CARNEGIE MELLON UNIVERSITY

School of Architecture

College of Fine Arts

Thesis

Submitted in Partial Fulfillment of the requirements for the degree of

Master of Science in Computational Design

TITLE:
Specsync:Enhancing Privacy-Preserving Hand Tracking: An Indirect Sensing Approach Exploration for Wearables

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Abstract:

In recent years, the focus on wrist-worn devices for hand gesture and hand pose prediction and estimation has increased in the realm of research. Despite their remarkable accuracy, these devices have raised various concerns, particularly regarding user privacy. My thesis aims to address these concerns by exploring a system that utilizes a privacy-preserving approach to achieve hand tracking.

To mitigate privacy risks, the proposed system employs Electrical Impedance Tomography (EIT) as its primary sensing technique. EIT is a non-vision-based sensing method that acquires valuable data while ensuring data minimization, thus avoiding unnecessary information capture. This approach allows the device to function independently as a reliable hand pose estimation device.

With the incorporation of EIT, this research aims to enhance both the privacy and usability of wrist-worn devices for hand tracking applications. The proposed system holds large potential for addressing privacy concerns related to existing methods by employing the principles of data minimization through sensing technologies. The results contribute to the development of more secure and privacy preserving technologies for hand pose estimation.

Keywords: Hand-tracking, Privacy Preserving Sensing, Interaction Technique, Wearable Devices

Acknowledgments

First and foremost, I extend my deepest gratitude to my parents for their unwavering support throughout my journey studying abroad for my master's degree. This experience has undoubtedly opened numerous doors for me.

I am deeply thankful to Professor Eddy Man Kim for his guidance and suggestions for developing my thesis. I cherish the insights and encouragement provided by Jingyang Liu, which have been instrumental during my master's studies.

A special note of appreciation goes to Dr.Girad Laput. His talks revealed to me the vast potential of sensing techniques. Junyi Zhu's generosity in providing customized hardware, coupled with his expertise on EIT, has been invaluable.

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1. Background

1.1 Gestural Interaction and Wearable Device for Hand tracking

In the current digital transformation phase, we observe changes in how humans engage with digital tools and daily devices. The rise of (*Lyytinen and Yoo 2002*) and mixed reality technologies is shifting the boundaries of human-computer interaction, offering a more intuitive and immersive experience for everyone. One key development is the use of gestural interaction. Users can communicate with devices using natural movements of hands instead of relying on peripherals like a mouse or a keyboard. This intuitive and expressive interaction has potential applications across domains such as Mixed Reality (MR), IoT, and assistive technologies for individuals with physical disabilities.

The integration of wearable hand tracking enriches the immersive experience in Mixed Reality. It enables users to directly manipulate virtual objects with their hands, removing the need for holding bulky controllers. Moreover, it even supports free-hand interactions, allowing for intuitive user engagement even when hands are not in view(*Pei et al. 2022*). This capability offers novel interaction across diverse contexts.

Within the scope of ubiquitous computing, gestural interaction has the potential to transform our interaction with nearby devices. Consider(*"Home: Soli" n.d.*), which utilizes radar technology to detect hand gestures. This enables control over smart home appliances and facilitates interaction with digital information on devices. Such interactions contribute to a more seamless and intuitive engagement with both digital and physical environments.

Gestural interaction plays a crucial role in improving accessibility by providing an alternative to conventional input methods. Innovations like the "Assistive Touch" (*"Apple" n.d.*) feature on the Apple Watch allows users to navigate the screen without physically touching it. As a result, gestural technology fosters a more inclusive digital environment, broadening accessibility for diverse users.

While these new interaction paradigms promise to reshape how we interact with digital information, they pose new challenges. **In particular, as these devices collect, process, and transmit large amounts of personal and potentially sensitive data, privacy becomes a significant concern.** Addressing these issues is more than a technological solution but also involves considering user awareness and perceptions. Integrating privacy considerations into these new interaction paradigms' design and development process is vital as it could foster a secure and resilient digital interaction ecosystem.

1.2 Growing Concerns Regarding User Privacy in Wearable Device

Wearable devices, ranging from smartwatches to fitness trackers, seamlessly integrate computational capabilities into our daily environments and routines. This interaction seamlessly integrates computing into everyday existence. However, these technologies also give rise to privacy issues due to the personal and sensitive data they gather as outlined below.

a.Data Sensitivity and Monitoring

Wearable devices have access to an extensive collection of personal data about the user, including biometric data, health information, routines, and geographical locations. **Detailed profiles**(*Chen et al. 2007*) **are monitored due to continuous tracking.** Privacy concerns arise from who has access to this information and how it is used. For example, through daily activity tracking, a health band might reveal that a user typically wakes up around 8:00 AM, goes for a run around 9:00 AM, spends most of the workday seated before a laptop and has a break at 2:00 PM, and goes to bed around 11:00 PM. This data, combined with location information, can paint a detailed picture of a user's daily routine, habits, and lifestyle. The data may be recorded without the user's authorization and awareness.

b.Data Sharing and User Control

One of the crucial aspects to consider is data sharing. The data collected by wearables has always been shared with manufacturers and third parties to provide their services. Without transparent policies and shared control, data misuse can occur. For instance, once a health band collects a user's fitness data and shares this data with a third party, a user might suddenly receive targeted ads for sleep apps or health products, which they never anticipated. Furthermore, users often have limited control over the data-sharing process and might lack understanding of the full scope of data being collected.

c.Data Flow and Lack of Standards:

The boundary between digital and physical worlds is becoming increasingly blurred, with data continuously being communicated between devices and platforms. This constant data flow can be challenging to follow, raising serious privacy issues as it becomes increasingly difficult for users to keep track of where their data is going and who has access to it. Compounding this problem is the lack of standardized privacy guidelines across these devices and services. This absence of universal standards can lead to inconsistent privacy practices, making it more challenging for users to manage and protect their personal information effectively.

d.User Perception and Awareness:

The balance between the usefulness of devices and the need to protect personal data is hard to define for users(*Jeon and Lee 2022*). Many might be unaware of the depth of data collection, with control often being out of their hands. Factors such as the choice of sensors and the overall user experience can influence a user's perception of privacy. It's therefore essential for engineers and designers to thoughtfully consider how users perceive and can control their privacy when designing these technologies.

To address these concerns, we need a comprehensive reassessment of privacy considerations in the design and use of these technologies. **Users should be aware that they are involved in the decision making process about how their data is utilized, rather than just being passive sources of data.**

1.3 Privacy Concerns in Hand Tracking Devices

Privacy concerns with wearables have prominently emerged in hand-tracking technologies. These wearables, which often take the form of wristbands or camera mounted glasses, could capture and interpret hand and finger movements in real time through sensing technologies and machine learning algorithms. The resulting high-fidelity tracking offers support for intuitive gestural interaction but it also raises substantial privacy questions.

These devices' ability to sense an individual's hand and finger movements can potentially lead to **individual identification** such as facial features and bio-signals. Consider a device equipped with an Electromyography (EMG)(*McIntosh et al. 2016)* sensor that detects muscle signals for gesture interaction - this sensor can also theoretically be used to uniquely identify individuals based on their muscle patterns. If not handled carefully, this biometric data could be misused for identity theft or unwarranted surveillance.Thus, hand tracking technologies must be designed and deployed responsibly, ensuring the careful positioning of the sensor and handling of data to protect users' privacy.

Hand tracking devices, through their continuous monitoring of users' hand behavior, **gather a large amount of additional data.** This includes contextual information for patterns like typing, writing or even the location of objects in a user's surroundings. Furthermore, some of these devices use **sensor fusion**, an approach that merges data from different sensors to improve tracking accuracy. When combined with geographical or time data, this accumulation of information can create **detailed user profiles** of their daily activity pattern. Moreover, if the device's security measures are inadequate, connectivity features like Bluetooth or Wi-Fi may expose this information for unauthorized access. These information leaks can seriously infringe upon the privacy of the users and those around them.

The complexity of algorithms used in hand-tracking devices can leave users uncertain about how their raw data is being processed. These concerns are particularly evident in mixed reality (MR) applications, a key domain utilizing gestural interactions. MR experiences often engage third-party applications or services from big tech companies for their varied business interests. While this enhances MR functionality, it also risks data storage with third parties, who might use it for other business purposes. Spatial mapping(*Schwartz 1977*), aligns virtual and real-world environments but could involve capturing detailed 3D scans of the user's surroundings. Hand movements in MR can accidentally trigger functions, resulting in false alerts or unwanted data sharing. This scenario intensifies privacy issues linked to hand-tracking devices such as exposure of personal information and unauthorized data transfers.

Given these privacy challenges, it's evident that a proactive approach is needed in designing wearable systems. Ensuring that users have trust in these devices is paramount, and the solutions lie largely in the design and function of the wearables themselves.

1.4 Approaches to Improve Privacy in Designing Wearables System

An essential first step towards privacy preserving wearable systems is **data minimization** and **on-device processing**. Daily wearable devices equipped with several sensors require strict oversight over data collection practices. These Wearables devices should be designed to collect only essential data, omitting unnecessary contextual information. For example, hand tracking devices should only capture a specific user's hand movement. Moreover, on-device processing could substantially enhance privacy. Data can be processed locally by embedding sophisticated computing capabilities directly into the wearable device. On-device processing will reduce the need for data transmission to external servers or the cloud, Thus minimizing potential risks of data leaking or unauthorized usage.

In wearables, **Explicit and informed consent mechanisms** should be in place, giving users a clear understanding of what data will be collected, how it will be used, and who it might be shared with. Additionally, these mechanisms must specify when and why the data will be collected, which will foster transparency and user trust. **Having control over data granularity** is another approach that puts users in command of their privacy. Users should have the flexibility to decide the level of granularity about their data exhibits when collected and processed. For example, they might choose to share their recording from the smart band to better improve their sleeping quality but not their exact GPS coordinate; This option enables them to configure the amount of personal information and grant them greater control over data sharing.

From a corporate standpoint, **regular security audits and privacy assessments** are essential to maintain continuous privacy protection. These evaluations pinpoint vulnerabilities and ensure up-to-date regulatory compliance. With insights into evolving privacy policies, corporations can guide designers and developers to integrate appropriate privacy features into wearables before production. Additionally, user education on the significance of privacy and wearable functionalities is crucial. An unambiguous privacy policy provides direction on data management and safeguards.

2.Metric

From my extensive review, I've highlighted two distinct projects published recently, each utilizing a unique sensing method for hand tracking. Despite their differences, both projects aim to create wearables for precise hand pose estimation. My evaluation focuses on their privacy practices, specifically data minimization. I delve into the strengths and weaknesses of their strategies. Furthermore, through my proprietary metrics, I assess these projects using my own measures regarding data minimization, offering a platform for reflection and improvement.

Drawing from my research, I've developed a set of metrics to assess data minimization in hand-tracking technologies. With these metrics as a foundation, I conducted a comprehensive review of recent literature and spotlighted two significant projects(*Devrio and Harrison 2022*)(*Kim and Harrison 2022*), each employing a unique sensing method for hand tracking. Though they differ in approach, both projects converge on a common ambition: designing wearables for precise hand pose estimation. My evaluation focuses on their privacy practices, specifically data minimization. I delve into the strengths and weaknesses of their strategies. Furthermore, through my proprietary metrics, I assess these projects using my own measures regarding data minimization, offering a platform for reflection and improvement.

2.1 Design Metric

I've established these metrics for evaluating Data Minimization in sensing technique.

1. **Data Complexity:** This metric evaluates the **complexity of the data** required for hand pose estimation, considering factors such as data type (2D, 3D, depth, etc.), sensor fusion, and the potential risk of merging this data. A less complex dataset may not only enhance processing efficiency and device performance but also bolster privacy preservation.

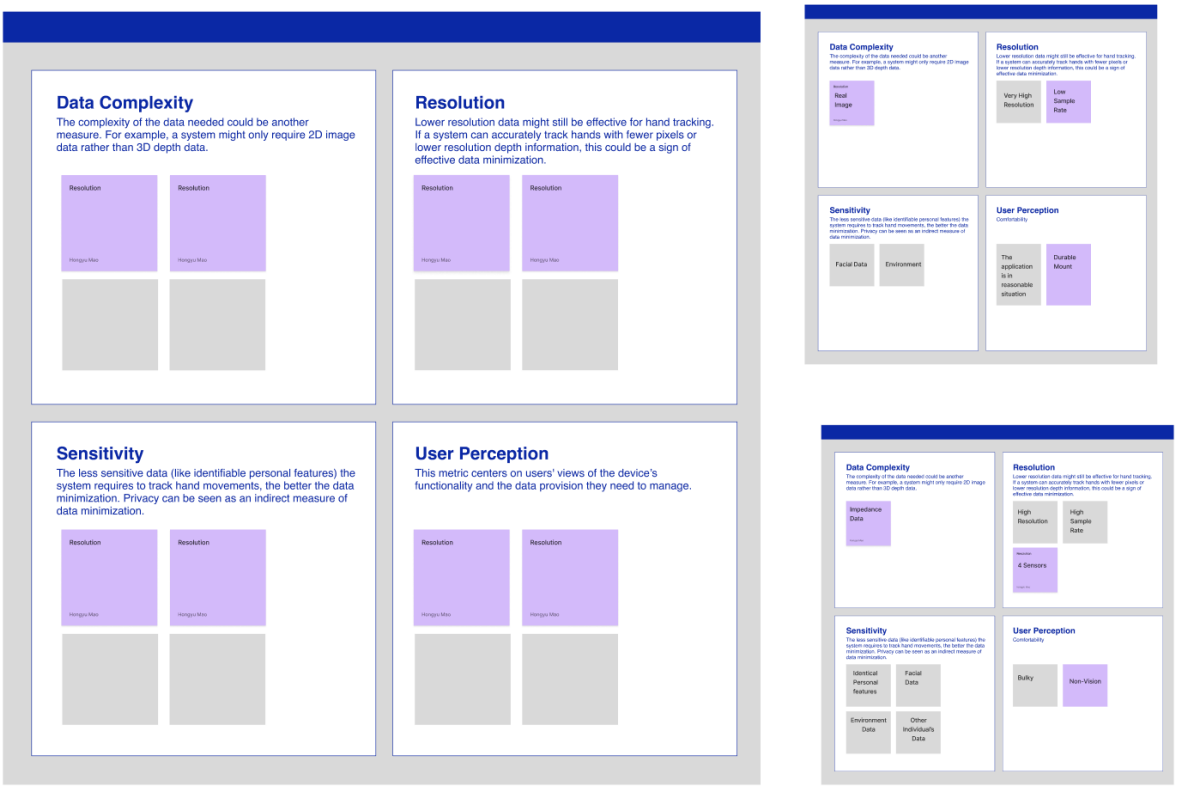
2. **Data Resolution:** This relates to the **granularity of details** captured by the sensing modality. In the realm of depth sensors, a higher resolution offers a more detailed depiction of hand structure and motion but could increase data usage and thereby pose privacy risks. It's crucial to strike an optimal balance between accuracy and data reduction to uphold privacy.

3. **Data Sensitivity:** This refers to the device's potential to capture **personal or sensitive data**, including identifiable features or private environments like bio-information. High sensitivity of information implies a greater likelihood for the device to capture personal or sensitive data, which could increase privacy risks. Thus, it's necessary for the device to have built-in measures that limit the collection of unnecessary or sensitive data to maintain user privacy.

4. **User Perception:** This metric centers on users' views of the device's functionality and the data provision they need to manage. It gauges factors like user comfort, usability, perceived accuracy, and any user privacy worries. This can be assessed via user feedback, surveys, or user testing sessions. A favorable user perception can substantially boost the device's acceptability about the usage of sensors while providing a feeling of security.

2.2 Evaluation Form

To further aid in our assessment, an **interactive evaluation form** was devised. Each column and row on this form corresponds to one of the evaluation metrics mentioned earlier. Each metric is clearly defined beneath its title. During project analysis, gray sticky notes symbolize "Cons," while purple represents "Pros" pertaining to each sub-category. This distinction facilitates a structured evaluation. When I execute the test, I consult the specifics provided in the research paper, subsequently aligning pertinent details with the metric form. This approach not only streamlines the evaluation process but also enriches my comprehension of data minimization.

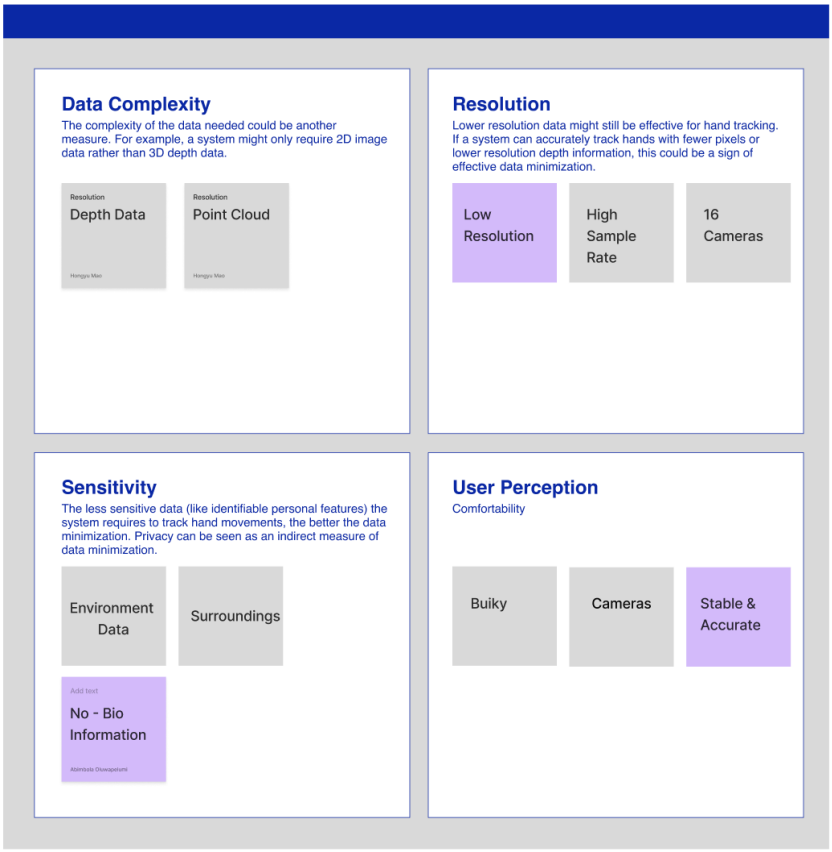


Img1: Metrics Developed for Evaluating Data Minimization in Sensing Modalities

2.3 Review of Current Sensing Modality for Hand Tracking:

Point Cloud Fisheye Cameras

DiscoBand(*Devrio and Harrison 2022*) is equipped with an 8x8 resolution depth sensor that's strategically mounted around the wrist. This cutting edge technique is capable of detecting not just dynamic hand movements, but it also tracks arm movements, body pose, and even the immediate surroundings. Even with its camera components, DiscoBand maintains a slim profile with a thickness of merely 1.2 centimeters.



Img2: Evaluation of DiscoBand

Data Complexity: The device employs a depth camera to collect three-dimensional point cloud data, This process might entail gathering more spatial or environmental data than is typically necessary, thereby increasing the complexity.

Resolution: The fidelity of the device is relatively low with a 8*8 pixel resolution, restricting the ability to distinguish specific shapes or faces when the camera scans the surroundings.

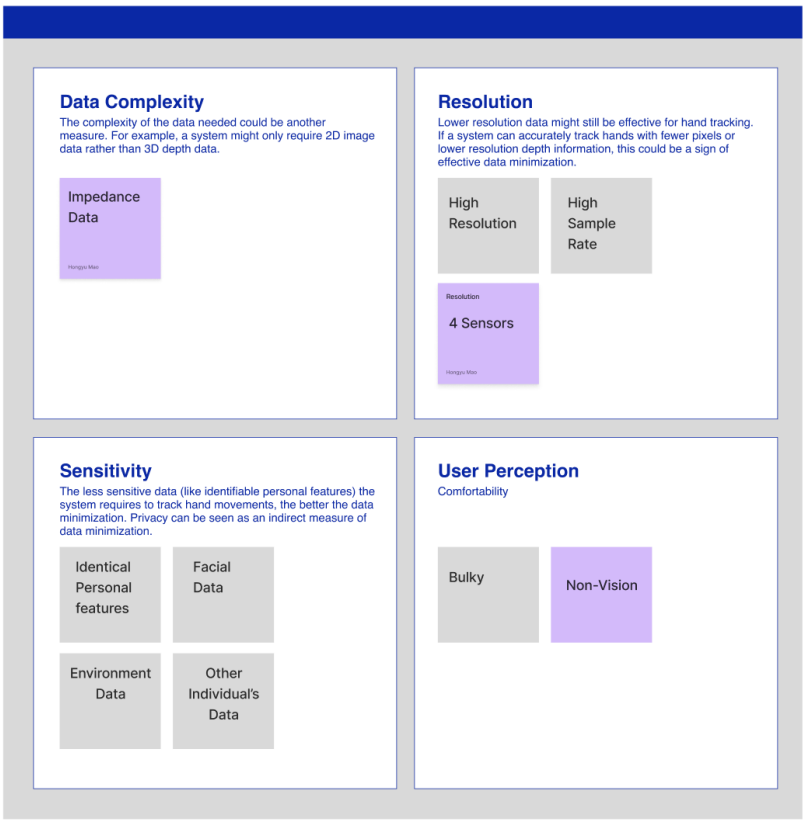
Sensitivity: Depth cameras do not capture personal bio-signals, reducing potential privacy breaches. However, due to the camera's wide Field of View (FoV) and its orientation towards the surrounding environment, the device may unintentionally record extraneous scenery or individuals nearby, potentially infringing upon their privacy.

User Perception: While the inclusion of a camera could raise privacy concerns, the device's direct sensing approach ensures reliable measurements, and its slim profile boosts wearability.

In conclusion, despite using a depth camera, DiscoBand operates at a modest resolution of 8x8. This lower resolution offers an advantage in that it filters out excessively detailed information, preserving user privacy by not capturing personal biometric data. This can be attributed to its indirect sensing approach, which is inherently less intrusive. However, one potential drawback is its tendency to record the surroundings due to some cameras being outward-facing. On the other hand, when direct sensing methods are employed, the device tends to generate more stable and accurate signals. This project demonstrates a careful balance between data collection and privacy preservation.

RF Sensor (Radio frequency)

Another approach comes from **EtherPose**(*Kim and Harrison 2022*). In this method, the author employs two RF sensors to analyze changes in the phase and magnitude of signals, which correspond to a user's hand pose. It's unclear if this should be categorized as an indirect or direct sensing approach. Although it doesn't utilize a camera, the high resolution of the device allows for inference of the user’s hand shape and even facial features based on the signal.



Img3: Evaluation of DiscoBand

Complexity: RF sensing is primarily designed to detect impedance data, specifically the impedance of an object without requiring strong connectivity. This method identifies changes in an object based on shifts in impedance, but it doesn't provide direct or complex datasets.

Resolution:The RF sensor boasts a very high resolution coupled with an impressive sampling rate. Such a high resolution can image people’s faces and even gather data on nearby individuals.

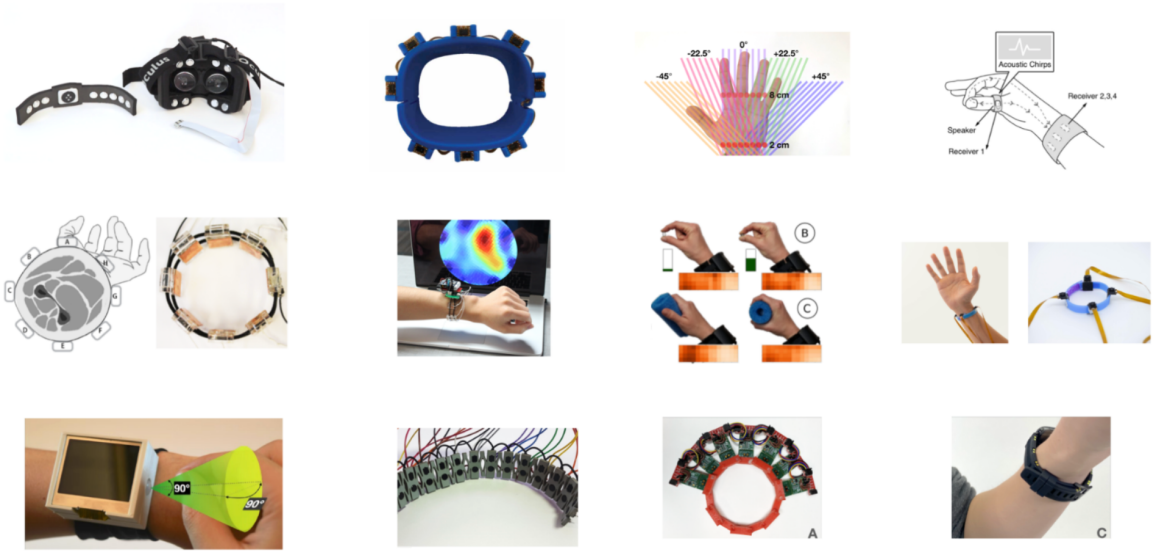
Sensitivity: While the data collected might not be equivalent to a camera's capture, it's still highly sensitive. RF sensing can obtain personal features, facial data, identity markers, and details of the surroundings, including data from others within the sensor's range. This high sensitivity could lead to potential privacy concerns.

User Perception: The design of the RF sensing device can be perceived as bulky, primarily due to the necessity of affixing two antennas on either side. Many commercial antennas are large, which adds to the device's bulkiness. However, it offers a non-vision-based approach to sensing, which may appeal to some users.

RF sensing's capability to penetrate walls and other physical barriers brings forth concerns about unintentionally tracking individuals in private spaces without their consent. As a result, signals can often encounter environmental noise. Reflections, refractions, and scattering of RF signals introduce noise that impacts sensing performance. In environments with multiple reflecting surfaces, RF signals can undergo multipath interference, leading to signal distortion and potentially affecting the accuracy of RF sensing systems.Furthermore, RF sensing can capture the unique patterns and characteristics of a person's hand movements. These biometric markers might be used to identify or track individuals across varied locations or devices without their awareness, posing a significant threat to personal privacy.

3. Methodology

3.1 Sensing modality Investigation



Img4: List of sensing band for hand tracking using different sensing modality

My investigation began with a comprehensive examination of past projects related to hand tracking, as seen in Figure 1. This involved delving into major research domains such as Human-Computer Interaction (HCI) and Interaction Techniques, as well as evaluating commercial products like the Myo ArmBand(*Di Donato n.d.)* developed by various tech companies.

The review process included a study of the related research papers and product descriptions, focusing on factors like project duration, pricing, and detailed hardware specifications. This in-depth review provided me with a broader understanding of the types of sensing modalities commonly employed for hand tracking and the respective advantages and drawbacks associated with each approach.

	Title	Sensing Modality	Notes
Direct Sensing			
	FingerTrak: Continuous 3D Hand Pose Tracking by Deep Learning Hand Silhouettes Captured by Miniature Thermal Cameras on Wrist*(Hu et al. 2020)*	Thermal Cameras	Bio-signals
	Interferi: Gesture Sensing using On-Body Acoustic Interferometry*(Iravantchi et al. 2019)*	Interferoni	
	Silhouette-Based Synthetic Data Generation For 3D Human Pose Estimation With A Single Wrist-Mounted 360° Camera*(Hori et al. 2021)*	360° Camera	Fish-eye cameras
	Opisthenar: Hand Poses and Finger Tapping Recognition by Observing Back of Hand Using Embedded Wrist Camera*(Yeo et al. 2019)*	RGB Camera	
	BeamBand: Hand Gesture Sensing with Ultrasonic Beamforming*(Iravantchi, Goel, and Harrison 2019)*	Ultrasonic	
	ThumbTrak: Recognizing Micro-finger Poses Using a Ring with Proximity Sensing*(Sun et al. 2021)*	proximity Sensors (VL6180X)	Micro Gestures detection
	Back-Hand-Pose: 3D Hand Pose Estimation for a Wrist-worn Camera via Dorsum Deformation Network*(Wu et al. 2020)*	RGB Camera	NN, works on DL pipeline
	Hand with Sensing Sphere: Body-Centered Spatial Interactions with a Hand-Worn Spherical Camera*(Arakawa et al. 2020)*	Spherical Camera	Mechanism + direct sensing
	Pyro: Thumb-Tip Gesture Recognition Using Pyroelectric Infrared Sensing*(Gong et al. 2017)*	Infrared Sensing	
	WristWhirl: One-handed Continuous Smartwatch Input using Wrist Gestures*(Gong, Yang, and Irani 2016)*	Infrared Sensing + Piezo + IMU	

	DiscoBand: Multiview Depth-Sensing Smartwatch Strap for Hand, Body and Environment Tracking*(Devrio and Harrison 2022)*	Depth Camera detect 8*8 pixel point cloud	8*8 resolution Point cloud data
	FingerTrak: Continuous 3D Hand Pose Tracking by Deep Learning Hand Silhouettes Captured by Miniature Thermal Cameras on Wrist*(Hu et al. 2020)*	Thermal Camera	
Indirect Sensing Approach	RFID-based 3D human pose tracking: A subject generalization approach*(Yang, Wang, and Mao 2022)*	RFID Sensing	Antenna based
	SmartLens: sensing eye activities using zero-power contact lens*(Li et al. 2022)*	EOG Sensor	
	CRH: A Contactless Respiration and Heartbeat Monitoring System with COTS RFID Tags*(Zhao et al. 2018)*	RFID	
	A Novel PPG-FMG-ACC Wristband for Hand Gesture Recognition*(Wang et al. 2022)*	PPG + FMG + ACC	Health related band
	Sensing Hand Interactions with Everyday Objects by Profiling Wrist Topography*(Rudolph et al. 2022)*	Capacitive Sensing	Non - touch interaction
	CapBand: Battery-free Successive Capacitance Sensing Wristband for Hand Gesture Recognition*(Truong et al. 2018)*	Capacitive Sensing	
	GestureWrist and GesturePad: unobtrusive wearable interaction devices*(Rekimoto 2001)*	Capacitive Sensing	
	Tomo: Wearable, Low-Cost Electrical Impedance Tomography for Hand Gesture Recognition*(Y. Zhang and Harrison 2015)*	Electrical Impedance	
	A wearable biosensing system with in-sensor adaptive machine learning for hand gesture recognition*(Moin et al. 2020)*	EMG	Muscle signals
	SensIR: Detecting Hand Gestures with a Wearable Bracelet using Infrared Transmission and Reflection*(McIntosh, Marzo, and*	IR	

	Fraser 2017)		
	GestEar: combining audio and motion sensing for gesture recognition on smartwatches*(Becker, Fessler, and Sörös 2019)*	Sound Emitting	
	fSense: Unlocking the Dimension of Force for Gestural Interactions using Smartwatch PPG Sensor*(Buddhika et al. 2019)*	PPG	
	FingerPing: Recognizing Fine-grained Hand Poses using Active Acoustic On-body Sensing(*C. Zhang et al. 2018)*	Contact Microphone/Speaker - Chirp Signal	contact-required
	Myo Armband	EMG Sensor	Commercial products

Fig1: Sensing modality analysis of previous research projects

These sensing modalities can be broadly classified into three categories:

Direct Sensing Approaches: Direct sensing modalities directly measure hand or finger position, orientation, or movement. For instance, optical sensors like cameras(*Devrio and Harrison 2022*) could be included, which can track hand movements by processing the image data. The primary advantage of direct sensing is that it can provide highly accurate and detailed tracking. However, it may be influenced by environmental factors, such as lighting for optical sensors, and typically requires line-of-sight to the hand or fingers.

Indirect Sensing Approaches: Indirect sensing modalities infer hand or finger position, orientation, or movement from other types of data. For example, Electrical Impedance Tomography (EIT)*(Y. Zhang and Harrison 2015)* is an indirect sensing approach that infers hand position from measurements of electrical impedance on the wrist. Acoustic sensors, which infer position from sound waves, are another example of indirect sensing. The advantages of indirect sensing include less susceptibility to environmental factors and potentially more privacy-preserving, as they don't require visual data. However, they may be less accurate or more complex to implement than direct sensing approaches.

Mechanical Methods Combined with Sensing Approaches: These are systems that merge mechanical setups with sensors to record hand movements. For instance, a unique method is the use of mirror balls*(Arakawa et al. 2020)* to reflect the image of the hand. Through computer vision techniques, this reflected image can be analyzed to extract information about hand joints and movements and surroundings. Mechanical Methods can theoretically reduce the amount of

sensors used, and reduce the size of the devices. However, they may require a more complex setup and could be perceived as more obtrusive or less comfortable by the user compared to non-contact sensing techniques.

Evaluating hand tracking methods involves assessing five key factors: privacy implications, accuracy, user comfort, cost-effectiveness, and manufacturing feasibility. These metrics address potential privacy issues, precision in tracking, comfort for the user, affordability, and practicality in large-scale production.

Study Conclusions:

Upon completing the initial phase of research, I gained the following insight:

Direct sensing methods are precise but often bulky, power-consuming, and may raise privacy concerns. Indirect sensing, while more flexible and privacy-conscious, might produce ambiguous signals. Both approaches demand intricate calibration. This process is often complex and not user-friendly, thereby limiting user control and customization options.

To achieve high-accuracy hand tracking that preserves privacy, several critical factors need to be considered:

1. Data Minimization: How might we streamline the hand tracking process to gather only essential data, ensuring accuracy without unnecessary data collection?

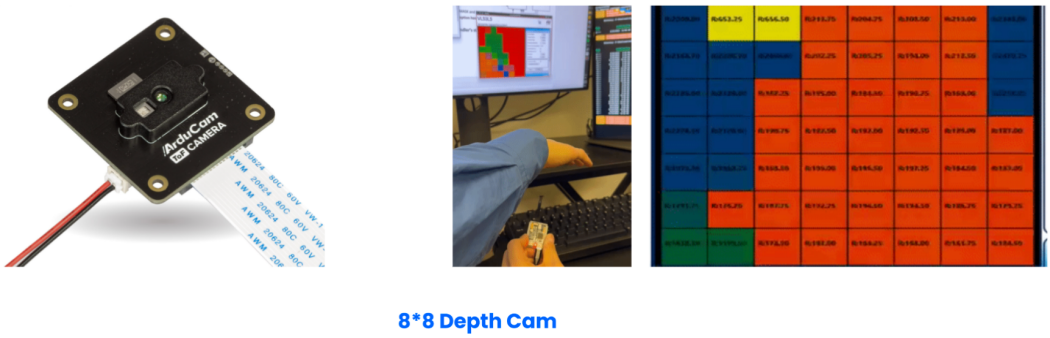
2. Long-term Wearable Reliability: For devices intended for long-term wear, what mechanisms can be implemented to guarantee sustained accuracy while making users feel safe and reliable?

3. Vision-assisted Accuracy with Privacy: When integrating a vision-based approach for enhanced accuracy is necessary, in which situations can we address and alleviate user privacy concerns most effectively?

With this inquiry in mind, I started my sensing modality exploration. Drawing from prior reviews, I identified potential candidates then proceeded to craft a range of prototypes to evaluate their signal outputs. By weighing the advantages and disadvantages of these modalities for hand tracking, I've documented both my prototype construction process and the insights from my experiments. This systematic approach allowed me to deeply examine and understand the balance between data collection and device functionality.

Direct Sensing: Fisheye Camera & Cloud Point Camera

A cloud point camera is a depth-sensing device that employs infrared light projection in tandem with an image sensor to create a 3D visualization of the surroundings. Such a system not only offers a larger Field of View (FOV) but also upholds user privacy more effectively. In my prototype, I incorporated the VL53L5CX module, previously tested on another platform. My investigation centered on the module's accuracy and real-time responsiveness in capturing object changes, versus its depth perception capabilities. Given its low resolution of 8x8, the module often struggles to represent the exact shape of an object, making it challenging to identify the captured object. Interestingly, this ambiguity is advantageous for privacy concerns. Furthermore, the camera's ability to swiftly capture real-time movements indicates high accuracy. When juxtaposed with alternative cameras, the VL53 proves to be a more suitable option.



Img5: Depth camera exploration, the right image shows the detected signals for hand

Pros: Advantages of the current system include accurate hand-tracking with low resolution and a level of privacy protection that is superior to conventional RGB cameras. Furthermore, the system has proven to be stable and reliable.

Cons: The disadvantages include its camera-based nature, high energy consumption as each module requires a battery, and potential intrusion on user privacy as it can record the surroundings. Also, the smallest module has a size of 1cm, which might be considered somewhat bulky.

Biometric sensors

Biometric sensors are specialized instruments capable of identifying and quantifying physical and behavioral characteristics. In the context of hand tracking, these sensors detect the pressure change caused by muscular shifts that manifest when a user initiates various gestures. The

prototype, equipped with a network of 30 such sensors embedded around the wrist, successfully identified a repertoire of approximately ten distinct gestures with an accuracy of around 80%.

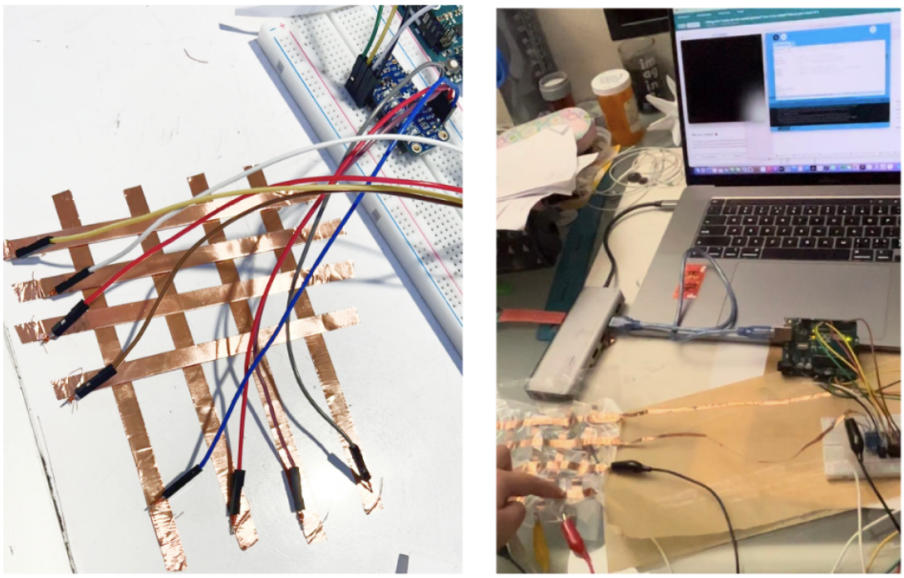
While biometric sensors were effective in identifying standard gestures, they struggled to accurately detect micro-gestures due to their limited resolution. Further, the readings were affected by external factors like temperature changes, which introduced complexity and inconsistency in data interpretation. For improved hand-tracking accuracy, future work may require temperature-adjusted readings or alternative, more resilient sensor technologies.

Pros: The sensors can be embedded into silicon, making the device comfortable to wear. Additionally, these sensors require minimal power to function, which could potentially extend battery life.

Cons: On the downside, the sensors can be unreliable and prone to malfunctioning. Furthermore, the device requires a significant number of sensors, which could complicate its design and construction.

Indirect Sensing Modality: Capacitive sensing

Capacitive sensing is a sensing modality that can detect changes in an electrical field. It operates based on the principle that the human body, being an electrical conductor, can alter the electrical capacity of a nearby sensor. This change in capacity can be measured and used to detect various states or events. Using the Multi Touch Kit's *(Pourjafarian et al., 2019)* guidelines, I created a wrist-wearable capacitive sensing prototype. Its lightweight property made the design comfortable, but the test signals revealed two main challenges. First, its extreme sensitivity detected even minor skin changes, leading to 'body noise' and numerous minor false positives. Second, it struggled to capture deeper internal muscle movements. It is less effective than other body signal detection methods in accessing comprehensive physiological insights.



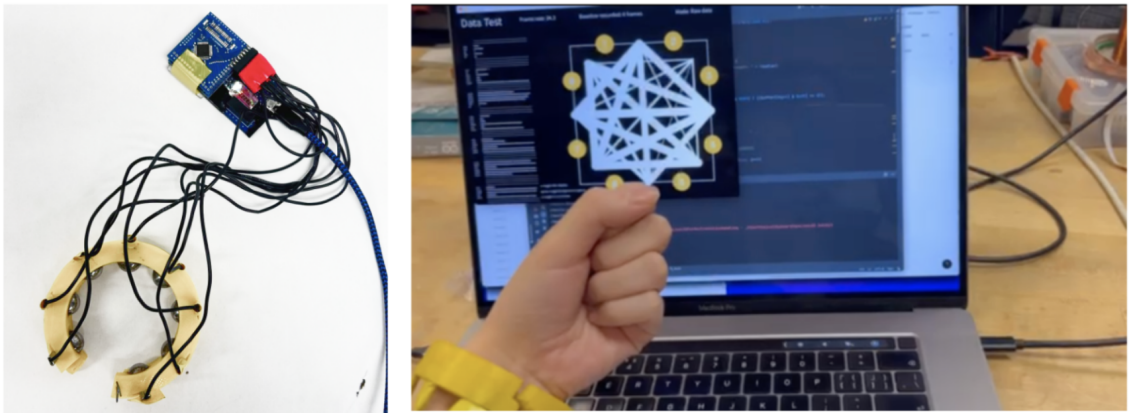
Img6: Prototype of capacitive sensing, the library is from Multi Touch Kit(Pourjafarian et al. 2019)

Pros: Capacitive sensing offers the ability to detect gestures without any physical contact, thereby ensuring a more comfortable user experience while reducing wear and tear on the device. Moreover, their high sensitivity to changes in the electric field makes them capable of capturing even the most nuanced hand movements. A key benefit of capacitive sensors is their low power consumption which is a crucial factor for wearable devices aiming for longevity. Additionally, they are relatively cost-effective to manufacture, making them a good choice for budget-conscious applications.

Cons: Capacitive sensing can be sensitive to environmental changes, such as temperature fluctuations and variations in humidity, which could lead to inaccurate gesture readings. Furthermore, capacitive sensors typically have a limited range, potentially restricting the types and scale of detectable hand gestures. The presence of other electronic devices or conductive materials could cause interference, resulting in false detections. Lastly, their performance is reliant on the surface properties of the object. Factors such as moisture, skin, hair or dirt on the surface can potentially affect the sensor readings.

Electrical Impedance Tomography:

Electrical Impedance Tomography (EIT) is a non-invasive imaging technique that creates images based on the electrical conductivity, permittivity, and impedance of an object or a part of the body*(Y. Zhang and Harrison 2015)*. It uses surface electrodes to inject small electrical currents and measure the resulting electric field. EIT operates by detecting changes in internal electrical properties. This technique aids in producing detailed 2D or 3D images. The sensitivity of EIT signals to tissue composition and structure allows them to identify subtle hand movements. To understand this better, I assembled a preliminary prototype to examine these signals.



Img6: Prototype build for electrical impedance tomography

Pros: The primary advantage of EIT is its non-invasive nature. No radiation is involved and it can be applied in real-time, making it safe and suitable for continuous monitoring. This method is used in various fields, including medical imaging, industrial process monitoring, geophysics, and more recently, in detecting and tracking hand gestures.

In the context of hand tracking, EIT uses electrical currents to generate images of the hand's internal structure, including the complex network of muscles and tendons. By observing how this internal structure changes during different hand gestures, EIT can determine the specific hand gesture being made.

Cons: EIT as an indirect sensing method, can introduce certain complexities. The most pressing one is the requirement for a robust training dataset and regular calibration processes to compensate for the indirect measurements, leading to potentially confusing signals that can make data interpretation more challenging. Therefore, despite its potential, EIT demands careful handling and advanced analysis techniques to mitigate these inherent difficulties.

In contrast to capacitive sensing, EIT provides a more detailed understanding of the interior structure of the human body. The ability to view beneath the skin enables accurate tracking of muscles and tendons, essential for precise gesture recognition. However, one of EIT's advantages is its focused data acquisition. Unlike capacitive sensors, which can pick up environmental changes and other irrelevant information, EIT solely measures changes in electrical properties within a defined area. This characteristic leads to a more targeted and potentially cleaner dataset, enhancing its utility for hand tracking applications. Nonetheless, the interpretation of this data requires complex processing techniques due to its indirect nature.

3.2 Electrical Impedance Tomography (EIT) as a Privacy-Preserving Sensing Modality

After several experiments, I've decided to employ electrical impedance tomography (EIT) as the sensing approach due to several compelling reasons. First and foremost, **EIT does not involve the collection of visual data**, thereby significantly reducing privacy concerns. It also allows for **local processing**, which means that sensitive data can be processed on the device itself, eliminating the need for potentially vulnerable data transmissions. Furthermore, EIT provides high spatial resolution and is **less susceptible to environmental noise**, making it a robust solution in a variety of settings.

However, as with any method, there are trade-offs associated with using EIT. One of the challenges is that the information collected can be **less straightforward** compared to a vision-based approach, potentially leading to some confusion in interpreting the data. Also, EIT collects certain biological information that could potentially identify an individual. This could raise privacy concerns while serving as a functional feature if user identification is part of the device's purpose. Another drawback is the need for training and calibration, which may pose usability challenges for the end-user. Lastly, EIT could potentially struggle with accurately sensing complex movements, a limitation that would need to be addressed in the design and application of the device

To obtain the optimal signals from electrical impedance tomography (EIT), various factors come into play.

Electrode Placement: The location on the body where the electrodes are placed significantly impacts the quality of the data captured. Based on experiments, placement on legs requires more inject current compared to arms; The muscles in the elbow are more sensitive to movement.

Electrode Selection: Electrode selection is crucial for the effectiveness of Electrical Impedance Tomography (EIT). It's not just about the number of electrodes, but also their material, size, and use of conductive gels. Electrode material, chosen for its electrical properties and skin compatibility, influences signal clarity. The electrode size, balancing broad skin contact and user comfort, impacts signal stability. Conductive gels can enhance signal quality by improving the skin-electrode interface, but their use must consider practicality and user comfort.

Measurement Approach: The technique used for measurement, such as a 4-pole*(Y. Zhang, Xiao, and Harrison 2016)* or 2-pole *(Y. Zhang and Harrison 2015)*method, can affect the

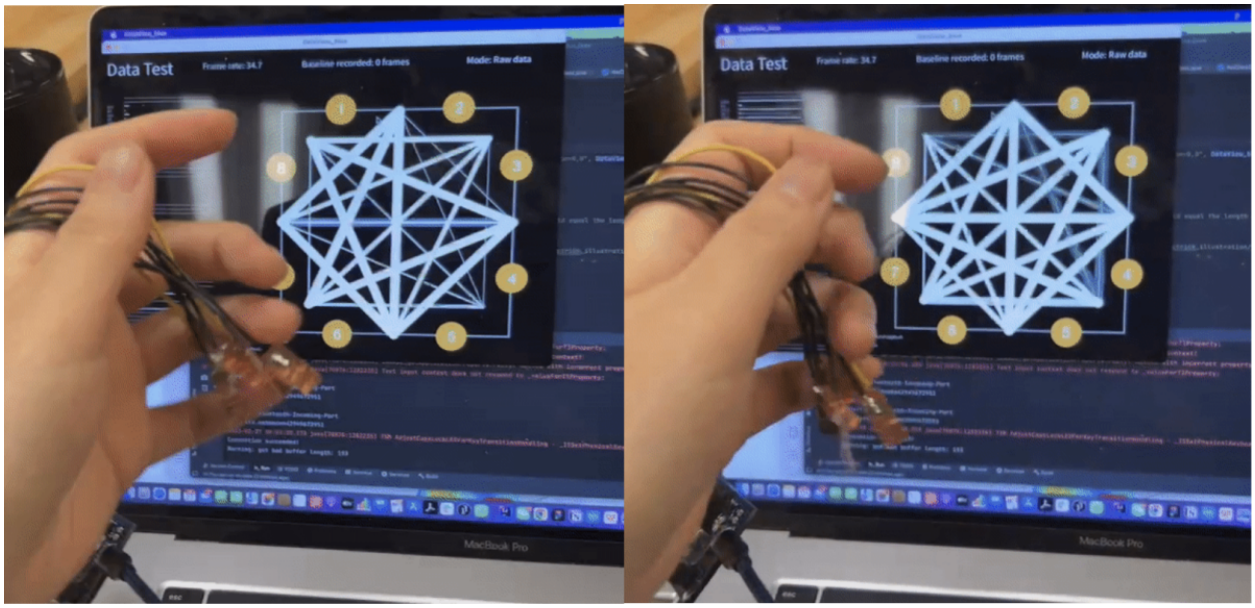
accuracy and precision of the EIT readings. 4 pole technique leads to more accurate measurements.

Sensing Board Selection: The type of sensing board, whether it's a current-injecting board, a TOMO board, or a board specifically designed for EIT, can have a considerable effect on the performance and reliability of the EIT method.

So I made combinations as follows:

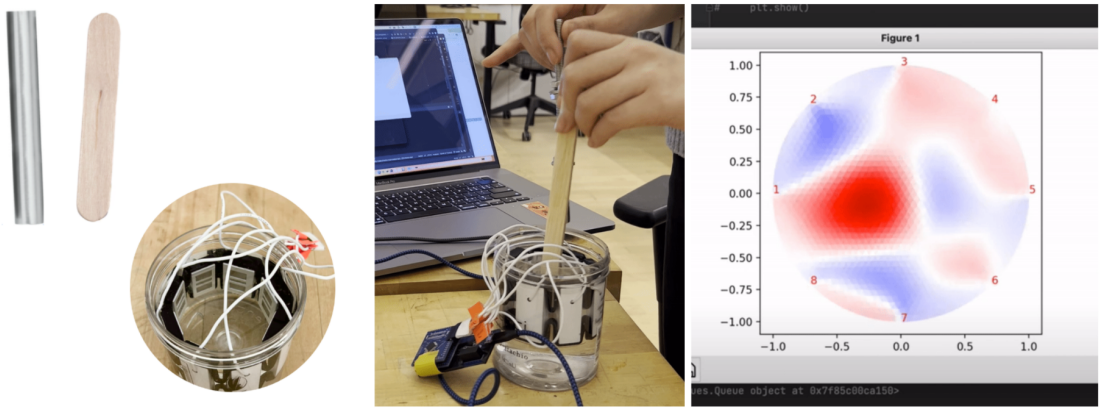


Img7:Prototype shows different combinations of Electrical Impedance Tomography



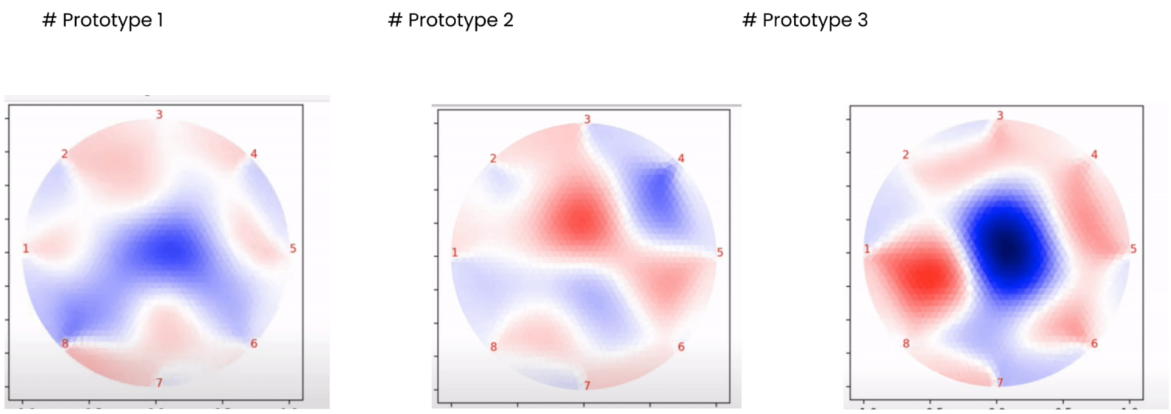
Img8:Visualizer for live raw signals from EIT

Several tools were used to analyze the data obtained from the EIT device. The first tool was designed to examine raw signals, effectively displaying voltage values that could be translated into impedance values representing tissue characteristics.



Img9: Left:experiments set up to test devices' signals
Middle: Conducting the test
Right:Reconstructed image of EIT signals

The second tool employed specific algorithms, such as PyEIT(Liu et al. 2018), to generate reconstructed images based on the data. These images provided a more intuitive representation of the information captured by the device.



Img10: :Reconstructed images for different combinations of prototypes

I conducted an experiment using a stainless steel stick and a wooden stick, given their differing impedances. When placed in the same container outfitted with EIT electrodes, they should be distinctly represented by different colors in the visualizer. After several trials, I identified an optimal combination of components for the device. Initially, I considered using 16 electrodes for better signal reception, but the practical application presented challenges. During gesture execution, maintaining consistent connectivity across all 16 electrodes proved to be difficult. Consequently, I opted for an 8-electrode setup, constructed from stainless steel, using a 4-pole measurement system, which offered a reliable and manageable solution.

3.3 Wearable Device for Hand Tracking

In designing the final prototype that uses electrical impedance tomography for hand tracking, three key principles must be considered: reliability, data minimization.

Ensuring reliability and high accuracy is critical for a dependable hand-tracking experience. The device should consistently track hand movements with precision across a variety of conditions, including different hand sizes, user postures, and activity levels. This will enhance user trust and satisfaction, while ensuring accurate data capture for effective hand movement analysis.

Data minimization is about ensuring the device collects only the necessary data to accurately track hand movements. This respects user privacy and complies with best practices for data handling. An effective hand tracking device must identify what data points are essential and exclude any unnecessary data collection.

After considering various options and going through several rounds of iterations, I decided to use the **Myo Armband** as the basis for my final prototype. This decision was based on the Myo Armband's superior conductivity, flexibility, comfort, and connectivity for various arm positions and extended wear.

The device was placed near the arm's pulse to capitalize on the muscle and vascular structures, enhancing the EIT readings. While the Myo Armband offered a reliable framework, it required significant modifications to meet my specifications for hand tracking.

I conducted a comprehensive teardown of the Myo Armband to understand its function and design. This not only informed my adaptation process but also helped me visualize the signals my modified device would interpret. These insights were invaluable during the subsequent testing phases, where I closely monitored the signals' responsiveness to hand movements.

The final prototype involved several crucial modifications on Myo Armband to suit the purpose of this research

Case Design: The original case design of the Myo Armband was retained, ensuring a flexible fit for various arm sizes and positions.

Electrode Selection:The eight stainless steel electrodes from the original design were maintained, essential for injecting current into the arm and capturing data.

PCB Replacement: The original PCB was removed and replaced with a EIT sensing board

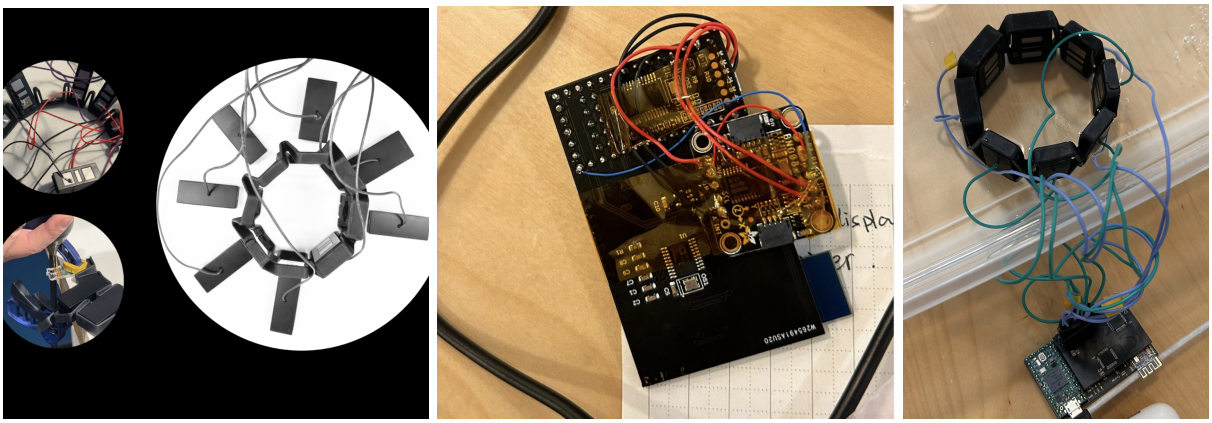
Connectivity and Data Processing: The design integrates the **HM-18**, a Bluetooth Low Energy (BLE) 5.0 module, for efficient data communication and real-time processing with a PC.

Additional Sensor: To enhance the device's accuracy and performance, I equipped it with an IMU sensor that provides complementary data and detects arm rotation.

The final prototype offers a balance of accuracy, comfort, and user-friendly design. It represents a reliable and tailored solution for hand tracking, making optimal use of the features offered by the original Myo Armband while incorporating necessary modifications to suit my requirements.



Img11: Left:Original MyoArmbandRight: Tear down of MyoArmband



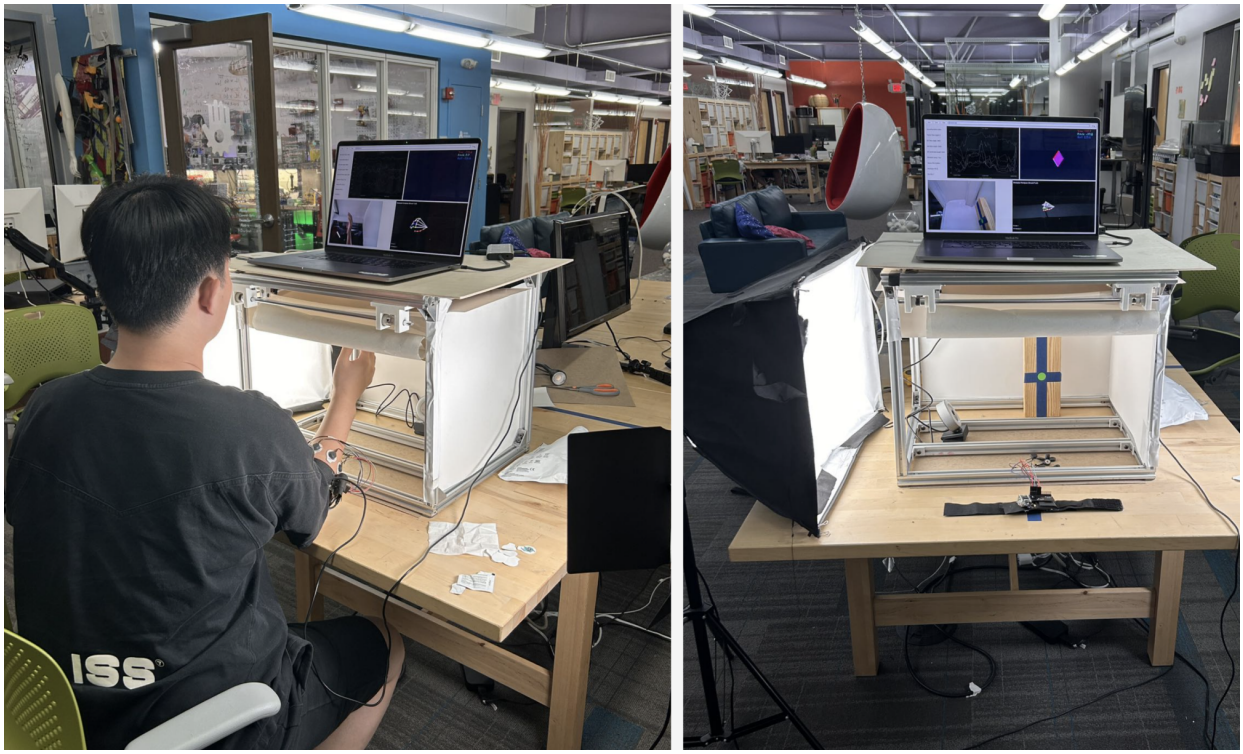
Img12: Left: Re-assemble Right: Adding IMU to the sensor board that share the same SPI

3.4 Data Collection Process

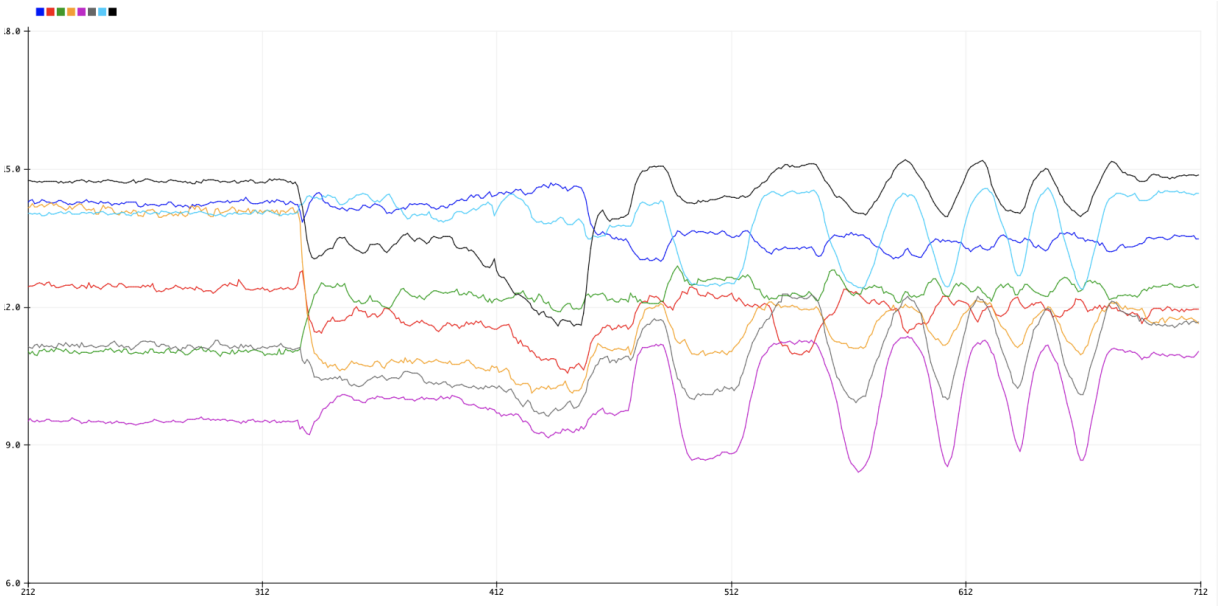
"To assess the performance of the newly developed device, I initiated by collecting hand pose data from users. Ensuring privacy, each user's data was anonymized to create a foundational dataset. This was utilized for a pilot test to verify the device's capability. For the comprehensive study, data from six users was gathered, illustrating the device's proficiency in maintaining accuracy across different users

Firstly, each user's arm was cleaned with an alcohol pad, after which I assisted them in wearing the prototype wristband on their right hand. A signal check was conducted on each participant to confirm solid device connectivity and robust signal across all channels. The customized EIT board has a calibration process as a benchmark for a healthy signal status. For electrode placement, medical-grade ones were used, and they were arranged uniformly on the user's arm.

I guided each participant through two recording sessions, each roughly 25 minutes long. In each session, they were asked to perform 10 different poses, repeated 8 times. This gave me a total of 160 data points per participant, with data collected from six users in all. The user was asked to perform 10 specific poses - Fist, Pointing, Gun, Stretch, Neutral, Left Flexion, Right Flexion, Ulnar Flexion, and Radial Flexion. These are all poses that have been used before in hand-tracking research. The actual movements were captured using a webcam, and I processed this data on my laptop. I used a software called Mediapipe to identify the 21 hand joints, running at around a 28 Hz frequency.



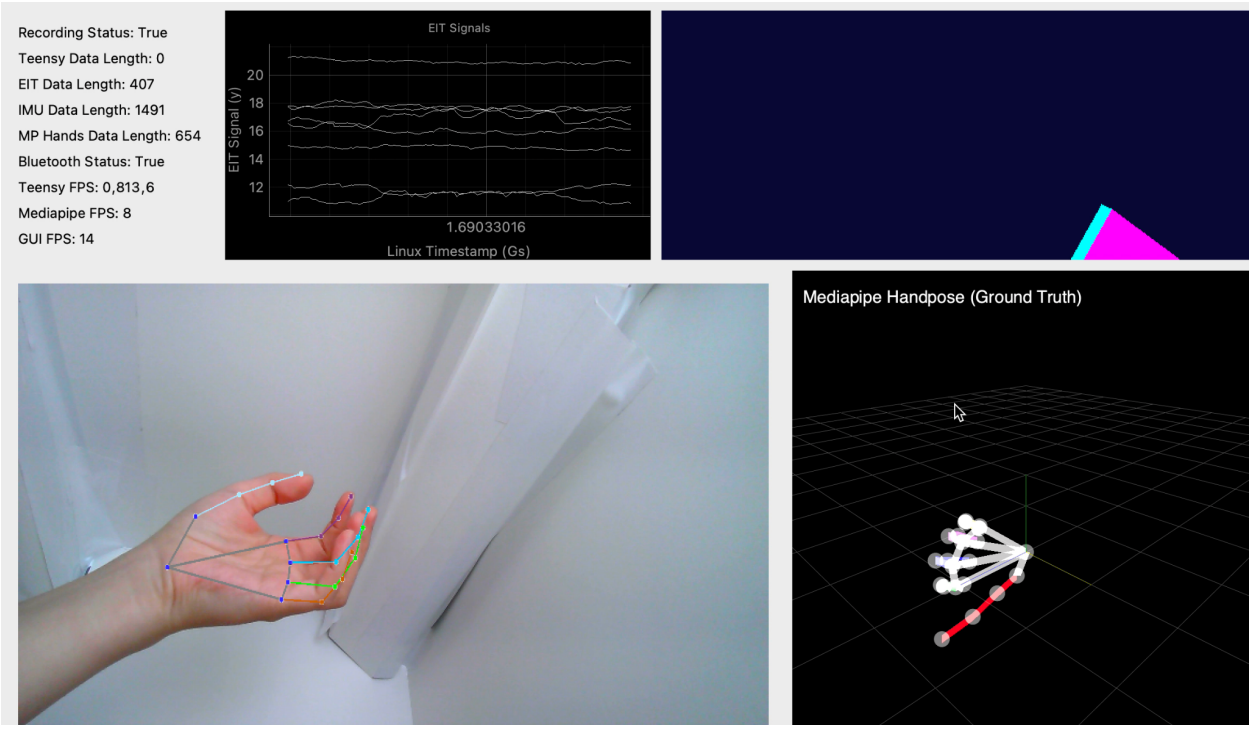
Img13: Data collection setup



Img14: Raw signals of 8 electrodes channel on EIT

The data collection took place inside a white cube, each side approximately 50 cm long. I covered all six sides with white paper to create a completely white background. A webcam was placed on one side of the cube, and users were directed to sit in front of it. I adjusted the height

of the cube according to each user's arm length and position to ensure that their right hand was directly in front of the camera.



Img14:Data collection platform
Left to Right: EIT - IMU - MediaPipe - Reconstructed hand

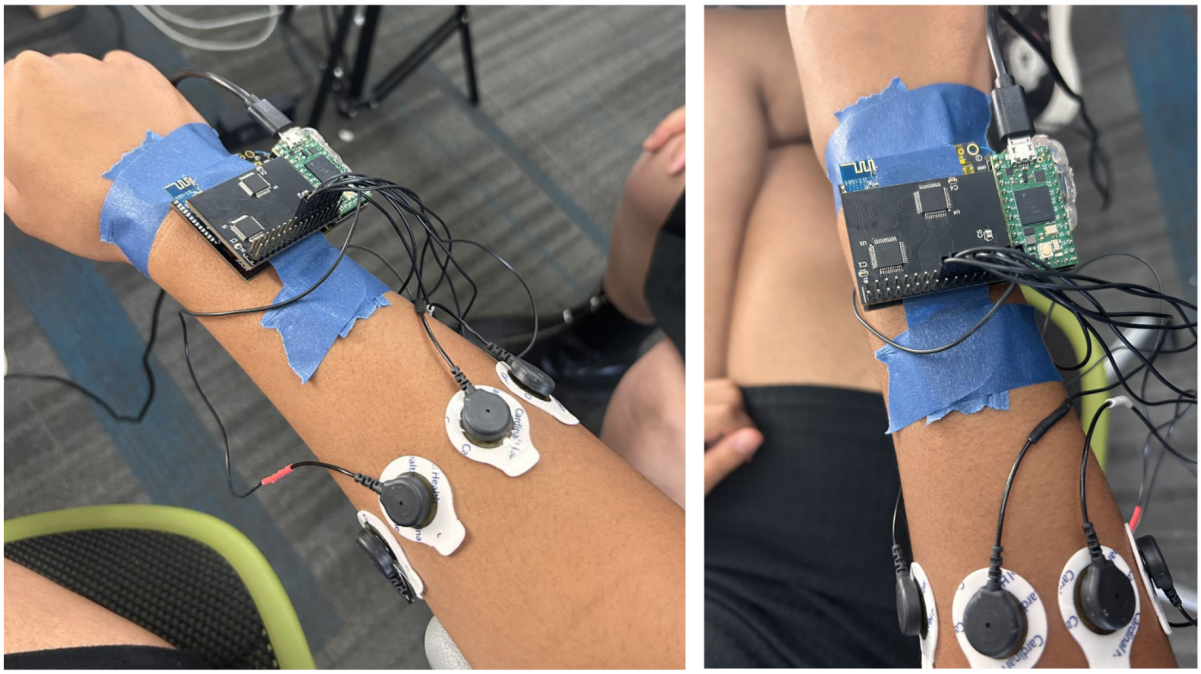
The platform I used to record the data was split into two parts: a visualizer and a data recorder. The visualizer displayed the live image of the hand and the hand joints extracted by Mediapipe. It also showed a 3D model of the hand joints, which helped me visualize what was being captured. I used the IMU's quaternion data to illustrate the user's arm movements. The EIT signals were shown as averages calculated from eight values, representing data from the eight channels. The left side of the screen displayed the recording status and the sample rate of all three sensors, making it easy to understand what was happening.

Throughout the data collection phase, a camera was employed solely for capturing ground truth data related to hand joint positions, rather than recording full videos. This process envisions future users utilizing camera-mounted glasses to gather calibration or training datasets, ensuring device accuracy without needing a wrist-mounted camera.

4.Result and Analysis

4.1 Reliability and Accuracy

The device's reliability and accuracy were assessed through three distinct methods: **the MPJPE(Mean Per Joint Position Error) metric, live prediction visualization, and a comfort test.** The objective of these evaluation criteria is to confirm that the device consistently delivers accurate hand tracking predictions while maintaining both comfort and stability. Upon collecting 96 rounds of data for 6 users (286), I fed this data into a machine learning pipeline. I utilized a straightforward Tree Regression Model, segregating the dataset into testing and training subsets, validating the result by using k-folder. Below are detailed evaluation results.



Img15: User are wearing EIT Kit and testing the signals

The MPJPE is a commonly employed metric designed to gauge the precision of skeletal joint predictions, as seen in applications like hand or body tracking. By measuring the average Euclidean distance between anticipated and observed joint positions, it provides a clear indication of the model's prediction fidelity. Our collected data yielded a hand pose MPJPE of **12.6mm and a wrist angle deviation of 7 degrees**. Although these results are slightly higher than those from previous studies like EtherPose (11.4 mm)*(Kim and Harrison 2022)* and FingerTrack (12.0 mm)*(Hu et al. 2020)* , it's important to contextualize: our methodology hinges on an indirect sensing approach, as opposed to the direct analysis of hand shapes employed in the other studies. This difference in approach reasonably accounts for the observed gap. Especially

noteworthy is that our use of indirect sensing enhances the security features of our devices, marking a significant stride in that direction.

In the live demonstration, I constructed a real-time visualizer. Users initially record some data and then execute a series of poses. The visualizer subsequently displays the predicted outcomes. For the specific set of poses I chose, the results depicted a commendable accurate representation.

To verify the stability of the devices, I had the user wear the devices for a duration of 30 minutes while observing the signals. I then compared values at different timestamps. The results showed that, despite some noise being introduced into the signals over time, the overall quality of the signals remained quite discernible for gesture classification. This indicates that the EIT device, using current electrodes, experiences minimal signal degradation in terms of stability.

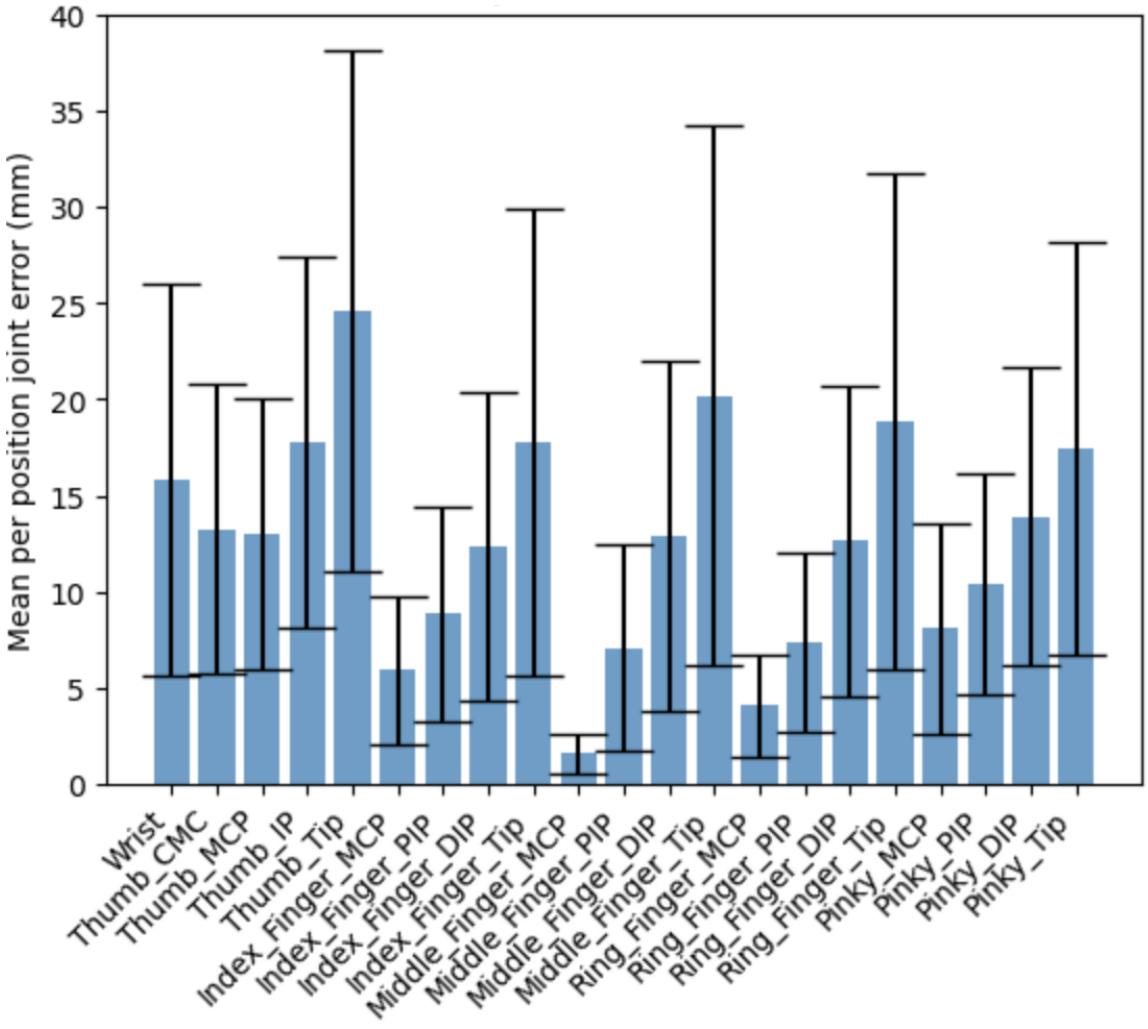


Figure 2: Bar chart displaying MPJPE results for continuous hand pose tracking using the EIT band. The chart details the prediction errors across 21 hand joints

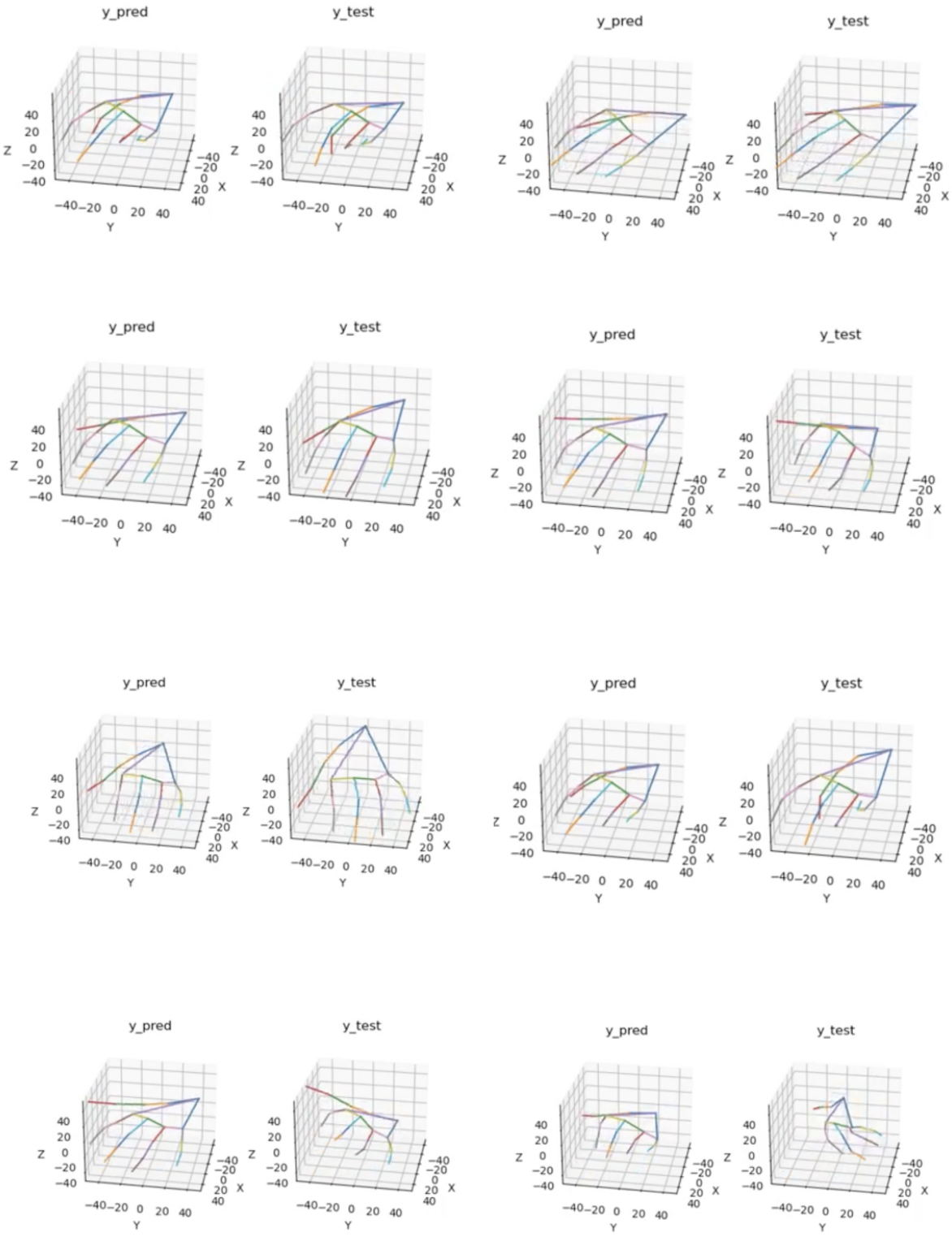


Figure3: Visualizer for predicted hand joints vs. ground truth hand joints

4.2 Data Minimization

One of the guiding principles of this research was the concept of data minimization, which is collecting the minimum amount of data required to achieve a specific purpose. Reflecting back on the design of my device and its usage through the previous metric I defined, several factors stand out.

Data Complexity: One of the advantages of my approach was the reduction in data complexity. Using EIT and IMU data eliminated the need to capture or interpret any external data, focusing solely on the internal changes in the wearer's body. However, the usage of EIT brought about challenges due to the large volume of data it generates. Additionally, increasing the number of electrodes for complex measurements can slow down processing speed. An avenue for future research could be optimizing this aspect, ensuring that the system can handle large data volumes efficiently without sacrificing performance or speed.

Data Sensitivity: My device scored highly on the aspect of data sensitivity. Unlike many other wearable devices, it does not capture any external environmental or facial data. Nevertheless, one potential privacy concern does exist: the possibility of reconstructing images of the arms using raw EIT data and specific image algorithms. To mitigate this risk, future iterations could look into enhancing the privacy-preserving mechanisms of the system, such as exploring algorithms that offer high accuracy while minimizing the risk of revealing unique user identifiers.

Data Resolution: The flexibility in adjusting data resolution provided by EIT is a key feature of the system. The resolution can be increased by adding more electrodes, offering a degree of customization based on specific needs. While this might lead to a decrease in sampling rate, the focus of EIT on internal movements and changes in the wrist ensures high reliability. Further research could look into striking a balance between resolution and sampling rate, ensuring that neither is unduly compromised.

User Perception: One significant success of this approach was the increased level of trust and engagement shown by users. EIT, being a minimally intrusive indirect sensing technology, was generally perceived as more acceptable and less privacy-invasive than traditional camera or other vision-based hand-tracking methods. Many users expressed a preference for this method, suggesting they felt more comfortable and secure. This not only met but surpassed our initial expectations, highlighting the potential of such privacy-centric methods in improving user trust. As we can continue to refine and enhance the system, maintaining this high level of user trust will remain a priority. This also reinforces the importance of data minimization and privacy-centric design in future wearable technology developments.

Notably, feedback from users offered valuable insights for improvement that were unexpected. For instance, although the amount of **electricity** used in the measurements was minimal and safe, some users were still apprehensive. This highlights the importance of communicating the safety measures effectively to users. **Comfort** was another key area of feedback. While the device size was generally acceptable and the material comfortable against the skin, there were minor issues. The presence of **arm hair could potentially affect data stability** and the comfort level could drop when using medical electrodes for more than about 30 minutes. Moreover, preferences varied regarding **how long users were willing to wear the device**. Future improvements could focus on enhancing user comfort and acceptance, such as investigating more comfortable materials or designs that cater to a wider range of user preferences.

5 Conclusion

In general, this research project successfully demonstrated the potential of Electrical Impedance Tomography (EIT) for privacy-preserving hand tracking. The system's data minimization approach, which combined EIT and Inertial Measurement Unit (IMU) data, provided effective tracking with privacy-preserving mechanisms. With careful control of variables such as electrode number and contact area, data stability was achieved and reduced the need for calibration. User perception of the device was generally positive, with concerns primarily related to the use of electricity and potential discomfort from prolonged use. Notably, user trust and engagement were significantly enhanced with this non-intrusive approach to sensing. This research sets a strong foundation for further exploration in privacy-centric hand-tracking technologies, with clear areas for improvement and potential for user-friendly, privacy-preserving advancements.

Limitation

It should be kept in mind that this is a preliminary exploration phase of a research project, our primary emphasis is on data minimization, on-device processing, and fostering trust among a select group of users. However, transitioning from this research-centric stage to a **commercialization phase** will undeniably present a more complex set of challenges and considerations.

For instance, how will the data be processed if a central server is involved? This brings about concerns of **data storage, secondary use of the collected data**, and the challenges associated with on-device processing. Furthermore, we need to consider how to educate users about their data rights and how to allow them control over the granularity of their data.

Moreover, the system does collect some **identifiable information**, which brings up the question of how to build trust with users if this data needs to be stored by a third-party authority. Anonymization techniques might be necessary to maintain privacy, but they need to be well balanced with data usability.

Finally, there's the question of **how to balance adding more sensors for improved functionality against increasing potential privacy concerns**. The number of sensors impacts not only the amount of data collected but also the resolution of data, which in turn affects user privacy.

Future Work

The future plans include integrating more electrodes to heighten the device's accuracy and optimizing its design for enhanced comfort while minimizing disturbances from skin hair and connective tissues. Furthermore, I plan to harness the power of Tiny ML systems, which boast advanced computational abilities, to facilitate real-time data processing, thereby bolstering data security. This technology will be integrated with the existing EIT board. Alongside these technical enhancements. Moreover a more comprehensive user study is needed, aiming to delve into users' authentic feelings and concerns regarding privacy.

While EIT offers a promising way forward for privacy preserving hand tracking, it also prompts us to rethink our general approach to privacy in wearable technology. As we navigate these challenges, it becomes increasingly clear that we need a holistic approach that equally considers technical aspects, user perception, and ethical implications. **There is no definitive solution for privacy concerns associated with wearables.** This research seeks to pave a new path to strike a balance between data collection and device functionality, thus enhancing focus on privacy.

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