Detecting Position of a Device by Swept Frequency of Microwave on Two-Dimensional Communication System

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Abstract: In this paper, we propose a method to detect the position of a device embedded with an antenna by sensing the amount of 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 predict the position of the device. We also evaluated the accuracy of the position detection was 79.1% when the antenna is moved at 12mm intervals.

Keywords: Two-dimensional communication, Position detection, Sweep frequency.

1. INTRODUCTION

Detecting the position of objects is important in the field of ubiquitous computing, tangible user interfaces, and robotics as this feature allows feedbacks to any interaction. Generally, camera systems are often used to track objects, where two common placements of the camera are to place it overhead in an environment or to embed it into an object. However, when placing overhead, occlusion often happens when the objects are covered. On the other hand, embedding the camera will solve this occlusion problem, but the size of the table has to be large enough to keep sufficient distance between the camera and the objects.

Another common method to detect position is to embed a sensor into the object. Simultaneous Localization and Mapping (SLAM) is an example technique of this method to locate an object without the need of external sensors in the environment. However, the disadvantage is that the embedded sensor is relatively expensive and large in size. In this paper, we focus on constructing a system to detect the position of objects placed on a 2D plane, without being affected by occlusion or object size.

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

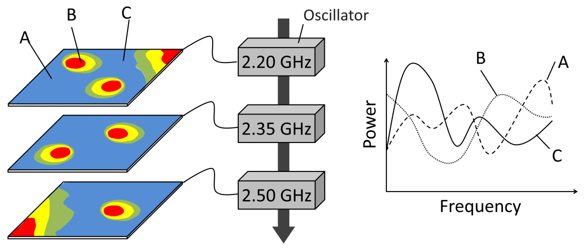

Fig.1 Principle of our sensing system

In this paper, we developed a position detection system by shifting the frequency of 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 a XY-plotter. The XY-plotter can move the antenna accurately to any position on the sheet. The system will collect 2D power maps for each frequency collected to be used as learning data and will perform position detection by using these data as classifiers.

Our method has several advantages. First, it does not require cameras, preventing the occurrence of occlusion and it does not require large and expensive sensors to be attached to the objects. In addition, since 2DC sheet is thin and soft, it can be easily installed in our everyday environment and to flexible objects [11].

2. RELATED WORK

2.1 Two-dimensional communication system

A 2DC system transmits information and power by electromagnetic waves propagating in thin sheets [25][21]. Starting from the bottom, a 2DC sheet has a conductive layer, a dielectric layer, and a mesh-shaped conductive layer, which leak evanescent waves. This system enables devices placed on the sheet to communicate one another and to receive power by wireless. Shinoda et al. developed flexible artificial skin with 2DC system [22].

Many researchers have proposed device position estimation on 2DC sheets based on electrostatic capacity distribution where they measured the position by using deformed mesh conductive layer and direction information marker [10]. The position and direction are added to the 2DC sheet by considering the undeformed square as 0 and the deformed square as 1 and combining them for every 5 × 5 squares. A capacitance sensor that measures the pattern of the mesh conductive layer estimates the position and direction. However, the device containing the sensor is usually large and heavy. In this research, we modified the system at a large scale to add position and direction information to the 2DC sheet. We proposed a method to sense position in the framework of existing 2DC system.

2.2 Position detection for table top system

A common method to detect position is to place a camera overhead in the environment to measure the position and distance of the object by attaching a visual marker to the object [4]. 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 to perceive its position [26]. Bokode has succeeded in miniaturizing visual markers by devising an optical system for cameras [9]. Researchers have also investigated the detection of objects without visual markers by learning about the target objects itself [17]. However, with these methods, it becomes challenging to estimate a position if there is a shielding object in between the camera and the target objects.

Various researchers have also proposed methods to embed camera under the table to detect an object placed on top of it. Abstract Fourier transform infrared spectrometer (FTIR) enables touch detection by providing a sheet that reflects infrared light on the surface [3], allowing the detection of object placed on the table and the state of users manipulating the object [23]. FTIR does not cause occlusion, but it requires the usage of a large table. Radio frequency identification (RFID) tag installed on the plane in advance will allow object to read the tag to detect the position of the object [12]. In another approach, a Polhemus sensor can detect the position by applying magnetism to the target object [14]. A cloth type sensor that can detect the pressure on the contact position can also be applied to 2D position detection [1]. SmartSkin can detect the position of an object with a capacitance array [16]. These approaches can measure the position of an object without any occlusion. However, our method is not just limited to position detection, it can also supply electric power to the object simultaneously.

Numerous researchers also mounted sensors on the target object to detect the position without placing an external sensor in the surrounding environment. For example, a computer mouse can generally detect its own amount of movement by sensing the unevenness of the surface it is on with a camera. Inertial measurement units (IMUs) equipped with sensors internally to measure acceleration and angular acceleration are commonly used for self-position detection. A method has been proposed to construct a 3D map of the environment and to recognize the object's position with a depth camera [2]. These researches advantage by detecting the position using the object itself and it is possible to acquire the amount of spatial relative movement. However, the sensor could be relatively big and the amount of absolute movement cannot be measured.

Display based computing is a system that shows unique pattern images to the objects by projectors placed over them, where the object detects the images using internal photo sensors. This method can be implemented in a compact system, but occlusion occurs occasionally [20] [5]. Our system detects the position of the device by providing an active signal from the environment side.

2.3 Identification by frequency sweep

There are techniques to detect the states of deformation and grasp posture on the objects by measuring their own changes while producing dynamic active signals. Sato et al. proposed a system called "Touché" which recognized not only two conventional ON/OFF states but also various users' gripping states by performing electrostatic capacitance sensing in a wider frequency band [18]. Touch & Activate is a simple hardware system configuration to recognize the interactions with the user by using machine learning on the frequency spectrum captured by the microphone when providing a wide range of sound frequency bands to the object [13]. Acoustruments is a method where deformed objects made by a 3D printer are attached to a smartphone. The smartphone's speaker will resonate sound through them to be sensed by the microphone to measure the deformed state of the 3D printed objects [6]. Laput et al. also applied this technique to detect changes in the geometry of the environment [7]. SpecTrans enables the recognition of various materials such as glass, metal, plastic, etc. by capturing reflected images obtained by sequentially irradiating four different wavelengths of LEDs and laser light on an object [19]. Google Soli is a sensor that can identify hand gestures by using the radar method, and by utilizing this sensor, RadarCat enables the recognition of objects [8] [24].

Our research focuses on detecting the position of the object by sweeping the frequency of the microwave propagated on a 2DC sheet.

3. PRINCIPLE

Our proposed method consists of two stages; the first stage is to obtain learning data of the power detected at every point in the sheet and the second stage is to place a device at any area on the sheet and compare it with the learned data to predict the position of the 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 changes as well, creating a unique power pattern for each point as shown in the graph at Fig. 1. The system will combine all the power points on the sheet at a certain frequency to create a power map and will use 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 [27]. However, the actual power map is rarely the same as the one 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 the sheet may change and the shape of the 2DC sheet is not fixed. Therefore, we plan to create power maps from real measured data using an antenna placed on the 2D sheet.

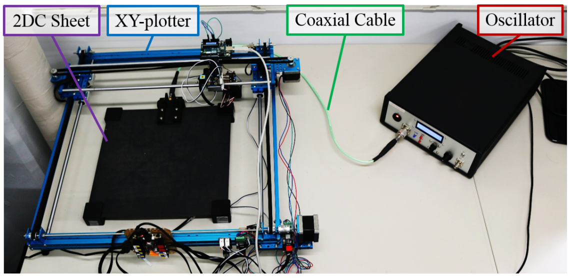

Fig. 2 Automatic Electrical Field Mapping System

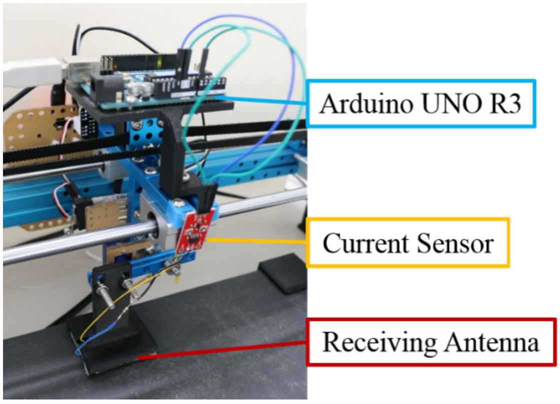

Fig. 3. Power Receiving Antenna of Automatic Electrical Field Mapping System

4. IMPLEMENTATION

Our proposed system consists of 5 components; a high-frequency oscillator, a 2DC sheet, a coaxial cable, a power receiving antenna and a XY-plotter as shown in Fig. 2 and 3. The high-frequency oscillator will first generate microwaves from 2.20GHz to 2.50GHz at 0.01GHz intervals to create 31 states of standing waves. This oscillator is connected to a desktop PC where the frequency changes according to the serial command sent form the PC. The 2DC sheet is fixed on the table and a coaxial cable will transmit the generated microwave to the 2DC sheet. The output power of the microwave is 9W. A power receiving antenna, consisting of a rectifier circuit, a current sensor, and a microcontroller (Arduino Uno R3) senses a current and transmit the values to the PC, after being stabilized through a low pass filter in the microcontroller. We referred to Sakai et al's[21] method to create this antenna. Lastly, the XY-plotter will control the antenna position in relative to the position specified from the computer.

4.1 Creating power maps for learning data

The system will send a serial command to the XY-plotter to move the receiving antenna automatically to a specific position. It will then sweep the frequency of the microwaves generated by the oscillator several times at this position. The antenna will measure the electrical power by reading data from the current sensor attached to it. The system will perform this process on the whole area of the 2D plane to create power maps. In this paper, the system generated a total of 5632 classifiers with 31 dimensional inputs. Fig. 4 visualized an example of the electrical power distribution on the 2DC sheet when the antenna is moved at an interval of 12mm. 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 apply these data to a supervised machine learning algorithm, support vector machine (SVM) by using the Support Vector Machine for Processing (PSVM) library [15]. Before applying the data to the SVM, the data was normalized to a range of 0-1.

4.2 Position detection in real-time

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

5. EVALUATIONS

Using our proposed system, we conducted 4 different experiments to find the optimal values to perform a fast and accurate detection. We first evaluated the change of sweeping speed of the microwave, followed by identifying the accuracy according to the quantity of data. We then identified the accuracy according to the resolution and observed the influence of rotation of the device detected.

5.1 Effect of sweeping speed of the microwave

We first experimented to observe 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 70ms, we collected the data while gradually increasing the time interval from 70ms and measured the accuracy of position detection at each time interval. We defined 64 points with an interval of 24mm on the 2DC sheet and the system collected each data when it sweeps 15 times at each position. Fig. 5 illustrates the results of the experiment. As the time interval increases, the recognition accuracy increases as well, as the microwave generated requires time to be stabilized. From the experiment, we found that the accuracy is optimal at around 175ms intervals. Under this condition, the system requires a total time of 5.5s to detect the position.

5.2 Identification accuracy corresponding to learning data quantity

We then experimented to observe the changes in the accuracy of the detection depending on the amount of learning data. For this experiment, we fixed the interval of movements of the receiving antenna to an interval of 24mm. To obtain the learning data, the system will perform 2 to 30 times of sweeps at an interval of 175ms with reference from the previous experiment, from 2.20GHz to 2.50GHz in steps of 0.01GHz at each position and will obtained the accuracy by cross

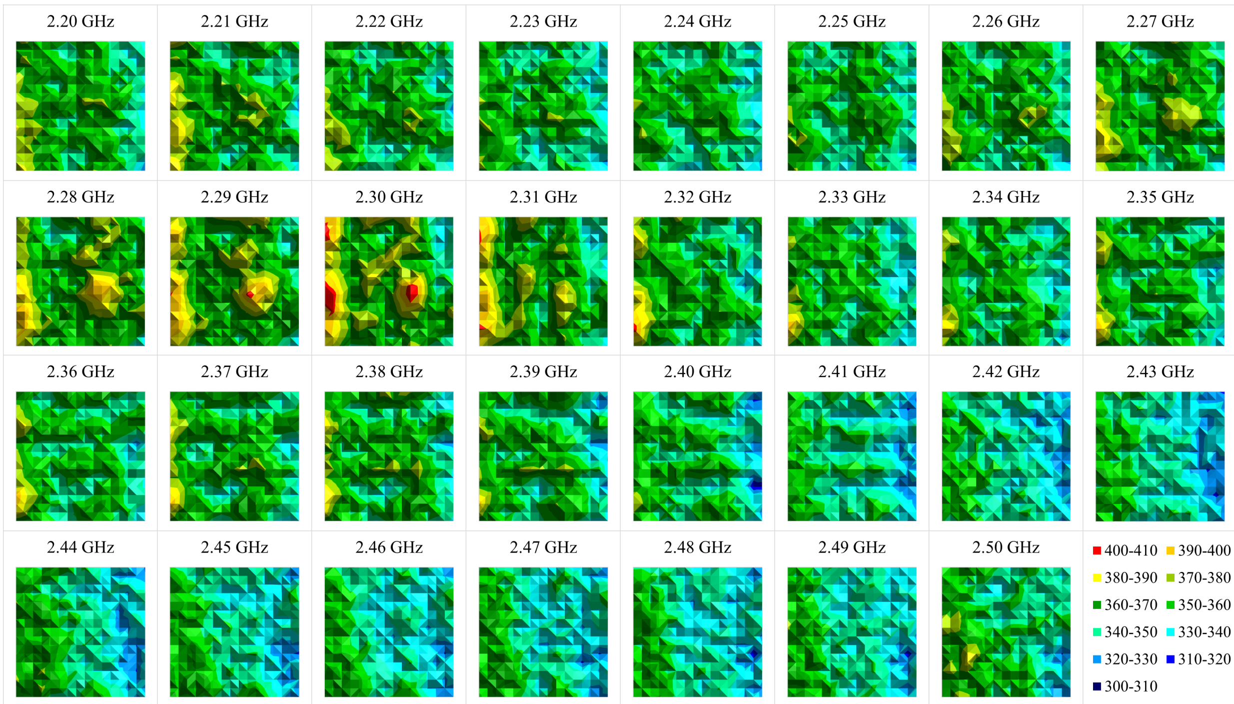

Fig. 4 State of electric field map acquired when manipulating frequency of electromagnetic waves output from transmitter in increments of 0.01 GHz. A total of 31 electric field maps were generated. Numbers of legend are the value received from Arduino.

validation. Fig. 6 shows the detection accuracy according to the amount of learning data. We can observe that the accuracy of detection increases as the amount of the learning data increases. However, we can also observed that the change has become negligible after 22 or more sweeps, showing that the data correction is sufficient with 22 sweeps at each position.

5.3 Resolution of position detection

For this experiment, we performed 22 times of frequency sweeping on each point from 2.20GHz to 2.50GHz in steps of 0.01GHz, and obtained the detection accuracy using the data acquired by the receiving antenna. We positioned the antenna at intervals of 12 mm, 24 mm, 36 mm, 48 mm, 72 mm and 96 mm, collecting data at each point. Table 1 shows the number of positions that can be measured depending on the position interval used. We utilized these data as a learning data with SVM and a radial basis functional (RBF) kernel. In this experiment, we performed 22 fold cross validation to estimate the accuracy. Fig. 7 shows the recognition accuracy in relation to the position interval of the antenna where we can observe that the accuracy increases as the interval increases. This is because longer interval has less the number of classifiers, and thus, increasing the detection accuracy. Fig. 8 shows the detection accuracy of each point with an interval of 12 mm where we observed that the accuracy is 79.1% with a false detection of 60.7% at 8 points adjacent to the true position. By classifying at 8 points adjacent, the probability of detecting within 17mm from the true position was 91.8%. We also observed that the electrical power patterns of neighboring points are similar. Therefore, even if the position is not identified accurately, it can be identified in the surrounding area.

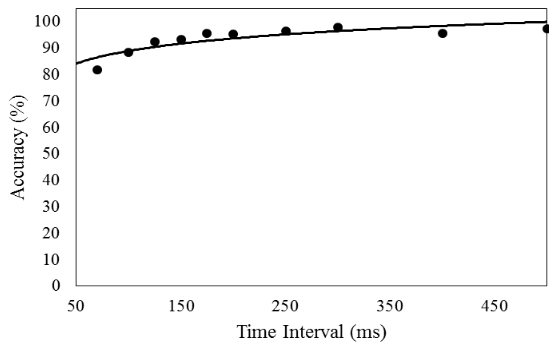

Fig. 5 Relationship between sweeping speed and accuracy of position detection

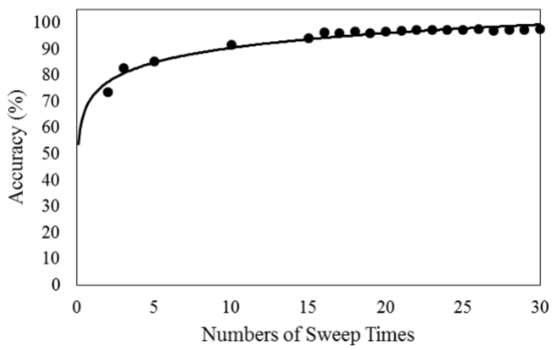

Fig. 6 Relationship between accuracy of position detection and amount of learning data

5.4 Influence of rotation of power receiving antenna

We obtained the detection accuracy by rotating the antenna manually by 45 degrees at a time to collect the data of 8 states per point for 4 points, equaling to data in 32 states. We used two types of methods to obtain the detection accuracy in order to observe the influence of rotation. The first method is by using cross validation

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

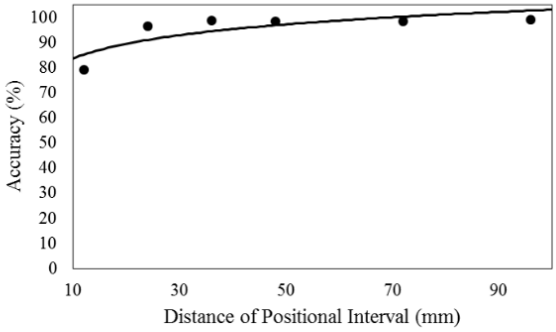

Fig. 7 Relationship between resolution and recognition accuracy of position detection

77.8	84.0	72.0	83.3	100.0	61.5	56.0	73.7	95.0	59.3	69.6	82.6	76.0	87.5	86.4	81.0
95.5	76.2	81.8	75.0	66.7	90.9	40.0	70.4	100.0	75.0	76.2	72.0	81.0	79.2	63.6	68.0
91.7	95.5	87.0	77.3	73.9	77.3	64.7	77.8	93.8	50.0	64.0	64.0	85.7	68.4	65.0	62.5
100.0	87.5	87.5	81.8	81.8	90.0	73.9	77.3	68.4	87.5	90.9	80.8	60.0	81.0	54.2	55.0
86.4	80.0	83.3	65.2	75.0	78.3	66.7	72.0	85.7	85.7	95.2	91.7	87.0	95.0	75.0	82.6
61.9	70.0	95.5	90.0	87.0	80.0	66.7	70.8	90.5	83.3	91.3	100.0	100.0	95.7	88.9	74.1
82.4	76.9	87.0	78.3	75.0	81.8	78.9	87.0	95.7	70.4	86.4	95.5	100.0	100.0	80.8	89.5
80.0	95.0	79.2	77.3	60.9	65.4	69.2	95.0	83.3	90.5	76.5	87.0	95.2	71.4	94.1	100.0
87.0	95.2	90.9	90.0	85.0	65.0	52.4	83.3	90.5	65.0	72.7	78.3	100.0	91.3	95.5	100.0
81.8	85.0	81.0	82.6	63.6	47.4	66.7	65.4	58.3	65.2	55.6	80.0	85.7	85.0	90.0	91.3
65.4	78.9	94.7	54.2	66.7	65.2	74.1	82.4	84.0	58.6	84.2	46.2	56.5	74.1	69.6	76.2
90.5	86.4	95.5	60.0	66.7	82.6	72.0	73.7	81.0	85.7	84.0	85.7	63.6	85.7	78.3	85.7
86.4	73.1	95.2	82.6	63.0	76.5	71.4	75.0	78.3	60.0	73.7	90.0	84.2	91.3	95.0	100.0
76.0	75.0	90.9	68.0	56.5	61.1	79.2	80.0	94.4	83.3	77.3	87.5	70.8	86.4	87.0	95.5
71.4	68.2	76.2	65.0	64.0	85.7	79.2	84.6	94.7	73.7	90.0	90.5	91.7	90.9	71.4	84.2
90.5	87.5	85.7	60.0	56.3	95.5	90.9	94.4	66.7	85.0	87.0	90.9	76.9	94.4	70.0	66.7

Fig. 8 Accuracy of each point when moving antenna at 12mm intervals

with 32 states as different classes, where we found the accuracy to be 95.7% and the second method is by using cross validation on 4 points without rotating the antenna, observing an accuracy of 70.9%. This shows that the state of the current flowing through the antenna changes according to the rotation. Therefore, it is necessary to learn and estimate the direction and position of the power-receiving device when using a device that requires changing direction.

6. LIMITATIONS AND FUTURE WORK

As the frequency of the oscillator used in our study lacks the ability to switch faster, it consumes time to create electrical power maps and to perform real-time recognition. In the future, we will utilize a better oscillator to quickly create a stable microwave. In addition, we can reduce the sweep time by selecting only relevant frequencies.

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

In this paper, we did not consider cases in which two or more antennas are placed on the 2DC sheet. For this case, there is a possibility that the electric field distribution may change as compare to utilizing one antenna. In the future, we will examine the use of two or more antennas and consider how to distinguish the learning data.

In our method, it is also necessary to recreate the learning data when the shape of the 2DC sheet changes or when the contact position between the coaxial cable and the sheet changes.

6. CONCLUSION

In this paper, we proposed a method to detect 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 recognize the position of the device. We also conducted a few experiments to evaluate the accuracy of the position recognition of the system by changing different properties. The results showed that the accuracy was about 79.1% when the antenna is moved at 12mm intervals.

ACKNOWLEDGEMENTS

This work was supported by JSPS KAKENHI Grant Numbers JP26700017.

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