TouchWave: Exploring mmWave-based Non-contact Fingertip-force Sensing in Activities of Daily Living

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***Abstract*—Fingertip forces are important biomarkers for the detection and management of various conditions, including stroke and Parkinson's disease. This paper presents TouchWave, a non-contact sensing system designed to monitor fingertip forces during activities of daily living (ADL). TouchWave leverages under-cabinet millimeter-wave (mmWave) sensors to capture both macroscopic hand movements and subtle biomechanical cues associated with fingertip force production. A novel signal processing scheme is developed to suppress noise while preserving force-related information in the mmWave signals. Additionally, a hybrid deep neural network model is proposed to estimate high-fidelity fingertip forces. A comprehensive evaluation involving 21 participants demonstrates the effectiveness of TouchWave in both controlled settings and ADL scenarios.**

***Index Terms*—fingertip force, non-contact sensing, digital biomarker, mmWave**

I. Introduction

Fingertip force production is a complex neuromechanical process involving the integration of sensory receptors and motor neurons, and is critical for functions such as grasping, object manipulation, and fine motor control. Recent studies have highlighted the significant potential of fingertip force metrics as biomarkers for various neurological disorders, including stroke [1] and Parkinson's disease [2]. However, despite their promise, the measurement of fingertip forces remains largely confined to laboratory settings, requiring specialized equipment and in-person visits, which limits their utility for daily-life disease progression tracking and management.

An intuitive approach to enabling fingertip force perception during activities of daily living involves integrating pressure sensors into or onto everyday objects (e.g., cups [3]). However, such solutions often require customization steps that can be challenging for users without a technical background. To eliminate this barrier, researchers have explored repurposing built-in smartphone sensors, such as barometers in air-tight smartphones [4], for fingertip force sensing. These approaches, however, are typically constrained by specific hardware designs, limiting their generalizability. Wearable fingertip force sensors offer a more pervasive alternative. Wearable solutions include attaching thin-film sensor [5] directly to the fingertips, as well as inferring fingertip forces through biomechanical cues measured at other body locations. Such cues include nail deformation [6], wrist blood volume [7], and arm electromyography (EMG) signals [8]. Nevertheless, these methods often interfere with natural hand movements or exhibit instability during everyday activities. As a result, how to monitor fingertip forces from activities of daily living in a non-intrusive manner remains an unsolved challenge.

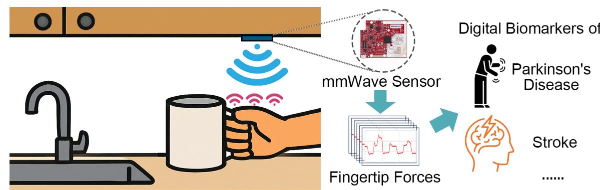

Fig. 1. Application scenario of our proposed system

In this work, we propose a non-contact mmWave sensing system using touching and pressing interactions in activities of daily living (ADL) to monitor fingertip force patterns. As is shown in Fig. 1, the system uses down-looking mmWave sensors under the cabinet to capture the user's fingertip force patterns while the user is conducting daily activities such as holding cups and using folks. Our key contributions are as follows:

- We found mmWave is sensitive to the hand micro-motion induced by the different levels of fingertip forces. Based on the observation, we introduce the first non-contact ADL fingertip forces monitoring system.
- We design a novel mmWave signal processing scheme to preserve both macroscopic and subtle motion information from hands. A two-stream deep neural network is proposed to extract both long-range and short-term temporal finger dynamics for accurate force estimation.
- We evaluated our system on 21 participants at different activities of daily living. The accuracy achieved satisfies the need for biomarker tracking for multiple diseases.

II. Non-contact Sensing of Fingertip Forces: Concept and Feasibility

Biomechanical cues of fingertip forces. Forces on fingertips are generated through a complex interplay of anatomical and biomechanical elements, including muscle contractions, tendon mechanics, and the structure of the bones and joints in the hand and fingers [9]. When intrinsic muscles within hands, such as the thenar, hypothenar, and interossei muscles, actuate to generate fingertip forces, they induce subtle muscle shape change and minute joint angle variation, externalized as barely visible skin deformation.

mmWave sensing of biomechanical cues. The Frequency Modulated Continuous mmWave measures object distances and velocities using intermediate frequencies (IF), which is proportional to the wave's Time-of-Flight. Recent studies demonstrated that mmWave IF can capture the skin deformation associated with voices [10] and vital signs [11]. The amplitude spectrum of IF reflects macro centimeter-level deformation, and the phase spectrum of IF shows better sensitivity to micro sub-millimeter displacement. Based on such background knowledge, we hypothesize that mmWave is capable to sense the above biomechanical cues induced by applying fingertip forces and the sensing results should be correlated to the applied fingertip forces.

Proof-of-concept. To validate our assumption, we conduct a proof-of-concept. To see how the mmWave responds to the change of fingertip forces, we first positioned a mmWave sensor above a desk at a 50 cm distance. Then, we asked two study participants to press the force sensors on the desk surface slightly with their fingers. Fig. 2 reports the force sensor readings and the corresponding mmWave IF signals spectrum (amplitude and phase). We observed that both IF amplitude and phase demonstrate a strong correlation to the fingertip force, which validates our hypothesis.

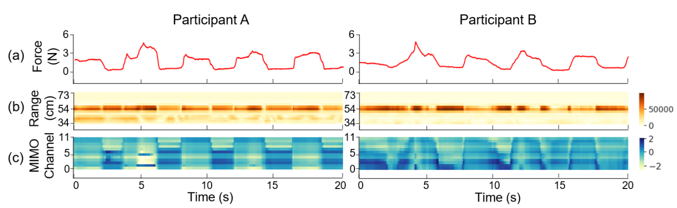

Fig. 2. Proof-of-concept study results on two participants: (a) Fingertip force readings from a force sensor. (b) Change of amplitude within a span of 40 cm, centered at the pressing hand. (c) Change of phase signal at the pressing hand.

III. Methods

A. *TouchWave's Macro-micro Signal Processing Scheme*

Based on our insights from the preliminary study, TouchWave utilizes both the macro amplitude and micro phase spectrum of the mmWave IF for fingertip force estimation. Here, the spectrum frequency bins are often referred to as range bins as they are linearly correlated to distances[1]. For the amplitude spectrum, traditional mmWave signal processing first identifies a range bin corresponding to each hand. While the thickness of hands is typically smaller than the bin width $\frac{c \cdot f_s}{2S}$ (c is the speed of light, f_s is the mmWave sensor ADC sampling rate, and S represents chirp slope), we found fingertip force-dependent varying patterns in amplitude spectrum are shown in multiple range bins due to natural bending and rotation of the palm during operation (Fig. 2). We conducted an empirical study using a depth camera to record 21 participants interacting with everyday objects using their hands. The results indicate that, for the majority of the time, participants' fingertips remained within ± 7 cm of the palm, which is a range that aligns with the typical length of human fingers. Based on this observation, we utilize the amplitude spectrum of the range bin corresponding to the local maximum amplitude (i.e., the palm) and its immediate neighboring bins covering the ± 7 cm to retain the macroscopic force characteristics associated with fingertip interactions. For the phase spectrum, instead of using signals from multiple range bins, we extract phase information from the range bin exhibiting the peak amplitude within the range bins selected above to optimize signal-to-noise ratio (SNR). The reason is two-fold: first, extracting phase information from a single range bin reduces human body motion interferences [10]; second, this bin is closest to the hand exhibiting the strongest phase patterns correlated to fingertip force applied. Since the absolute phase readings vary greatly due to slight changes of hand position, we instead compute the differential phase signals to highlight dynamic variations and suppress irrelevant background components. To enable higher spatial resolution for force estimation on different fingertips, TouchWave further performs beam steering based on Multiple-input-multiple-output (MIMO), which is commonly supported by mmWave sensors. Finally, the amplitude channels and differentiated phase channels are segmented using moving windows and fed to TouchWave's fingertip force estimation model, which is detailed next.

[1]A full description of the mmWave range profiling is beyond the scope of this paper and can be found in [10]

B. *High-fidelity Fingertip Force Estimation*

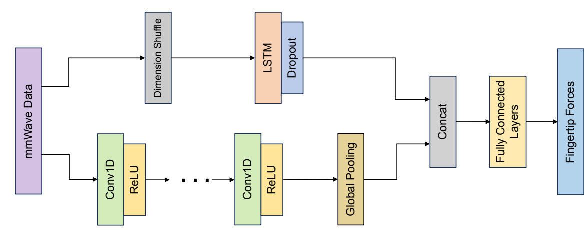

Fig. 3. The two-steam model for high-fidelity fingertip force estimation.

Model architecture. We adopt an encoder-decoder architecture to map the pre-processed mmWave signals to forces on multiple fingertips. The encoder-decoder framework is particularly effective and has proven successful in problems where physiological information embedded in mmWave signals must be extracted and reconstructed into continuous and highly dynamic signals, such as vital signs [11] and voices [10].

Extract fingertip force features in mmWave. In our design, the encoder is to extract meaningful features from the pre-processed mmWave signals that are predictive of fingertip force. Fingertip force evolves over time and is influenced by both short-term changes (e.g., brief taps or slips) and long-term patterns (e.g., sustained pressure). Accurately capturing these temporal dependencies is essential for robust prediction. In deep neural network design spaces, LSTM can model the long-range temporal dynamics and suppresses transient noise, while the convolutional component efficiently captures local signal patterns. We adopted a hybrid design where LSTM and CNN form two streams. This design ensures both networks can retain detailed force features.

Decoder for force estimation The decoder takes the encoded temporal features and maps them to continuous fingertip force values. The decoder is implemented using fully connected layers that process the encoder's output into a sequence of predicted force values. This setup allows the decoder to directly interpret the high-level features extracted by the encoder and convert them into physically meaningful force readings.

C. Evaluation

Setup. We evaluate TouchWave with the data collection setup depicted in Fig. 4. This setup integrates a mmWave sensor (IWR6843ISK-ODS [12], configured as shown in Table I with 3Tx-4Rx TDM MIMO), calibrated high-precision force sensors (10 N capacity, 0.02 N resolution, 50 Hz [13]), a stereo reference camera [14], and a hosting laptop (Intel i7-11800H). The force sensors were strategically placed on the desk surface and various daily-use objects (cups, tweezers, and pens) to capture precise fingertip forces that evaluation participants apply to them. We use an Arduino Uno to collect the force sensor readings. All components are synchronized with the laptop's internal clock.

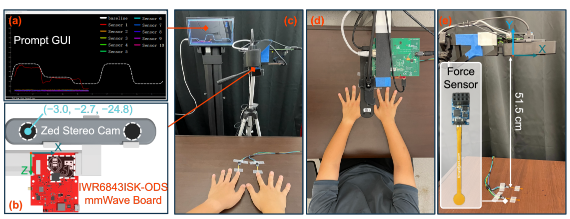

Fig. 4. TouchWave is evaluated against high-accuracy force sensors. The stereo camera videos are for reference only and are not used in the evaluation.

TABLE I
MMWAVE SENSOR WAVEFORM CONFIGURATION

Parameter	Value	Parameter	Value
Start Frequency	60 GHz	ADC Sample Rate	10 MHz
Frequency Slope	61.520 MHz/μs	Idle Time	5 μs
Bandwidth	3998.8 MHz	Ramp End Time	65 μs
ADC Start Time	6 μs	Chirp Periodicity	1 ms
ADC Samples	512	Rx Gain	30 dB

Protocol. In our experiment, each participant needs to complete 18 distinct hand-object interaction activities. A total of six fingers, including the thumb, index finger, and middle finger from both hands, were involved. The study was divided into two parts. In the first part, participants interacted with objects *under controlled conditions*. Specifically, participants put hands on desk, extended all fingers, and pressed the force sensors with 1) a single finger, using each of the six fingers mentioned above; 2) two fingers from the same hand at the same time (e.g., left thumb and left index fingers or right thumb and right middle fingers); and 3) the same fingers from both hands simultaneously (e.g., left index and right index fingers together). In addition, participants were instructed to control their fingertip to follow a force prompt on screen (Fig. 4b), which varied between five levels evenly spaced from 0 to 5 N. This design aimed to ensure balanced data collection across different force levels. In the second part, participants performed activities *freely* using their dominant hand *without force restrictions*. These activities included pinching a cup on a table, using tweezers to pick up an object, and writing on paper, all with their dominant hands. Two one-minute trials were collected for each activity.

Population. We recruited 21 participants in this study, including 9 females and 12 males. The participants were aged 21-28 years, with a mean age of 25 years. The participants' heights ranged from 156-195 cm, weights from 43-93 Kg, and middle finger lengths from 7.0-9.5 cm. Our study is reviewed and approved by the Institutional Review Board (IRB).

Data preparation and evaluation metrics. In total, we collected 8.4 hours of data. We apply an 800-ms moving window with 200-ms stride to segment signals, which leads to 297 samples for each trials. Samples where a data packet loss occurs are dropped. For evaluation, we used the root mean squared error (RMSE) of the predicted force across all relevant fingers as a metric.

IV. RESULTS

A. Results under Controlled Conditions

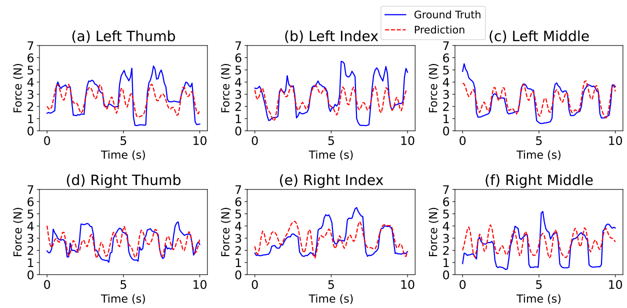

Fig. 5. Single fingertip forces estimated under controlled conditions.

We first trained our model separately on the left and right hands based on *single-finger pressing activities* on the flat desk surface. The data are split by trials on an 80%-20% ratio for training and testing, with 102 minutes of data provided for each training. As shown in Fig. 5, the model-estimated fingertip forces follow the general trend of the ground-truth sensor readings. As reported in Table II, the models reached an RMSE of 1.33 N and 1.28 N.

For *two-finger pressing*, our model is separately trained for the settings where the fingers are from left hand, right hand, and both hands. For the setting with both hands, the model reaches an RMSE of 1.31 N. For one-hand two-finger pressing activities, our tests report a combined RMSE of 1.72 N and 1.66 N on the left and right hands, respectively. These results show that the performance of the system decreases when more fingers from the same hand are tracked. Compared to the two fingers from both hands, fingers from the same hand are much closer, bringing more inter-finger interferences.

B. Results on ADL under Naturalistic Conditions

In this part, we evaluate the system's performance on everyday activities, which involve multiple-finger cooperation in dynamic settings. Models are trained on each activity individually and reported in Table III. *Pinching on the cup* using two fingers from the same hand show comparable RMSE to

TABLE II
PERFORMANCE UNDER CONTROLLED CONDITIONS

Number of tracked fingers	Fingers from	RMSE (N)
1	Left Hand	1.33
1	Right Hand	1.28
2	Both Hands	1.31
2	Left Hand	1.72
2	Right Hand	1.66

controlled conditions. Our system reached a low RMSE (1.08 N) in the *handwriting* activity. This is because participants tend to apply smaller forces when using a pen than a cup. Among the three activities, the force on *tweezers* shows the worst accuracy. The deformation of metal tweezer legs may have introduced significant noise into the mmWave sensing data. In summary, in ADL, TouchWave demonstrates force estimation performance comparable to that under controlled conditions, except when participants directly interact with deformable metal tools.

TABLE III
PERFORMANCE ON ACTIVITIES OF DAILY LIVING

Number of tracked fingers	Activity	RMSE (N)
2	Pinch on Cup	1.61
2	Tweezers Pick Up Item	2.67
5	Handwriting with A Pen	1.08

C. Performance on Unseen Persons and ADL

Our model is further examined on its ability to predict forces on unseen objects and unseen contact surfaces. We excluded data from 2 participants from the training trials of right-hand single-finger pressing activities, and further tested the trained model on these participants. The model reaches a slightly higher RMSE of 1.42 N on unseen participants. We then used our model trained on two-finger right hand activities under controlled conditions to estimate the uncontrolled force in cup-pinching activities. The tracked fingers in the two activities both include the right thumb and index finger, yet the operation was performed differently on distinct contact surfaces. The RMSE reported is 2.03 N. The results above show that only a minor accuracy decrease is brought by unseen users. Compared to unseen users, TouchWave's force-sensing performance drops more when generalizing to new objects. We plan to introduce more activities in the system-building phase to increase system generalizability.

V. DISCUSSION AND FUTURE WORK

A natural question arises as to whether TouchWave's precision is sufficient to support the identification of biomarkers for conditions such as stroke. Prior studies have shown that, in stroke patients, the difference in fingertip forces between impaired and unimpaired hands can be as high as 9.3 N [1]. Our evaluation indicates that TouchWave consistently achieves an RMSE below 2 N in most scenarios, which is well below the clinical threshold. This result demonstrates TouchWave's potential for distinguishing fingertip force-related biomarkers.

In future work, we plan to conduct targeted case studies to further assess the system's validity in disorder prediction and monitoring. Additionally, we aim to expand its application to a broader range of daily activities. To further enhance estimation accuracy, future developments may incorporate advanced spatial filtering in mmWave signal processing and integrate biomechanical priors into our deep learning models.

VI. CONCLUSION

In this paper, we presented TouchWave, a novel non-contact sensing system for monitoring fingertip forces during activities of daily living (ADL). By leveraging under-cabinet mmWave sensors, our approach captures both macroscopic and subtle hand movements associated with force production, without requiring wearable devices or object instrumentation. We introduced a robust signal processing pipeline and a two-stream neural network to extract multi-scale temporal features for high-fidelity force estimation. TouchWave achieves accurate and reliable force sensing in both controlled and naturalistic settings, meeting the performance requirements for potential use in health-related biomarker tracking.

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