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Detecting Position and Direction of a Device by Swept Frequency of Microwave Using Two-Dimensional Communication System

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Abstract : We propose a system of detecting the position of a device embedded with an antenna by sensing the electrical power from a two-dimensional communication (2DC) sheet. The system obtains a characteristic power pattern at each position by sweeping the frequency of the microwave supplied to the 2DC sheet. Our system uses a machine learning technique to learn the accumulated power-pattern data to detect the position of a device. The position-detection accuracy of our system was 79.1% when the antenna was moved in 12 mm intervals. In addition to detecting the position of a device, we also estimated the direction.

Key Words : two-dimensional communication, position detection, sweep frequency.

1. Introduction

Detecting the position of objects is important in ubiquitous computing, tangible user interfaces, and robotics as it allows feedback to any interaction. Generally, camera systems are often used to track objects. The camera is placed overhead in an environment or embedded into an object. However, when placing a camera overhead, occlusion often occurs when objects are covered. Embedding a camera under the table will solve this occlusion problem, but the size of the table has to be large enough to maintain a sufficient distance between the camera and objects.

Another common method of detecting position is to embed a sensor into an object. Simultaneous localization and mapping (SLAM) is an example of such a method and is used to locate an object without the need of external sensors in the environment [1]. However, the electric power of an internal sensor mounted on a robot is mostly supplied from a mobile battery. Therefore, every time the battery needs to be charged, the robot needs to return to the charging station or the user needs to replace the battery. Thus, we developed a system of measuring the position of the device without occlusion problems or the need of replacing the battery.

We used a two-dimensional communication (2DC) system as the foundation of our system. This system provides electric power and transmits information to a device via a 2DC sheet. In this sheet, a microwave is propagated, and at the edges, a microwave is reflected causing interference that generates standing waves. These standing waves generate evanescent waves that leak from the 2DC sheet, supplying electric power to an antenna. Manipulating the microwave frequency causes the intensity distribution of the electric field to change, which can also change the standing waves.

Our system shifts the frequency of the microwave on the 2DC sheet (Fig. 1). An oscillator generates swept microwave frequencies on the sheet to be collected by the antenna placed at the top of an XY-plotter. The XY-plotter can accurately move the antenna to any position on the sheet. The system collects 2D power maps for each frequency to be used as learning data and detect a position of a device embedded with an antenna by using these data as classifiers. Although the above experiments were published in [2], we conducted another evaluation to estimate the direction in which the antenna is oriented at the same time as position estimation.

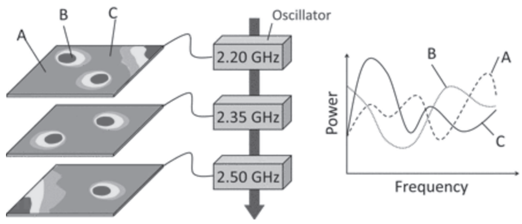

Fig. 1 Principle of our sensing system.

Our system has several advantages. First, it does not require cameras, prevents the occurrence of occlusion, and it does not require large and expensive sensors to be attached to devices. In addition, the device itself is lightweight because our system can construct the oscillator far from a 2DC sheet and the size of the antenna instead of the power supply is 47 mm × 47 mm × 2 mm. Therefore, it is possible for a robot to move under a sofa or a floor in a home environment without using an external or internal sensor even in a narrow space. Also, in an environment where cameras cannot be placed due to privacy, it is possible to estimate the standing position without the need of a battery if the user wears a device in his/her shoes. It may be possible to create a tabletop input interface as a tangible interface that does not require battery replacement.

2. Related Work

2.1 Two-Dimensional Communication System

A 2DC system transmits information and power by electromagnetic waves propagating in thin sheets [3],[4]. In order from the bottom, a 2DC sheet has a conductive layer, dielectric layer, and mesh-shaped conductive layer which leaks evanes-

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cent waves. This system enables devices placed on the sheet to communicate with one another and receive power wirelessly. Since the 2DC sheet is thin and soft, it can be easily installed in an everyday environment and to flexible devices [5]. Shinoda et al. developed a flexible artificial skin with a 2DC system [6].

A system for detecting the position of a device on 2DC sheets based on electrostatic capacity distribution was proposed by using a deformed mesh conductive layer and direction-information marker [7]. The position and direction are added to the 2DC sheet by considering the non-deformed square as 0 and the deformed square as 1 and combining them for every 5×5 square. A capacitance sensor array reads the marker using an image-processing technique to detect position and direction information. This requires a 32×32 capacitance sensor array placed on a 7 cm × 7 cm area and a two-dimensional communication sheet with a unique mesh pattern. The size of this mesh should be designed according to a high-frequency wavelength to generate an evanescent wave. Therefore, there is a limitation to the pattern that can be generated. Also, increasing this pattern increases device size. Compared to their system, measurement is done with a smaller device than them, and even if the measurement area is further expanded, it is not necessary to increase the size of the sensor device.

2.2 Position Detection for Tabletop System

A common method of detecting an object's position is to place a camera overhead in the environment by attaching a visual marker to that object [8]. Sugiura et al. developed a robotic cooking system with a visual marker attached to the robot to control it. A camera is placed overhead in the environment to detect the marker as the robot's position [9]. Bokode succeeded in miniaturizing visual markers by devising an optical system for cameras [10]. The detection of objects without visual markers by learning about the target objects has also been investigated [11]. However, with these systems, it becomes challenging to estimate a position if there is a shielding object between the camera and target objects.

Systems of embedding a camera under a table to detect an object placed on top of it have been proposed. Frustrated total internal reflection (FTIR) enables touch detection by providing a sheet that reflects infrared light on the surface [12], allowing the detection of an object placed on the table and the state of users manipulating the object [13]. FTIR does not cause occlusion but requires a large table. A radio frequency identification tag installed on the plane in advance will allow an object to read the tag to detect the position of another object [14]. In another system, a Polhemus sensor is used to detect an object's position by applying magnetism to that object [15]. A cloth-type sensor that can detect the pressure on the contact position can also be applied for 2D-position detection [16]. SmartSkin can detect the position of an object with a capacitance array [17]. Project Zanzibar [18] uses NFC tags to acquire information from objects on the sheet and estimate its position, and also supply electric power. However, it can supply 50 mW of electric power, but the two-dimensional communication sheet can supply more electric power depending on the power of the oscillator. Therefore, two-dimensional communication is possible for various purposes of outputting such as lighting LEDs and running a motor. These systems can measure the position of an object without any occlusion. However, our system is not just limited to position detection, and it can also supply more electric power to an object simultaneously.

Numerous researchers also mounted sensors on a target object to detect its position without placing an external sensor in the surrounding environment. For example, a computer mouse can generally detect the amount of its movement by sensing the unevenness of the surface it is on with a camera. Inertial measurement units equipped with sensors internally to measure acceleration and angular acceleration are commonly used for self-position detection. A system has been proposed for constructing a 3D map of an environment and detecting an object's position with a depth camera [19]. These systems detect an object's position using the actual object and can acquire the amount of relative spatial movement. However, a sensor can be relatively large, and the amount of absolute movement cannot be measured.

Display-based computing displays unique pattern images to around objects by using projectors placed over the objects, where the objects detect surrounding pattern images using internal photosensors. This system can be implemented in a compact system, but occlusion occasionally occurs [20],[21]. Our system detects the position of a device by providing an active signal from the environment side.

2.3 Identification by Frequency Sweep

There are methods of detecting the states of deformation and posture of objects by measuring the objects' changes while producing dynamic, active signals. Sato et al. proposed a system called "Touché", which recognizes not only two conventional ON/OFF states but also various users' gripping states by executing electrostatic capacitance sensing in a wider frequency band [22]. Touch & Activate is a simple hardware system configuration for recognizing the interactions between a user and an object by using machine learning on the frequency spectrum captured by a microphone when providing a wide range of sound frequency bands to the object [23]. Acoustruments is a method with which deformed objects made using a 3D printer are attached to a smartphone. The smartphone's speaker resonates sound through them to be sensed by the microphone to measure the deformed state of the 3D printed objects [24]. Laput et al. also applied this method to detect changes in the geometry of an environment [25]. SpecTrans enables the recognition of various materials, such as glass, metal, and plastic, by capturing reflected images obtained by sequentially irradiating four different wavelengths of LEDs and laser light on an object [26]. Google Soli is a sensor that can identify hand gestures by using the radar method, and RadarCat enables the recognition of objects with this sensor [27],[28].

We focused on detecting the position of an object by sweeping the frequency of the microwave propagated on a 2DC sheet.

3. Principle

Our proposed system consists of two stages; the first stage involves obtaining learning data of the power detected at every point in the sheet, and the second stage involves placing a device at any area on the sheet and comparing it with the learned data to detect the position of that device.

Each point on the sheet may have a distinct generated standing wave, but the wave remains constant for a constant frequency. When the frequency changes, the standing wave on any position also changes, creating a unique power pattern for each point, as shown in the graph of Fig. 1. The system combines all the power points on the sheet at a certain frequency to create a power map and uses a collection of these power maps from different frequencies as the learning data.

Some researchers have taken on the challenge of simulating standing waves on a 2D sheet without actually measuring the electrical power on the sheet [29]. However, the actual power map is rarely the same as that generated in the simulation, as it is difficult to perfectly simulate the microwave reflected at the edge of the sheet. In addition, the contact point between the coaxial cable and sheet may change, and the shape of the 2DC sheet is not fixed. Therefore, we created power maps from real measured data using an antenna placed on a 2D sheet.

4. Implementation

Our proposed system consists of five components; a high-frequency oscillator, a 2DC sheet, a coaxial cable, a power receiving antenna, and an XY-plotter, as shown in Fig. 2. The high-frequency oscillator first generates a microwave from 2.20 GHz to 2.50 GHz at 0.01 GHz intervals to create 31 states of standing waves. This oscillator is connected to a desktop PC at which the frequency changes according to the serial command sent from the PC. The 2DC sheet is fixed on a table, and the coaxial cable transmits the generated microwave to the 2DC sheet. The output power of the microwave is 9 W. The size of the 2DC sheet we use is 300 mm × 300 mm. A power receiving antenna, consisting of a rectifier circuit, a current sensor (ACS712 (Low Current)), and a microcontroller (Arduino Uno R3), senses a current and transmits the sensor values to the PC after being stabilized through a low pass filter in the microcontroller (Fig. 3). We created a 47 × 47 mm antenna that has four electrodes with a rotationally symmetrical arrangement (Fig. 4) to receive stable power from the 2-DC sheet (Fig. 5). Both the microcontroller and the oscillator work synchronously. After switching the frequency of the oscillator by 0.01 GHz, the system saves the sensor value to the memory of microcontroller at some time intervals. After repeating up to 2.50 GHz, the microcontroller sends the sensor value to the PC. The current sensor has built-in semi-fixed resistance and can adjust the value of the sensor. Therefore, it is possible to estimate the position with only the sensor of the same one which acquired the data. Finally, the XY-plotter controls the antenna position relative to the position specified from the computer.

4.1 Creating Power Maps for Learning Data

The system sends a serial command to the XY-plotter to move the receiving antenna automatically to a specific position. It then sweeps the frequency of the microwave generated by the oscillator several times at this position. The antenna measures the electrical power by reading data from the current sensor attached to it. The system executes this process on the whole area of the 2D plane to create power maps. Figure 6 illustrates an example of the electrical power distribution on a 2DC sheet when the antenna was moved at intervals of 12 mm. We obtained the sensor values at 256 points on the 2DC sheet. This power distribution changes according to the frequency of the microwave because the shape of the standing wave varies depending on the frequency. We then applied these data to a support vector machine (SVM), a supervised machine learning algorithm, by

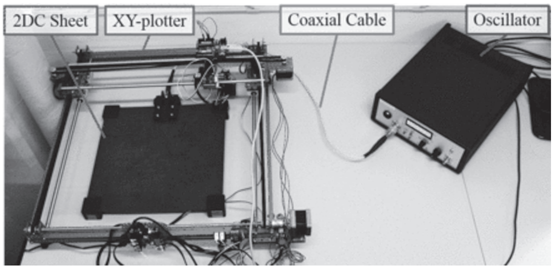


Fig. 2 Automatic electrical field mapping system.

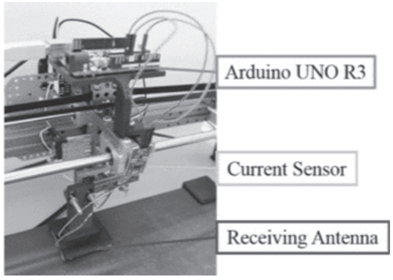


Fig. 3 Power receiving antenna of automatic electrical field mapping system.

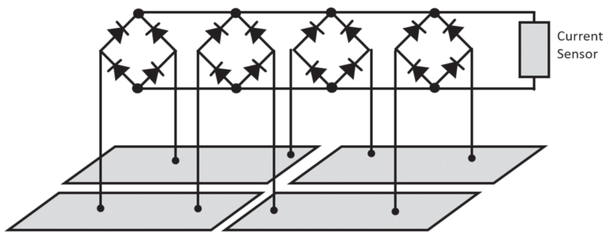
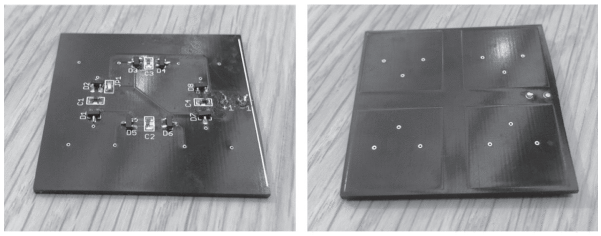


Fig. 4 The rectifier circuit of a receiving antenna with a current sensor.



(a) Top (b) Bottom

Fig. 5 A receiving antenna, which size is 47 mm × 47 mm.

using the SVM for Processing (PSVM) library [30]. Before applying the data to the SVM, the data were normalized to a range of 0 to 1.

4.2 Position Detection in Real-Time

When a device is placed on a 2DC sheet, our system classifies the data detected from the device with the learned data to predict the device's position. The sweep of frequency from 2.20 GHz to 2.50 GHz at intervals of 0.01 GHz to predict this position takes at least 2.1 s. Although increasing the learning data increases the classification rate, the time required will be much higher as the sweeps have to be repeated as many times as the amount of data.

5. Evaluations

We conducted four experiments on our system to find the optimal values of sweeping speed and learning data quantity to carry out fast and accurate detection. We first evaluated

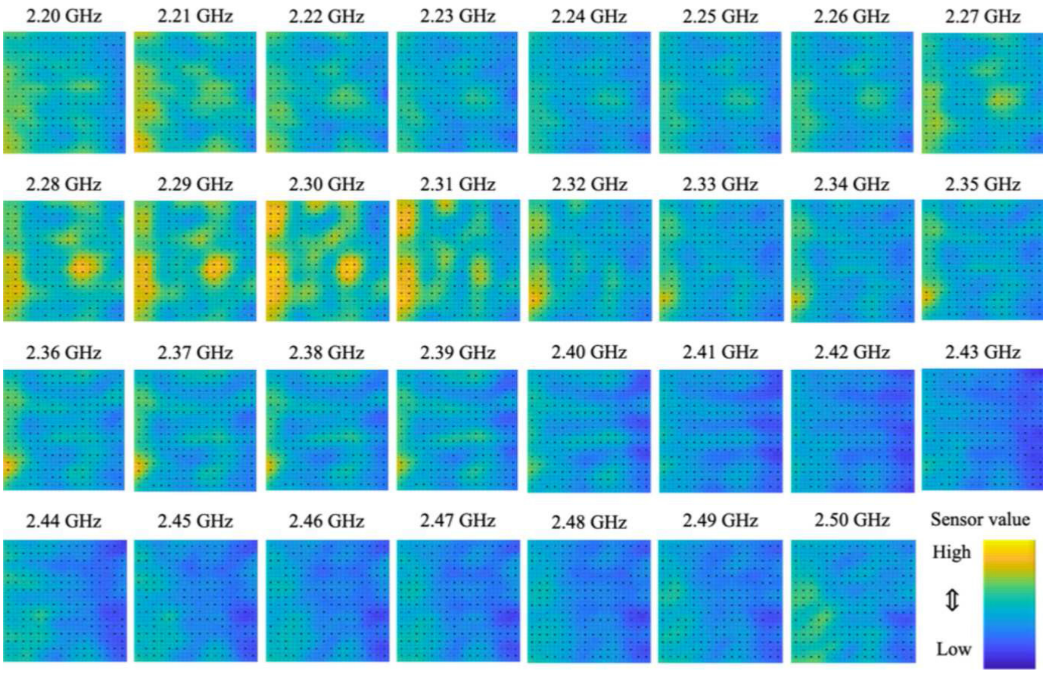


Fig. 6 State of electric field map acquired when manipulating frequency of electromagnetic waves output from transmitter at intervals of 0.01 GHz. Total of 31 electric field maps were generated.

the change in the sweeping speed of the microwave, followed by evaluating this accuracy according to the quantity of data. We then evaluated this accuracy according to the resolution of learning position and observed the effect of the detected device's direction. In the evaluation of position detection, we use 180 mm × 180 mm of the part of the sheet. In an experiment where position and direction are simultaneously measured, we use 84 mm × 84 mm of the sheet.

5.1 Effect of Sweeping Speed of the Microwave

We first observed the efficiency of our system depending on the time interval at which the frequency of the oscillator is shifted. As the oscillator cannot switch frequencies more than once every 70 ms, we collected the data while gradually increasing the time interval from 70 ms and measured the position-detection accuracy at each time interval. We defined 64 points with an interval of 24 mm on the 2DC sheet, and our system collected data when it swept 15 times at each position of the device. Figure 7 illustrates the experimental results. As the time interval increased, the position-detection accuracy increased since the generated microwave requires time to stabilize. We found that the position-detection accuracy was optimal at around 175 ms intervals. Under this condition, the system required a total time of 5.5 s to detect the device's position.

5.2 Position-Detection Accuracy Corresponding to Learning Data Quantity

We then observed the changes in position-detection accuracy corresponding to the amount of learning data. We fixed the interval of movement of the receiving antenna to 24 mm. To obtain the learning data, the system carried out 2 to 30 sweeps at an interval of 175 ms, with reference from the previous experiment, from 2.20 GHz to 2.50 GHz at intervals of 0.01 GHz at each position of the device and evaluated position-detection accuracy from cross-validation. Figure 8 shows the position-

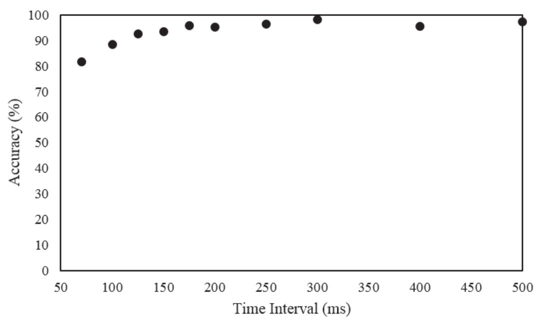


Fig. 7 Relationship between sweeping time interval and accuracy of position detection.

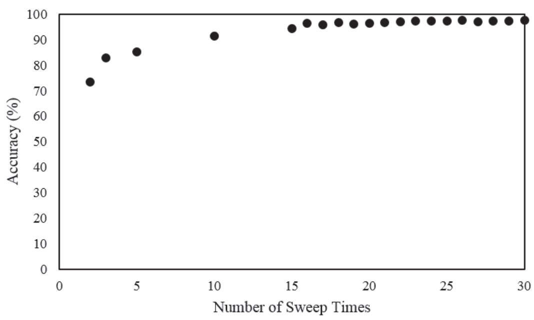


Fig. 8 Relationship between position-detection accuracy of position detection and amount of learning data.

detection accuracy according to the amount of learning data. We observed that this accuracy increased as the amount of learning data increased. However, we also observed that the change became negligible after 22 or more sweeps, showing that data correction is sufficient with 22 sweeps at each position of the device.

Table 1 Number of learned positions relative to distance of positional interval.

Distance of positional interval	Number of points
12 mm	256
24 mm	64
36 mm	25
48 mm	16
72 mm	9
96 mm	4

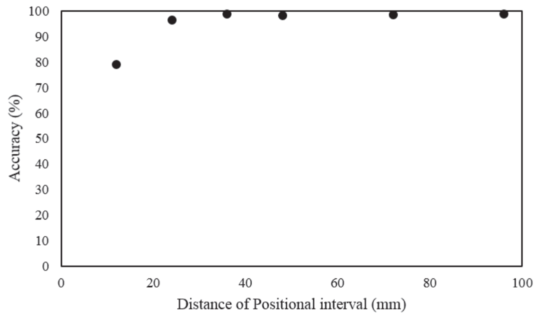


Fig. 9 Relationship between resolution of learning position and position-detection accuracy.

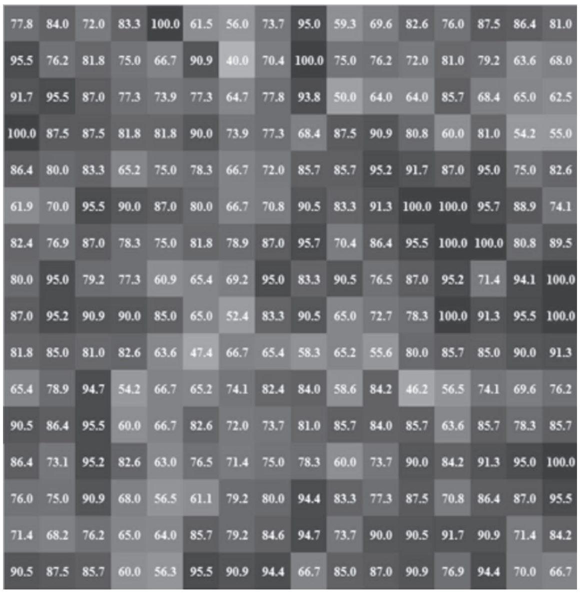


Fig. 10 Position-detection accuracy of each point when moving antenna at 12 mm intervals.

5.3 Resolution of Position Detection

We carried out 22 frequency sweeps at each point from 2.20 GHz to 2.50 GHz at intervals of 0.01 GHz and evaluated position-detection accuracy using the data acquired from the receiving antenna. We positioned the antenna at intervals of 12 mm, 24 mm, 36 mm, 48 mm, 72 mm, and 96 mm and collected data at each point. Table 1 shows the number of positions that we measured depending on the position interval used. We used these data as learning data with the SVM and a radial basis functional kernel. We conducted 22-fold cross-validation to evaluate position-detection accuracy. Figure 9 shows the position-detection accuracy in relation to the position interval of the antenna and observed that this accuracy increased as the interval increased. This is because a longer interval has less classifiers; thus, increasing position-detection accuracy. Figure 10 shows the position-detection accuracy at each point at intervals of 12 mm and observed that this accuracy was 79.1% with a false detection of 60.7% at 8 points adjacent to the true position. By classifying at the adjacent 8 points, the probability of detecting within 17 mm from the true position was 91.8%. We also observed that the electrical power patterns of neighboring points were similar. Therefore, even if the position is not accurately detected, it can be detected in the surrounding area.

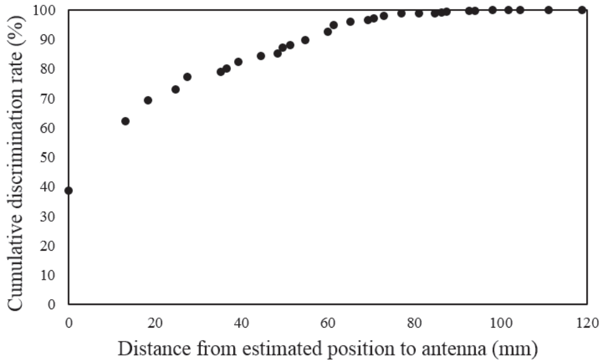


Fig. 11 Results from data set created by merging data of an antenna rotated in different directions.

5.4 Effect of Rotation of a Device on Position-Detection Accuracy

In the previous experiments, we collected data while keeping the antenna angle constant. In actual use cases, however, the direction of the antenna is determined randomly; thus, we acquired data. We evaluated the position-detection accuracy as well as the rotation angle. We developed a mechanism to rotate the antenna 15° at the tip of the XY plotter. The antenna was then moved at intervals of 12 mm in a square area of 84 mm and further rotated 15° to collect data. We collected a total of 714,240 sensor values (64 positions × 24 directions × 15 sweeps × 31 steps). We created this data set by conducting cross-validation and comparing the classification rates.

The first method involves classifying the data into the same class and the same position without distinguishing a difference in antenna direction. In this case, we created 64 classes, and the classification rate was 38.3%. Also, the average error distance from the estimated position to the position where the actual antenna was located was 18.8 mm. Figure 11 shows the probability relationship estimated within the distance from the location where the antenna was located. There was a maximum of 21 points that could be identified within 30.0 mm, but the probability of position-detection within that range was 75%. From these results, detecting a position close to that where the antenna is actually placed may be possible.

The second method involves distinguishing differences in antenna direction and classifying all conditions such as device's position and direction as different classes. With this method, we created 1536 (64 positions × 24 directions) classes, and the classification rate was 55.9%, which was higher than that from the first method. From these results, as the antenna rotates at the same position, our system recognized different conditions. There was a tendency to detect the position of the device at a nearby place even if the position of the antenna was erroneously detected (Fig. 12). The average distance error was 8.0 mm, and the probability of the device being detected without distance er-

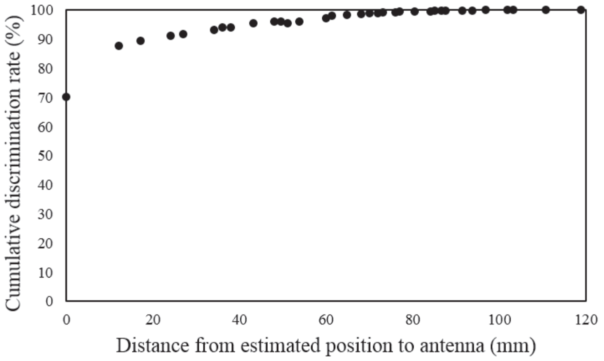


Fig. 12 Results of data set created with different directional an antenna as different identification classes.

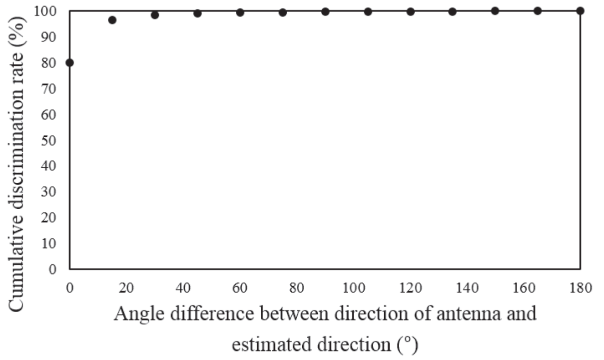


Fig. 13 How the antenna direction is estimated when estimated to the correct position with different directional antennas as different identification classes.

ror was 70%. The probability of which position was detected within 30.0 mm from the antenna position was 90% or more. Even if our system misidentifies the direction of the antenna, it detects the position where the antenna was regardless of the direction. We also analyzed how the antenna direction is estimated when the correct position of the device was detected. The average error angle in the device direction was 4.4°, and the position-detection accuracy was 80%. The probability of a position being detected within 15° of error was over 95% (Fig. 13). Our system could detect the device in a direction similar to that.

The antenna is made intended for non-directionality, and the electrodes are rotationally symmetrical in the antenna. However, our evaluation showed the directional difference. This is presumably because wiring other than the electrode and the output part to the sensor is not arranged symmetrically. On the other hand, it was found that our system can recognize the direction in addition to the position by using this directionality well. In order to further improve this direction estimation, devise to make this unique antenna shape.

6. Limitations and Future Work

Since the frequency of the oscillator used in our study lacks the ability to switch faster, it consumes time to create electrical power maps and carry out real-time detection. In the future, we will use a better oscillator to quickly create a stable microwave. We will also reduce the sweep time by selecting only relevant frequencies.

Also, although we have found that the detection accuracy decreases as the bandwidth decreases, we have not yet revealed proper bandwidth.

In this study, we used an XY-plotter to place the antenna at an accurate position. However, due to the size limitation of the XY-plotter, it is challenging to use it on larger sheets. Therefore, we aim to replace it with a vehicle-type robot that can freely move on a 2D plane.

In the experiment on position and rotation, we reduced the measurement area since the number of data measurement times increased. If the area is large and the number of classifications increases, the accuracy may decrease. We believe highly accurate estimation of direction and location in such a large area is possible by sweeping using multiple oscillators and generating characteristic data.

We did not consider cases in which two or more antennas are placed on a 2DC sheet. For this case, the electric field distribution may change compared to using one antenna. Therefore, we will examine the use of two or more antennas and consider how to distinguish the learning data.

With the current method, it is difficult to estimate the position on the plane where many objects are arranged. When an object is placed or moves, reconstruction of learning data is required.

As long as the shape of the antenna is the same, our system can work correctly. If the pattern of electrodes in the antenna is changed, the system cannot detect the antenna's position and direction.

In our system, since the 2DC sheet we used in this time has no flexibility, the standing wave pattern does not change. In the case of a flexible sheet, the position estimation in this system does not work. It will also be necessary to recreate the learning data when the shape of the 2DC sheet changes or when the contact position between the coaxial cable and sheet changes.

The antenna we used is made intended for non-directionality and the electrodes are rotationally symmetrical on the antenna. However, our evaluation showed the directional difference. The main reason is that the grid type electric pattern is printed on the top layer of a 2DC sheet, so the relation between electrodes of antenna and sheet changes. Another reason is that the internal wires of the circuit and the output part to the sensor are not arranged symmetrically. However, based on such unintentional features, we found that our system can recognize the antenna's direction as well as the position. In future work, to improve the accuracy of direction estimation, we will make the new type of antenna which has unique design pattern of an electrode.

7. Conclusion

We proposed a system of detecting the position of a device embedded with an antenna by sensing the amount of electrical power from a 2DC sheet. The system obtains a characteristic power pattern at each position by sweeping the frequency of the microwave supplied to the 2DC sheet. Our system uses a machine learning technique to learn the accumulated power-pattern data to detect the position of a device. We also conducted experiments to evaluate the position-detection accuracy of the system by changing different properties. The results indicate that this accuracy was about 79.1% when the antenna was moved at 12 mm intervals. In addition to detecting the position of a device, antenna direction was also estimated. The position-detection accuracy when estimating 1536 classes when rotating the antenna 15° at intervals of 12 mm was 55.9%. This enabled accurate position detection where the antenna is located, resulting in small direction error.

Acknowledgments

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