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Wandering Pattern Sensing at S-Band

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***Abstract*—Increasing prevalence of dementia has posed several challenges for care-givers.Patients suffering from dementia often display wandering behavior due to boredom or memory loss.It is considered to be one of the challenging conditions to manage and understand. Traits of dementia patients can compromise their safety causingserious injuries.This paper presents investigation into the design and evaluation of wandering scenarios with patients suffering from dementia using an S-bandsensing technique. This frequency band is the wireless channel commonly used to monitor and characterize different scenarios including random, lapping and pacing movements in an indoor environment.Wandering patterns are characterized depending on the received amplitude and phase information of that measures the disturbance caused in the ideal radio signal.A secondary analysis using support vector machine is used to classify the three patterns. The results show that the proposed technique carrieshigh classification accuracyupto 90% and has good potential for healthcare applications.**

***Index Terms*—S-Band sensing, wandering patterns, dementia.**

I. INTRODUCTION

Wandering behavior is a common trait found in the patients suffering from dementia and Alzheimer's disease (AD).Studies estimate that 67% of the dementia patients may exhibit a wandering behavior as the disease progresses because of the memory loss and weariness[1].Wandering behavior is a complicated and unconscious phenomenon.Itcan arise due to loss of cognitive skills as well asexternal environmental factors. Awandering dementia patientcanget into trouble, fall down and injure himself. Study of this behavioral abnormality through detection of the wandering patterns is considered helpful intimely intervention for managing and ensuring safety of the dementia patients. In some cases, patients are only allowed to move inan indoorenvironment. In this paper, we aim at detecting wanderingbehavior using wireless sensing in S-band frequency range (2 – 4 GHz).This method helps detection of abnormal motions in a timely manner, preventing physical overexertion due to excessive exercise. With a technique of non-contactor explicitly with no wearable devices on the subject's body we are able to show the effectiveness of such recordings.

This paper primarily characterizes the wandering behaviors by using non-contact detection method consisting of small wireless devices, omnidirectional antenna, etc.The S-Band frequencies are used for the detection. Two primary indicators namely variances of amplitude and calibrated phase information obtained are used to identifyrandom behaviors of wandering. With a support vector machine (SVM) algorithm, we classify the measured data for quantifying and identifying each wandering behavior. This enables us to differentiate the activity used to observe the stages of dementia and provide timely care.

Following the introduction in this section, rest of the paper is organized in five sections. Section II givesdetailed description of the proposed S-Band technique to sense the wandering patterns; Section III gives the experimental design, section IV provides results and discussion on the performance of the proposed technique while conclusions are drawn in SectionV.

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WANDERING BEHAVIOR

A. Evolution of the Definition

Studies about wandering behavior is new research topic.It was assumed that wanderingwasanaimless movement. Pacing or random entry into other people's rooms are also considered aswandering.Similarly, leaving a particular place without notifying others is also termed as the wandering behavior. Later, ambulation and locomotion were also defined as wandering though the movement is not completely random and aimless. The definition of wanderingbecame more specific by stating behavior such asarriving to the same destination repeatedly; moving from one place to another frequently; walking around to look for a place that becomes impossible to reach; leaving the home unconsciously; walking for a long period of time without a specific aim; could not find the target in a familiar environment; etc [2].

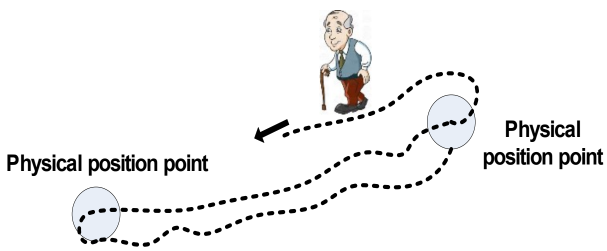
In 2007, Algase et al. developed complete definition of the wandering behavior[3]. They stated that:wanderingcan be seen as the syndrome of abnormal movements; it can be characterized as the disorder categorized with a moving frequency, number of repetitionsand spatio-temporal modes, including lapping, random or pacing mode, leading to lossof one's direction. We take a closer look at wandering particularly in the spatio-temporal mode.

B. Spatio-temporal Mode

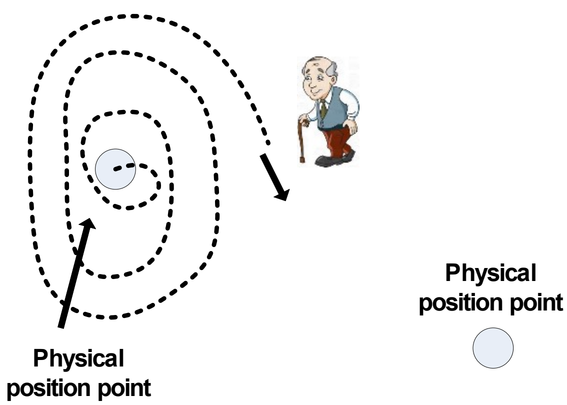
Wandering behavior are classified for monitoring purposes based on frequency, spatial-disorientation and temporal disorientation. These variations in motion is evident in lack of coordination and will manifest into observant clinical conditions. According to Martino-Saltzman, wanderingmovement in the elderly has both spatial movement that varies over time, as seen in certain activities such as [4]:

1) *Pacing*: Moving back and forth between two physical location points.
2) *Lapping*: Circumvolution around a physical position.
3) *Random*: Walking without rules, no repeat position in the trace.

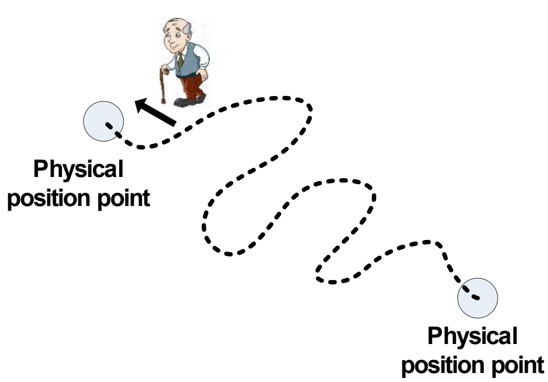
Figure 1 illustrates the three typical movement patternsof the wanderingbehavior.



(a). Pacing



(b). Lapping



(c). Random
Figure 1- Spatialmodesfor wanderingbehavior

Algase et al. have characterized the wanderingmovement as a spatio-temporal locomotion[3].It includes two stages namelywalking and non-walking. Walking stage represents movement in the mode of pacing, lapping or random movement, while non-walking stage shows non-movable intermittent motion between two neighboring walking stages as illustrated in Figure 2.

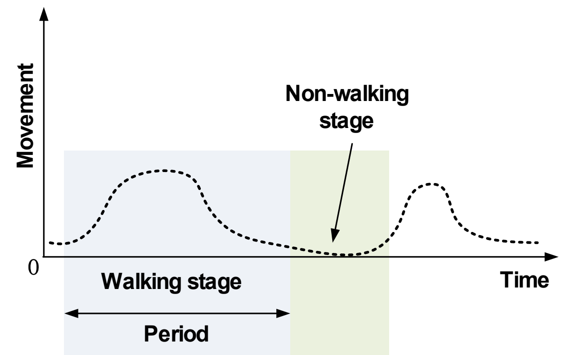


Figure 2 –Spatio-temporal movement

SVM is a simple and effective technique that relies on a set of data-points for classification. Machine learning algorithms such as Random Forests[5],Naieve Bayes classifier[6],and K-nearest neighbor (KNN) algorithm [7] have complexities in terms of computation while SVM provides higher efficiency in practical problems[8].The transformation of an optimal set of data points to a higher dimension using the inner-product kernel functions can solve the linearly non-separable datasets adequately.

Theexisting studiesthatdetecthuman wandering behavior can be grouped into three main categories: detection based on thedegree of locomotion, detection using monitoring of boundary transgression and detection throughobservation of travel pattern.

The systems based on thedegree of locomotion primarily utilizebiomechanical devices[9].Detection of the wandering behavior is based on tracking number of steps taken by the person or leveraging accelerometers to record locomotion in three-dimensional space. This technique however, does not consider the variation in movements from person to person while the detection accuracy also varies.

On the other hand, monitoring dementia patients using a global positioning system (GPS) providessafety within a particular area. It aimsat issuing an alert to the caregiver when an elderly person crosses a pre-defined boundary. Ogawa *et al.*[10]have introduced an automatic system using a smart phone to locate the position of the dementia patient to provide timely assistance. The system sends the location to the caregiver when the wandering subject leaves the house. Mulvenna *et al.*[11]have investigated using a GPS-equipped personal digital assistance (PDA) that can be used to monitor disoriented patients by helping them get back home. While Palomino *et al.*[12]haveused a mobile phone embedded with a GPS system to monitor the walking behavior of a dementia patient. The drawback of these solutions is that they only provide the location of the subject rather thanwandering behavior over a period of time. Thus, limiting the purpose of identification of the behavior in itself.

The last category for monitoring a dementia patient is travel pattern recognition. Martino-Saltzman *et al.*[4]have designed a system that recognizes travel patterns of dementia patients. The system primarily works by deploying electronic tags on thepatient'sankle and continuously monitoring the subject's travel activity using video recording. The authors concluded that dementia patients typically walk in a pacing, lapping and random manner. This technique is not contactless and uses body-worn tags. Thecomputational overheads for signal conditioning are expensive.

II. S-BAND SENSING AND DATA PROCESSING

The proposed method uses an S-Band sensing technique that functions from 2 GHz to 4 GHz. The technique uses wireless channel information.The Wireless link works using Orthogonal Frequency Division Multiplexing (OFDM) system which divides the single data stream (20 MHz) into several orthogonal channels (56), called subcarriers. The WCI now reveals group of 30 subcarriers to upper layer users depicting the amplitude and phase information of each subcarrier[13].Each WCI packet is made up of a group of 30 subcarriers containing amplitude and phase information. The WCI information or a packet can be expressed has a group of 30 subcarriers represented as follows:

$$WCI = [WCI(f_1), WCI(f_2), ..., WCI(f_n)] \quad (1)$$

Each WCI packet's amplitude and phase information of an OFDM subcarrier is related as seen in equation (2):

$$WCI_n = |WCI_n| e^{j\angle WCI(f_n)}, \quad (2)$$

where, $|WCI_n|$ denotes the amplitude information of the WCI also termed asthe channel frequency response (CFR)) for the n^{th}subcarrier operating at a central frequency of f_n, and $\angle WCI(f_n)$ represents the corresponding phase information.

To continuously monitor the walking behavior of the dementia patient, WCI data is recorded for a number of N measurements for timeduration, represented as:

$$WCI_{total} = [WCI^1, WCI^2, WCI^3, ..., WCI^N], \quad (3)$$

Nnumber of measurements serves as primary input for detecting and differentiating the wandering behaviors of adem… patient. It should be noted that the phase data collected is random and is not applicable for classifying pacing, lapping and walking randomly.It is therefore, passed through the phase calibration process.

A. WCI Phase Calibration.

The phase data measured using the S-Band sensing technique are random. Using an unsynchronized clock between the transceiver pairmakes it inadequate for detecting the three wandering behaviors. The calibrated phase information is unavailable [14]. In this paper, our attempt is to derive calibrated phase information for detecting the three wandering behaviors, couple it with amplitude measurements. Obtaining the true phase information solely through the hardware and associated tool-chain makes the data overlap. Thus, to obtain calibrated phase information by mitigating random noise, we apply linear transformation on the raw WCI phase information as recommended in [15]. The random phase offsets due to reflections in the line-of-sight (LOS) signals are mitigated by physical measurement setup and using of true phase values given by equation (4). Analytically, using linear combination of ψ_i' on the measured WCI LOS and non-line-of-sight (NLOS) phase data we reduce the variances.

The phase information Φ_i' obtained from the WCI raw data for the i^{th} subcarrier can be expressed as:

$$\psi_i' = \psi_i - \frac{2\pi K_i}{L}\sigma + \beta. \quad (4)$$

Here, ψ_i' is the true phase while σ and β represent the timing offset and unknown phase offset, respectively, at the receiver side that causes phase error. K_i indicates the subcarrier number of the i^{th} subcarrier. With, $L = 64$ is the size of the FFT according to IEEE 802.11a/g/n standard.

Firstly, the entire frequency band is considered to eliminate the timing offset (σ) and phase offset (β).Then, we introduce x and y defined as [15]:

$$x = \frac{\psi_i' - \psi_1'}{K_n - K_1} = \frac{\psi_i - \psi_i}{K_n - K_1} - \frac{2\pi\sigma}{L}. \quad (5)$$

$$y = \frac{1}{n}\sum_{i=1}^{n}\psi_i'. \quad (6)$$

$$\therefore y = \frac{1}{n}\sum_{i=1}^{n}\psi_i - \frac{2\pi\sigma}{nL}\sum_{i=1}^{n}K_i + \beta. \quad (7)$$

Making the subcarrier frequency in equation 6 symmetrical, $\frac{2\pi\sigma}{nL}\sum_{i=1}^{n}K_i = 0$ results in:

$$y = \frac{1}{n}\sum_{i=1}^{n}\psi_i + \beta. \quad (8)$$

Subtracting $xK_n + y$ from the raw WCI phase ψ_i', the calibrated phase information $\psi_i^{\sim}$ is obtained as follows:

$$\psi_i^{\sim} = \psi_i' - xK_n - y. \quad (9)$$

$$\psi_i^{\sim} = \psi_i - \frac{\psi_n - \psi_1}{K_n - K_1}K_n - \frac{1}{n}\sum_{i=1}^{n}\psi_i. \quad (10)$$

B. Support Vector Machine for Data Classification

Support vector machine is a powerful tool for data classification. A data classification process typically involves separation of dataset training and testing data. The *class labels* or *target values*and many *featured variables* or *attributes* are defined for each part in the training process. Based on the training datasets, an SVM algorithm generates a model of support vectors that predicts the class labels of the test dataset for the given test dataset attributes. The prime reason for feature set is to maximize the margins to have a greater number of support vectors that translate to an increased accuracy.

Considering a training dataset $(x_i, y_i), i = 1,2,3,...l$ with $x_i \in R^n$ and $y \in [1,-1]^l$, the SVM gives a solution to the required optimization problem as [16] :

$$\min_{w,b,\xi} = \frac{1}{2} w^T w + C\sum_{i=1}^{l} \xi_i \ .(11)$$

It provides $y_i(W^T \phi(x_i)+b) \geq 1-\xi_i, \xi_i \geq 0$.

The function ϕ in this case, maps the training vectors x_i into high dimensional feature space and finds a linearly separable hyperplane with a maximal margin. The term $K(x_i,x_j)=\phi(x_i)^T \phi(x_j)$ is the kernel function and $C>0$ indicatesthe error term for the penalty parameter. The three kernel functions, linear, polynomial and radial basis functions (RBF) used in this work for classifying the three wandering behaviors are as follows:

Linear kernel function:

$$K(x_i,x_j)=x_i^T x_j \ . \ (12)$$

Polynomial kernel function:

$$K(x_i,x_j)=(\gamma x_i^T x_j + r)^d, \gamma>0 \ . \ (13)$$

RBF kernel function:

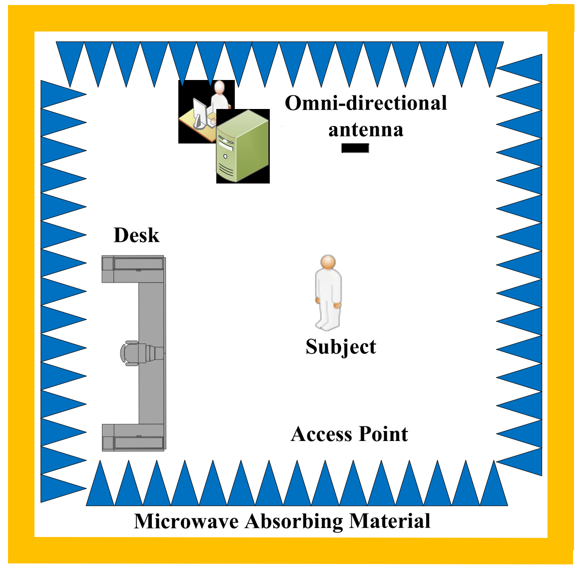
$$K(x_i,x_j)=e^{(-\gamma \|x_i - x_j\|^2)}, \gamma>0, (14)$$

where γ, r and d are kernel parameters.

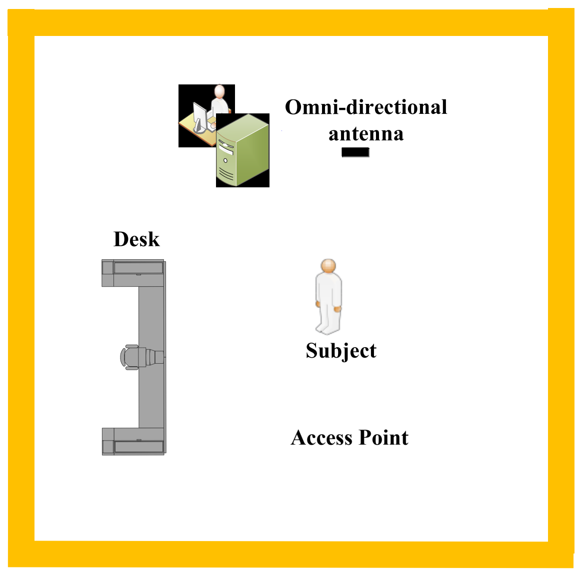
The combination of the kernel parameters are used to optimize and maximize the margins of the hyperplane between two datasets.

III. EXPERIMENTAL DESIGN

Our indoor set up for measurement of perturbed signals was conducted atSchool of Electronic Engineering, Xidian University. The proposed method is implemented using an S-Band (2 – 4 GHz) signal sourcetransmitter and a Hewlett-Packard desktop computer with Intel(R) Core i5-4590 CPU for data acquisition. An omnidirectional antenna is connected to the desktop computer to work as a receiver. The experiment was performed in a 12 x 12 m room as shown in Figure 3. The room contains a desktop computer, three sofas, and a table. A volunteer mimicking the three wandering behaviors has been used as the dementia-suffering test subject. The distance between transmitter and receiver was kept at 7 m. The wandering subject is walking within this range in terms of distance so that the wireless signal perturbation is maximized. Human behavior perturbs the signal causing aconstant shift between LOS and NLOS signal propagation. Each motion of a person has a unique signature in both LOS and NLOS signal in theindoorenvironment.This results in a unique WCI signature that is being sensed and will be utilized for the pattern detection.



(a) With microwave absorbing materials walls



(a) Without microwave absorbing materials walls
Figure 3 – Experimentaldesign for three wandering behavior detections (with and without microwave absorbing materials walls)

The amplitude measurements are used for an analysis that classifies the wandering behavior based on the clinical conditions with a greater precision.

IV. DATA EVALUATION AND DISCUSSION

The proposed method uses two evaluation metrics;variances of amplitude information, andvariances of calibrated phase information. When the test subject walks across the room, the wireless medium is constantly disturbed.

Table 1Inner-Product Kernel Functions

Type	Kernel Function
S(c,ci), i=1,2,3,…P	
Linear $c^T c_i + x$	
Quadratic $\left(x^T x_i + c\right)^2$	
Radial-basis function (RBF) $e^{\left(\frac{-\lvert c-\lvert c_i \rvert\rvert^2}{2\sigma^2}\right)}$	

Table 2 Five Features

$$Mean\ value\left(Y_{MV}\right) = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$Root\ mean\ square\ \left(Y_{RMS}\right) = \sqrt{\frac{1}{P}\sum_{i=1}^{P} x_i^2}$$

$$Kurtosis\ value\ \left(Y_{KV}\right) = \frac{1}{P}\sum_{i=1}^{P}\left(\frac{[x_i - \mu_x]}{\sigma}\right)^4$$

$$S\tan dard\ deviation\left(Y_{STD}\right) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \mu_x\right)^2}$$

$$Square\ root\ amplitude\left(Y_{SRA}\right) = \left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert x_i \rvert}\right)^2$$

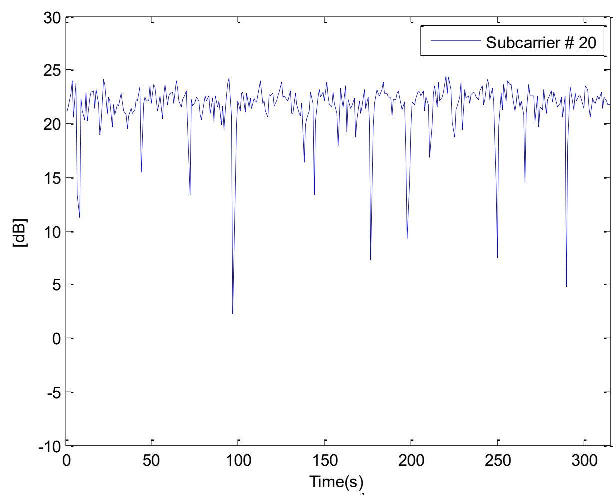
Table 3- SVM error rate (%) for detecting the three wandering behaviors (without microwave absorbing materials)

Kernel		5 Features		
Function	S	Random	Pacing	Lapping
	40	30.10	28.00	27.16
Linear	80	24.56	23.50	24.12
	120	23.16	23.11	29.72
	40	17.81	19.98	15.22
Polynomial	80	14.12	15.12	13.13
	120	11.21	12.31	10.22
	40	9.46	9.11	9.60
RBF	80	10.25	9.97	10.11
	120	9.88	9.98	10.15

Table 4-SVM error rate (%) for detecting thethree wandering behaviors (with microwave absorbing materials)

Kernel		5 Features		
Function	S	Random	Pacing	Lapping
	40	25.50	23.00	21.75
Linear	80	18.75	20.50	18.25
	120	18.25	19.50	17.40
	40	12.00	15.75	11.00
Polynomial	80	11.25	10.25	10.75
	120	9.70	9.50	8.00
	40	8.91	9.25	9.60
RBF	80	9.25	9.00	9.25
	120	6.50	8.75	8.75

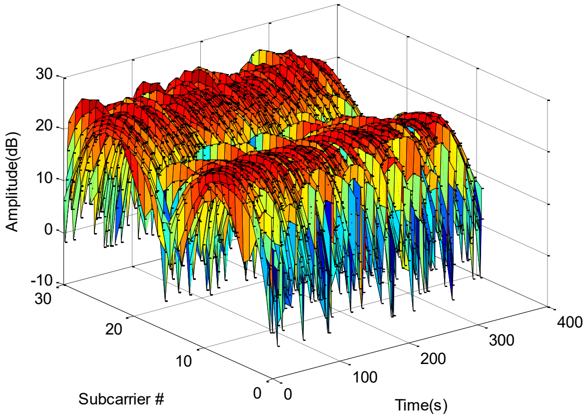
Figure 5(a) and 6(a) are 3D plots that illustrate the signal propagation in terms of amplitude strength of a particular sub-carrier frequency. The time axis shows the temporal variations as the packets arrive at the receiver. The 3D plot gives a visualization of perturbations that needs to be consistent and discerning.



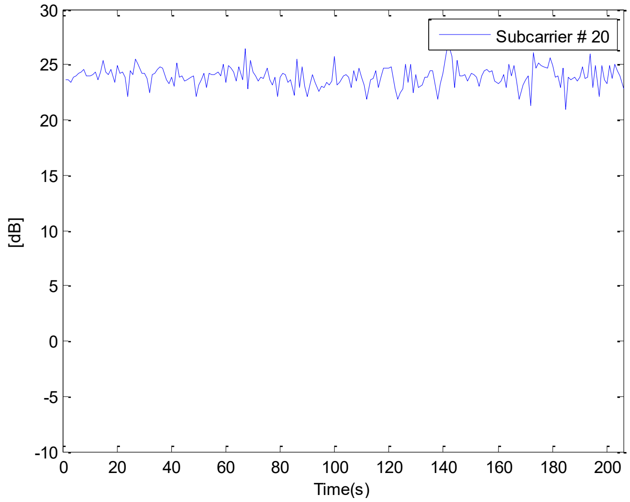
Time history of the 20th subcarrier

Figure 4 – Raw wireless channel state information obtained during the experiment when the person was walking in a random manner

By fixing a subcarrier, considering the 20th, the amplitude (in dB) verses time is as shown in figure 4. Subject's movement is random, theinduced WCI signature is unique as observed in Figure 4(b). The time history for a total of 315 seconds when the subject walks in the wireless sensing range. The perturbations of the signal as captured by the hardware indicates the variance in amplitude. The WCI amplitude information, in this case,fluctuatesbetween 3dB to 23 dB.



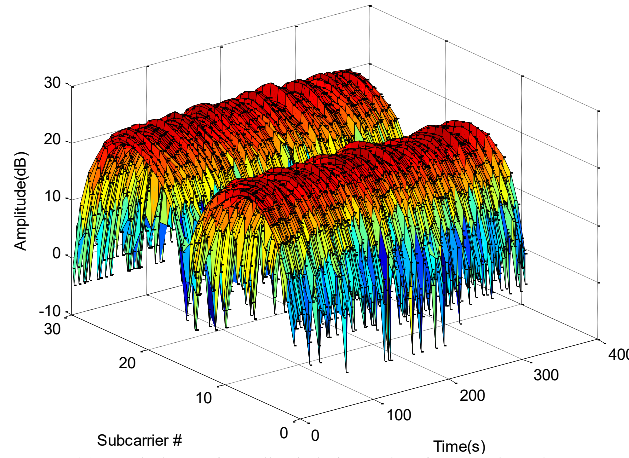
(a). Variations of amplitude information for 30 subcarriers



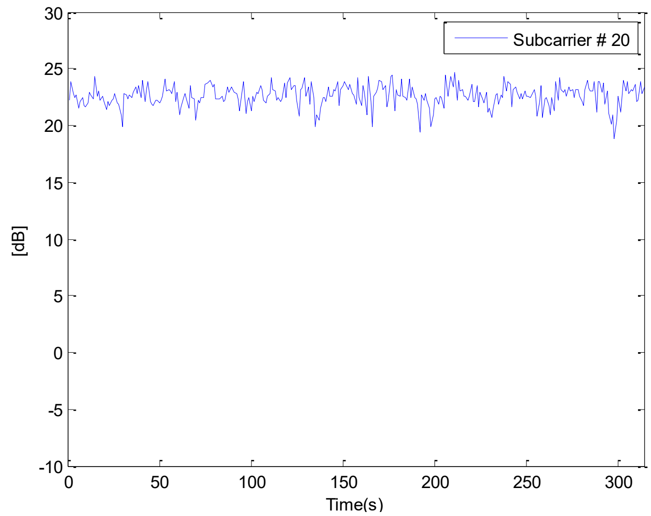
(b). Variances of amplitude information for an individual subcarrier
Figure 5 – Raw WCI data recorded for a person with a pacing behavior

Considering the three wandering behaviors as our base class for measuring and classifying namely *pacing, lapping and random* wandering behavior, we capture the signal for a period of 212 seconds. Figure 5(a) shows the raw WCI data for 30 subcarriers. Similarly looking at figure 5(b) a plot of time history of amplitude information for a particular subcarrier provides a comparison between the behaviors. The plots in terms of amplitude and a chosen sub-carrier do not allow a clear identification of the activity. A closer look at the specific subcarrier and its variance is significant by getting the features per packet data.

A*pacing* behavior for a period of 212 seconds as shown in Figure 5(a) shows the raw WCI data while figure 5(b) illustratesthe time history of amplitude information considering the 20th subcarrier.



(a). Variations of amplitude information for 30 subcarriers



(b). Variances of amplitude information for an individual subcarrier
Figure 6 – Raw WCI data obtained during theexperiment when thesubject was moving in a lapping manner.

Figure 6(a) showsthe raw data recorded for lapping behavior. The amplitude information for subcarrier #20 fluctuates between 20 dB to 24 dB as in Figure 6(b) for lapping behavior.

A plot of combined time history versus amplitude information for the three wandering behaviors is given in Figure 7. A transient shift in the power level can be seen when a person moves from one activity to another.

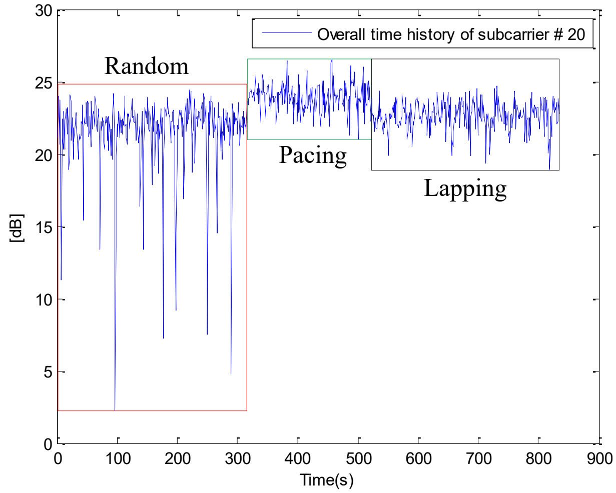
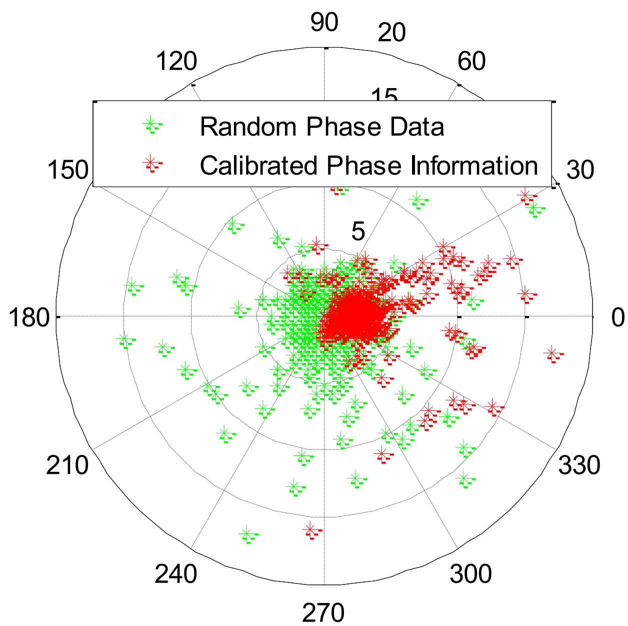
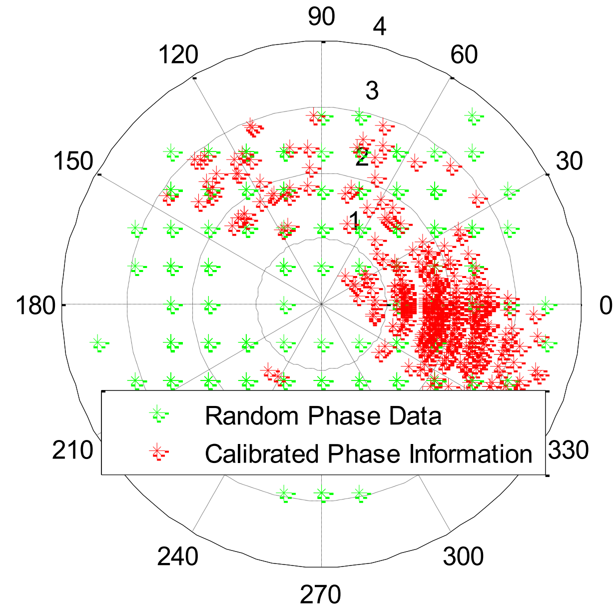


Figure 7 – Combinedtime history of lapping, pacing and wandering randomly

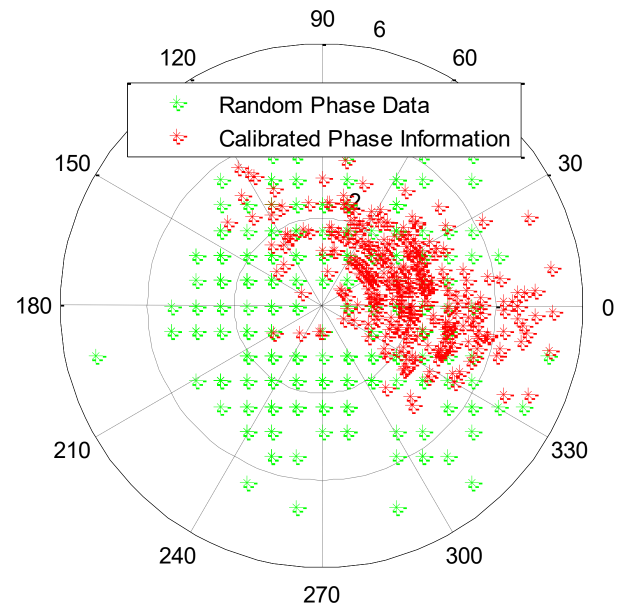
WCI signatures are observed in a particular subcarrier for the three wandering behaviors are clearly distinguishable. The power levels fluctuate between 3 dB to 23 dB, 23 dB to 26 dB and 20 dB to 24 dB for *random*, *pacing* and *lapping* behaviors respectively. As observed that there are instances when the power level for each behavior is similar to one another in the steady state of an activity while a slight variation during the switching. For example, the power level for the random behavior ataround 250th second is similar to the pacing behavior occurring around 420th second. Power level for the*pacing*behavior around 500th second and *lapping*behavior occurringaround 550th second are the same. Therefore, to further highlight the distinctive nature of the three behavioral patterns and validatingWCI signature's uniqueness, the calibrated phase information is obtained during theexperiment and is analyzed.



(a). Random



(b). Pacing



(c). Lapping

Figure 8 – Calibrated phase information for the three wandering behaviors.

Figure 8 shows the calibrated phase information obtained after transforming of raw WCI data. The phase data recorded usingthe hardware interface tool-chain is extremely random as evident from the data points illustratedingreen. Thus, we only consider the calibrated phase information for detecting the three wandering behaviors. The result in Figure 8(a) shows that the calibrated phase information mostly clustered in the range of $90^0$to 300^0, indicating the random behavior. The data for the pacing behavior lies between 150^0 and 300^0as illustrated in Figure 8(b) while the data for lapping behavior is spread between 130^0 to 330^0 (Figure 8(c)).In summary, each wandering behavior induces unique WCI dataset. However, there is a cluster of data between 30^0 to 300^0,which is similar to the two behaviors.

To specifically identify the behavior and classify them based on the measurements of amplitude we use a support vector machine. CFR datasetscontaining amplitude information of 30 subcarriers per packet is collectively used by the algorithm. We have taken measurements for each wandering behavior and used it as a training dataset in the SVM algorithm. The *svmtrain* function in MATLAB was used to classify the three datasets representing the three wandering behaviors. A one-versus-rest approach was adopted for each class and the cost parameter *C* was selected as 1 (default value). The optimal decision boundary was obtained using a sequential minimal optimization solver. The first three samples including 40, 80 and 120 were used to train the SVM and each model was tested using the last 40 samples. The three kernel functions; linear, polynomial and radial-basis; as defined in equations 12, 13, and 14 respectively, were used scale the data into higher dimensional feature space.

The five features we have extracted from our training data set are listed in table-2. Each of them signify the measurements per packet uniquely. The SVM results obtained are represented in terms of percentage error as shown in Table 3 and 4. The first column denotes the type of kernel function used for the training, the second column represents the training samples, and the last three columns gives the percentage error obtained for classifying the three wandering behaviors. The results show that when the linear kernel function was used to classify the three wandering behaviors from 40 training samples, the percentage error isbetween 27.16% to 30.10%. The error rates obtained while using 80 training samples for *random*, *pacing* and *lapping*are24.56%, 23.50%,and 24.12% respectively. When 120 training samples were considered, the error rates for the three wandering behaviors are reduced to23.16%, 23.11%,and29.72%. An increase in the dataset changes the errorrate, decreasing with an increase in training samples when ten-features are used.

Analyzing the results obtained usingthe polynomial kernel function from the ten features space, the error rates for random, pacing and lapping classification are 17.81%, 19.98%, and 15.22%,respectively. The percentage errors with 80 samples for the three wandering behaviors are 14.12%,15.12%,and13.13%respectively. Similarly, with the increase in training samples, the error rates keep on decreasing. The error rate for 120 samples for the three wandering behaviors decreased to become less than 13%. Using the RBF kernel function brings down the error rate below 10.22%.

Table 3 and 4 show the comparison between the three kernels that transform the data.It is evident from accuracy rate comparison that a set of five features per training set influences the outcomes. For a sample set of S=120, a linear kernel for all the three behaviors provides a consistent accuracy rate with a difference of 0.5 and an increase in 67% from previous calculations of 80. By comparing all the three kernel we find the non-linear kernel such as RBF provides a good accuracy rate as against the other two kernels. That is an increase in training samples, the error rate can be reduced while the highest accuracy level achieved using the RBF kernel function.

V.CONCLUSION

This paperhas presented a novel method for the detectionof three wandering patterns exhibited by thepatients suffering from dementia. This technique is based on the clinical wandering behaviors that if not monitored can result in other conditions such as delusions and harm.The proposed technique employs acquisition of wireless channel characteristics and data classification to detect and distinguish between random, pacing and lapping wandering behaviors. Performance of the proposed scheme has been evaluated in terms of amplitude, calibrated phase information. An analytical approach for a greater precision is carried out using SVMalgorithms. It is evident from accuracy rate comparison that number of features per training set influences the outcomes. The number of features and samples are a combination that determine the uniqueness and variation of the behaviors. An increase in the feature set say to 10 or more will mitigate this disparity providing a greater precision in classification.

The experimental results for the tests performed in an indoor environment have showed that the proposed method is reliable, efficient and accurate. We have considered two scattering environments that provide a baseline for future measurements. The secondary analysis using support vector machine provides an accuracy level that can be used as base values since our numerical calculation show a rate close to 90%. High efficiency, good accuracy and use of small contactless wireless devices makethis technique a good solution for healthcare systems that can be easily installed in homes or hospitals.

VI. REFERENCES

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