RFitness: Enabling Smart Yoga Mat for Fitness Posture Detection with Commodity Passive RFIDs

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***Abstract*—Yoga is popular in our daily lives for body fitness practice. We can practice yoga on a specific mat for body fitness. It's important to have the smart yoga mat, which can adjust the surrounding environment based on user's physical activities on the yoga mat. For example, we can adjust the ambient light, music and temperature based on the yoga practitioner's pose on the yoga mat.**

In this paper, we present RFitness, a system that can detect the fitness posture on the yoga mat. To do so, we can attach multiple commodity passive RFID tags on the yoga mat, such that the different fitness postures can affect different RFID tags. Based on the signal strength readings from all the tags, we can estimate the yoga fitness posture using the model-driven deep neural networks. We implement the prototype of RFitness using commodity passive RFID tags and USRP reader. Our extensive experiments show that RFitness can achieve the median accuracy of 0.96.

***Index Terms*—Smart Yoga Mat, Fitness Posture Detection, Commodity Passive RFID System, Deep Convolutional Neural Network**

I. Introduction

To keep a supple and fit body, regular workout is important for body building. People like to do the free-weight exercises, which can provide plenty of health benefits. Free-weight exercises and aerobic exercises can stabilize the bones and muscles to loss weight and burn calories.

Yoga is one of body fitness practices, which can do more than burning the calories and toning the muscles. Yoga is a practice to stop slouching and stand straight. Yoga is also a kind of mind-body workout, which can strengthen and stretch poses with deep breathing and meditation. Therefore, practicing yoga on the mat is more popular for body fitness and mental health (e.g., anxiety, stress and depression). However, practicing the right and accurate yoga posture is important for building the supple body and benefiting the mental health. Therefore, we need to monitor the fitness postures during yoga practice. Moreover, we can adjust the surrounding environments based on the physical activities on the yoga mat to improve the experience of practicing yoga. For example, we can adjust the temperature, light and the music based on the different fitness postures practiced on the yoga mat.

However, there are no effective ways to detect the fitness postures on the yoga mat. A personal trainer is not a common solution to yoga practice monitoring, since it will cost too much. Camera based posture detection is another way to monitor the yoga practice, but it cannot work properly in non-line-of-sight (NLOS) scenario and fails to protect the yoga practitioner's privacy. Since the commodity passive RFID tags are widely used in indoor localization [1], [2], gesture recognition [3], touch sensing [4], [5] due to the low-cost and small form-factor, we believe commodity passive RFID system is a good choice to achieve fitness posture detection for yoga practice.

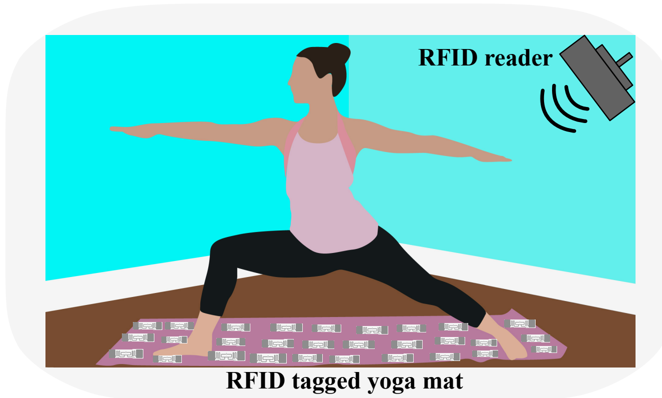

Fig. 1: **RFitness**: Yoga mat is attached with the commodity passive RFID tags to enable fitness posture detection by analysing signal strength of the backscattered signal from all the tags.

In this paper, we propose RFitness, a system that can detect the fitness posture with commodity passive RFIDs on the yoga mat. To do so, we attach the commodity passive RFID tags on the yoga mat, which will be interrogated by the reader to extract the signal strength of backscattered signals from tags as shown in Fig. 1. The commodity passive RFID tags will be arranged in rows and columns on the yoga mat to formulate a rectangular tag matrix. The key point is that the body posture between the tag and the reader will alter the backscattered signals received at the reader. Therefore, we can analyze the backscattered signal to differentiate the different body postures.

After obtaining the signal strength of the backscattered signals from the tags, we can detect the fitness posture using the analytical model-driven deep learning approach. Specifically, we can collect signal strength of the backscattered signal from each RFID tag at the reader. To mitigate the effect of tag diversity and multipath effect, we use the differential signal strength which is defined as the difference of signal strength

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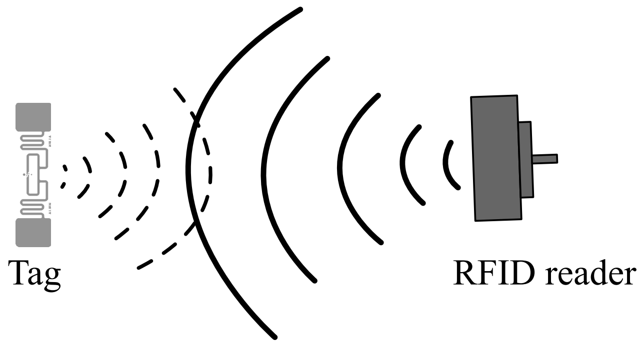

Fig. 2: Commodity passive RFID system consists of tag and reader. The battery-free RFID tags should be activated and interrogated by the external reader.

with or without yoga practice on the mat. Moreover, the different yoga practitioners will perform same yoga posture differently due to the heterogeneous body size. So, we treat differential signal strength from all the tags as an image. Then, our problem becomes classifying these images. We propose to use deep convolutional neural network (CNN) to predict the yoga postures based on these images.

The contributions of this paper are summarized as follows:

- We propose a commodity passive RFID based yoga posture detection system, which can detect and monitor yoga posture to achieve healthy yoga practice and improve experience of practicing yoga.
- We propose a deep convolutional neural network to analyze signal strength of backscattered signals from multiple tags attached on the yoga mat.
- We implement a prototype of RFitness using commodity passive RFID systems and experimentally evaluate the performance of yoga posture detection. The experiments show that the median accuracy of yoga posture detection is around 0.96.

Paper roadmap. We first present the background of commodity passive RFID system in Section II. Then, we describe overview of our design's operation workflow in Section III. We illustrate our core design in Section IV followed by the implementation and evaluation in Section V. Then, we present the related work in Section VII, which is followed by the discussion in Section VIII. At last, we conclude our paper in Section IX.

II. Primer on commodity passive RFID system

In this section, we present the background of using commodity passive RFID tags to do sensing. First, we show the working principle of commodity passive RFID system. Then, we will mathematically model RFID based sensing.

A. Working principle

The commodity passive RFID system consists of reader and tag as shown in Fig. 2. The reader is capable of full-duplex communication, which has to query and activate the tag. The battery-free tag has to rely on the RF signals (i.e., continuous wave) transmitted from the reader to be illuminated and backscatter the impinged signals. The tag just consists of a chip and antenna printed on the substrates. The chip of the tag can change its impedance to match or mismatch its antenna's impedance, such that '0' bit or '1' bit is transmitted (i.e., ON-OFF keying modulation). As we can see, the commodity passive RFID system has two cool features (i.e., low-cost and small form-factor), which enables them to be widely used in different kinds of applications. Next, we illustrate the medium access protocol employed by the commodity passive RFID systems.

The commodity passive RFID systems employ EPC Gen2 standard with slotted ALOHA protocol for communication. The communication process between the reader and the tag mainly consists of two steps (i.e., tag selection and communication). At the beginning of the communication, the reader has to activate the tags by sending the constant continuous waves (cw). The tag within the reader's communication range should response with RN16 (i.e., a 16-bit random number generated by each tag). The reader will acknowledge one tag after successfully decoding its RN16. The other tags without receiving the acknowledgement from the reader should keep silent and wait for the opportunity to communicate with the reader in the next round. Then, the reader will just communicate with the chosen tag by sending queries, and the chosen tag will transmit its EPC (i.e., tag ID) back to the reader.

B. Modeling backscatter communication

RFID-based sensing approaches leverage signal phase and signal strength of the backscattered signal to achieve indoor localization [1], gesture recognition [3] and material identification [6].

The reader has to transmit $S_{r_{Tx}} = |S_{r_{Tx}}| e^{j\theta_r}$ to activate the tags within its communication range. The tag will receive the signals from the reader as follows:

$$S_t = S_{r_{Tx}} h_{r\to t} h_t \tag{1}$$

$$h_{r\to t} = |h_{r\to t}| e^{j\theta_{r\to t}} \tag{2}$$

$$h_t = |h_t| e^{j\theta_t} \tag{3}$$

where $h_{r\to t}$ is the channel from reader to tag, and h_t denotes the tag's antenna gain. The tag will backscatter the impinged signals from reader with an reflection coefficient $\alpha = |\alpha| e^{j\theta_\alpha}$, which is a constant value for each specific tag. The reader will receive backscattered signal from tag as follows:

$$\begin{aligned} S_{r_{Rx}} &= S_t \alpha h_t h_{t\to r} \\ &= S_{r_{Tx}} \alpha h_t^2 h_a^2 \\ &= \left| S_{r_{Tx}} \alpha h_t^2 h_a^2 \right| e^{j(\theta_r + \theta_\alpha + 2\theta_a + 2\theta_t)} \end{aligned} \tag{4}$$

where $\theta_a = \theta_{r\to t} = \theta_{t\to r}$ and $h_a = h_{r\to t} = h_{t\to r}$. This is because the wireless channel has the property of reciprocity.

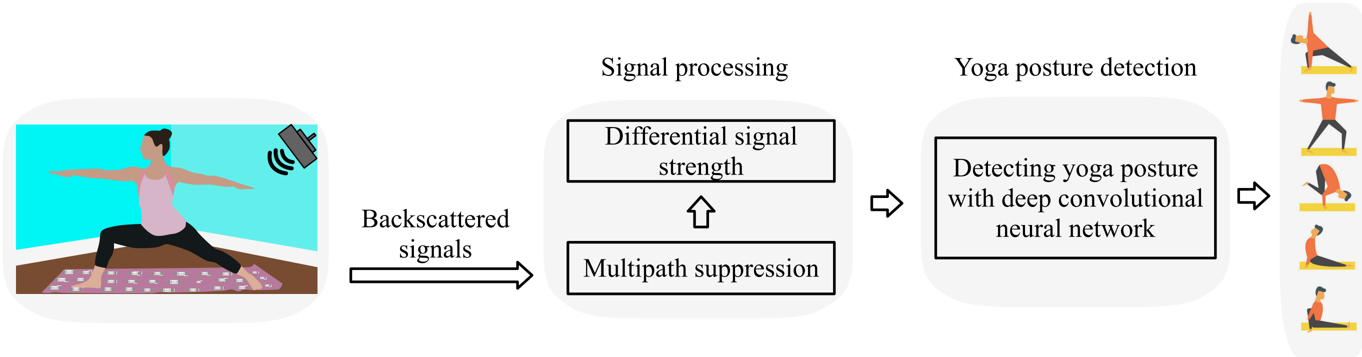

Fig. 3: **RFitness's operation workflow**: After RFitness collects backscattered signals from the RFID tags attached on the yoga mat, we first process the backscattered signals to suppress the multipath effect and extract the differential signal strength. The differential signal strength from all tags can be regarded as an image, which will be the input of the deep convolutional neural network (CNN). The output of CNN will be used to predict the yoga postures.

Then, the reader can decode the backscattered signal after channel estimation. So, the signal strength of the backscattered signal is as follows:

$$Signal\ strength = 20log\,|S_{r_{Rx}}| = 20log\,|S_{r_{Tx}}| + 20log\,|\alpha| + 40log\,|h_a| + 40log\,|h_t| \quad (5)$$

The received signal phase at the reader is denoted as follows:

$$Signal\ phase = \theta_r + \theta_\alpha + 2\theta_a + 2\theta_t \quad (6)$$

Since the yoga practitioner performs yoga between the tagged yoga mat and reader as shown in Fig. 1, we mainly use signal strength of the backscattered signals from the tags to detect the yoga posture. Next, we will illustrate RFitness's operation workflow.

III. Overview

Our RFitness consists of two main components as shown in Fig. 3. The first component is signal processing component, which includes multipath suppression and differential signal strength extraction. The second component is yoga posture detection component, using the deep convolutional neural network (CNN) to predict the yoga postures.

Signal processing component. The reader will interrogate RFID tags attached on the yoga mat. We mainly analyse signal strength of the backscattered signals from all tags attached to the yoga mat to predict yoga postures. To mitigate the mutlipath effect and tag diversity in the indoor area, we leverage the differential signal strength for yoga posture estimation. The differential signal strength is defined as the difference of signal strength with or without yoga practice on the mat, which can help us to suppress the multipath effect.

Yoga posture detection with CNN. After obtaining differential signal strength from all the tags, we will treat the differential signal strength of the backscatter signal from all the tags as an image, which will be the input of the convolutional neural network. The output of the convolutional neural network will be the predicted yoga poses.

IV. RFitness Design

In this section, we will present the system design of RFitness. First, we present the analysis of the backscattered signals and multipath suppression. Then, we use CNN to classify the yoga postures based on the images created by the differential signal strength.

A. Capturing the yoga posture with backscattered signal

To capture the yoga poses on the yoga mat, we first need to consider where to deploy these RFID tags for capturing the yoga poses. Then, we need to suppress the multipath effect in rich scattering indoor environment for accurate yoga posture estimation.

RFID tagged yoga mat. We attach the commodity passive RFID tags on the yoga mat, which will be unobtrusive to the yoga practitioner. The tags are arranged in rows and columns of the rectangular yoga mat as shown in Fig. 5, which can formulate a rectangular matrix A_{mn} with size of $m \times n$. Note that A_{ij} denotes the tag at i-th row and j-th column. We deploy the reader nearby the yoga mat to interrogate the tags for collecting the tag IDs and signal strength of the backscattered signal. The signal strength of backscattered signal from tag at i-th row and j-th column is denoted as r_{ij}. Note, our deployment is fundamentally different from RFID-based gesture recognition applications, since they mainly use the signal phase to capture the gestures. Our core idea is to leverage the touch sensing to capture the variation of signal strength from all the tags attached on the yoga mat.

Multipath effect suppression. From the backscattered signals, we can obtain two main characteristics: signal strength and signal phase. They are widely used for RFID-based sensing. Since the reader and tags are relatively static, the backscatter signals are mainly affected by the body posture. The human's body primarily consists of the water, which will absorb more RF energy. When the human's body blocks the RFID tags attached on the yoga mat, the signal strength of the backscattered signal is significantly degraded. Therefore, we

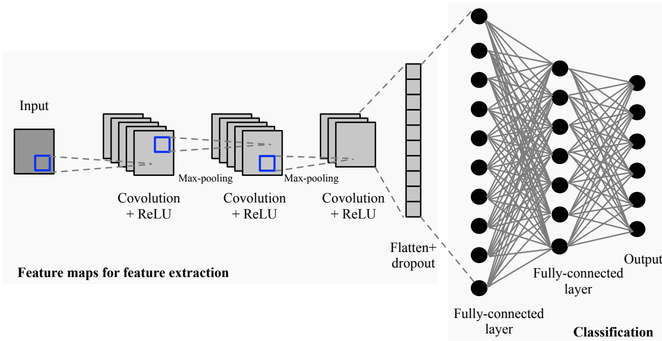

Fig. 4: **Deep convolutional neural network structure**: It mainly consists of feature extraction component and the classification component. The feature extraction component consists of multiple convlutional layers with ReLU activation, Max-pooling layers and dropout layers to avoid overfitting. The classification component consists of multiple fully-connected layers followed by the softmax output for multi-class classification.

use signal strength of backscattered signal from tags to predict the yoga posture.

However, the signal strength is susceptible to the multipath effect, as the backscattered signals are constructively or destructively added at the reader. This will degrade the accuracy of the yoga posture detection. Therefore, we propose to use the differential signal strength, which is defined as the difference of signal strength with or without the yoga practice on the yoga mat. Specifically, we first obtain the signal strength of backscattered signal from tag located at i-th row and j-th column on the yoga mat, which is denoted as $r_{ij}^{'}$, when there is no yoga practice. When we practice yoga on the mat, we obtain the signal strength of backscattered signals from tag located at i-th row and j-th column on the yoga mat, which is denoted as r_{ij}. To mitigate the multipath effect, we derive the differential signal strength denoted as $r_{ij}^{d} = |r_{ij} - r_{ij}^{'}|$. Then, we can create a $m \times n$ matrix $R = r_{ij}^{d}, i = \{1, 2, ..., m\}, j = \{1, 2, ..., n\}$, which can be regarded as an image. Then, our problem becomes how to classify these images to predict the different yoga postures.

B. Yoga posture detection with CNN

After we obtain the differential signal strength from all the tags, we need to predict the yoga posture based on the differential signal strength profile (we can regard it as an image). Since the deep convolutional neural network has been proved to achieve surprising performance in image classification and computer vision, we employ the convolutional neural network to detect the yoga posture using differential signal strength profile as the input.

Convolutional neural network structure. We develop a multi-layer neural network to estimate the yoga postures. The input of the convolutional neural network is the differential signal strength profile obtained in Section 4. We design a 11-layer deep convolutional neural network. The output of the deep convolutional neural network is the estimated yoga postures. There are two main components in this deep convolutional neural network: feature extraction component and classification component. The feature extraction component consists of multiple convolutional layers and maxpooling layers. The classification component consists of multiple fully connected layers followed by the softmax layer for yoga posture estimation.

Specifically, the differential signal strength profile is a matrix with size of 3x9. There are three convolutional layers constructed upon the input layer, which can extract the high-level representation of the input data. To do so, we use some filters to achieve the convolution operation with same stride of 1 in both the vertical and horizontal directions. We use zero-padding to maintain the dimension of the output. The Rectified Linear Unit (i.e., ReLU) is used for each convolutional layer. The Max-pooling layer with size of 3x3 kernel and different strides simplify the connections with the following layers. To avoid overfitting, we add dropout layer after the convolutional layers. After the dropout layer, we add three fully-connected layers for classification, which can connect with all the neurons in the previous layer. We still use ReLU layer between two fully-connected layers. The last layer is softmax layer, which can output the probability of the estimated yoga posture.

Training details. In the training stage, we use Adam optimizer [7] to update the weight parameters with the learning rate of 0.001. Since our objective is to classify the yoga postures, this is a multi-class classification. We use the cross-entropy loss with softmax activation as follows:

$$Cross\ Entropy\ Loss = -\sum_{j} t_j log o_j \tag{7}$$

where t_j and o_j denote the target and output at neuron j.

V. Implementation and Evaluation

In this section, we first present the details of our prototype. Then, we show the experimental setup for yoga posture detection at home.

RFID reader. Since we just need to extract the signal strength information from the backscattered signals, we use USRP N210 with SBX daughter board as RFID reader to interrogate the RFID tags. The implementation of USRP reader [8] is compatible with EPC Gen2 standard for UHF RFID communication with frequency band between 902-928MHz. Note that we can also use commodity RFID reader for tag interrogation. The RFID reader will connect with the HP laptop through Ethernet cables for data analysis and processing. Our laptop runs on Ubuntu 18.04 with Intel Core i5 processor and 8GB RAM. Note, since we just need to extract the signal strength from USRP reader, our implementation is compatible with commodity RFID readers (e.g., Impinj Speedway RFID reader [9]). So, our RFitness can achieve ubiquitous sensing, considering commodity passive RFID systems are widely available.

RFID tag. We evaluate RFitness with commercial, off-the-shelf, passive UHF RFID tags. They are widely available and

Fig. 5: **Experimental setup at home.** There are 3x9 commodity passive RFID tags attached on the yoga mat. The reader's antennas are deployed nearby the yoga mat, which is around 2 meters above the yoga mat. The yoga practitioner will perform the yoga on the tagged yoga mat.

each tag costs around 5 cents. Specifically, we use Alien Squiggle RFID tag ALN-9640 [10] and Alien Short ALN-9662 [11]. Since we use the differential signal strength as the features to predict the yoga posture, the diversity of tags and locations will not affect RFitness's performance.

Yoga mat. Our yoga mat with size of 71x24 inches is attached with commodity passive RFID tags. We attach 3x9 tags on the mat as shown in Fig. 5. Three tags are deployed on each row of the yoga mat, and nine tags are deployed on each column of the yoga mat. Since the half wavelength for UHF RFID communication is around 16cm, the distance of two adjacent tags should be larger than 16cm. Therefore, we do not need to worry about the tag coupling effect between the adjacent RFID tags. Note, the tags attached on the yoga mat is unobtrusive, which will not affect yoga practice on the yoga mat.

Experimental setup. The experimental setup is shown in Fig. 5. We deploy RFID tagged yoga mat in the living room for yoga practicing. There are different kinds of furniture around our settings (e.g., tables and chairs), which can create a rich scattering environment. We collect data, when four participants practice yoga on the yoga mat. There are five data collection sessions for each participant. In each data collection session, the participant will perform five yoga postures with duration of 3 seconds as shown in Fig. 6. After data collection, we take half of data set for training the deep covolutional neural network, and the other half of data set will be used for test. We report the accuracy of yoga posture detection on the test set.

VI. Result

In this section, we present the results of our experiments. We mainly show the differential signal strength profiles for different yoga postures and the accuracy of yoga posture detection.

A. Differential signal strength profile for different yoga poses

Method. We show the differential signal strength profile, which is obtained with or without yoga practice on the yoga mat. To do so, the yoga practitioner will practice one yoga pose on the yoga mat. The commodity passive RFID system will obtain the signal strength of backscattered signals from all the tags attached on the yoga mat.

Result. Fig. 6 shows five yoga poses and the corresponding differential signal strength from all the tags. As we can see, different yoga poses will affect different tags attached on the yoga mat, such that we can differentiate the yoga poses based on the differential signal strength from all the tags. Note that the backscattered signals will be degraded significantly, when the tags are touched or blocked by the human body. Therefore, the differential signal strength from these tags will be larger. Next, we will classify these yoga postures based on the differential signal strength profiles using deep convolutional neural networks.

B. Accuracy of yoga pose estimation

Method. We show the accuracy of yoga pose classification with RFitness. To do so, the yoga practitioner will perform the five yoga poses on the yoga mat. Then, our RFitness will obtain the differential signal strength profile mentioned in the above subsection, which will be the input of the convolutional neural network. The output of the convolutional neural network will be the estimated yoga poses.

Result. Fig. 7 shows the confusion matrix of five yoga poses classification. As we can see, the median accuracy of yoga poses classification is around 0.96. Therefore, our RFitness can accurately estimate the yoga poses based on the differential signal strength profiles from all the tags attached on the yoga mat.

VII. Related work

The commodity passive RFID tags are widely used in indoor localization and gesture/activity recognition [12] and RFID security [13], [14]. To resolve the multipath effect, the past literature usually uses the tag array or antenna array to obtain the angle-of-arrival information to do localization. For

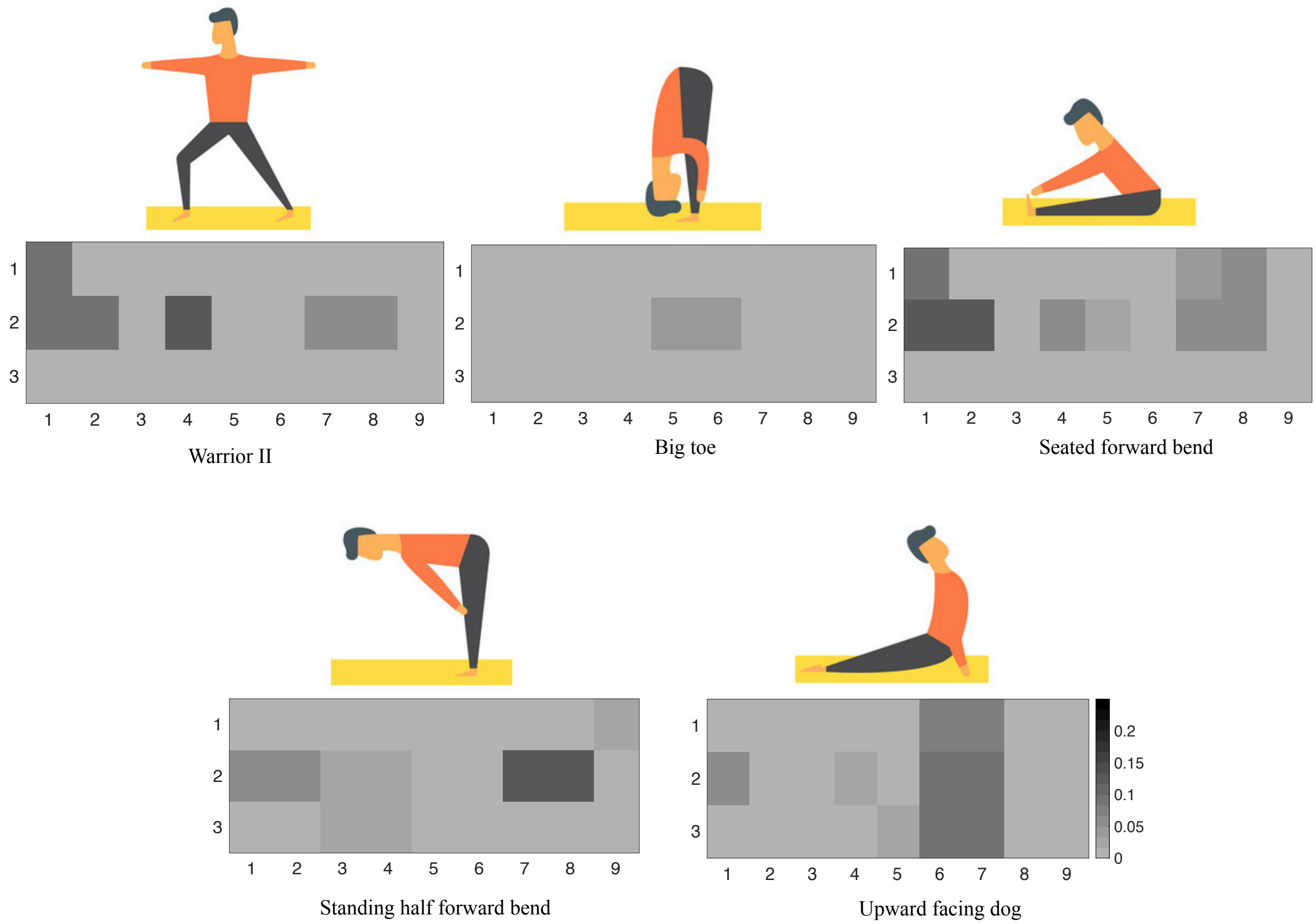

Fig. 6: We mainly focus on five yoga postures: warrior II, big toe, seated forward bend, standing half forward bend and upward facing dog. Under each yoga posture, there is a figure showing the differential signal strength of backscattered signals form all the tags attached on the yoga mat. As we can see, the differential signal strength from all the tags can clearly differentiate the yoga postures.

example, PinIt [1] deploys the reference tag in the indoor area to obtain the multipath profile from the reference tag using the emulated antenna array. Then, comparing the multipath profile from reference tag with the multipath profile from sensing tag to achieve accurate localization. RF-IDraw [3] targets the gesture recognition by exploiting the tag spacing of tag array. Tagyro [15] tracks the object's orientation through the tag array attached to the object. Tadar [16] attaches multiple tags on the wall formulating an array to achieve through-wall localization. Recently, people exploit time-of-flight (ToF) with large bandwidth to achieve localization using the band limited RFIDs. For example, RFind [2] emulates a large bandwidth to do localization based on ToF. Later on, TurboTrack [17] uses the emulated large bandwidth to track the small robots and help the robots to maneuver the objects. RF-Compass [18] leverages the robot's consecutive movements to localize the objects spatially. However, we use multiple RFID tags attached on the yoga mat to formulate an image to predict the posture during yoga practice, using deep convolutional neural network.

RFID based touch sensing is more related to our work. However, the current RFID based touch sensing mainly focuses on crafting tags and leveraging the impedance variation of RFID tag's antenna. For example, RIO [4] leverages the impedance variation to achieve touch sensing, as the finger touches the tag's body. There are some papers trying to craft RFID tags to achieve robust touch sensing [5], [19]–[21]. However, our RFitness leverages tens of RFID tags to sense yoga posture based on signal strength's variation of the backscattered signals.

Our work is also related to the RF signal based sensing for healthcare. For example, FEMO [22] attaches the RFID tag to the fitness equipment such as dumbbells to monitor the free-weight exercise. TagSheet [23] attaches the tag to the bed, such that we can monitor the sleeping posture. However, it does not use the deep learning to classify the sleeping postures, which is susceptible to the dynamic environment and suffer from the poor performance. Tagbreathe [24] uses RFID tags

Fig. 7: **Confusion matrix of yoga posture classification.** Our deep neural network can classify five yoga postures with median accuracy of around 0.96.

to monitor breathing. Recently, people also use RFID tags to monitor the food and liquid quality. For example, RFEAT [25], [26] leverages the RFID tags to detect the quality of food and liquid with deep learning, which can resolve the multipath for ubiquitous sensing. TagScan [6] uses one RFID tag to identify the liquid and uses multiple RFID tags to do imaging for some specific objects (e.g., triangle and square objects). RFitness focuses on the yoga posture practiced on the yoga mat, which is more difficult than triangle and square objects sensing. We believe RFitness can further improve the experience of yoga practice on the yoga mat for physical and mental health.

VIII. Discussion

In this section, we discuss the limitations and future work of RFitness.

Contact-free sensing. In RFitness's design, we attach RFID tags to the yoga mat for posture detection. So, the tags need to be attached to the yoga mat properly for accurate yoga posture detection. It is important to achieve contact-free sensing without attaching anything to the yoga mat. One possible solution is to attach the tags on the wall. Then, the yoga practitioner practices the yoga between the reader's antenna and the tags. However, this setup requires the tags to be attached on the wall (i.e., infrastructure based sensing). Moreover, it cannot detect some yoga postures, when the yoga practitioner's body does not block any tags on the wall. Another solution is to leverage the other techniques for contact-free sensing such as mmWave sensing and WiFi sensing. However, mmWave is expensive and WiFi is not very accurate to achieve fine-grained posture estimation.

Posture detection without training. To detect the yoga posture, we leverage deep convolutional neural network. So, it requires the well-trained model for accurate posture estimation. Can we detect the yoga posture without training process? We think it is difficult to achieve training-free posture detection, since some yoga postures have tiny difference and we cannot attach more tags on the yoga mat to improve the resolution. But, the deep covolutional neural network is capable to exploit high-level representation of the data, such that we can differentiate more yoga postures with tiny difference.

Group yoga fitness. In yoga fitness, we mainly focus on the individual yoga practice on one yoga mat. But, it is very common to see multiple yoga practitioners practicing yoga together as a group. Each of them practices yoga on the individual mat. Can RFitness detect the yoga posture for all of these yoga practitioners? With deploying RFID readers for each individual yoga practitioner, we can achieve yoga posture detection for group yoga fitness. However, we need to consider the inter-reader interference, which will degrade the tag reading rate and thus the resolution is reduced. If we just deploy one RFID reader to interrogate all the tags attached on all the mats, we still need to consider the low tag reading rate due to the collisions and short communication range of commodity passive RFID systems that cannot activate all the tags with one reader.

More than five yoga postures. We evaluate the performance of RFitness on detecting five yoga postures, since some yoga postures are difficult to perform for beginners. We believe that RFitness can detect more than five yoga postures after collecting enough data to well train the deep convolutional neural network. We can still leverage the signal processing and image processing modules to bootstrap the accuracy of yoga posture detection. This will be left for our future work.

IX. Conclusion

This paper presents RFitness, a system that can detect the yoga posture by attaching the commodity passive RFID tags on the yoga mat. To do so, we use differential signal strength of the backscattered signals from all the tags to suppress the multipath effect. Then, we regard the differential signal strength of backscattered signals from all the tags as an image, which will be the input of deep convolutional neural network. The output of the deep convolutional neural network will be used to predict the yoga postures. Our experimental results show the median accuracy of yoga posture estimation is around 0.96.

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