Z-Pose: Continuous 3D Hand Pose Tracking Using Single-Point Bio-Impedance Sensing on a Ring

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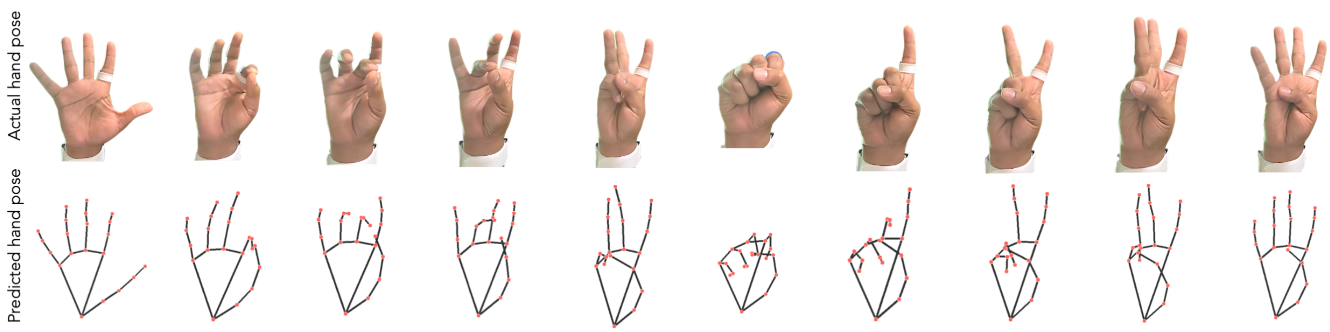

Figure 1: Z-Pose, a wearable ring device, enables RF-based hand pose tracking by analyzing the user's performed hand poses (upper row) and generating corresponding pose predictions (lower row).

ABSTRACT

This paper introduces Z-Pose, a method for continuous 3D hand pose tracking that uses swept-frequency RF sensing via a worn ring device. By modeling the hand as an RF antenna and analyzing its geometry-dependent impedance, Z-Pose performs real-time hand tracking based on the unique impedance signature of each pose. Unlike camera-based systems, this sensing technique is robust to occlusion and illumination, performing well in our evaluation studies even with obstructions such as sleeves and gloves. The results indicate that the system achieves an average Euclidean error of 7.2mm across individual hand joints, lending itself to a variety of interactive applications.

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CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile devices**; **Interaction devices**; **Interaction techniques**.

KEYWORDS

Wearable Computing; Virtual Reality; RF Sensing; 3D Hand Pose Tracking; Human-Computer Interaction

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1 INTRODUCTION

Continuous, fully articulated hand tracking enables precise remote operation of robots [10], aids in enhancing motor skills in medical rehabilitation [21], adds realism to animations in gaming and film through motion capture [20], and permits immersive interactions with digital content in augmented and virtual reality [18].

The first methods of digitization involved a glove-like apparatus that used mechanical methods to encode joint position [22]. As computer vision machine learning (ML) methods evolved, optical approaches have become increasingly commonplace. These aim to minimize the encumbrance on the hand, such as through IR retroreflective marker motion capture [5], or to completely eliminate the need for instrumentation, such as with active depth or RGB camera-based tracking [2]. Nevertheless, these approaches require external camera mounting, limiting the field of view and thereby reducing the interactive area and mobility. Researchers have also explored alternative camera placements, such as on the wrist [11, 14, 27], but these methods are still susceptible to occlusion and dependent on ambient light conditions.

In this paper, we propose the application of injected, swept frequency bio-impedance sensing, first described in [24], to ascertain a three-dimensional hand pose. While [24] explored this approach for input based on discrete gestures, we take it further to enable continuous 3D full-hand tracking. This sensing methodology treats the hand as an RF (radio frequency) antenna with RF properties, including impedance, that vary based on its geometry. As the hand transitions through different poses, its RF characteristics change accordingly. Since each unique hand pose generates a distinct impedance profile, we can measure and analyze these profiles to accurately determine corresponding hand poses. Compared to the optical-based approach, this sensing technique has no field-of-view constraints and requires minimal instrumentation of the hand, using only a low-profile ring worn at the base of the index finger.

We develop a proof-of-concept prototype by 3D printing a ring outfitted with electrodes on a Flexible Printed Circuit Board (FPCB) for hand impedance measurement. Measurements are facilitated through a portable vector network analyzer. We translate impedance readings into hand poses using ML and train our model with ground truth data from the MediaPipe framework [4]. To evaluate our system's effectiveness, we conducted a two user studies. The first study examined the system's performance with the user's hand fully exposed. The second tested the system when the hand was physically occluded, thereby assessing the robustness of our approach in various real-world scenarios.

Our research makes the following contributions to the field of hand tracking:

- A proof-of-concept prototype that uses swept-frequency bio-impedance sensing for 3D continuous hand tracking
- The development and integration of a hardware and software pipeline for our hand-tracking system
- Evaluation studies across various users and scenarios that provide empirical evidence of the system's effectiveness and potential utility

2 RELATED WORK

We first describe the work related to continuous hand pose tracking via the most common sensing methodology, optical, and then focus on related electrical systems for hand-based input and interaction.

2.1 Continuous Hand Pose Tracking

Continuous hand tracking has been explored since the emergence of virtual reality devices. Early approaches, such as the Sayre Glove [9], DataGlove [31], and CyberGlove [23], used worn glove devices with flex sensors. They provided novel interactive capabilities within virtual reality but were cumbersome due to their size and total hand coverage, limiting touch.

Since then, optical methods have become more prevalent. High- precision tracking can be achieved using IR marker-based motion capture, e.g., Vicon [7] or OptiTrack [5]. However, these systems require the user's hand to be outfitted with retroreflective or active LED markers and typically employ many cameras to avoid occlusion and maintain precision. Modern augmented and virtual reality headsets have eliminated these markers using advancements in computer vision and ML. They capture the hands using stereo RGB or depth cameras mounted on headsets to handle partial self occlusions or oblique hand views [2, 3, 19]. Most recently, performant monocular hand models, such as MediaPipe Hands [4], have been developed that can derive hand landmarks from a single RGB camera. However, each of these methods require an externally mounted camera that offers a limited field of view, restricting the interactive area.

Therefore, researchers began to explore mounting cameras on the wrist instead. Digits [14] uses a wrist-mounted IR camera and a projected laser line along with a forward kinematics model to derive a hand pose. FingerTrak [11] uses four thermal wrist-mounted cameras to observe the changing silhouette of the hand shape. Similarly, Back-Hand-Pose uses a wrist-mounted RGB camera to image the hands' silhouette. However, as with other optical systems, each is subject to illumination constraints and cannot perform with occluded hands, e.g., while wearing gloves. As a result, systems based on electrical signals that do not require line-of-sight have been explored.

2.2 Electrical-Based Hand Sensing

Electromyography (EMG) techniques employ the electrical signals produced by the user's own muscle activity. WR-Hand [16] and NeuroPose [17] both use deep learning methods to derive a full hand pose from a set of eight electrodes on a band worn on the forearm. However, the number and placement of electrodes in an awkward location on the forearm make these systems cumbersome to use. Z-Pose also employs electrical signals to avoid occlusion and illumination constraints of optical systems. Unlike EMG, we explore the use of radio frequencies (RF) that require only a single point of instrumentation on the hand.

RF- and capacitive-based methods can sense changes in motion and pose by observing the hand's effect on transmitted or propagated electric fields. Soli [15] utilizes 60 GHz radar via an externally worn chip to detect subtle motions of the fingertips. With such a high frequency, this Doppler radar technique generally senses velocity rather than absolute position and was not shown to recover a full set of hand poses.

Lower frequency methods measure the capacitive loading of the body to sense motion. EF-Ring [8] uses self capacitance measurements to target small microgesture motions between the thumb and index finger, like Soli. Aurasense [30] uses a similar method to located the finger around a smartwatch. More similar to our work, eRing [26] and PeriSense [25] both use capacitive measurements from external electrodes on a ring to classify a set of discrete hand poses, though neither of these works evaluate continuous articulated hand poses.

Between these frequencies is the RF spectrum across which the human body acts as an electrical waveguide. ElectroRing [12] senses the thumb and index fingers joining to form a pinch by propagating an 11 MHz AC signal through the fingers. SkinTrack [29] uses an AC signal injected by a worn ring sensed via a smartwatch to detect skin touches and relative location. Tomo [28] presents a worn band that performs electroimpedance tomography, a technique that takes a dense cross-section of the impedance within the arm via pair-wise measurements between eight surrounding electrodes; that work measures the pair-wise attenuation of a 40 kHz AC signal to produce a bio-impedance profile to classify eleven distinct hand poses.

Most similar to the application of this paper is EtherPose [13], which derives full 3D hand pose by using capacitive loading of two wrist-worn antennas excited at 1.4 GHz via a vector network analyzer (VNA). Our work builds upon the sensing techniques first described in Z-Ring[24]. Like Etherpose, we leverage a VNA for measurement, but rather than measuring load on external antennae, we instead propagate signal through the body, enabling a much more compact form factor. Similar to Tomo, we measure bioimpedance; however, we use reflected measurement across a swept range with higher frequencies from 1 MHz to 1 GHz. The benefits of this technique are twofold: (1) by using a swept measurement, we can collect a richer bio-impedance profile that captures power and phase information across frequency, enabling continuous hand tracking, and (2) by using reflected RF, we can both inject and measure signal through the same electrode, resulting in only a single point of instrumentation at the base of the index finger.

3 Z-POSE

3.1 Sensing Principle

Z-Pose appropriates the hand as a transceiver radio frequency (RF) antenna. It measures a common property of RF antennas, i.e., impedance, to facilitate pose estimation. The impedance of an RF antenna is dependent on its geometry. Therefore, with the hand acting as an antenna, changes in hand pose correspond to changes in hand impedance. Since each hand pose presents a unique impedance signature, fingerprinting this impedance characteristic lets us determine the pose of the hand.

The impedance measurement of the hand is calculated by injecting a low-power wideband RF signal into the finger via a ring electrode and analyzing its reflected signal. The measurement technique that we employ for this purpose is known as *S11 measurement*. In RF engineering, the S11 measurement, also called the *reflection coefficient* measurement, is a technique used to assess the reflection of a signal at a specific point in a system. In the context of Z-Pose, by examining the characteristics of the reflected signal, such as its amplitude and phase, we can derive valuable information about hand impedance. This impedance data is closely associated with the hand pose and serves as a basis for estimating the current hand pose.

3.2 Prototype

The Z-Pose system configuration consists of a ring (shown in 2) with two electrodes constructed on a flexible PCB. One electrode serves as an active signal electrode, and the other connects to a local ground via a 2MΩ resistor. The configuration and construction of the electrode resemble that detailed in [24]. However, unlike [24], we use smaller electrodes (20 mm × 5 mm) to reduce the ring's size. The electrodes are affixed to a 3D-printed ring and securely attached to the user's finger using velcro straps. Figure 2 shows the ring prototype.

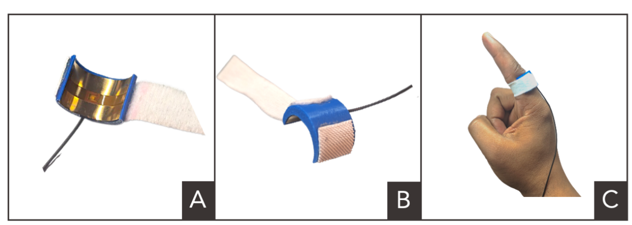

Figure 2: (A) Prototype ring electrodes, (B) the 3D printed mount and velcro for strapping, and (C) a user wearing the ring.

The ring's electrodes connect to a portable VNA (LiteVNA [1]) that performs the S11 measurement. The VNA is mounted on the user's wrist and connected to a laptop computer, allowing data streaming via USB. Our setup configures the VNA to sweep across the frequency range of 1 MHz to 1 GHz, which contains rich impedance information [24]. The measurements are conducted at a rate of 40 Hz, with an average output power of 5 dBm. Each measurement yields a 51-point array of complex numbers that contain the magnitude and phase values at various frequencies.

3.3 Hand Pose Tracking

Z-Pose utilizes the S11 measurements captured by the VNA to compute the continuous 3D hand pose. Each hand pose is associated with a distinctive impedance profile, and we establish a mapping between the impedance profile and the hand pose using an ML model. By collecting S11 measurements and corresponding hand pose information, we construct a regression model that can accurately determine unseen hand poses.

To obtain the ground-truth 3D hand pose information, we use MediaPipe's [4] camera-based hand tracking model, which delivers 21 key points of the hand and their corresponding 3D (x, y, and z) coordinates in real-world space. As a user performs hand actions in front of the camera, we capture hand pose coordinates for each image frame at a rate of 30 frames per second. Simultaneously, we capture S11 data and ensure synchronization of both the S11 and pose data by utilizing their respective timestamps.

We construct a regression ML model based on the acquired pose and S11 data, where each image frame is treated as an individual sample. The input feature vector for a frame is formed from the corresponding S11 measurement by concatenating the S11 phase and magnitude to form a 102-point feature vector (51 for phase + 51 for magnitude). The output label for the frame is a flattened array of all 21 hand coordinates detected in the frame, with a length of 63 (21 * 3). To build and train the regressor model, we use the RandomForestRegressor (number of trees = 500) along with the MultiOutputRegressor from the Scikit-learn [6] Python package.

4 EVALUATION

Our evaluation focuses on assessing the performance of hand pose tracking across a diverse range of hand poses. Additionally, we examine how the prototype performs when the hand is covered, such as when the user is wearing long sleeves or gloves, which can partially or completely occlude conventional optical hand tracking systems.

To evaluate our approach, we conducted two studies. The first study focused on the performance of hand pose determination. For this study, we instructed participants to execute a predefined set of 10 hand poses (Figure 1 upper row) inspired by previous work [11, 13], encompassing a wide range of hand configurations. Additionally, we captured data for intermediate hand poses that occurred during the transition from one predefined pose to another. The first study consisted of four sessions, each lasting 60 seconds, with short breaks between. In each session, the participants performed each pose four times. Throughout the study, participants received guidance on how to perform the poses via a pre-recorded video.

For the second study, our objective was to examine the impact of partially or fully covered hands. To achieve this, we asked participants to wear gloves while performing the ten proposed hand poses. During our tests, we experimented with various types of gloves and, as expected, found that MediaPipe had difficulty tracking hands when colored gloves were worn since the model was primarily trained on exposed hand data. To collect ground truth data even with gloves, we opted for transparent latex gloves, which Mediapipe could track. However, we observed that tracking performance was less stable than it was for exposed hands. Therefore, we limited this study to one session to demonstrate the proof-of-concept. In future iterations, alternative ground truth systems like a data glove could be considered for evaluation, letting us fully demonstrate Z-Ring's performance in optically occluded situations. Participants followed the same protocol as in Study 1, performing all ten poses, and we recorded data for both the proposed and intermediate poses.

During each study, participants were seated in a chair while wearing the prototype device, with a computer positioned in front of them that provided instructions for the actions to be performed.

5 RESULTS

Our initial evaluation included a total of 4 users. For the first study, we randomly selected 80% of the data from each session to train the ML model, with the remaining 20% used for testing. We built a separate model for each user. As a result, each model had approximately 5760 samples (0.8 * 60 sec * 4 sessions * 30 fps) for training and 1440 samples for testing. We present the mean Euclidean position error per key point for all 21 key points across all participants and the average error across all key points and participants.

Figure 3 shows the average error per key point in the estimation of hand pose for the first study. Among the key points, the highest mean Euclidean error of 15.51 mm was observed at point PINKY_TIP, while the lowest minimum error of 1.15 mm was recorded at point MIDDLE_FINGER_MCP. Generally, the error was more pronounced at the fingertips compared to finger bases due to the former's broader range of movement and articulation. The overall mean error across

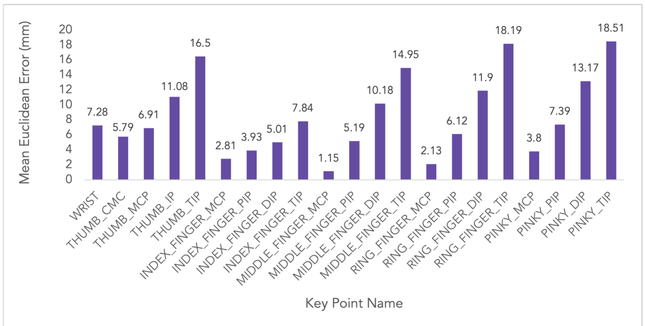

Figure 3: The mean Euclidean error for each key point across all participants, with the key point names as presented in MediaPipe [4].

all key points was 8.5 mm. Moreover, the error tended to be higher for fingers located farther from the index finger, where the ring was positioned, potentially resulting from signal attenuation as the distance from the ring increased. As a result, the pinky finger exhibited higher error rates. Additionally, despite the thumb being next to the index finger, it is spatially further away, leading to higher errors in thumb tracking, as well. This outcome is illustrated in Figure 4. Additionally, the mean error for individual participants P1-P4 was measured at 10.1 mm, 9.24 mm, 6.7 mm and 8 mm, respectively.

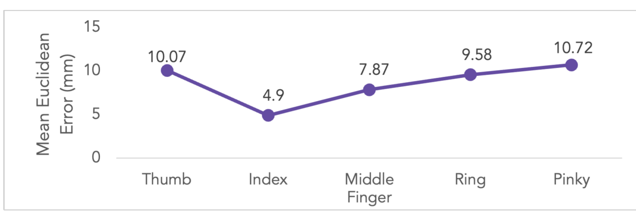

Figure 4: The mean Euclidean error for each finger, calculated by averaging the mean error of the four key points associated with that particular finger.

In the second study of occluded cases, we followed a similar approach to the first, developing individual models for each user. These models were trained using 80% of the data (1440 frames) and evaluated on the remaining 20% (360 frames). The results obtained were comparable to those of study 1. The average error across all key points was measured at 7.2 mm. The highest error of 11.13 mm was observed at the point PINKY_TIP, and the lowest error of 0.67 mm occurred at the point MIDDLE_FINGER_MCP. These results provide significant evidence of the capability of Z-Pose sensing to perform accurately even when the hand is partially or fully covered.

6 LIMITATIONS AND FUTURE WORK

One key limitation of our current work is that the system's performance declines in cross-session and cross-user scenarios. The decrease is due to the strong influence of electrode contact and hand anatomy on impedance measurement. As electrode contact changes (across sessions) or hand anatomy varies (across users), impedance profiles also change. One potential solution is to adopt derived features instead of absolute impedance values, which can provide greater stability across different configurations. Additionally, incorporating an inverse kinematics hand model can be utilized to constrain the predicted hand coordinates, enhancing realism and accuracy by avoiding impossible predictions.

Another limitation is that our current study involves a relatively small number of participants. In the future, we aim to conduct a more extensive user study with more participants and a more expansive range of scenarios to comprehensively identify the system's performance across diverse situations. Additionally, while our current version uses the ring worn on the index finger, exploring the impact on system performance when the ring is worn on other fingers, or when multiple rings are worn concurrently, is an intriguing avenue for future research.

7 CONCLUSION

This paper presents Z-Pose, a ring wearable that can track a full 3D hand pose using swept-frequency RF sensing with a single instrumentation point on the base of a finger. Through evaluation studies, we demonstrated the effectiveness of Z-Pose in accurately determining hand poses across various scenarios, including occluded cases. Areas for improvement remain, such as addressing the limitations in cross-session and cross-user scenarios, and we suggested potential solutions, such as incorporating derived features. We believe that Z-Pose offers a promising approach to continuous, fully articulated hand tracking, paving the way for enhanced interaction and control in numerous domains.

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