Cognitive Healthcare System and Its Application in Pill-Rolling Assessment

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Abstract: Directional antennas have been extensively used in wireless sensor networks (WSNs) for various applications. This work presents the application of a four-beam patch antenna as a sensor node to assess the pill-rolling effect in Parkinson's disease. The four-beam patch is small in size, highly directive, and can suppress the multipath fading encountered in indoor settings that adversely affects the measurements. The pill rolling effect refers to tremors in the hands, particularly in the forefinger and the thumb, which the patient involuntary rubs together. The core idea is to develop a low-cost framework that effectively evaluates the particular movement disorder to assist doctors or clinicians in carrying out an objective assessment using the S-band sensing technique leveraging small wireless devices operating at 2.4 GHz. The proposed framework uses the perturbations in amplitude and phase information to efficiently identify tremors and non-tremors experienced in the fingers. The unique imprint induced by each body motion is used to determine the particular body motion disorder. The performance of the framework is evaluated using the support vector machine algorithm. The results indicate that the framework provides high classification accuracy (higher than 90%).

Keywords: Parkinson 's disease, sensing technique, ward environment

1. Introduction

In the past few years, increasing attention has been given to the applications of wireless sensor networks (WSNs), which include the monitoring of ill patients, body temperature, body position, heart rate, and body disorders [1]. WSNs primarily use small devices, such as sensor nodes, and radio communication to obtain the particular objectives in the healthcare sector.

The present research work deals with the assessment of pill rolling, a common neurologic disorder in patients with Parkinson's disease (PD). In pill rolling, the patients periodically experience tremor in

hands, particularly in the forefinger and the thumb, which they rub back and forth for a period of time. In this study, an easy-to-use framework is presented, which uses a four-beam patch (FBP) antenna [2] in conjunction with the S-band sensing technique to evaluate the tremors in the fingers so as to assist doctors or clinicians in carrying out an objective assessment. The frequencies between 2 GHz and 4 GHz are referred to as the S-band. The wireless devices used in the proposed technique to sense specific body motions, works at 2.4 GHz, hence it is called the S-band sensing technique. The rationale of using an FBP antenna as a sensor node is due to its operation at the S-band, high directivity, low cost, and suppression of the interference caused by multipath fading in indoor settings [2]. The radiation pattern of the FBP antenna used is presented in figure 1.

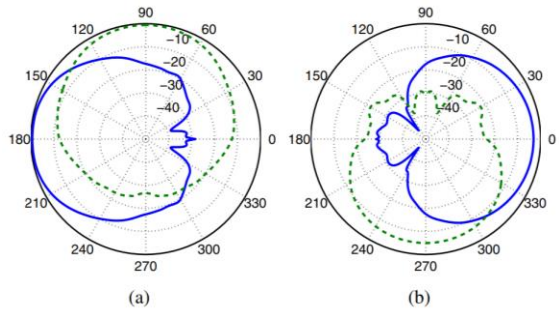

Figure 1 - Radiation pattern of the four-beam patch antenna.

a). Patch 1- solid and patch 2 - dashed, b): Patch 3 - solid and patch 4 – dashed

2. Related Work

Many researchers around the world have introduced devices that could objectively quantify the tremors in hands. Several systems exploited the wearable accelerometers sensors that could retrieve and transmit the data through a wireless medium to a personal computer for data analysis. The numerical methods including spectral analysis were used to identify the tremors [3]-[6]. However, all these solutions come up with limitations in terms of cost and expertise needed for its usage. Moreover, these wireless devices are only capable of transmitting the data within wireless range, so the user must be in close proximity in order to receive the signal. Leveraging embedded sensors has been in use for past few years. Literature review indicate that LeMoyne et al. [7] were one of the first research team to exploit the sensors embedded in a smartphone to record acceleration data via android-based application. Many other studies have detected the motor dysfunction using inertial sensor. The Parkinson's disease patients were

monitored to quantity the tremor [8]-[10], bradykinesia [11] and rigidity [12]. In all of these studies, the data is recorded using dedicated devices that have to be deployed patient's body which make it uneasy at times.

3. Sensing and data acquisition

The S-band sensing technique operates at 2-4 GHz and uses small wireless devices as sensor nodes. The network interface card used is slightly modified to extract the amplitude and phase information of the wireless medium since the method exploits the wireless channel information. The information is retrieved in a group of 30 OFDM subcarriers known as channel frequency response (CFR), which comprises one received packet and can be written as:

$$\text{Sensing Information} = \mathbf{WCI} = \left[h^1, h^2, h^3, ..., h^n \right]. \tag{1}$$

Here, H(i) represents the channel frequency response of individual subcarriers, n=30 is the total number of subcarriers, and WCI denotes the data received from one packet. Each packet contains the amplitude and phase information, expressed as:

$$\mathbf{H}(i) = |\mathbf{H}(i)| e^{(j\angle \mathbf{H}(i))}, \tag{2}$$

where H(i) denotes the wireless channel information received for the ith subcarrier, where i = 1 to 30; $|\mathbf{H}(i)|$ is the amplitude information, and $\angle \mathbf{H}(i)$ is the phase information for the ith subcarrier. The wireless channel information stream received through the FBP antenna within a certain time period k for assessing the tremors in the fingers can be expressed as:

$$Stream = WCS = [\mathbf{H}^1, \mathbf{H}^2, \mathbf{H}^3, ..., \mathbf{H}^k]. \tag{3}$$

The phase information retrieved solely through the FBP antenna in conjunction with the card when connected with the access point is largely random [13] and inapplicable for accurately detecting the

tremors in the fingers, due to the random noise between the transmitter and the receiver. Also, the unsynchronized clock between the transceiver pair makes it inapplicable for any application [14]. Thus, to use both the amplitude and phase information received through the FBP, linear transformation is applied on the raw phase information to obtain the calibrated phase information.

The raw phase information obtained can be written as γ_i':

$$\gamma_i' = \gamma_i - 2\pi \frac{C_i}{K} \alpha + N + \beta, \tag{4}$$

where γ_i is the measured phase, *Ci* is the subcarrier number of the ith subcarrier, α is the time lag, β is the phase offset, N is the random noise, and K is the size of the fast Fourier transform (FFT). The known terms α and β make the phase information infeasible for particular motion detection when only the FPB antenna and network interface are used. To remove the impact of the random noise present in the wireless channel phase information, a linear transform function is applied on the retrieved data [15]. For this purpose, the phase values for the entire bandwidth are considered. Thus, to remove the values of α and β, the terms A and B are introduced, which describe the slope of the phase and the phase offset, respectively [16]. The overall system architecture is shown in figure 2. The volunteer primarily places the forefinger and the thumb in line-of-sight between the transmitter and the receiving directional antenna. The system in this case will only detect the movements of particular body parts i.e. forefinger and the thumb in this case. However, too much or limbs and torso might result in false alarm.

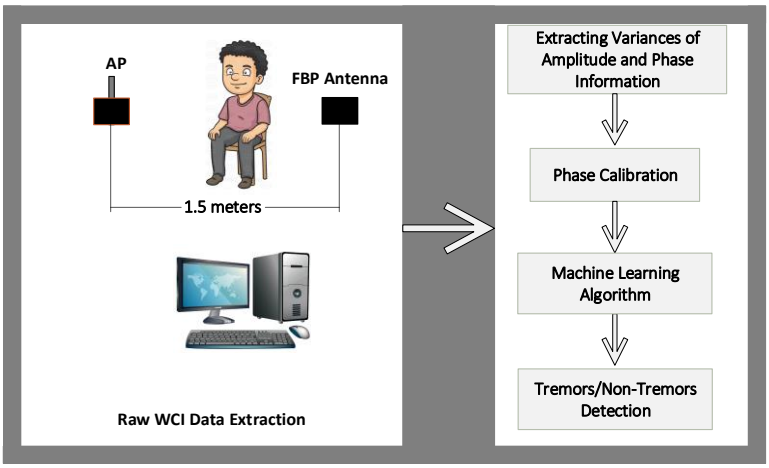

Figure 2- System architecture for pill-roll assessment

The data is first retrieved when the access point is connected to the four-beam patch antenna. The core idea is to leverage the variation in the wireless channel information cause due to the movements of finger and the thumb. When the forefinger and thumb is place between the transmitter and the receiver , the RF signal propagation path is changes, the movements of the specific body part continuous changes the signal propagation path, as a result the electromagnetic waveform received by the receiver will be unique in case of tremors and non-tremors. The data is then processed using MATLAB version 2015 tool where raw amplitude and phase information is extracted. The raw data as discussed earlier is random, hence phase calibration is applied. The useful amplitude and phase information is then plugged into the support vector machine (a machine learning classifier) to evaluate the performance of the system and differentiate tremors from non-tremors.

4. Experiment setup

The experiment was done in an approximate ward environment, as shown in Figure 3. An RF signal generator (AIM-TTI INSTRUMENTS, TGR Series) working as an access point operating at the S-band (2.4 GHz) was used as the transmitter, and a network card embedded in a desktop computer connected to an FBP antenna was used at the receiving side. The host computer would constantly ping the access point and receive two wireless channel packets per second. The transmitter and receiver were placed closed to the subject's body and were kept 1.5 meters apart from each other at 0.5-meter height.

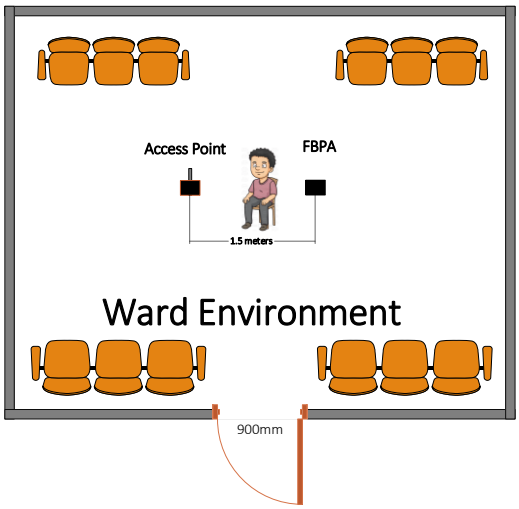

Figure 3 – Experiment setup for the pill-rolling evaluation using an FBPA

The core idea of the proposed framework is to use the perturbations in the amplitude and calibrated phase information to assess the tremors in the fingers. The human body acts as an obstacle to an RF signal; as a result, a unique wireless channel imprint is induced that can be used to identify the tremors in the fingers. Thus, to accurately identify the tremors, the experiment was carried out in two parts. The first part consisted of a volunteer bringing the forefinger and the thumb in close contact with each other without mimicking the tremors in the fingers. In the second part, the volunteer was asked to mimic the tremors in the forefinger and the thumb, replicating the pill-rolling movement. In both cases, the activity was done by placing the hand between the lines of sight of the transceiver pair. The experimental setup was made in a controlled environment where it was made sure that no external movement should affect the data extraction process. The reason for using a four-beam patch antenna at receiving was due to the fact that it radiates the electromagnetic signals in specific direction that and protects the received power from interference from other directions. Hence, any surroundings movements and noise are suppressed by FBPA. If the patient would move torso to tremors, the performance of the system would not be affected because the transmitter and receiving antennas (which is highly directional) are placed at 0.5 meter height. The receiving antenna would only detect movement within line of sight to the transmitter. For optimization, we have tested the system by varying the distance between transceiver model from 1 meter to 5 meters and each time a highly classification accuracy was received. Unnecessary movements between the transceiver model other than the fore-finger would result in false detection. The direction antenna may sense the other object movement as well, for that purpose, the experiments were performed in a controlled environment i.e. in laboratory setting where it was made sure that no external movements were observed. Movements other than the fore-finger between the transceiver pair would result in false detection. The authors in future would take other external movements into account to make a generalize system independent of indoor settings.

5. Results

This section discusses the measurement results obtained by using an FBP antenna in conjunction with S-band sensing to assess the pill-rolling effect.

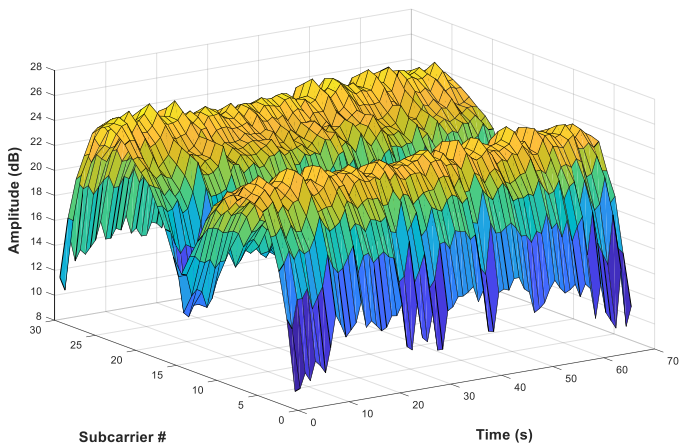

Figure 4 – Raw wireless channel information obtained for non-tremors in the fingers

The experimental campaign was conducted in a controlled environment so that to examine whether the proposed technique could be used to assess the pill-rolling effect. The volunteer was initially asked to put forefingers and the thumb in line-of-sight to the receiver with mimicking the tremors in hands. Figure 4 shows the raw wireless channel information obtained when the volunteer was not experiencing tremors in the forefinger and the thumb. Apparently, the raw data presented in terms of time-frequency do no indicate any information about the tremor/non-tremors in hands. The raw information only present the variations in the wireless medium for 30 subcarriers for 70 packets (35s). It should be noted that the network interface card, when connected to the FBP antenna, receives 2 packets/second, which implies that the data are obtained over a period of 35 seconds.

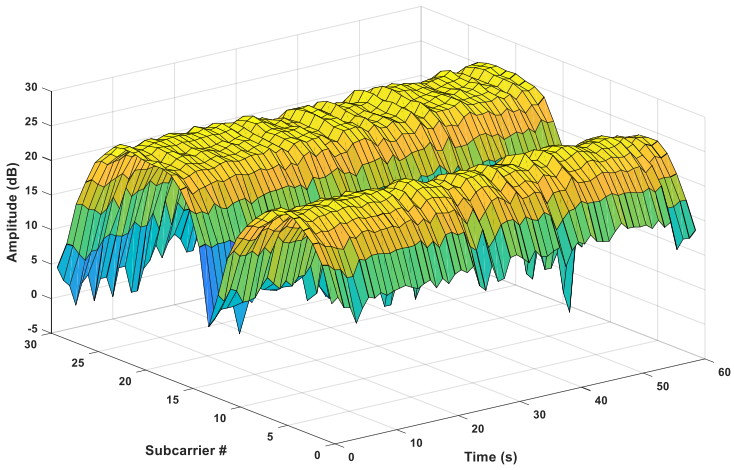

Figure 5 – Raw data obtained for tremors in the fingers

Similarly, in the second part of the experiment, we also examine the time-frequency data to see signs of variations in hands. The volunteer in this case as well, placed the hand between the transceiver pair and mimicked the tremors in the forefinger and the thumb by rubbing these two fingers for a period of time. It is shown the variances in amplitude information for 30 subcarriers for 30 seconds. However, by analyzing only figure 4 and figure 5 do not provide any information about the pill-rolling effect. Thus for that purpose, we examine all the 30 subcarriers retrieved and analyze them on individual basis in the context of time-history.

As previously mentioned, each human motion induces a unique imprint that can be used to assess pill rolling in PD patients. Thus, individual subcarriers were examined by extracting the variations in amplitude information from figure 4 and figure 5 for non-tremors and tremors in the fingers, respectively.

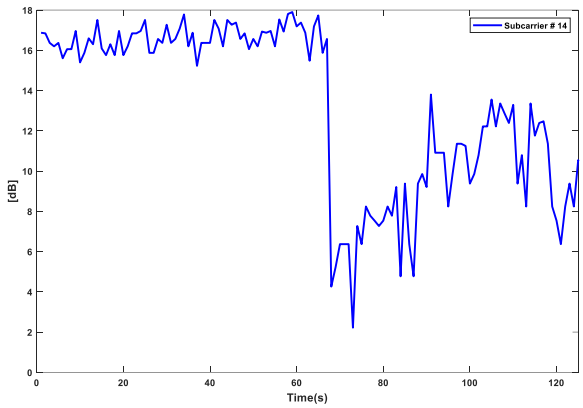

Figure 6 – Combined time history of the pill-rolling assessment

One of the advantages of the S-band sensing technique is that it provides an analysis of the time history of individual or multiple subcarriers [17]. Hence, we selected subcarrier #14, as shown in figure 7, which describes the variances in amplitude information at around 19 dB from packet #1 to packet #60 (30 seconds) when the volunteer was not experiencing tremors, as well as the fluctuations in amplitude information from -5 dB to 11 dB, which indicate that the tremors in the forefinger and the thumb show the pill-rolling effect in PD patients.

To further validate our argument, the calibrated phase information was examined, as shown in Figure 7 and 8.

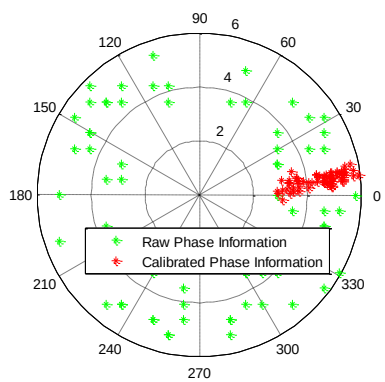

Figure 7 – Wireless channel phase information received for non-tremors

As previously mentioned, the raw phase information is extremely random and inapplicable for any motion detection; thus, the calibrated phase information is considered, as shown in Figure 7. The calibrated phase information is plotted at 3 dB to 6 dB from 00 to 100 when the volunteer was holding the forefinger and the thumb together without observing tremors in the fingers. Because there were no

movements observed in the fingers, the slight variations in phase information are attributed to small-scale body movements.

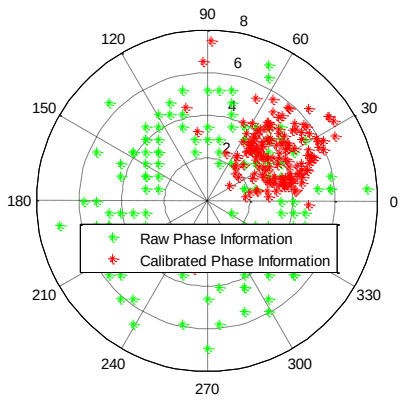

Figure 8 – Calibrated phase information recorded when tremors were observed

The calibrated phase information, as shown in figure 8, indicates major variations. The tremors experienced due to the pill-rolling effect in PD patients tended to shake the hand of the volunteer; as a result, the wireless medium and the data received constantly varied. Thus, variances in the calibrated phase information could be observed from 00 to 1100 at 2dB to 8dB.

As indicated in figure 7 and figure 8, which show the data received for non-tremors and tremors in the fingers, respectively, the wireless channel imprint is unique for a particular body motion and can thus be used to assess the pill-rolling effect in PD patients.

In the subsequent section, the wireless channel data is classified to evaluate the accuracy level of the proposed framework.

The amplitude and phase information received by using the FBP antenna and network interface are classified by applying the machine learning support vector machine (SVM) algorithm. The SVM algorithm classifies the two sets of data by drawing a hyperplane [18]. Suppose that a data set has to be classified in data space D belonging to one of the two classes, either T or T'. The feature vector $\vec{t}$ represents the data point t in the feature space, $\vec{Z} \subseteq \Re^k$. The training data set is represented by $t\{x^1, x^2, x^2, ..., x^n\}$, with the labeled data points described as $\{y^1, y^2, y^2, ..., y^n\}$; here, $y_i = 1$ when $x_i \in P$ or is -1 otherwise. The aim is to determine the new data points t in one of the two classes. The SVM algorithm precisely solves this problem. Typically, the SVM algorithm takes the following steps into account when there is a finite data space. Initially, a kernel function is defined such that

$Y : Z \times Z \rightarrow \Re$, and the $t \times t$ matrix $\left[D(x_i, x_j)\right]_{i,j=1}^{t}$ should contain nonnegative integers.

The final decision function can be written as:

$$F(z) = \sum_{i=1}^{k} z_i - \frac{1}{2} \sum_{i,j=1}^{k} y_i y_j z_i z_j D(x_i, x_j) , \tag{5}$$

when

$$\sum_{i=1}^{k} y_i z_i = 0 , \text{ where } 0 \le z_i \le C, i \in (1,k) . \tag{6}$$

Consider the $(x'_1, x'_2, x'_3, ..., x'_t)$ matrix as a solution to obtain the optimal decision boundary to classify the two data sets. We select $y_i L_D(x_i) = 1$ for all data points of I, where $0 \le z'_i < C$. The training data set that corresponds to (i, z'_i) is known as support vectors [19]. The final decision function that classifies the data point x is $x \in G$ when $sign(L_D(x)) = 1$ is written as [20]:

$$L_D(x) = \sum_{i=1 \rightarrow k, x_i \text{ is a support vector}} z'_i y_i \,|\, D(x, x_i) + b' . \tag{7}$$

Equation 7 describes the hyperplane in $\vec{Z}$ that separates the training data set Z. The data retrieved by using an FBP antenna in conjunction with a network interface card is classified to obtain the percentage accuracy so as to evaluate the performance of the proposed framework.

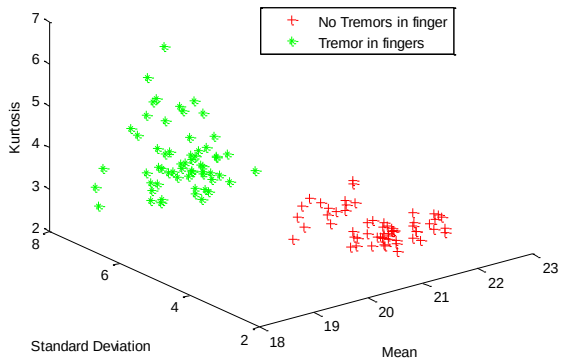

Figure 9 – Tremors and non-tremors in the fingers presented in their feature space

The wireless channel information obtained for 30 subcarriers is used to classify the two data sets, i.e., tremors and non-tremors in the forefinger and the thumb. The two data sets are classified by using three SVM features, namely, the mean, standard deviation, and kurtosis. In figure 9, the two data points represent the non-tremors (red) and tremors (green) in the fingers as described in the feature space. The SVM results obtained indicate an accuracy of higher than 95% considering the two classes.

6. Conclusions

This research presented the application of a small-size four-beam patch antenna at the S-band to objectively evaluate the pill-rolling effect in Parkinson's disease. The FBP antenna was deployed at the receiving side in conjunction with a network interface card and received the wireless channel information in the form of WCI packets. The proposed framework used the perturbations in the amplitude and calibrated phase information to differentiate the tremors and non-tremors experienced in the fingers. The raw phase information was shown to be inapplicable for motion detection; thus, linear transformation was applied to obtain the desired calibrated phase information for detecting the tremors in the fingers. The SVM algorithm was used to evaluate the performance of the proposed framework, and the results indicated an accuracy of 100% considering the two classes. In general, the system can be considered as an effective complement of the existing mechanism [9, 10].

Acknowledgments:

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