it is also possible to conduct elicitation study to generate new interaction techniques that supported by our system.

9.4 Ring Form Factor

As described in study 1, although we chose fingernail for our study and application, for the detection of touch status of a moving finger, attaching the IMU to the middle phalanx also has a good performance. According to previous research [11], the middle phalanx is also of higher preference for users. Thus, research could be conducted for this specific form factor.

9.5 Interaction Potential

In this paper, we focused on the touch sensing capability of the system, as it has not been fully explored in previous research. Previous work have investigated other modalities of touch interaction, such as tapping, finger orientation, finger movement tracking, and object recognition, to name a few. All these interaction modalities are not exclusive and could be integrated into a single system. A finger-mounted IMU is thus a quite versatile sensing solution. In particular, a fingernail-mounted IMU might improve performance of previous work that placed the sensors farther away from the fingertips, such as on phalanges, palms, or wrists. Our technique also provides new interaction possibilities by cooperating with on-device IMUs. One example is to pair ActualTouch with a smartwatch by simply tapping it and correlating their IMU data.

9.6 Tips for Implementation

Although ActualTouch had a fairly good performance in our study, some consideration might need to be taken when implementing this technique in real interaction scenarios. First, ActualTouch would register touch events whenever the finger touches any object, even when the user does not intend to interact. Therefore, there needs a mechanism to detect user intentions of interaction. Second, the system could be worn all the time, but need not be always on. We envision ActualTouch to be implemented as a wireless device that attach to the fingernail, but that has implications on the form factor, power consumption, and battery life. One solution inspired by emerging technologies is to use wireless charging technologies to provide ad-hoc operations around other powered devices, such as around a laptop with embedded wireless charging coils. Alternatively, a future implementation could use energy harvesting circuitries to power the device from ambient energy sources, such as the motion of human body.

10 CONCLUSION

In this work, we introduced ActualTouch, a new technique to sense finger touch and finger movements on everyday uninstrumented surfaces. We conducted studies to benchmark the sensing capability of our system. Our technique only needs a single IMU to be worn on the finger. It can transform daily surfaces to touchpads for 2D pointing. It can also be used as a "middleware" for integration with existing IMU-based sensing technologies. We introduced some possible use cases and hope to inspire future research in this direction.

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