Are you sitting right?-Sitting Posture Recognition Using RF Signals

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***Abstract*—Today, sedentary behaviors and bad sitting postures are the main causes of modern health musculoskeletal disorders and illnesses. Previous works either used a camera to record the image or attached wearable sensors on human body to recognize sitting postures. However, video-base approaches may face privacy issue while the wearable sensor-based approaches may cause uncomfortable to the user. This paper introduces SitR, the first sitting posture recognition system using RF signals alone. We demonstrate that with just three tags pasted to one's back, SitR can successfully recognize three habitual sitting postures. Our design exploits the correlation between the phase change of RFID tags and the sitting postures. By extracting effective features from the measured phase sequences and employing machine learning algorithm, SitR can achieve robust and high performance. We evaluated SitR through extensive experiments including 14 volunteers under 3 different scenarios. The experiment results show that SitR can recognize sitting postures with an average accuracy of 99.27%. Our system can further detect the abnormal respiration and provide sitting posture history for sedentary people.**

***Index Terms*—Sitting Posture Recognition, RFID**

I. Introduction

Sitting posture plays a vital role in one's health. It was reported that most sedentary people spent 54.9% of their waking time in sedentary behaviors [1]. In fact, sedentary behaviors [2], [3] and bad sitting postures are closely related to modern health musculoskeletal disorders [4], [5], such as cervical spondylosis, chronic back pain, joint and muscle pain, improper spine alignment, spine discs damage [6]–[10]. Diagnosing these diseases requires the long-term sitting posture monitoring, which can provide the useful information for the doctor.

Typically, sitting posture recognition approaches can be divided into two categories: video-based and wearable sensor-based. The video-based approaches require a camera to record the video streams and identify different sitting postures using the computer vision graphics processing [11]–[15]. Specifically, these approaches mainly employed Kinect to extract features which can be further used as the input of the machine learning algorithm. Although their accuracy is high, the privacy concern is a big issue, especially in a private environment. In contrast, the wearable sensor-based approaches [16]–[18] can recognize sitting postures without compromising the privacy. However, the user are required to wear dozens of sensors on his/her body, which is intrusive and uncomfortable for the long-term use. Also, some products for correcting the sitting postures, such as vibocare [19] are popular among the young people. However, wearing this kind of products is uncomfortable and it cannot provide the useful information (e.g., the sitting posture history in a long term) for diagnosing diseases. Here, we ask the following question: can we recognize sitting postures in a way that neither compromises the privacy nor requires wearing various sensors on the human body?

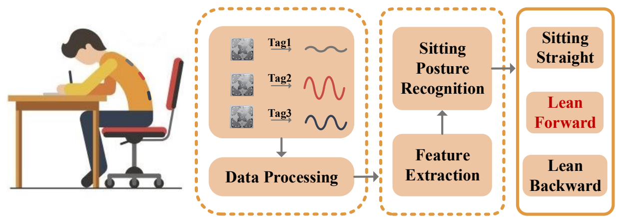

Figure 1: An example of SitR system

This paper introduces SitR, the first sitting posture recognition system using RFID tags. With only three lightweight and low-cost RFID tags pasted to the user's back (i.e., pasting to one's clothes), SitR can successfully recognize the habitual sitting postures including sitting straight, lean forward and lean backward (See Fig. 1).

The basic idea of SitR is as follows: *(i)* with three tags pasted to the user's back and one reader antenna placed on the back of the chair (see Fig. 2), the distance between each tag and the antenna varies under different sitting postures; *(ii)* when the distance and angle of the tag to antenna changes, the received signal phase at the reader changes accordingly. Note that the phase variation for different sitting posture is unique, which can be used as a reliable primitive for sitting posture recognition (see Fig. 3). Besides, these three tags can sense the user's respiration and we find that the observed respiration patterns from the measured phase sequences are different under different sitting postures. Therefore, SitR can recognize sitting postures by carefully processing the mea-

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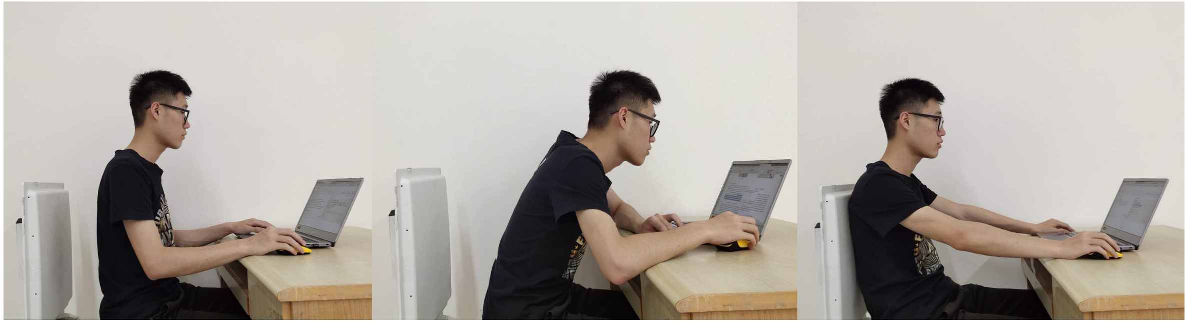
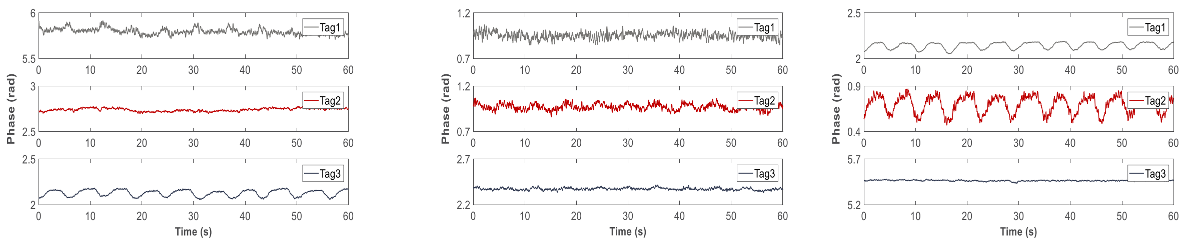


(a) Sitting Straight (b) Lean Forward (c) Lean Backward

Figure 2: The three habitual Sitting Postures



(a) Sitting Straight. (b) Lean Forward. (c) Lean Backward.

Figure 3: Phase of three Sitting Postures.

sured phase sequences without compromising the privacy nor wearing dozens of sensors. Although the basic idea of SitR sounds straightforward, there are three challenges to realize the system.

The first challenge is how to deploy the tags to effectively recognize the sitting postures without bringing any uncomfortable experience to the user. To deal with this challenge, we find that pasting tags on one's back is sufficient to capture effective information for distinguish sitting postures, while keeping unaware to the user. The second challenge is how to obtain an obvious phase changing pattern in the presence of hardware noise and multipath effect. We propose a data preprocessing method to remove the outliers and eliminate the multipath effect. The last challenge is how to extract effective features from the phase measurements to represent sitting postures to achieve high accuracy. By jointly considering the features from the time-domain and frequency-domain, SitR can successfully recognize sitting postures in both person-dependent and person-independent scenarios.

We implement and evaluate SitR through extensive experiments including 14 users in three different common scenarios. The result shows that SitR can recognize sitting postures with an average accuracy of 99.27%. Our system can further detect the abnormal respiration and provide sitting posture history for sedentary people.

II. SitR Design

SitR employs just three low-cost and lightweight RFID tags pasted to a user's back and a reader antenna placed on the back of a chair to recognize sitting postures. At a high level SitR goes through the following three steps: data preprocessing, feature extraction, and sitting posture recognition. We detail each step in the following.

A. Data Preprocessing

The in-air raw signals from RFID devices are noisy due to the hardware imperfection and multipath effect, which may cause false edges and affect the recognition accuracy. We therefore propose a two-step data preprocessing method to filter out the noise.

The first step is to remove the phase shift caused by the hardware. For an RFID system, the reader emits the RF signals through the antenna, and then the tag receives the signals and backscatters them back to the reader. There exist constant phase shift of π or 2π caused by hardware circuits [20]. We remove this kind of phase shifts by comparing the two continuous phase measurements and applying a threshold to calibrate the phase shift (See Fig. 4). The second step is to eliminate the multipath effect of the indoor environment. To do so, we employ the wavelet denoising filter (i.e., Daubechies 2 wavelet) to remove the high-frequency noise in the measured phase sequences (See Fig. 5).

B. Feature Extraction

The key part of SitR is to extract rich features from the phase sequences to represent different sitting postures. Intuitively, we can use the features (i.e., 14 features from both the time domain and frequency domain) that are widely used in RF-based activity recognition systems [14], [21]. However, we find that some features are confuse rather than help with

Table I: Recognition average accuracy in different Scenarios

Basic properties of signals	Feature
Time Domain	Variance Periodic Reversal Mean Range
Frequency Domain	Dominant Frequency Ratio Energy Entropy

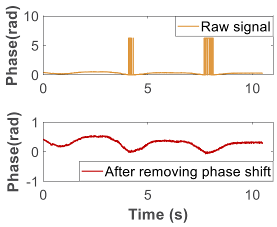


Figure 4: After removing phase shift

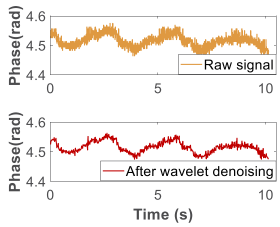


Figure 5: After wavelet denoising

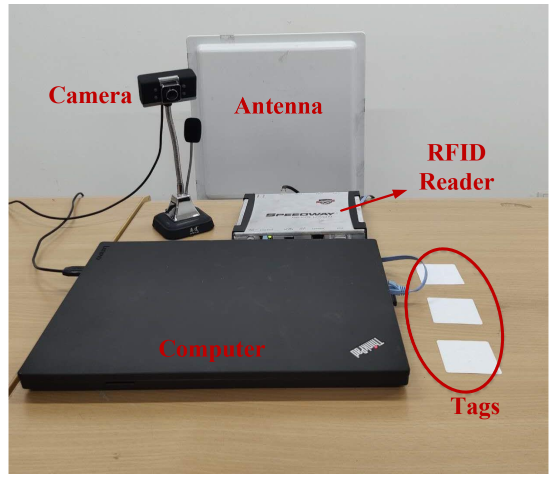


Figure 6: Experimental equipment

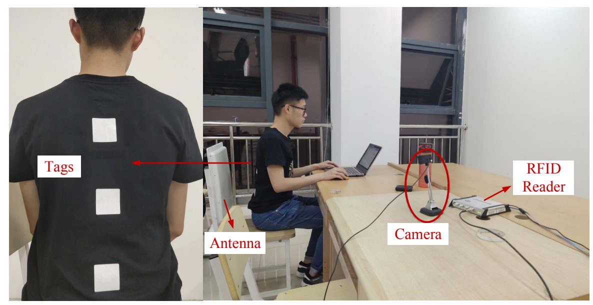


Figure 7: Office scenario

each other. Thus, we need to exclude those features that do not contribute to the accuracy.

To do so, we analyze the distributions of each feature both within the same sitting posture and across different postures. We select the features that have large variations among different sitting postures while keep stable within the same posture. Conversely, features that do not have the above characteristic are likely to cause interference in sitting posture recognition, and we avoid selecting such features. Eventually, SitR selects 7 effective features shown in Table I as the input of sitting posture recognition model. Note that we use a sliding window with a window size of 20 seconds to divide the phase sequence into several segments. We then extract the features for each segment.

C. *Sitting Posture Recognition*

The machine learning method is widely used in wireless sensing applications [22]–[24]. With the effective features extracted from the measured phase sequences of the 3 tags, SitR employs Random Forest (RF) classifier to recognize sitting postures. In fact, other widely used classifiers such as Decision Tree (D-Tree), Bayes, K-Nearest Neighbor (KNN), and Integration Learning can be used as well. Here, we choose RF just because it can achieve high performance without complicated parameter adjusting.

III. PERFORMANCE EVALUATION

We implemented SitR with three RFID tag and one reader. The reader is connected to a laptop through an Ethernet cable and the laptop is used for data collection. We also used a camera to record the ground truth and we labeled the sitting postures manually (See Fig. 6).

To evaluate SitR, we recruited 14 volunteers, including 8 females and 6 males with the age varying between 18 to 27 years old. The volunteer sat naturally on the chair while studying/working, and we pasted 3 tags on his/her back within three key regions of the spine including the thoracic, thoraco-lumbar and lumbar. Note that the 3 tags are not required to be precisely pasted to the same locations for different people. Roughly pasting them within the tree key regions is enough to achieve high accuracy. The antenna is placed on the back of the chair at an angle of 90 degrees to the ground. To demonstrate the robustness of SitR in different environments, we evaluated the performance in three different scenarios including an office, a bedroom and a classroom (See Fig. 7 and Fig. 8). We performed 45-minute sitting posture monitoring for 10 volunteers and 3-hour (or 4-hour) sitting posture monitoring for 4 volunteers in the three scenarios, respectively. We have totally collect 9495 exemplars from 14 volunteers for sitting posture monitoring. The proposed sitting posture recognition method is programmed in MATLAB R2018b. Specifically, we set K=5 for KNN classifier and the number of decision tress as 50 for RF classifier. For integration learning, we applied the widely used AdaBoost algorithm.

We use the cross validation and employ two metrics including the accuracy and F1 score which are widely used in machine leaning field to evaluate the system performance. For each volunteer, we divided his/her data into training set (4/5) and testing set (1/5), respectively. We trained/tested our model until all the samples are trained/tested at least once.

Figure 8: Classroom (left) and bedroom (right) scenarios

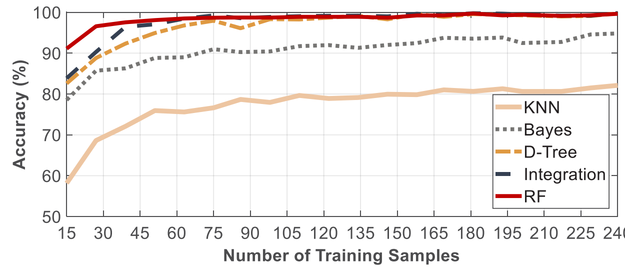


Figure 10: Accuracy of different training samples

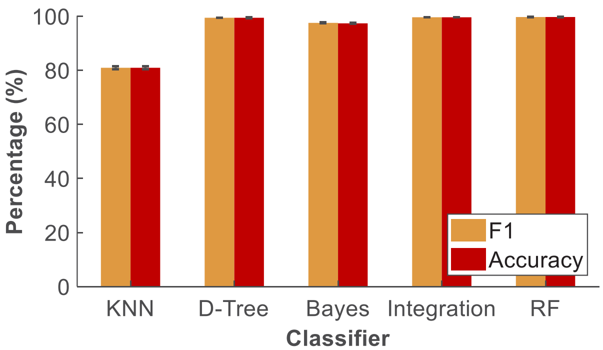


Figure 9: Classifier comparing

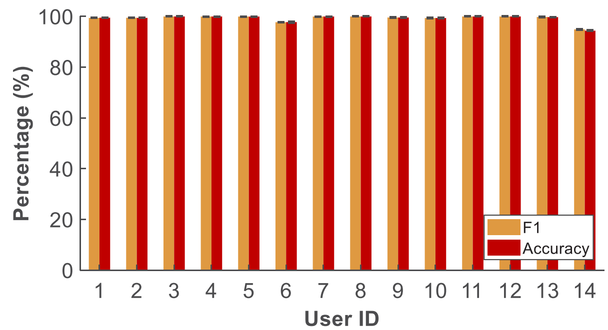


Figure 11: Recognition accuracy of different users

Table II: Recognition average accuracy in different Scenarios

Scenario	Accuracy	Size
Bedroom	99.39 %	15 m^2
Classroom	99.33 %	40 m^2
Office	98.96 %	70 m^2

The performance of classifiers: Fig. 9 shows the average accuracy and F1 score of all volunteers when using different classifiers. As we can see, RF achieves the accuracy of 99.74% for sitting posture recognition, while the performance of KNN is lower (80.96%). The other classifiers such as 'D-Tree', 'Bayes', and 'Integration' can also achieve high accuracy (i.e., above 98.8% on average). This result indicates that SitR can successfully recognize different sitting postures through careful tag deployment and effective feature extraction. Fig. 10 shows that RF performs better even with less training samples. According to the above comparison, we use RF classifier in the following evaluation.

The performance in different scenarios: As shown in Table II, we evaluate SitR in three different scenarios with different amounts of multpath effects. The sizes of the three room are $15m^2$, $40m^2$ and $70m^2$, respectively. Obviously, the average accuracy of the three scenarios is around 99%, which indicates that SitR can achieve robust performance in different environments.

The performance across people: Fig. 11 illustrates the average sitting posture recognition accuracy of 14 volunteers, respectively. Among them, volunteers #11 to #14 are monitored for a long time (3-hour or 4-hour), others are 45-minute. As we can see, SitR can achieve high accuracy for each volunteer with an average accuracy of 99.27%. To see the performance of each sitting posture clearly, we further plot the confusion matrix as shown in Fig. 12. Obviously, SitR can recognize 'Sitting Straight (S.-S.)' and 'Lean Forward (L.-F.)' very well (i.e., 99.51% and 99.5%), while only in some cases, our system cannot distinguish 'Lean Backward (L.-B.)' and 'Sitting Straight'.

Comparison with the state-of-the-art work: SitR is the first system to use wireless signals for sitting posture recognition. Because of the different data types, we cannot give the other works (video-base and wearable sensor-based approaches) the collected RFID data for comparison. Therefore, for a fair comparison, we summarize the reported accuracy from each system. Specifically, we compare SitR against literature [13] and [16] on the sitting recognition accuracy. As shown in Table III, the accuracy of SitR is 3.67% higher than [13] and 4.7% higher than [16]. In addition, SitR is comfort and can preserve user's privacy compared to those two works.

The abnormal respiration detection: We emulate apnea (approximately 14 s) in the experiment. As shown in Fig. 13 , the phases of the three tags become a straight line between 30th and 50th seconds. Therefore, when an apnea occurs, the system can give an alarm immediately.

Sitting posture history for sedentary people: Fig. 14 shows the sitting postures distribution of sedentary people. We perform sitting posture analysis on volunteers with a long sitting duration, such as volunteers #11 to #14. We obtain the

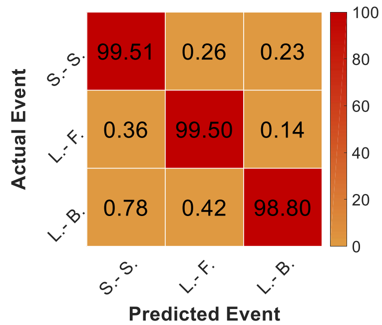


Figure 12: Confusion matrix of recognition accuracy

Table III: Comparison with the state-of-the-art work

System	Technique	Method	Accuracy
[13]	Video	Faster R-CNN	95.6 %
[16]	axis accelerometer	SVM	94.57 %
SitR	RFID tags	RF	99.27 %

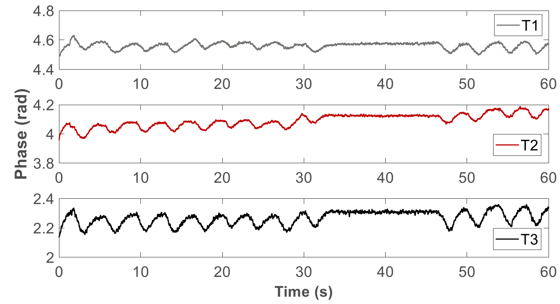


Figure 13: The abnormal respiration detection

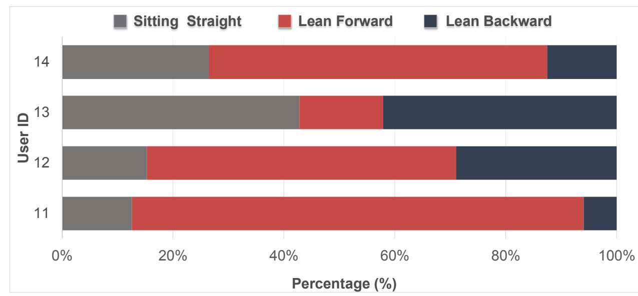


Figure 14: Sitting postures distribution

sitting habits of the 4 volunteers. Volunteer #13 has better sitting habits. Conversely, volunteers #11 and #12 have a poor sitting habit. As we can see, during 3-hour monitoring, only 27 minutes (30 minutes) of the total time is for the sitting straight posture. In the workplace or study place, sitting still for a long time even in correct posture will cause a partial muscle burden on the neck and lumbar region [4]. However, keeping a wrong sitting position for a long time can easily cause health problems, such as musculoskeletal disorders.

IV. Related work

SitR is related to the following existing works.

Video-based: The video-based approaches require a camera to record the video streams and identify different sitting postures using the computer vision graphics processing. However, the privacy concern is a big issue, especially in a private environment.

For example, work [11] used the camera to capture 3D posture and classified with a max-margin classifier. Although low-cost and easy deployment makes 3D posture possible, the average classification accuracy is low. The unhealthy sitting posture is recognized in [12] mainly by the measurement of the neck and the torso angle, and the two features are extracted based on the depth image using the kinect sensor. The accuracy is only 73.3% and it cannot be detected correctly when people move frequently. [13] used a scene recognition and semantic analysis approach to unhealthy sitting posture detection. Kinect is mainly used to fuse the relevant features in the scene and the bone features extracted from the human body into the semantic features to distinguish various sitting postures. However, multi-target detection and bone extraction require different equipment. As the cost increases, the corresponding recognition accuracy is not improved. In [14], the real-time skeleton data stream collected by the Kinect camera is mainly used for data mining classification. And it used the microcontroller's alarm device to monitor the time of sitting. Kinect and alarm device are separately tested, making the cost increasing. [15] needed to extract the contour of sitting posture and the position and size of the face. Then, it compared them with the standard contour to remind the user to correct the wrong sitting posture. This may prevent myopia and spine/neck diseases caused by wrong sitting posture in front of the computer. However, the method would fail when skin color cannot be recognized for the light intensity.

Wearable sensor-based: The wearable sensor-based approaches can recognize sitting postures without compromising the privacy. However, the user is required to wear sensors on his/her body, which is intrusive and uncomfortable for the long-term use.

Work [16] used a three-axis accelerometer which was connected to the back of the volunteer to retrieve the acceleration data. Acceleration data were transformed to the feature vectors of principle component analysis. Support vector machine (SVM) and K-means clustering were used to classify sitting posture with the transformed feature vectors. Only the sitting posture corresponding to the lumbar disc herniation was studied. Obviously it was extremely uncomfortable to wear accelerometers all the time. [17] used three gyroscope worn on the back to recognize right/wrong sitting postures. The mobile devices connected to the gyroscopes record the data from gyroscopes. Although a small gyroscope is used, it needs customization and to be connected to other devices.

In our system, we use three lightweight and low-cost RFID tags pasted to user's back. We recognize sitting postures in the way that requires neither charging nor wearing various sensors on the human body.

V. Discussion

We discuss some limitations and opportunities for system improvement.

Diversities of the same sitting posture. The performance of SitR may decrease when monitoring for a long time. As the monitoring time increases, the sitting posture becomes more diverse (especially sitting straight and lean forward). For example, the primitive of sitting straight is discrepant with different time periods. In fact, we recognize more than three sitting postures. In the future work, we will recognize the fine-grained sitting posture.

Limitation on training set. We need to update the training set to obtain a high recognition accuracy. We verify it in the following test. We divide a 4-hour monitoring data into 4 parts (represented in the order of time as h1, h2, h3 and h4), each part being one hour of monitoring data. First, we use h1 as the training set and h2 (h3, h4) as the test set, and the average recognition accuracy is low (average 64.31%). Secondly, we select h4 as the test set and the training set is the sum of h1, h2 and h3. And the average recognition accuracy is 73.24%. It shows that the accuracy increases when the training set is updated (add new data). Finally, we add part of h4 in the training set from the previous step, and the rest of h4 as the test set, then we get a higher recognition accuracy (average 98.52%). This means that we need to update the training set to keep a high recognition accuracy.

Antenna deployment. During the experiment, we attach the antenna to the back of the chair. For commercialisation, we can integrate the antenna into the chair in the future. It will be more convenient for people to work or study.

VI. Conclusion

This paper introduces SitR, the first sitting posture recognition system using RF signals alone. We demonstrate that with just three tags pasted to one's back, SitR can successfully recognize three habitual sitting postures. The experiment results show that SitR can achieve robust and high performance. Our system can further detect the abnormal respiration and provide sitting posture history for sedentary people.

VII. Acknowledgments

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