Nail+: Sensing Fingernail Deformation to Detect Finger Force Touch Interactions on Rigid Surfaces

Min-Chieh Hsiu[1] , Chiuan Wang[1] , Da-Yuan Huang[1] , Jhe-Wei Lin[1] , Yu-Chih Lin[1]
De-Nian Yang[2] , Yi-ping Hung[3] , Mike Chen[3]
National Taiwan University [1,3], Academia Sinica[2]
[1]{r03922073, r03922001, d99944006, r02944056, b01902044}@ntu.edu.tw,
[2]dnyang@iis.sinica.edu.tw, [3]{hung, mikechen}@csie.ntu.edu.tw

ABSTRACT
Force sensing has been widely used for bringing the touch from binary to multiple states, creating new abilities on surface interactions. However, prior proposed force sensing techniques mainly focus on enabling force-applied gestures on certain devices. This paper presents Nail+, a technique using fingernail deformation to enable force touch sensing interactions on everyday rigid surfaces. Our prototype, 3×3 0.2mm strain sensor array mounted on a fingernail, was implemented and conducted with a 12-participant study for evaluating the feasibility of this sensing approach. Result showed that the accuracy for sensing normal and force-applied tapping and swiping can achieve 84.67% on average. We finally proposed two example applications using Nail+ prototype for controlling the interfaces of head-mounted display (HMD) devices and remote screens.

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation (e.g. HCI): User Interfaces

Author Keywords
Natural User Interface (NUI); Fingernail; Strain gauges; Nail deformation; Force sensing;

INTRODUCTION
We apply different levels of finger force in our daily life to manipulate physical objects, such as holding, grabbing, or pushing. In the aspect of digital input, researchers use finger force as an additional input dimension for enriching the finger touch interactions such as drawing, selecting menu [19], short cutting within mobile apps [9], and multimedia browsing [8]. Recently, commercial products, *e.g.*, an iPhone 6s or an Apple Watch, have also been equipped with the force-sensing features for richer mobile interactions.

To sense finger force during the interaction, many prior works use force-sensitive resistors (FSRs) sensor underneath [11] or on the sides [18] of the device for sensing purpose. Other approaches use accelerometers embedded in smartphones [10] or external cameras [13] for distinguishing different touch behaviors. However, these techniques not only require sensors embedded within the device, but also have limited input area for force sensing.

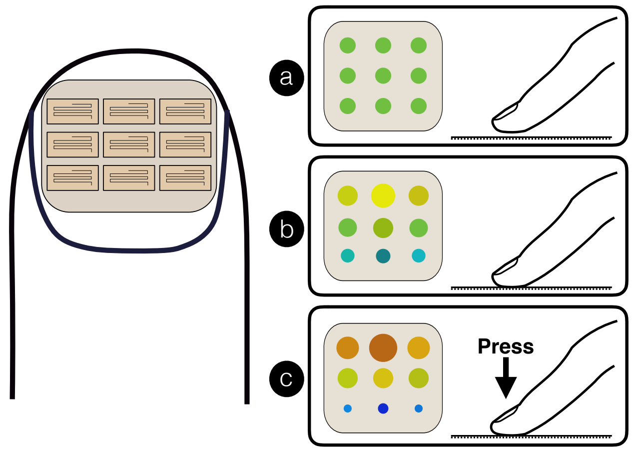

Figure 1. Nail+ utilizes deformation changes on a fingernail as an input source. The sizes and colors of the 3×3 circles indicate zero (normal-sized and green circles), positive (large and red circles), and negative (small and blue circles) strain changes shown in (a), (b), and (c) where the finger is not in contact with, makes light presses on, and presses hardly on a rigid surface, respectively.

This paper aims to propose a sensing technique that can constantly sense the changes of finger force, allowing users to perform force-applied gestures on rigid surfaces rather than on specific devices. We therefore adopt a different nail-sensing approach to extract information from the fingertip, and indirectly derive the finger force during the interaction. Moreover, nail-sensing technique also provides the ability to detect dynamic forces over time and path. For this approach, we implemented a Nail+ prototype, shown in Figure 1, a nail-mounted sensor grid worn on the fingernail which consists of 3×3 strain sensors. Since the sensor grid is worn on fingernail, the tactile feedback during the interaction is preserved. To assess the feasibility of our technique, we conducted an evaluation on our prototype. The result showed that our prototype can reach an 84.67% accuracy of distinguishing ten different gestures including taps, swipes in four directions, force-applied taps, and force-applied swipes in four directions.

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In summary, the main contributions of this paper are that (1) we developed a nail-mounted prototype and explored the ability of fingernail deformation to be used as an input technique, that (2) we conducted system evaluations for detecting both normal and force-applied tapping and swiping, and that (3) we showed scenarios using Nail+ prototype to explore interactions for head-mounted display devices and remote screens.

RELATED WORK

Sensing Force from Surfaces

Prior works use different approaches to sense the finger force by attaching sensors with surfaces. Jared *et al.* [3] use two force-sensitive resistors (FSRs) on the sides of mouse for mode switching and scaling parameters. ForceDrag [11] and ForceGesture [9] also use FSRs under mobile devices for exploring force gestures on touch screens. Different from above, Forcetap [10] adopts accelerometer signals to sense the touch strength on screen. Boring *et al.* [2] use contact area sizes on screen to infer the simulated pressure from fingertips. However, these techniques require embedded sensors in the devices for enabling force-sensing interactions, thus having limited sensing area. The main goal of our paper is to propose a finger force sensing technique that enables users to apply force gestures not only on certain devices, but also on everyday rigid surfaces.

Interacting with Fingernail-worn Devices

Prior researchers propose nail-mounted device for enriching input area. Magic finger [20] uses a finger-mounted camera to extend interactions by sensing multiple textures. NailO [14] proposes a capacitive sensor grid on top of the fingernail to sense tap and swipe gestures. uTrack [6] and FingerPad [4] place small magnets on the fingernail, and use a magnetic field to track finger movements. TouchSense [12] uses 3-axis accelerometer to detect finger postures for switching modes of touch input. While these works have proven the versatility of a device mounted on top of a fingernail, yet have not explored the characteristics of a fingernail itself as a signal source.

Sensing Finger Force Through Fingernails

Our fingernails are constantly on top of our fingertips and have changes in color and shape upon different finger force. This characteristic makes fingernail an ideal indicator for finger activities. Grill *et al.* [7] put a single strain gauge on the fingernail to sense the grasp state of holding an object. Nakatani *et al.* [17] place a finger pad with two strain gauges on the sides to estimate contact force. However, such arrangements of sensor pattern are not appropriate for sensing more comprehensive touch interactions on surfaces. Also, denser arrangements, such as sensor grid based ones, were not applied to exploring more advanced features on fingernail deformation. NailSense [13] proposes using an external camera from mobile device to sense the color changes from fingernail to derive contact states. Mascaro *et al.* [16, 15] implement a nail-mounted device for observing the changes of light reflection on the fingernail to sense the static finger force level, and static shear forces on a surface. However, further interactions involving dynamic forces over time and path on surfaces such as swipes and taps remain unexplored.

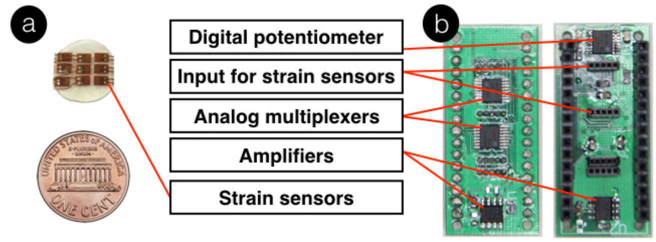

Figure 2. Nail+ prototype consists of (a) a 3×3 strain sensor grid as sensing part, and (b) an Arduino Nano Shield as computing part.

PROTOTYPE DESIGN

Before we implemented Nail+ prototype, a few main design requirements are taken into consideration. First of all, the device should minimize interference of haptic sense on fingertip. Secondly, it needs to be small enough to adhere to fingernails. Thirdly, it is supposed to be able to sense slight deformation changes on the fingernail. Fourthly, the sensing part of the prototype is reusable and easy to put on and take off. Based on aforementioned design requirements, we concluded that placing a 2D array of strain gauge sensors on the fingernail would be the most suitable solution for our approach. To determine the ideal fitting for typical users, we conducted a pilot study with 10 users (7 male) to collect the average fingernail size. The pilot study showed an average fingernail width of 1.14 cm (SD=0.14) and height of 1.21 cm (SD=0.17).

Hardware

Based on our pilot study, we developed Nail+ prototype using a 3×3 array composed of 120Ω 0.2-mm strain gauges (KFG-02-120-C1-11, San Lien Technology Corp. [1]) as sensors (shown in Figure 2 (a)). We used a stretchable and flexible hydrogel-based artificial skin as the sensor carrier for reusability purposes and as an easy approach for mounting on and removing from the user's fingernail as a strain sensor sticker. The size of the sticker is 1.0 cm×1.1 cm with a thickness of 1 mm which is smaller than a US penny. Each of the strain gauges is directly wired to the Arduino shield, as shown in Figure 2 (b). Since the artificial skin conforms to shape changes of the fingernail, the sensors will indirectly receive the same shape changes and subsequently result in changes in electrical signals.

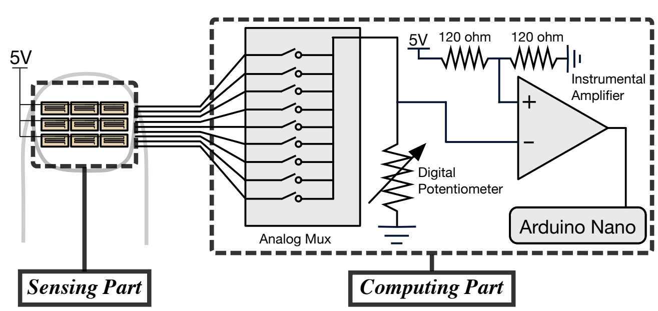

Figure 3. The complete circuit diagram. The sensing hardware consists of 9 strain gauges. The computation is performed by two analog multiplexers, a digital potentiometer, an instrumental amplifier (physically, two instrumental amplifiers in series), and an Arduino Nano.

The computing hardware consists of an Arduino Nano board, two 8-to-1 analog switches (MAX4617, Maxim Integrated), a dual digital potentiometer (AD5231, Analog Devices), and two instrumentation amplifiers (AD623, Analog Devices and INA122U, Texas Instruments). The IC chips are integrated onto an Arduino Nano shield, as shown in Figure 2(b). Both the sensing and computing parts operate under 5V and consume approximately 100 mA.

The diagram of the computing hardware is shown in Figure 3. First, the multiplexers are sequentially selected to connect to one of the strain gauges. Upon gauge selection, the strain gauge becomes one of the four resistors on the Wheatstone bridge. When forces are applied on the fingertip, the strain on the fingernail causes a slight bend or contour which causes a change in electrical resistance (Ω) of the sensors. The change in resistance then causes a change in voltage on one side of the Wheatstone bridge. Such minuscule voltage difference is amplified with a total gain of 4000. Finally, Arduino Nano reads the final analog value from the last amplifier's output. Due to the dynamic response time of the amplifiers, a 100 μs delay is placed between each sensor value acquisition resulting in a sampling frequency of 90 Hz.

Calibration Process

Since the sensor resistance values may vary even without any applied force, a calibration process compensates such phenomenon by adjusting the voltage reference on the negative input of the amplifier. The entire process is done programmatically as listed below.

1. Set a final analog value x and set the digital potentiometer to some resistance value r.
2. Arduino Nano reads an analog value y from the analog pin.
3. If $y < x$, we increment r by one step; otherwise, decrement r by one step.
4. Repeat step 2 and 3 until $y = x$.

In our case, since a 10-bit analog-to-digital converter is equipped in Arduino Nano, we set $x = 512$, the medium value of 0 to 1023, so that the sensor values can be measured under both compression (typically, analog values less than 512) and tension (analog values greater than 512) circumstances. The entire calibration process takes less than 5 seconds.

SYSTEM EVALUATION

In order to explore the ability of our Nail+ prototype, we conducted a user study to evaluate the classification of popular gestures. Participants were asked to perform 10 gestures on the surface, which included taps, swipes in four directions, force-applied taps, and force-applied swipes in four directions.

Apparatus

The apparatus is shown in Figure 4. We asked users to be seated in front of a computer desk (Figure 4 (a)) and wear our prototype on their index finger of the dominant hand (Figure 4 (b)). A cross with 10-centimeter equal-length bars was marked on the desk, shown in Figure 4 (c), as an indication for swipe path. The monitor showed the current gesture to perform and the status of user study progress. A keyboard is used as a recording button for the start and end of gesture.

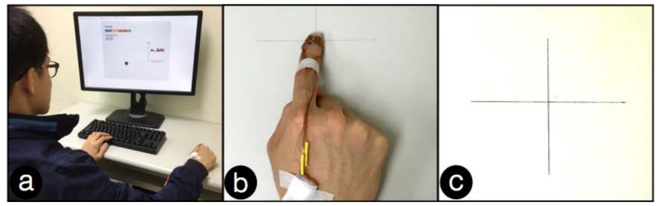

Figure 4. (a) The setup of our user study including an on-screen instruction, a keyboard to proceed through the trials, and a desk for users to perform swipe gestures. (b) The index finger equipped with our Nail+ device and bandages to affix the wires for the reduction of signal interference. (c) A cross drawn on the desk as indication of swipe paths.

Task and Procedure

We chose 10 kinds of gestures, including swipes in four directions (up, down, left, right), taps, force-applied taps and force-applied swipes in four directions as our gesture set. Initially, users were told to perform the gestures as if operating on a mobile device, and demonstrations of the force gestures were performed to the participants. In each trial, each of the 10 gestures was randomly selected. With 10 repeated trials, each user concluded with 100 trials of gestural data. Users were instructed to firstly press the space bar on the keyboard, which started the data recording, and subsequently performed the gesture on the desk. By the end of a gesture, users needed to press the space bar again to stop the data recording. A calibration process was required when each user put on our prototype but no further calibration was needed for the rest of the task.

Participants

We recruited 12 participants (8 male) between the ages of 20 and 25 (mean 22.91). All participants are right-handed and have experience in using mobile devices or tablets for over one year. Six of them have experience in using force sensing devices within two months. At the end of study, participants received $5 in reward for their participation.

Results and Observation

Sensor Value Visualization

To understand how interaction is made possible by utilizing nail deformation, visualized sensor values over time are shown in Figure 5. We firstly notice that waveforms of different gesture are distinct and discernible, thereafter creating a unique signal pattern for each gesture. Secondly, the sensors on the third row generate fewer signal changes among all gestures since the position of the third row is close to nail root which is more solid and has less deformation. Thirdly, force-applied gestures generate more significant signal changes than that of the normal gestures, and thereby normal-force gestures and force-applied gestures are distinguishable from each other. For example, as shown in Figure 5 (a) versus (b) and (c) versus (d), the waveforms of force-applied gestures have greater signal amplitudes than that of the normal gestures.

Data Processing

As stated in our task procedure, each trial of gestural data is segmented by users clicking the space bar on the keyboard from the start and at the end. With 12 participants

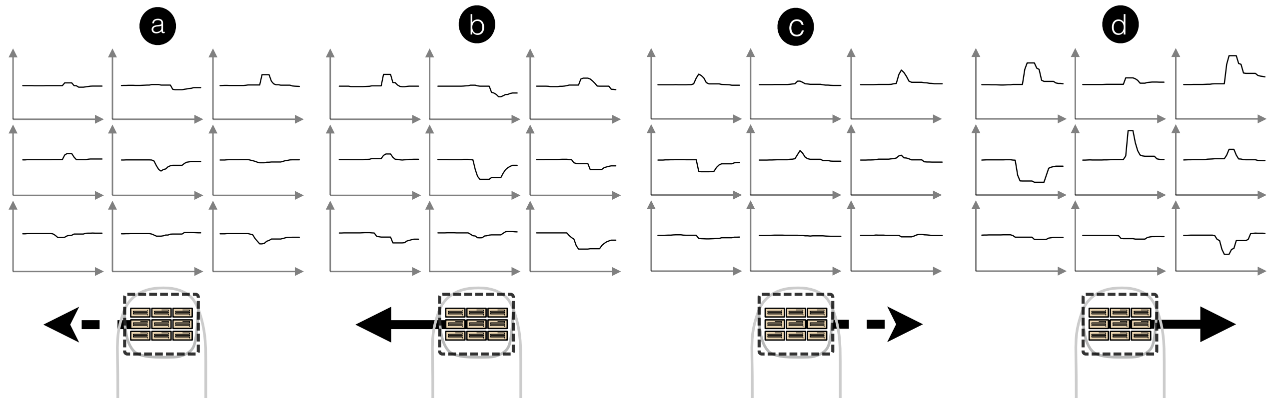

Figure 5. Visualization of 3×3 grid strain gauges sensor data from one of our participants. Each plot is the change in analog values (y-axis) over time (x-axis) of a strain gauge. (a) Left Gesture, (b) Force-applied Left Gesture, (c) Right Gesture, (d) Force-applied Right Gesture

and 100 trials per participant, a total of 1200 trials were collected in the study. The recorded sequential and time-based data is preprocessed by accumulating each datum's difference from the first received datum when user presses the space key on keyboard. Since the strain gauges may undergo tension (positive difference value) and compression (negative difference value) in a trial, the positive and negative difference values of each sensor are accumulated separately to preserve the features of tension and compression leading to $9\ sensors \times 2\ (positive\ and\ negative) = 18\ features$. Finally, we normalize the feature values to the range of -1 to 1 and then trained by a multi-class SVM classifier with a Radial Basis Function (RBF) kernel using LIBSVM [5].

Accuracy Rates and Confusion Matrix

As shown in Figure 6, each gesture accuracy rate is averages of 10-fold cross-validations across all 12 participants. The highest accuracy rates (91.67%) occur with the "tap" and "force right" gestures, whereas the lowest comes with the "right" gesture. The "tap" gesture being highly predictable is due to its short-duration recording and interaction leading to significantly small accumulated feature values. The "force-related" swipe gestures are also easily recognizable by the reason of the accumulation of significantly large values caused by apparent nail deformation. On the other hand, normal swipe gestures are at relatively low accuracy rates because of the slightly less apparent deformation on the fingernail caused by lighter contact between the finger and the desk.

Moreover, the normal swipe gestures are usually misclassified into the "tap" gesture showing lack of force while swiping as shown in Figure 7. The "left" and "right" gestures are at the lowest accuracy rates (79.17% and 75.00%, respectively) because left and right swipe paths usually have less frictional forces and thus effortless to perform compared to that of up and down swipes. Users performing up and down swipes tend to push harder against the desk causing slightly larger nail deformation. Hence, up and down swipes are at slightly higher accuracy rates (80.00% and 81.67%, respectively) among the normal swipe gestures.

For all gestures, the mean accuracy rate is 84.67%. As stated in our observation, the strain gauges which are close to fingertip

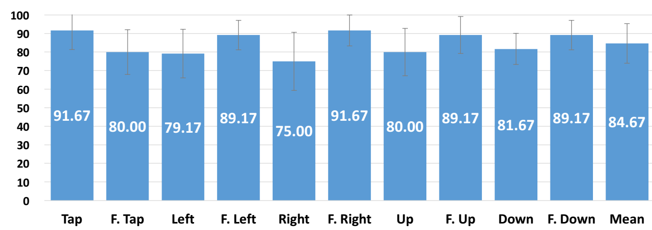

Figure 6. The mean accuracy rates of each gestures by 10-fold cross validations across all users. *F.* stands for *force-applied* gesture.

Predicted Class(%)

Actual Class(%)	Tap	F. Tap	Left	F. Left	Right	F. Right	Up	F. Up	Down	F. Down
Tap	91.67	0.00	1.67	0.00	4.17	0.00	0.83	0.00	1.67	0.00
F. Tap	2.50	80.00	1.67	3.33	1.67	0.00	5.00	0.83	1.67	3.33
Left	6.67	0.00	79.17	5.00	0.83	0.83	4.17	0.83	2.50	0.00
F. Left	0.83	1.67	7.50	89.17	0.00	0.00	0.00	0.83	0.00	0.00
Right	8.33	0.00	3.33	0.00	75.00	4.17	4.17	0.00	5.00	0.00
F. Right	0.00	0.83	0.00	0.00	5.00	91.67	0.83	1.67	0.00	0.00
Up	4.17	2.50	1.67	0.83	5.00	0.00	80.00	2.50	3.33	0.00
F. Up	0.00	2.50	0.00	1.67	0.00	0.00	5.83	89.17	0.00	0.83
Down	6.67	0.83	2.50	0.00	5.83	0.83	0.00	0.00	81.67	1.67
F. Down	0.00	1.67	0.00	0.83	0.00	0.00	0.00	0.00	8.33	89.17

Figure 7. Confusion matrix for each of the gestures in our user study. *F.* stands for *force-applied* gesture.

generate more deformation signal changes. The accuracy may be improved by changing arrangements of sensor patterns. For instance, smaller and denser strain gauges can be placed closer to the fingertip for better and finer data acquisition and accuracy.

Cross User Ability

In order to understand differences of nail deformation from person to person, we compute leave-one-user-out cross validation based on our data. The overall average accuracy is 35% (SD: ±8.51%), ranging from 22% to 50%. This is likely due to the differences of nail deformation among users caused

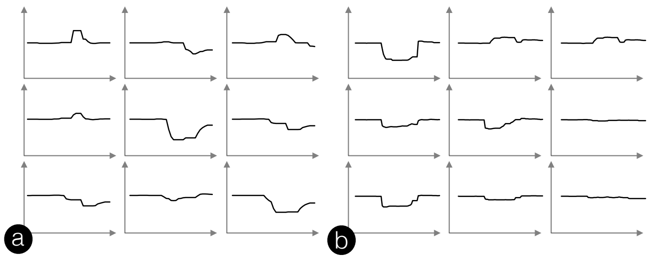

Figure 8. The *force-applied left* gesture data from two of the participants. Dissimilarities in signal waveforms between two users performing the same gesture indicate the lack of cross user ability.

by behavioral differences of finger force pressures and swipe durations while performing a gesture. From another point of view, the signal patterns in Figure 8 indicate several dissimilarities between a pair of users in spite of the exact same gesture performed. Accordingly, differences in signal waveforms for the same gesture and low accuracy rates across users both have suggested that building a general model is highly unlikely.

EXAMPLE APPLICATIONS

With the advantage of Nail+, we describe two examples utilizing this new sensing technique.

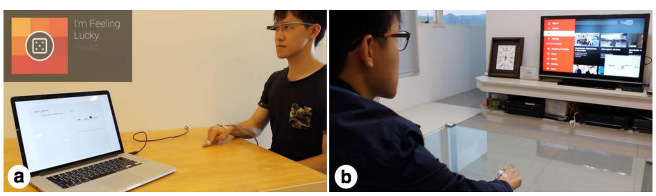

Figure 9. Applications using Nail+ for controlling (a) Head-mounted device (HMD) and (b) Remote screen.

Expanding HMD Device Input Space

Though head-mounted display devices provide rich visual feedback, such form factor (e.g. glasses) limits its input functionality to a tiny-sized touch pad causing limited interaction spaces. For such scenario, Nail+ expands the input area by direct contact with surfaces around for interface control. For example, normal taps and swipes navigate through contact cards as users normally operate on a touch pad, as shown in Figure 9 (a). By adopting force-applied gestures, users can use a short cut to quickly acquire information instead of endless and exhaustive swipes for surfing through multiple cards.

Remote screen controlling

Remote screen such as smart TV requires a handheld remote control. With Nail+, users can control remote TV by using simple finger gestures on a desk or nearby surfaces. For example, users are allowed to navigate through contents in the interface using normal swipes, and tapping for selecting the content, as shown in Figure 9 (b). By using force-applied gestures, users are able to easily and intuitively bring out the category panel on the side without the need of a remote control.

LIMITATION AND FUTURE WORK

Firmly adhering sticker to fingernail: In our evaluation of system, we noticed that the highly-reusable artificial skin still gradually loses adhesiveness over time. Also, since the artificial skin is flexible and soft, the strain gauges were unable to fully restore to their unstretched original states, calibration and training are necessary procedures for each use after previous removal. We continue to look for alternative solutions for device adhesion or directly integrate our system with nail arts to ensure greater system usability.

Minimizing hardware and power consumption: As shown in Figure 2 (b), the hardware computing part is currently an Arduino Nano shield. Our prototype is connected to a computer through a USB serial cable for power supply and data transmission. The Wheatstone bridge and the sensors consuming 40 mA, 40% of the total power consumption, can be replaced with the ones of greater resistance such as 1-kΩ strain gauges and 1-kΩ resistors drawing only 5 mA current (88% power reduction for sensing part). It will be future work to redesign our prototype into a nail-sized, battery-powered, wireless, and more independent system.

Multi-touch: In this work, we examined a single-fingertip interaction on a rigid surface. By mounting our hardware on all fingernails, we will enable multi-fingertip interactions such as pinch, zoom, two-finger scroll, grasp, spread, and so forth, potentially giving each with more semantic expressions and with "multiple states" through force levels.

CONCLUSION

Finger force interactions occur with physical object manipulation throughout our daily lives. Prior works have proposed various techniques to sense forces from the fingertip. However, in those works, either the input area is limited or fingernail-mounted devices have not yet explored dynamic forces over time and path on surfaces. In this paper, we explore the ability of using deformation on fingernail as an input technique that enables force-applied gestures on surfaces. To monitor the finger force through the nail deformation, we developed a nail-mounted prototype, Nail+, which is a strain sensor grid array small enough to fit on top of fingernails. We show that the prototype can detect 10 kinds of gestures, including normal and force-applied tap and swipe gestures, at an 84.67% accuracy. The visualization of sensor signals facilitates the understanding of nail deformation and illustrates unique, discernible gesture patterns. Also, we discover that the more force applied during gesture, the more apparent signals are generated, and thus the force-applied gestures are more recognizable. Finally, we proposed two interactions using Nail+ for HMD devices and remote screen to enrich the input space. For more future works, we plan to minimize current prototype to a nail-sized device and extend this system to all fingers for enabling force-sensing multi-touch input.

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