

Article

Radio Frequency Passive Tagging System Enabling Object Recognition and Alignment by Robotic Hands

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Abstract

Robotic hands require reliable and precise sensing systems to achieve accurate object recognition and manipulation, particularly in environments where vision- or capacitive-based approaches face limitations such as poor lighting, dust, reflective surfaces, or non-metallic materials. This paper presents a novel radiofrequency (RF) pre-touch sensing system that enables robust localization and orientation estimation of objects prior to grasping. The system integrates a compact coplanar waveguide (CPW) probe with fully passive chipless RF resonator tags fabricated using a patented flexible and stretchable conductive ink through additive manufacturing. This approach provides a low-cost, durable, and highly adaptable solution that operates effectively across diverse object geometries and environmental conditions. The experimental results demonstrate that the proposed RF sensor maintains stable performance under varying distances, orientations, and inter-tag spacings, showing robustness where traditional methods may fail. By combining compact design, cost-effectiveness, and reliable near-field sensing independent of an object or lighting, this work establishes RF sensing as a practical and scalable alternative to optical and capacitive systems. The proposed method advances robotic perception by offering enhanced precision, resilience, and integration potential for industrial automation, warehouse handling, and collaborative robotics.

Keywords: sensor; antenna; robotic hand; localization

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1. Introduction

Robotic hands are increasingly employed in automation systems such as assembly lines, smart factories, warehouses, and service robotics, where arranging parts in the correct order and orientation requires precise spatial positioning and alignment [1–3]. Achieving these goals demands compact, accurate, and versatile sensors [4] capable of operating reliably in confined spaces and under diverse environmental conditions.

Conventional sensing approaches in robotics often rely on optical systems—such as LiDAR, cameras, and infrared sensors—and proximity-based devices including capacitive, inductive, ultrasonic, and Hall-effect sensors [5–10]. Optical sensors [11] can capture detailed information about an object's shape, size, and color, but their performance is highly dependent on adequate lighting, a clean environment, and suitable viewing angles. Moreover, they require complex setup and calibration when adapting to new environments. Capacitive sensors are simpler to operate but are sensitive to the material

properties and grounding of detected objects, while inductive sensors are restricted to metallic targets. Many other proximity sensors face limitations in range, resolution, and accuracy at close distances, and are susceptible to environmental interference and high-power consumption [12,13].

In addition to vision- and capacitive-based sensing, wireless localization methods such as Wi-Fi, Bluetooth Low Energy (BLE), and Ultra-Wideband (UWB) have been explored in robotics. Wi-Fi and BLE are attractive for their low cost and availability, but their accuracy is typically limited to 1–3 m and is sensitive to multipath and interference. UWB provides sub-decimeter precision but requires dedicated hardware, higher costs, and faces coverage issues in cluttered environments. These trade-offs underline the need for compact, low-cost, and robust alternatives [14–16].

Alongside performance and cost, fabrication simplicity is a critical factor influencing sensor adoption in robotics. Additive manufacturing (AM) has emerged as a cost-effective and highly customizable solution for rapid prototyping, enabling the fabrication of both two-dimensional and three-dimensional structures with short production times [17]. This capability not only facilitates the development of novel sensor designs tailored to specific robotic applications but also supports the integration of alternative sensing modalities. Also, there is a need for a low-cost, compact, and vision-independent localization system capable of operating reliably under challenging conditions, including low lighting, occluded views, and variable material surfaces.

Among the available technologies, RF sensors [18,19] present a particularly promising option, as they operate reliably under adverse conditions such as dust, smoke, humidity, and poor lighting. Passive and chipless RF tags are especially attractive due to their low cost, maintenance-free operation, and robustness in harsh environments. Previous studies have investigated RF-based sensing and passive resonators for displacement monitoring and surface localization. Additionally, general RF sensing frameworks have demonstrated the feasibility of recognizing surrounding objects and environmental changes by analyzing multipath channel variations, further extending applicability to indoor robotics and autonomous navigation [20–22]. These findings collectively establish RF sensing as a viable alternative to vision- and capacitive-based systems, offering robustness under adverse environmental conditions and enabling high-accuracy near-field sensing [23]. However, there remains a need for compact, low-cost, and easily integrable solutions that maintain high effectiveness for practical robotic applications. Our work addresses this gap by developing an RF-based sensing platform tailored for integration with robotic hands, enabling pre-touch detection and grasping in diverse environments.

Figure 1 illustrates an object recognition scenario in which a robotic hand equipped with an RF sensor scans an array of tagged items. By detecting and distinguishing the embedded RF tags, the robotic hand can reliably identify the objects, even in cases where visual features are ambiguous or occluded. This capability has strong potential for integration into robotic systems across various domains. For example, in manufacturing, it enables precision positioning of robotic arms when handling transparent, reflective, or irregularly shaped objects that challenge optical sensors. In collaborative robotics (i.e., cobots), RF-based tactile localization supports safe and accurate interactions with humans and workpieces without requiring camera feedback. In warehouse automation, RF-tagged surfaces can guide robotic pick-and-place operations with high repeatability. Similarly, in medical and laboratory robotics, where sterile or enclosed environments limit the use of visual sensing, passive RF tags can provide reliable cues for instrument positioning. More broadly, such RF-based recognition is advantageous in dark, cluttered, or visually constrained environments where conventional sensing methods fail.

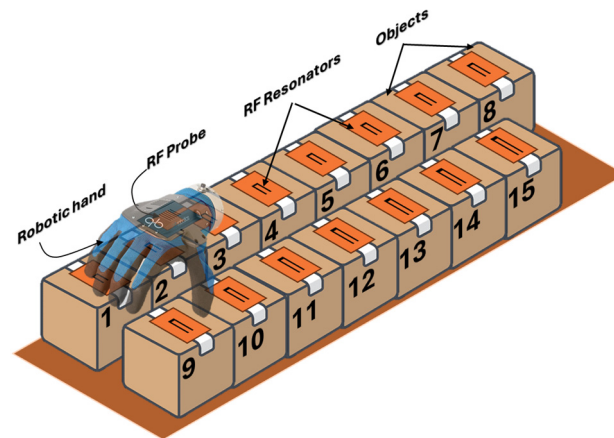


Figure 1. Illustration of a robotic hand equipped with an RF sensor module interacting with 15 objects, each tagged with a passive RF tag for object identification and localization.

This work introduces a novel RF-based pre-touch sensing system for robotic grasping applications. The proposed system integrates custom-designed passive resonators with a robotic hand to enable the identification and localization of objects within tactile range, regardless of their shape or size. By monitoring impedance variations as the hand moves in the X and Y directions, the system can determine the optimal grasping position and orientation. This compact, low-cost, and environment-agnostic approach provides a robust alternative to vision-based and conventional proximity sensing methods, enhancing the versatility and reliability of robotic hands in automated manipulation tasks.

The main contributions and novelties of this work are as follows:

- The design of a compact RF-based pre-touch sensing system capable of both planar and angular object recognition within tactile range using a single probe, independent of object shape and size.
- The integration of passive resonator tags to enable object differentiation and grasp optimization, even in environments where optical and conventional proximity sensors may fail.
- The development of a production method using patented flexible and stretchable conductive ink, enabling the creation of lightweight, conformable, and mechanically robust resonator structures.
- A cost-effective and rapid manufacturing process leveraging additive manufacturing for sensor components, ensuring scalability and customization for diverse robotic applications.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and establishes the context for RF sensing in robotics. Section 3 describes the design and simulation of the proposed RF sensor. Section 4 details the design correlation and manufacturing considerations. Section 5 presents the experimental process, while Section 6 reports the experimental measurements and performance evaluation. Finally, Section 7 concludes the paper and outlines directions for future research.

2. Literature Review

To address some of the challenges, recent research has explored advanced tactile and multimodal sensing solutions. Cui et al. [24] developed a vision-based tactile sensing system capable of generating high-resolution tactile point clouds. Guan et al. [25] proposed a multi-sensor fusion method combining visible light positioning, SLAM, LiDAR, odometry, and rolling-shutter cameras, achieving centimeter-level accuracy even under LED outage conditions. Zhu et al. [26] presented a multimodal capacitive sensor with both

pressure and localization capabilities for bio-mechatronics applications. Carvalho et al. [27] demonstrated active exploration strategies with a three-fingered robotic hand, reducing recognition uncertainty through guided touch. Additional works [28–30] have integrated high-dimensional tactile sensing arrays into robotic hands, combining contact pressure, temperature sensing, and machine learning techniques for robust object characterization.

In addition to tactile approaches, several wireless localization technologies have been applied in robotics, including Wi-Fi, Bluetooth Low Energy (BLE), Ultra-Wideband (UWB), and infrared systems. Fingerprint-based Wi-Fi localization is cost-effective and widely available but typically achieves only meter-level accuracy (1–3 m) in real-world indoor environments [31]. BLE-based methods offer similar coverage with low power consumption, but positioning errors generally remain around 1–1.5 m even under optimized conditions. In contrast, UWB systems have demonstrated superior indoor localization accuracy, with reported mean errors as low as 13 cm for static targets and 29.9 cm for moving robots, outperforming BLE and Wi-Fi in comparative evaluations [32].

Advances in sensing have included multimodal approaches that integrate tactile feedback with semantic or contextual cues to enable accurate recognition in visually constrained environments [33]. Beam-forming strategies leveraging reconfigurable intelligent surfaces have been shown to enhance detection and communication capabilities in complex propagation conditions [34]. Unsupervised domain adaptation methods have improved recognition accuracy across heterogeneous datasets without the need for extensive retraining [35], while adaptive filtering techniques have maintained reliable localization performance despite sensor failures and non-Gaussian noise [36].

Recent advances in RF-based sensing have shown strong potential for object localization and recognition in scenarios relevant to robotic manipulation. Experimental studies on device-free localization using RF sensor networks have demonstrated the ability to track human movement and object presence without requiring active tags, achieving sub-meter accuracy even in multipath-rich environments by exploiting RSSI variations from static nodes [37]. Moving target localization and gesture recognition systems have been developed using RF sensing to reliably identify motion patterns and spatial positions across varying postures, distances, and movement speeds, showing resilience to occlusion and environmental changes [38]. At higher frequencies, millimeter-wave (mm Wave) device-free sensing has enabled fine-grained human activity recognition and posture detection by leveraging wide bandwidths and high angular resolution, while remaining functional in low-light and visually obstructed conditions [39].

Together, these studies highlight a broader trend toward compact, low-cost, and environmentally robust sensing solutions—objectives directly addressed by the proposed RF-based pre-touch and grasping system.

3. Design and Simulation

3.1. Simulation Setup

In earlier studies [20,40], it was noted that the proposed probe-resonator setup enables the robotic hand to align with the object both angularly and planarly for effective grasping. Additionally, a 3D-printed setup featuring conductive ink on EVA foam [17] enables the identification of the hand's relative position to the resonators on the work surface with a high degree of accuracy. This is evident as the impedance value significantly increases when full alignment is achieved compared to a nearby point. Moreover, a frequency shift is observed when the hand moves toward a resonator of a different size.

In this study, electromagnetic simulations were performed using the CST Studio Suite (Dassault Systems) with the frequency-domain solver. Perfectly matched layer (PML) boundaries were applied to minimize reflections, and the excitation was provided via

a coaxial port feeding the probe structure. The simulation mesh was refined locally, with the maximum mesh cell size set to 0.2 (relative to the wavelength) for the resonator and narrow sections of the antenna, while a value of 0.5 was used for less critical regions. In all other non-critical areas, the mesh resolution followed the global mesh settings, with automatic mesh refinement enabled to ensure accuracy where required (Figure 2b). In order to distinguish between different plastic objects made of the same material, a probe-resonator system was utilized. The antenna, modeled as a Perfect Electric Conductor (PEC), was mounted on an FR-4 substrate measuring 65 mm × 55 mm, with a thickness of 0.16 mm ($\epsilon_r = 4.3$, $\text{tg}\delta = 0.025$ at 10.0 GHz). To achieve a higher impedance value, a polycarbonate substrate ($\epsilon_r = 2.9$, $\text{tg}\delta = 0.01$ at 1.0 GHz) was chosen, and resonators were placed on it. This substrate is thick at 1 mm. The resonators were designed with a resistive impedance of $0.6 \Omega/\text{sq}$, based on the characterization of a specialized conductive ink [41,42] intended for use in the fabrication process. In the first step of the simulation, the response of the antenna in air was evaluated, along with its coupling with a resonator having an arm length of 40 mm and its interaction with tagged objects. The objects considered in this study were made of two different materials, PVC ($\epsilon_r = 3.5$, $\text{tg}\delta = 0.03$ at 1.0 GHz) and Teflon ($\epsilon_r = 2.1$, $\text{tg}\delta = 0.0002$ at 10.0 GHz). These tagged objects were placed on a wooden table ($\epsilon_r = 1$), and components were sequentially added, with simulations running at each step to observe the effects (Figure 2).

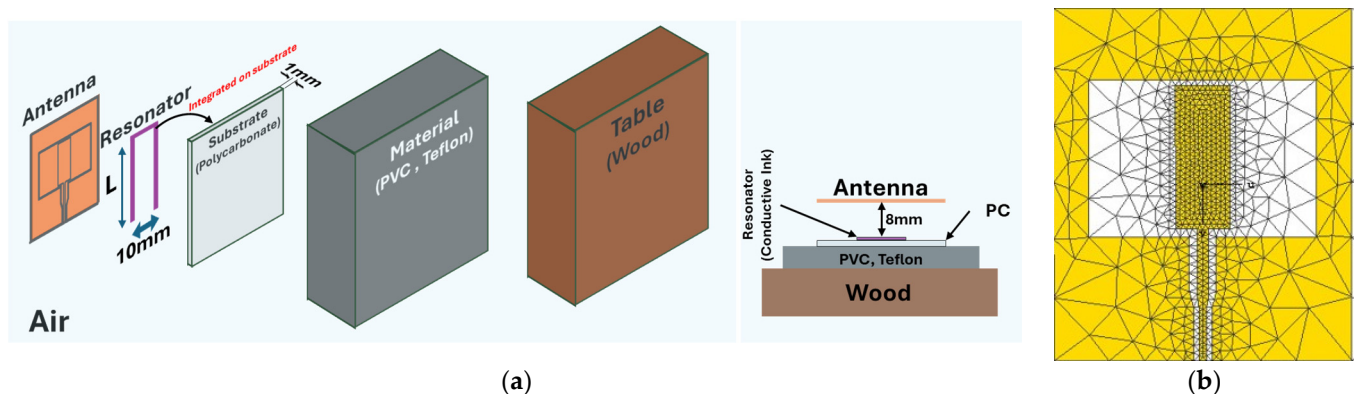


Figure 2. (a) Geometrical arrangement and sequential placement of components in the CST Microwave Studio simulation setup. (b) View of the adopted mesh for the numerical analysis of the antenna.

In the second step, resonators with varying arm lengths, ranging from 38.5 mm to 59.5 mm in increments of 1.5 mm, were used. The distance between the two arms remained constant at 10 mm across all resonators. This resulted in the total length variation of the resonators occurring in increments of 3 mm, leading to a set of 15 resonators of different sizes, which were placed on 15 objects made of PVC material. The table was also considered in these simulations. To ensure the functionality of the system, which comprises ink and polycarbonate, a simulation was conducted to replicate the full alignment of the probe with the resonator.

3.2. Numerical Results

The real part of the input impedance is analyzed across a frequency range of 1.0 GHz to 3.5 GHz for various coupling scenarios, as presented in Figure 3. The scenarios include the antenna being in the air, the tag placed 8 mm in front of the antenna, the addition of a polycarbonate substrate, and attaching the tag to an object on a wooden table. The tag measures 90 mm in length. Notably, when the tag is positioned close to the antenna, an additional resonance frequency appears between 2.0 GHz and 2.5 GHz, depending on

the scenario, indicating that this resonance is related to the tag. Introducing the object near the antenna alters the impedance values and the resonance frequency, but the overall behavior remains consistent, allowing the system to successfully read the tagged object. In contrast, while placing the object on the table does not make a big difference in terms of impedance value and resonance frequency, changing the material has a strong effect on both. This can create challenges in recognizing objects made of different materials. However, these issues can be resolved by selecting the correct tag for each object. Additionally, if two objects have different resonance frequencies, the system can still perform effectively.

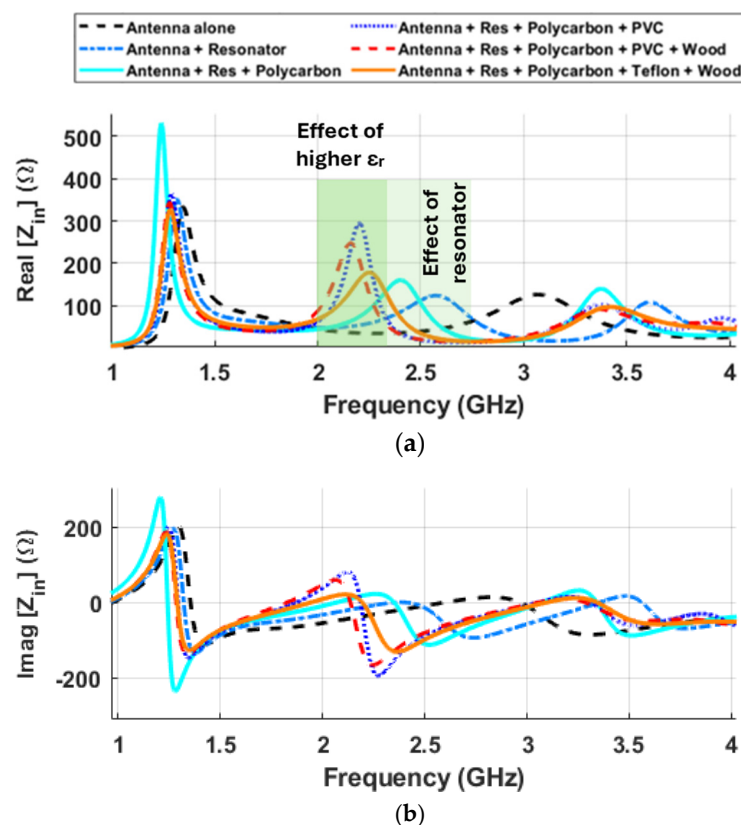


Figure 3. Numerical analysis (CST Simulation): (a) real and (b) imaginary parts of the impedance (Z_{in}) of the probe alone and coupled with the resonator, tagged objects, and objects on the table.

Furthermore, as is obvious, changing the length of the resonator will cause an upper or lower frequency shift depending on the increasing or decreasing of its total length.

This can be said for a general n -Wave Resonator using the following relationship:

$$L = \frac{\lambda}{n} = \frac{c}{nf} \Rightarrow f = \frac{nc}{L} \quad (1)$$

where λ is the wavelength, c is speed of the light in a vacuum, and f is the resonance frequency of the n wavelength resonator.

Figure 4 illustrates the real and imaginary part of impedance in a frequency spectrum while the probe aligned with a resonator of a different length. The designed resonators are appropriately sized, facilitating distinguishable searches for object recognition purposes. The figure shows that when the system is perfectly aligned with a larger resonator, the value of the real part of the impedance increases, and the resonance frequency shifts toward a lower frequency. All resonances were observed within the frequency band from 1.7 GHz to 2.4 GHz.

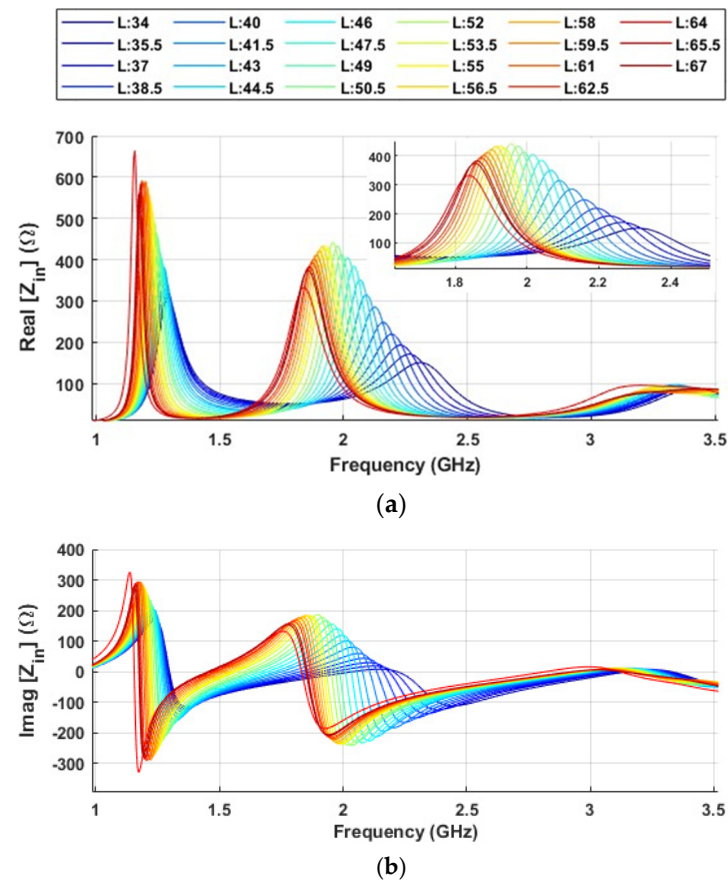


Figure 4. Numerical analysis (CST Simulation): (a) real and (b) imaginary parts of the impedance (Z_{in}) of the probe aligned with resonators with different sizes.

The imaginary part also shows a similar behavior to the real part with strong resonance and anti-resonance for tags. It should be noted that while the values change with the length of the resonators, there are some limitations due to the specifics of the probe. At shorter lengths, the value is low, which might be challenging at higher distances. Additionally, as the length exceeds 53.5 mm, the value starts to decrease, and the frequency shift becomes smaller. Generally, examining the impedance shows that the 3D-printed resonators on a polycarbonate substrate can be the right choice for achieving the object recognition goal.

4. Design Model and Manufacturing Considerations

To clarify the functional relationship between the RF sensing probe and its associated circuitry, Figure 5a presents the equivalent circuit model used in this work. This model links the physical geometry of the printed sensor to its electrical behavior, enabling both the simulation of probe–tag interactions and the interpretation of the experimental results.

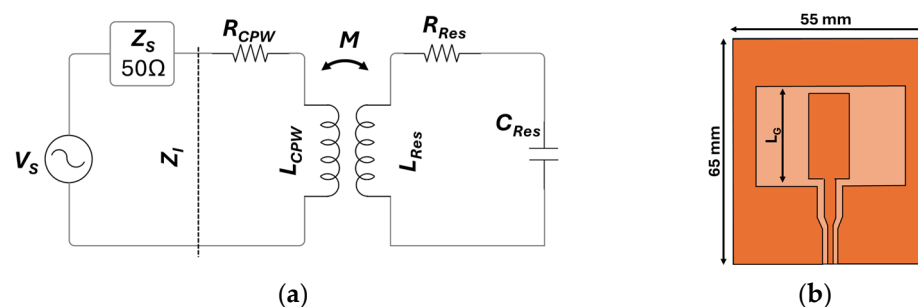


Figure 5. (a) Equivalent circuit of the adopted antenna. (b) Employed CPW antenna.

In the circuit, the source V_S with characteristic impedance $Z_S = 50 \Omega$ excites the coplanar waveguide (CPW) feed, modeled by its series resistance R_{CPW} and loop inductance L_{CPW} . The sensing probe couples magnetically to a passive resonator through the mutual inductance M . The resonator comprises an inductance L_{Res} , a capacitance C_{Res} set by its gap geometry, and a resistance R_{Res} determined by the sheet resistance of the printed flexible and stretchable conductive ink. Variations in M and the tag's resonant frequency f_0 alter the input impedance Z_I , producing the resonance peaks used for localization and identification.

The equivalent circuit mirrors the physical sensor layout. The CPW feed dimensions are selected to maintain a 50Ω match, reduce resistive loss, and control the magnetic near-field region represented by L_{CPW} . The resonator's L_{Res} and C_{Res} are determined by the printed spiral arm length and gap, while R_{Res} accounts for conductor loss in the patented conductive ink. The mutual inductance M is sensitive to lateral offset, angular orientation, and vertical spacing between the probe and tag, enabling position-dependent signal variations without mechanical contact.

The current CPW antenna design (Figure 5b) was selected from among eight different antenna prototypes that were designed, fabricated, and evaluated through experimental measurements. The shape, trace width, and length of the resonator were determined from preliminary investigations to achieve the desired resonance characteristics and coupling behavior. The trace width of the tags was fixed at 2 mm, taking into account the nozzle diameter of the printer, while ensuring both a high sensing response and long-term durability.

In tag arrays, mutual coupling between the probe and neighboring tags can cause undesired frequency shifts or broadened responses. For electrically small resonators, the magnetic near field decays approximately at a rate of $1/r^3$, where r is the distance between the probe and the tag [43,44].

When the probe is aligned directly over tag A, the following occurs:

- The distance to A (aligned tag) is $h = 8$ mm.
- The distance to the nearest neighbor tag B is $\sqrt{d^2 + h^2}$, where d is the lateral spacing between tag centers and h is the probe-to-tag vertical gap.

The neighbor-to-aligned coupling ratio is as follows:

$$r_{neighbor} = \left(\frac{h}{\sqrt{d^2 + h^2}} \right)^3 = \left(\frac{a_{eq}}{\sqrt{d^2 + h^2}} \right)^3 \quad (2)$$

and

$$a_{eq} = \frac{A}{\pi} \quad (3)$$

where a_{eq} is the equivalent loop radius, and A is the effective loop area (mm^2).

For the present geometry, with a tag spacing of 55 mm and a probe height of 8 mm, the neighbor-to-aligned coupling ratio is approximately 0.30%. For a representative resonance at 2.10 GHz, this level of coupling would produce a frequency shift of only about 0.95 MHz from the measured geometry using standard near field coupling relationships, which is negligible for identification and localization purposes.

In the case of the U-shaped tag used in this work (length = 43 mm), the enclosed conductive loop area is $A = 184 \text{ mm}^2$, corresponding to an equivalent loop radius (a_{eq}) of approximately 7.65 mm. Using this value in Equation (2) gives a ratio of about 0.26%, further confirming that the effect of the nearest neighbor is negligible. If the probe is positioned exactly midway between two tags, the distance to each tag (d) is half and the coupling ratio is approximately 2.2%, which would not meaningfully affect the measured resonance.

The spacing required to produce a “noticeable” simultaneous coupling of $p\%$ per tag can be estimated as follows:

$$d = 2h \cdot \sqrt{p^{-2/3} + 1} \quad (4)$$

The minimum spacing needed to create a noticeable simultaneous coupling between the probe and two tags depends on the percentage of coupling considered significant. For a probe height of 8 mm, this spacing is about 22 mm for 20% coupling, 31 mm for 10% coupling, and 40 mm for 5% coupling. In the present design, the tag spacing is 55 mm, which is equal to width of probe and is well above these values. This means the probe couples effectively to only one tag at a time, and any interaction with a neighboring tag is negligible. This ensures robust measures and allows for greater coverage of distance or the inspection of larger objects. However, the spacing could be reduced if required for more compact arrangements.

5. Fabrication

Based on the simulation results, 15 resonators with the strongest response and frequency distinction were chosen for fabrication. The arm lengths ranged from 38.5 mm for the shortest resonator to 59.5 mm for the longest one. Figure 6 depicts the fabrication process of a printed antenna and a set of printed resonators.

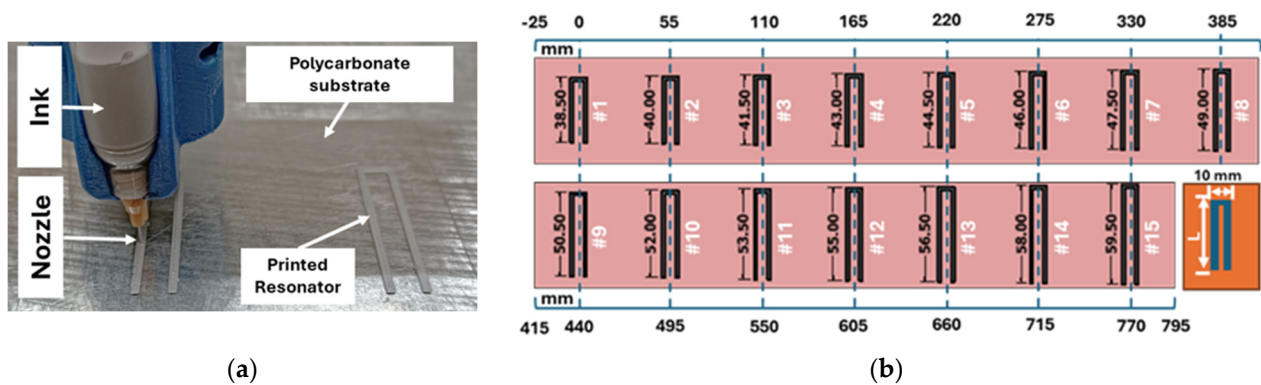


Figure 6. (a) Fabrication process of the tags using a 3D printer, and (b) details of the tags along with their placements for the experimental tests, (#1, #2, . . . indicate the number of tags).

To do this, we used an Ag-EGaIn-polymer ink previously developed in our lab, which permits the direct digital printing of electronic circuits without the need for sintering [45,46].

Being sinter-free permits printing this ink over any substrate, including heat-sensitive plastics, and textiles, which is important for extending this work to a wide range of applications. Moreover, ink permits interfacing microchips [42], which are important for the next generation of more advanced and active devices.

The possibility of digital printing allowed for the rapid fabrication of various resonators, and adjusting the printed line width and deposition rate permitted controlling the conductivity of each line. To do so, we used a custom-made 3D printer, enabling precise control over printing parameters including the extrusion speed, and nozzle velocity. For this specific application, we deposited six layers of the ink to achieve an electrical resistance of less than $1\ \Omega$ between the two farthest points of the resonator. This approach ensured the desired electrical properties while maintaining structural integrity and functional performance.

The custom printer used for fabrication offers precise motion and extrusion control, achieving micrometer-level resolution over a 330×330 mm working area, and surpasses typical commercial ink extrusion printers in feed rate. Regarding the printing parameters, a movement speed of up to 20 mm/s was utilized. It is important to note that this value is significantly influenced by the adjustments made during printing, using a pressure advanced value of 4.15. This allows the printer to calculate the feed rate and acceleration to maintain a consistent extruded volume, even during sharp corners and transitions between traces.

The printer employs a custom-made extrusion nozzle with internal needle diameters of 0.33 mm. The length of each trace depends on the geometry and infill settings defined in the slicer software, but it can print large traces continuously. When generating G-code using a Prusa Slicer, the concentric infill setting is maximized to ensure an even distribution of ink across the entire geometry.

To determine optimal printing parameters, a test print was conducted initially for a single resonator. During this process, the resistance between the two farthest points of the resonator was measured after each layer to achieve efficient conductivity and minimal resistivity. Based on these tests, it was found that three layers of ink were sufficient to achieve the required conductivity. By the end of the printing process, the resistivity of all resonators was less than 0.6Ω , demonstrating successful fabrication with consistent electrical performance.

6. Experimental Measurements

6.1. Experimental Setup

Experimental measurements were conducted to validate the simulation results and provide calibration data for programming the search system or robotic hand. The final step of the localization test involved setting up a 4D platform capable of movement along the X, Y, and Z axes, as well as rotation to adjust the alignment angle (Axis A). To enhance control and automation, a specialized control unit was developed to oversee the entire system and automate data collection using a MATLAB R2023b script.

With the 4D platform and dedicated control unit in place (Figure 7b), the test was conducted using a four-axis setup. The probe was aligned both angularly and within the XY plane relative to the resonators, maintaining a distance of 8 mm from the center of object 1. The probe moved along the Y direction, starting from object 1 and passing through all objects at intervals of 55 mm, which was the spacing between objects. The S11 parameter values of the probe and each resonator were measured using an Anritsu ShockLine MS46524B VNA device with high accuracy, along with Anritsu cables.

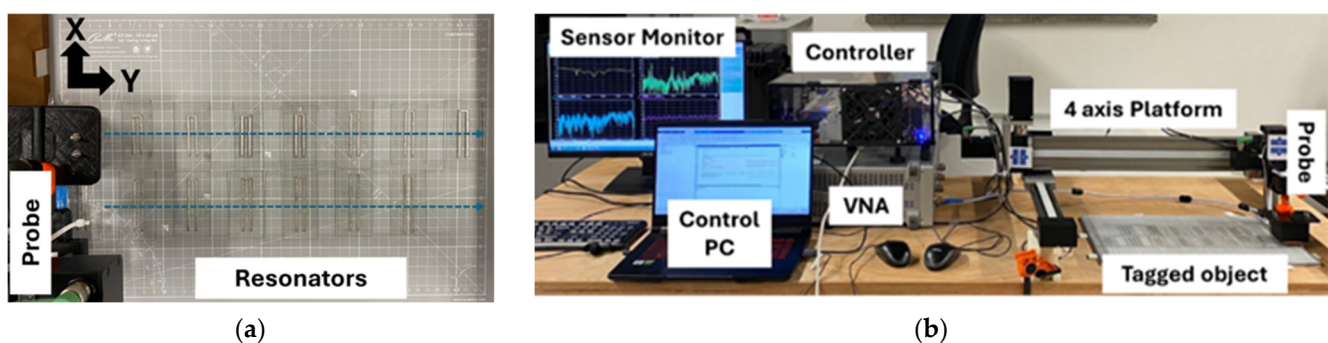


Figure 7. (a) Arrangement of the object and probe at the beginning of the experimental tests; (b) experimental setup, including the VNA test platform, controller, and PC.

The vector network analyzer (VNA) was configured to sweep over the frequency range of 0.5–4.0 GHz using 801 frequency points per sweep, with an IF bandwidth of 10 kHz to achieve a balance between noise suppression and measurement speed. During the scanning process, the sampling intervals along the X and Y axes were set to 5 mm and 15 mm, respectively. The typical acquisition time per measurement point was approximately 3000 ms. This value was selected to ensure robust measurements and does not represent the maximum achievable system speed. In practice, the actual speed is determined by hardware performance, while the underlying measurement calculations are simple and fast.

In the subsequent steps, smaller increments of 1 mm and 5 mm were selected to test the accuracy of the system. Tests were conducted on two objects tagged with short and long resonators. Angle changes were evaluated for one of the objects, and finally, the distance between the probe and the tagged objects was increased to assess system performance. The measurement setup and process details are illustrated in Figure 7.

The recorded S_{11} values were converted to input impedance using a MATLAB R2023b script, and the calculated values were plotted to analyze and validate the experimental measurements against simulation predictions. The formula is as follows:

$$Z_{in} = Z_0 \times \frac{1 + S_{11}}{1 - S_{11}} \quad (5)$$

where

- Z_{in} is the input impedance;
- S_{11} is the complex reflection coefficient;
- Z_0 is the system reference impedance (typically 50 Ω).

The overall measurement and data processing pipeline is illustrated in Figure 8.

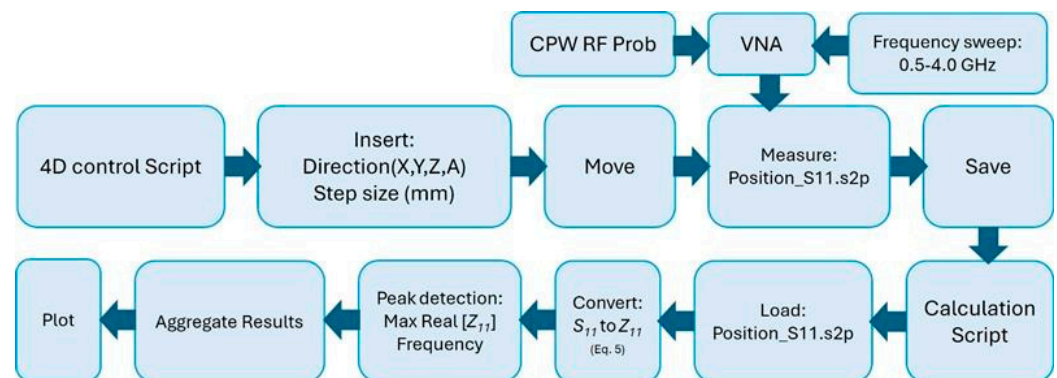


Figure 8. Block diagram of the experimental setup and processing pipeline.

6.2. Object Recognition Moving in Linear

The input impedance values for 15 different objects perfectly aligned with the probe illustrated in Figure 9. There is notable agreement between the experimental results and the simulated predictions, particularly in the frequency range corresponding to the objects (1.7 GHz to 2.4 GHz). Minor discrepancies are observed primarily at the first and third resonance points, which are attributed to the characteristics of the probe. However, overall, the frequency shifts and changes in values are significant enough for effective object recognition purposes. This alignment underscores the validation of the simulation results through experimental measurements, affirming their utility in practical applications such as object recognition systems.

Some conclusions can be drawn from this preliminary test. Firstly, increasing the size of the resonator results in a noticeable shift in frequency when moving between resonators of different sizes. Secondly, after conducting an initial general search and gathering basic information, introducing a threshold based on frequency intervals and impedance values can help mitigate ambiguities in object recognition.

The next approach should be the accuracy test and searching with smaller increments to align the hand with an object in different directions.

Figure 10 depicts the real part of the impedance value during a search along the Y direction around object #1 with 5 mm increments and around object #13 with 1 mm increments. Initially, when the probe is perfectly aligned with the resonator, a single resonance is observed between 0.5 GHz and 1.5 GHz. However, even a 1 mm movement of

the probe introduces an additional resonance point within this range due to asymmetric coupling. This additional resonance also shifts as the probe moves through objects tagged with different resonators. Around object #1, this resonance frequency is approximately 1.4 GHz, whereas around object #13, it shifts to around 0.9 GHz.

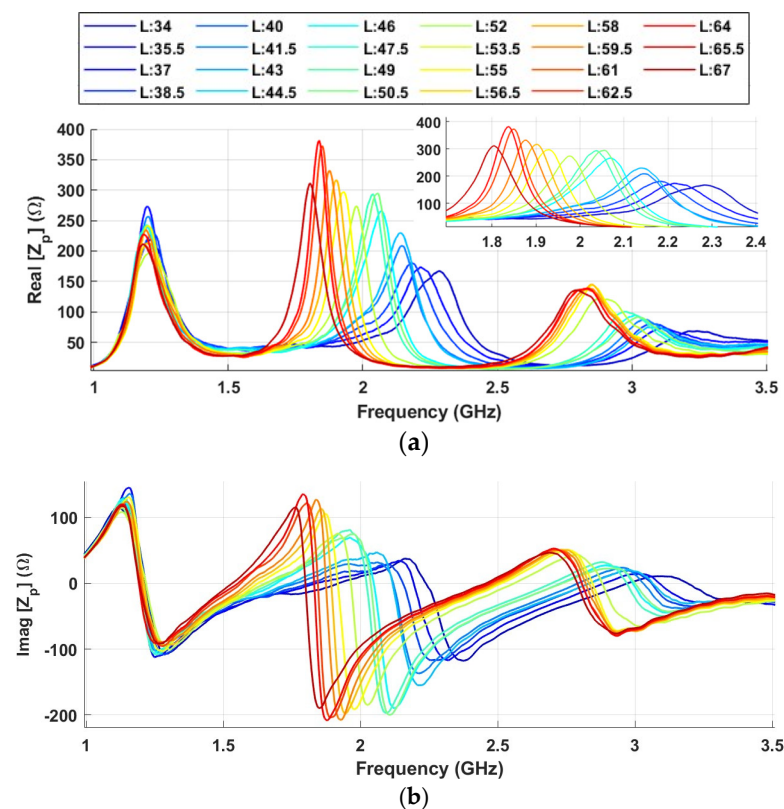


Figure 9. Measured (a) real and (b) imaginary parts of the impedance (Z_p) of the probe aligned with objects tagged with resonators of different sizes (Distance = 8 mm).

Based on this information, it can be concluded that the probe's alignment provides information about whether it is aligned with an object or near it. The highest resonance value occurs when the probe is aligned at 0 mm, precisely in the center of the resonator, and decreases as the probe moves away from this center alignment.

In the third frequency range, there is a shift in frequency and a change in value as the probe moves further away from the object. However, the lowest value at the highest frequency occurs when the probe is fully aligned. This shift in frequency and change in value are more pronounced for objects tagged with smaller resonators. These observations highlight the sensitivity of the measurement to the size and alignment of the resonator, providing valuable insights for object identification and localization.

Figure 11 depicts the variation in the real part of impedance with changes in hand position relative to the tag, with the frequency fixed at the resonance frequency of the tagged object. The graph highlights that when the hand is perfectly aligned, the impedance value reaches its maximum, decreasing with even a slight misalignment. This figure indicates that it might be feasible to precisely determine the vertical position (Y direction) of the hand by detecting changes in impedance. This is supported by the significant variations in impedance values observed across different hand positions, regardless of whether the objects had long or short resonators and whether the hand movement involved large or small increments.

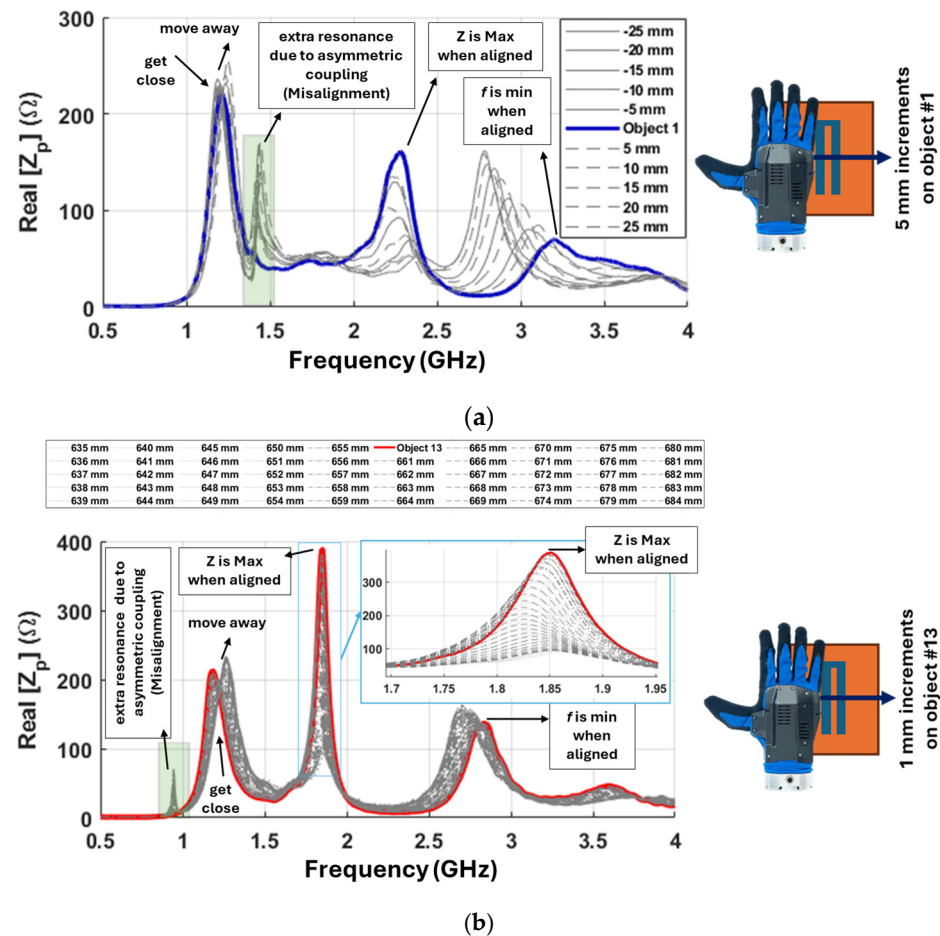


Figure 10. Measured real part of impedance vs. frequency while searching in direction Y (a) around object #1, and (b) around object #13 (Distance = 8 mm).

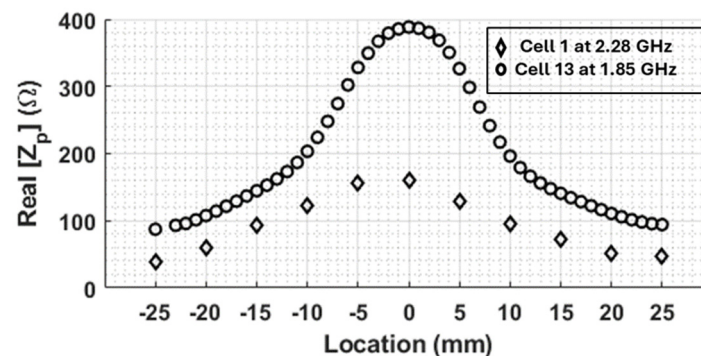


Figure 11. Measured real part of impedance vs location while searching in direction Y around object #1 (5 mm steps) and #13 (1 mm Steps) (Distance = 8 mm).

In a different approach, the system's behavior was analyzed by moving the hand on a specific path in direction X. The hand started 70 mm before the center of object #13, passed through the center, moved towards the center of object #5, and then continued moving another 70 mm after passing the center while the moving increments were 5 mm, at further distances. The moving increments were reduced to 2 mm and 1 mm close to the center of the object. As shown in Figure 12, due to the symmetric shape of the tags and the symmetric alignment of the hand in the X direction, the extra resonance in the previous case is no longer evident here. Instead, the graph reveals a concentration of resonances in two distinct areas: one between 1.5 GHz and 2.0 GHz around object #13, and another between 2.0 GHz and 2.5 GHz around object #5.

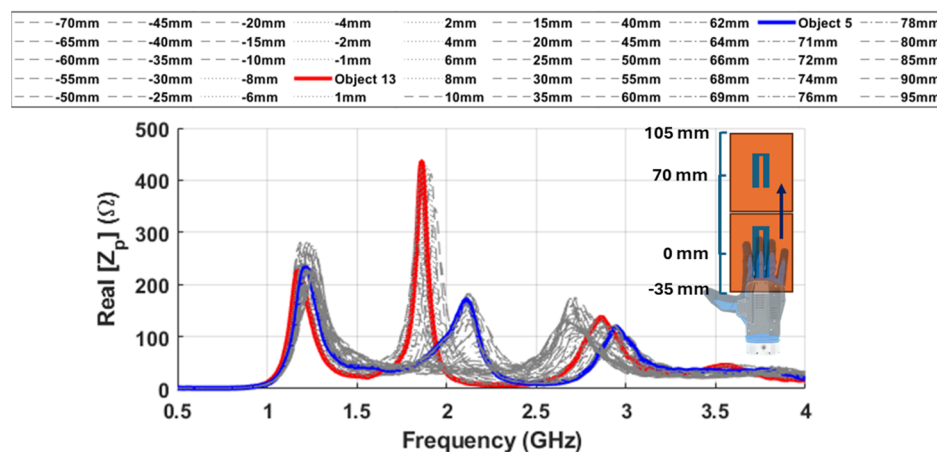


Figure 12. Measured real part of impedance vs. frequency while searching in direction X (shown with arrow) passing from object #13 to object #5 (Distance = 8 mm).

Figure 13 presents impedance values using these three methods while varying the hand position along the X direction. The first approach involves identifying the peak impedance values of each curve (corresponding to each position) within the frequency range of 1.5 GHz to 2.5 GHz, as illustrated in Figure 13a. In this method, it is possible to determine the location of each object with good accuracy, since the highest impedance value typically corresponds to a position near the center of the object. However, this approach requires a frequency sweep of 1.0 GHz. It is evident from Figure 13b that selecting specific frequencies such as 1.86 GHz or 2.11 GHz, corresponding to the resonance frequencies of the objects, allows for the detection of each object individually. However, finding a single frequency capable of detecting both tags would be advantageous.

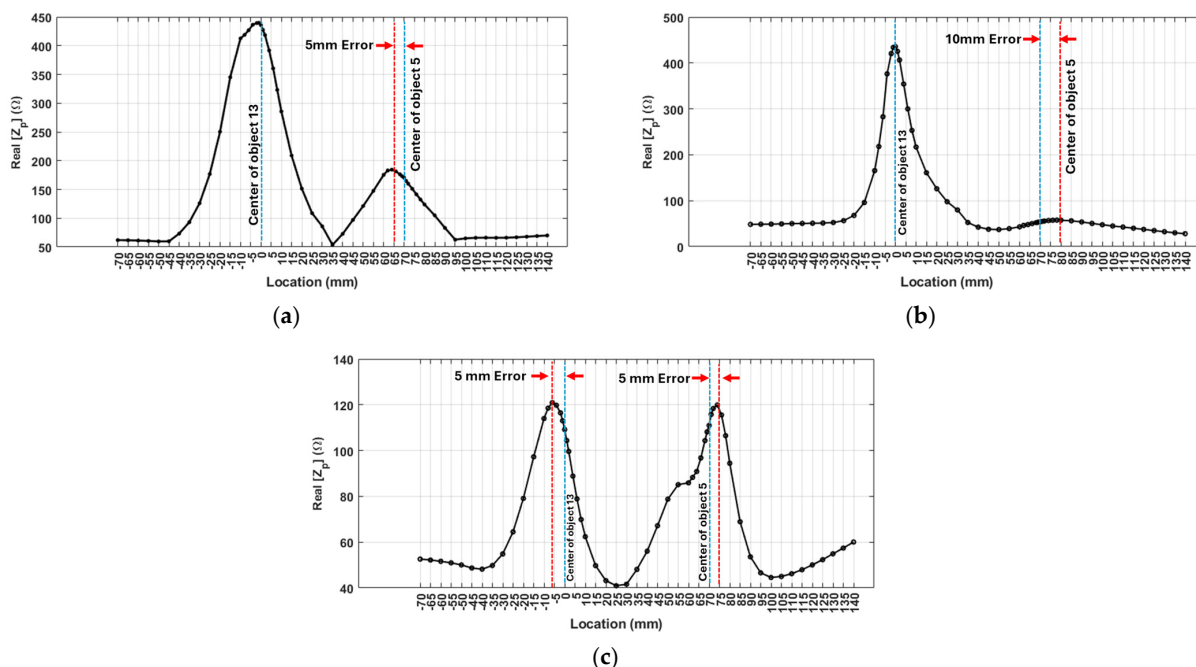


Figure 13. Measured real part of impedance vs. location while searching in direction X passing from object 13 to 5 while (a) selecting a maximum value of impedance in the range 1.5 GHz to 2.5 GHz, and when the selected frequency is (b) 1.86 GHz or (c) 2.92 GHz (Distance = 8 mm).

Upon examining frequencies between 2.5 GHz and 3.0 GHz, it was noted that both tags exhibit similar resonance patterns and behaviors across this range. Therefore, choosing

a frequency like 2.92 GHz (where the resonance curves intersect at 0 mm and 70 mm positions) might enable the detection of both tags simultaneously, as depicted in Figure 13c.

In Figure 13a, there are two distinct peak points near 0 mm (center of tag #13) and 80 mm (center of tag #5), indicating the feasibility of aligning the hand in this direction. However, a minor discrepancy exists: a 5 mm error for object #5 and a 2 mm error for object #13. This can be resolved by adjusting the position of the maximum impedance value to the center of the tagged cell. By selecting the resonance frequency specific to object #13 as shown in Figure 13b, the system can accurately locate object #13, but alignment with object #5 may not be as precise. Ultimately, choosing 2.92 GHz allows the system to align itself with both objects with a 5 mm error (Figure 13a).

Overall, the method of selecting the maximum impedance value across all curves proves to be the most reliable approach while all systems are operating within the frequency range of 0.5 GHz to 3.5 GHz, eliminating the need for a single fixed frequency. Table 1 presents the core functionality of the sensing system.

Table 1. Core functionality of sensing system.

Function	Approach	Outcome
Object Identification	Impedance/resonance fingerprint	Recognizes 15 distinct objects via unique tag responses
Position Alignment	Frequency shift tracking	Detects planar and angular object alignment
Tag Differentiation	Resonator length variation	Frequency shifts (1.5–3.5 GHz) distinguish objects
Angular Sensitivity	Impedance peak at 0° alignment	Δ Impedance signals angular misalignment
Distance Sensitivity	Resonance amplitude decay with distance	Optimal sensing range: 8–25 mm

6.3. The Effect of Angle Change

The next step involves investigating how the system behaves when the angle of the hand changes relative to the tagged surface, as shown in Figure 14.

In these tests, the rotation center was positioned at the lower point of resonator #13. If there are two objects nearby on the left and right sides of object 13, the angle of the hand relative to this object varies from -42 degrees to 42 degrees in 6-degree increments.

Figure 14a displays the real parts of the input impedance across the frequency spectrum, particularly at 1.86 GHz. When the hand is not angularly aligned, an additional resonance point around 1.0 GHz appears due to unsymmetric coupling in the Y-direction movement. Moreover, at the resonance point near 1.86 GHz, there is a significant change in the real part of the impedance value as the angle changes. The impedance value is highest at zero degrees, and this varies noticeably as the angle deviates from this position.

At the frequency of 1.86 GHz, the figure illustrates a substantial difference between different angles, with zero degrees showing the maximum value, highlighting the importance of aligning the hand angularly (Figure 14b). The asymmetry in the figure for positive and negative angles is due to the tags on both sides of resonator #13 having different lengths, which affects these values. This enables the system to detect if the hand is not properly aligned angularly and to subsequently align the hand with the object accordingly.

The system achieved a localization accuracy of ± 2 mm and angular recognition within $\pm 6^\circ$. It was hypothesized that the proposed radio frequency (RF) sensor would demonstrate high robustness under consistent test conditions, including minor variations in distance and tag orientation. The experimental results confirmed this assumption: the sensor consistently recognized and localized the tagged objects with high accuracy across repeated trials. Notably, small deviations in distance (within the calibrated operating range) or environmental conditions (e.g., ambient light or electromagnetic noise) did

not significantly affect the sensor's performance. Although such variations can alter the measured impedance values slightly, the sensor still reliably identifies the tag signatures due to the distinct and stable resonance characteristics of each tag. This consistency supports the reliability of the sensing system and its suitability for integration into robotic applications where stable performance under varying operational constraints is required.

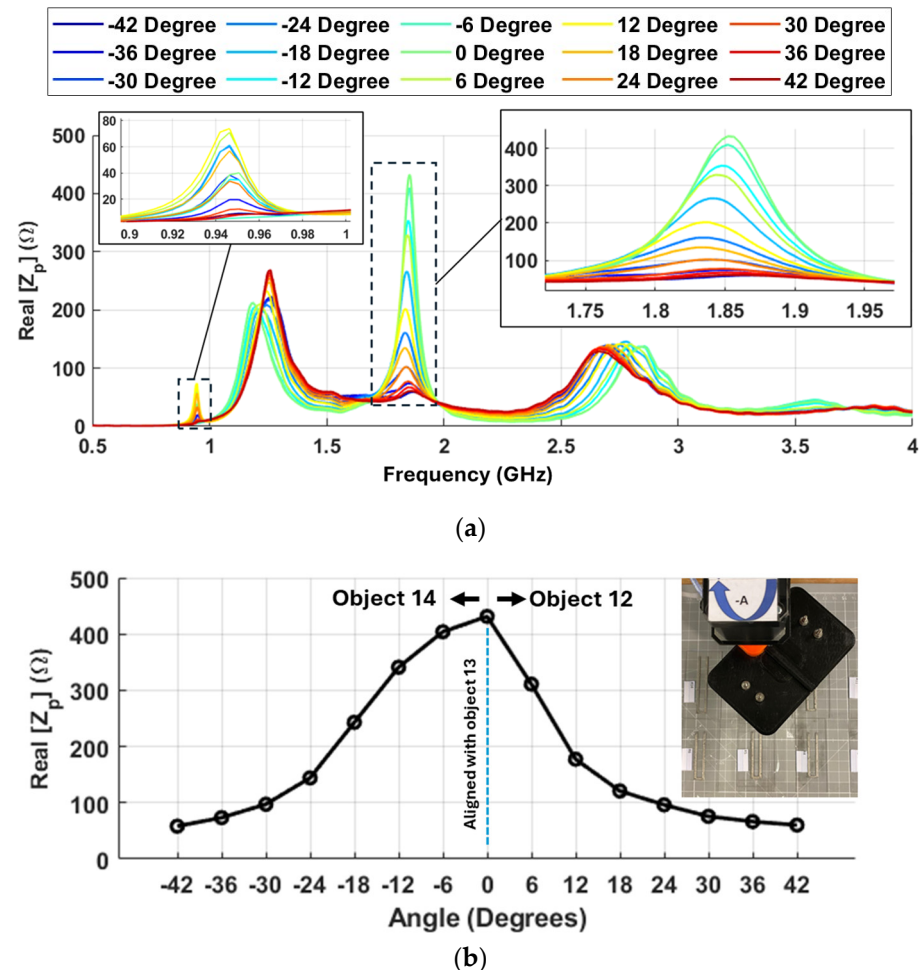


Figure 14. Measured real part of impedance in the (a) full frequency spectrum, and (b) Real part of the impedance versus angle during scanning toward direction A at $f = 1.86$ GHz (Distance = 8 mm).

6.4. The Effect of Distance Change Between the Probe and Resonators

In the final approach, the distance between the tagged surface and the hand varied from 8 mm to 25 mm, as shown in Figure 15. The hand was aligned in both the X and Y directions with the tags, and measurements were collected.

The results, shown as the real and imaginary parts of impedance, reveal several notable changes. The most significant change observed is a significant drop in the impedance value for resonances between 1.7 GHz and 2.4 GHz as the distance increases. Additionally, the curves exhibit smooth variations, but there is a shift in frequency and impedance values among different tags, enabling tag detection albeit potentially with lower accuracy. Another useful observation is that the impedance value at resonances between 2.5 GHz and 3.0 GHz increases with changes in distance and the curves are concentrated around a single frequency. Also, around 1.25 GHz the curves are smoother, and the value is lower. These observations suggest that by monitoring this impedance range, it can be determined whether the hand is at an appropriate distance for accurate alignment.

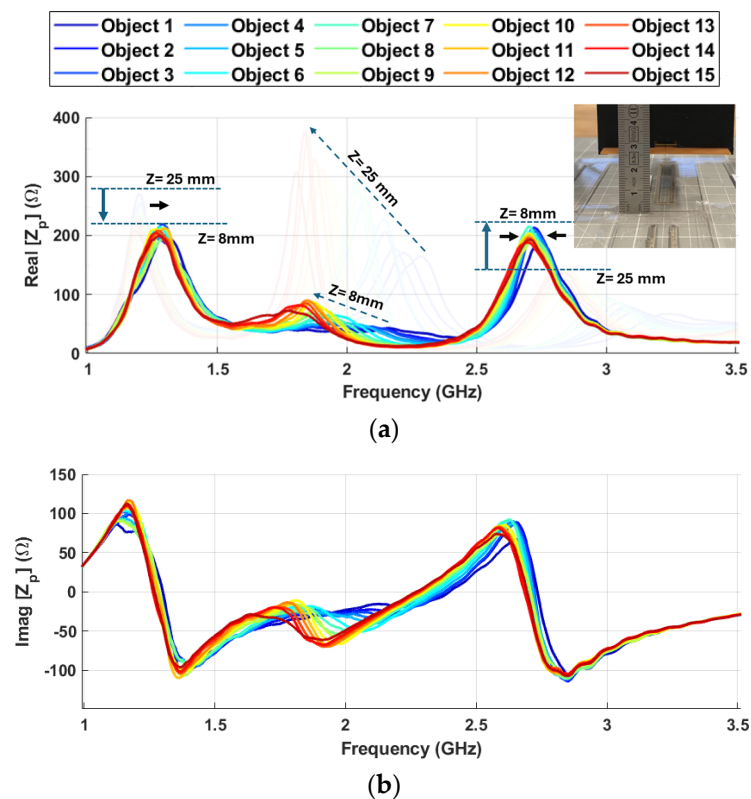


Figure 15. Measured (a) real and (b) imaginary part of the impedance of the probe aligned with objects tagged with resonators of different sizes (Distance = 25 mm).

It should be noted that one limitation of the current setup is its dependence on tag placement and material uniformity. Performance may degrade under electromagnetic interference, in outdoor environments, or when used with irregularly shaped or reflective objects. Moreover, real-time implementation is currently constrained by probe scanning speed and post-processing time.

To contextualize the advantages of the proposed RF sensing system, a qualitative comparison was made with three widely used pre-touch sensing approaches: traditional visual methods, capacitive sensing, and inductive sensing. The comparison considers key operational criteria relevant to robotic applications, including environmental robustness, material sensitivity, performance at varying distances, and implementation cost. As summarized in Table 2, visual methods offer high spatial resolution but suffer from light dependency, occlusion sensitivity, and blind spots at close range. Capacitive sensing is inexpensive and compact but is strongly affected by an object's material properties, especially for non-metallic or non-grounded targets, and is sensitive to moisture and grounding effects. Inductive sensing works well with metallic targets but is ineffective for non-metallic objects and has a limited sensing range. In contrast, the proposed RF sensing approach maintains stable performance across lighting conditions, object materials, and spatial orientations, while also offering low implementation costs and resistance to environmental challenges such as dust, smoke, and poor visibility.

Table 2. Qualitative comparison of pre-touch sensing technologies for robotic applications.

Criterion	Visual Methods	Capacitive Sensing	Inductive Sensing	Proposed RF Sensing System
Lighting dependency	High; stable light required	None	None	None
Occlusion sensitivity	High; needs clear line-of-sight	Low	Low	Low
Material effect	Affected by color/texture	Limited on non-metallic, non-grounded	Works only on metallic objects	Works on various materials
Blind spots	Close-range blind points	None	None	None
Posture robustness	Reduced at large angles	Limited by electrode geometry	Limited by coil geometry	Stable over wide orientations
Distance performance	Weak at extreme near/far range	<5–10 mm	<50 mm (geometry-dependent)	Broad pre-touch sensing range
Motion sensitivity	Motion blur possible	Low	Low	Low
Computation load	High; image processing	Low	Low	Low
Environmental sensitivity	Light, dust, smoke affect	Moisture, grounding effects	EM interference	Resistant to dust/smoke/low light
Cost	Moderate-high	Low	Low-moderate	Low

7. Conclusions

This work presented a novel radiofrequency-based sensing system for object recognition and localization in robotic hands. Using 3D-printed resonators and a customized RF probe, the system demonstrated the precise identification and alignment of identical-material objects across planar and angular displacements. Both the simulation and experimental results confirmed their reliability and effectiveness.

The proposed sensor platform offers a low-cost, customizable, and scalable alternative to conventional vision and proximity-based systems, which is particularly effective in challenging environments where lighting, transparency, or metallic interference may hinder optical methods. Once implemented on a robotic hand, the system collects impedance-based data that can assist in autonomous movement planning. Integrating artificial intelligence and machine learning for data analysis is a promising step toward the full automation of robotic manipulation tasks.

The proposed system's simplicity, low cost, and robustness to environmental factors make it a strong candidate for commercialization and seamless integration into existing industrial robotic platforms. Its compact design and passive sensing approach allow it to be retrofitted into a wide range of robotic arms without major hardware modifications, enabling enhanced positioning and orientation detection in environments where vision-based systems are unreliable. Potential applications include automated assembly lines, precision material handling, and quality inspection processes, where the system could provide consistent performance with minimal maintenance requirements. These attributes open opportunities for technology transfer to industrial partners seeking cost-effective and reliable localization solutions.

However, this work is not without limitations. The current system was evaluated only on objects made of a single material and under controlled conditions. Its recognition accuracy may be affected by factors such as environmental noise, improper tag placement, or variations in object geometry. In addition, sensing resolution decreases at distances beyond the calibrated proximity range, potentially limiting the system's applicability in more complex or larger-scale environments. Future work will address these limitations by expanding testing to objects composed of heterogeneous materials and exploring the system's robustness in cluttered, real-world, or dynamic scenes. Additionally, adaptive control of sensing parameters, real-time calibration, and integration with complementary

modalities such as tactile and vision sensors could enable a more robust and intelligent multimodal perception framework for next-generation robotic hands.

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Abbreviations

The following abbreviations are used in this manuscript:

RF	Radio Frequency
LiDAR	Light Detection and Ranging
AM	Additive Manufacturing
VLP	Visible Light Positioning
SLAM	Simultaneous Localization and Mapping
LED	Light-Emitting Diode
BoWs	Bag of Words
CNN	Convolutional Neural Network
EVA	Ethylene-Vinyl Acetate foam
PEC	Perfect Electric Conductor
PC	Polycarbonate
PVC	Polyvinyl Chloride
CST	Computer Simulation Technology
CPW	Coplanar Waveguide
VNA	Vector Network Analyzer
UWB	Ultra-Wideband
BLE	Bluetooth Low Energy
Cobots	Collaborative Robots

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