Activity Recognition using Ultra Wide Band Range-Time Scan

Arijit Chowdhury*, Taniya Das†, Smriti Rani‡, Anwesha Khasnobish§, and Tapas Chakravarty¶

TCS Research & Innovation
Kolkata, India
Email: (*arijit.chowdhury2, †das.taniya, ‡smriti.rani, §anwesha.khasnobish, ¶tapas.chakravarty) @tcs.com

***Abstract*—Automated detection of Activities of Daily Living (ADL) is gaining importance for its application in smart living, elderly car, healthcare, to name a few. In this paper a novel automated method for detection of human activity is proposed using range time scan data of Ultra Wide Band (UWB) radar. Unlike earlier methods of activity recognition using multi sensor fusion and multi radar setup, we have used a single UWB radar in monostatic mode. In this work, intensity of the reflected UWB signal is used to quantify the amount of scattering leading to formation of range time data matrix. Relevant feature extraction from the range time data via two-dimensional two-directional principal component analysis (2D2D-PCA) is carried out. These features are subsequently used by a random subspace ensemble classifier with k-nearest neighbors algorithm. The proposed method is highly efficient with an average training and testing accuracy of 91.4% and 86.4%, respectively, even on unknown subjects. Moreover the technique resulted in average precision and recall of 0.87 and 0.84, respectively.**

***Index Terms*—UWB radar, Activity detection, range time scan, 2D2DPCA, Subspace kNN**

I. Introduction

Recent developments in smart sensors [1], [2], internet of things (IoT) [3] and affordable machine learning techniques has increasingly contributed to the unobtrusive sensing and automated detection of Activities of Daily Living (ADL) applications [4]. Unobtrusively detecting human activities has attracted a lot of researchers in recent times [5] [6]. It serves as an important part in a number of applications revolving around smart homes, smart healthcare systems, elderly care and human-machine interface for intelligent device. These applications are important for improving quality of life.

Over the past decade, radar has been increasingly used for human activity monitoring with applications that include gait recognition [7], fall detection for elderly care [8] and activity recognition [5]. In recent years, Ultra Wide Band (UWB) radar technology has emerged as one of the promising system for such applications [9]. UWB enjoys a number of advantage over the existing technologies. The UWB signal does not need to adopt to traditional carrier modulation in wireless transmission and reception, and so can be conveniently processed even in time domain [10]. It enables short range, low power and ultra high speed communications in the frequency band 3.1 GHz to 10.6 GHz. It sends very short pulses which enables it to accurately determine distance with high resolution using Time of Flight (ToF) measurements, as compared to popular Received Signal Strength Indication (RSSI) techniques based on power determination. This helps overcome multipath propagation. Therefore, we propose to use UWB based Radar System [11] for activity recognition because of it's high resolution feature coupled with high bandwidth, enabling it to record different signature for each activity precisely.

Existing use of UWB radar is been found in vital sign detection system [12]. Activity detection has been researched based on computer vision, FMCW radar, to name a few, but detection using only range time intensity scans of UWB radar has not been well studied. Therefore, we propose to develop a system for the effective use of this revolutionary wireless technology for unknown person's activity detection using light weight Machine Learning (ML) techniques.In this paper a single UWB radar consisting of two antenna, for transmit and receive respectively, has been implemented in monostatic mode. In the proposed methodology, from radar data, intensity of the reflected signal is used to quantify the amount of scattering leading to a range time data matrix. Proposed work uses relevant feature extraction of the range time data via two-dimensional two-directional principal component analysis (2D2D-PCA) [13].Obtained features are then used by a random subspace ensemble classifier with k-nearest neighbors algorithm *(Subspace kNN)* [14] [15]for activity detection.

The paper is organised as follows. Detailed system setup with radar specifications are given in Section II. In Section III the implemented methodology is explained in details. The experimental results are discussed in Section IV while concluding remarks along with future work is presented in Section V.

II. Experimental Setup

In this work, the UWB radar used is the Humatics' P440 Monostatic Radar Module (P440-MRM) [11], as shown in in Fig. 1(a), is used to sense the environment.

P440-MRM is a portable UWB transceiver operating between 3.1 to 4.8 GHz. The operation of the radar on the revolutionary UWB technology makes it achieve an excellent accuracy of < 2 cm, with a resolution of 0.0091m, in high multipath and high clutter environments [16]. This UWB module works by precisely measuring distance using Two Way ToF measurements. The pulse waveform is generated as shown in Fig. 1(b), at a pulse repetition rate of 10MHz and received

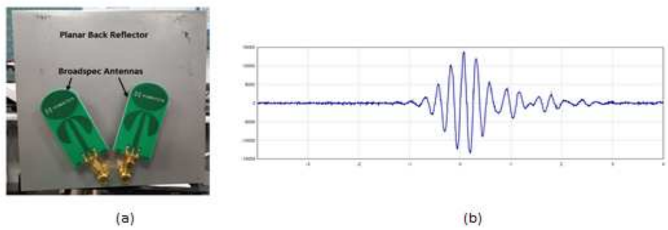

Fig. 1. Humatics P440 UWB Radar (a) Radar module front view with planar back reflector (b) Transmitted pulse waveform

at a sampling rate of 61 ps in fast time. The module is operated with the Broadspec Antennas (Toroidal Dipole Antenna) [17]. The main parameters of the antenna are summarised in Table I. We have also augmented a planar back reflector to the radar antenna to increase the gain to 5 dB (180%) and restrict the azimuth pattern to 100°. as shown in Fig. 1 (a). We have used a reflecting metal sheet of dimension16cm $\times$16cm $\times$1mm, and is kept at a distance of 19 mm from antennas as recommended in [16].

TABLE I
BROADSPEC ANTENNA PARAMETERS

S.no.	Parameters	Value
1.	Tx operating band	3.1 to 4.8 Ghz
2.	Rx operating band	3.1 to 4.8 Ghz
3.	centre frequency	4.3 GHz
4.	Maximum power spectral density	-41 DBm/MHz

The experiments were performed on 7 subjects (3 females and 4 males in the age group of 22-35 years). Each subject participated voluntarily in the experiments, on signing a consent form. We have chosen a subset of ADL, consisting of 4 activities (namely walk, sit down, sit up and *simulated* frontal fall). This subset is chosen focusing on our aim of elderly care and worker safety solutions. Frontal fall was exclusively added because of it's importance in elderly care applications. There were 5 trials for each activity. Users were instructed to perform each trial of each activity in 10 seconds. Following symbols were used to depict each activity.

- **A1**: Walk (subject walking approximately 3m towards the radar)
- **A2**: Sit Down (subject at 2m from the radar)
- **A3**: Stand up (subject at 2m from the radar)
- **A4**: Simulated frontal fall (subject at 2.5m and falling towards radar)

III. METHODOLOGY

Continuous short pulses are sent out by radar transmitter and the echos are collected back by the radar receiver. The echos are logged as raw radar return in log files which are pushed into preprocessing box to generate range time intensity data for activity classification. Once the raw data is received, it is arranged in a form of 2D matrix (range time). Such scans are filtered using second order difference filter (motion filter) along the fast time axis (described in III-A). Envelope of the filtered scan data is extracted and given as input to the next block. Here the relevant activity portion is obtained using statistical properties (explained in III-B). Further resizing is carried out to make 2D data of same size for all the activities, before proceeding with the feature extraction and classification. Entire process flow is depicted in Fig. 2. Here 2D2D-PCA [13] is used for feature extraction while different classifiers have been assessed before finalising optimal classification algorithm. All computations were carried out in Matlab 2019a.

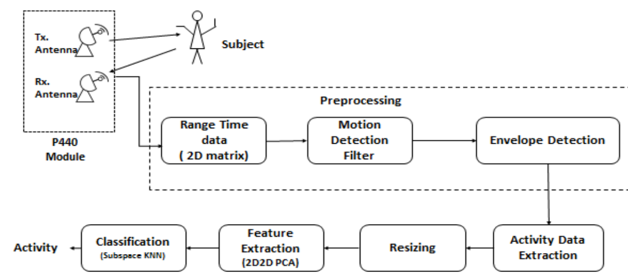

Fig. 2. Methodology for activity detection using UWB radar

We have configured radar to restrict the scanning range to 3.51 m (as all the activities were confined within this range) with sampling rate of 16.4 GHz [1]. It produces $N = 480$ number of samples and has resolution of 0.0091 m. Each scan data in $N = 480$ samples are actually obtained using,

$$b_s = 32\,bins \tag{1}$$

each bin having time duration of

$$t_b = 1.907\,ps \tag{2}$$

MRM is designed for coherent operation, thus it is possible to integrate multiple scans to improve received Signal-to-Noise Ratio (SNR). This integration parameter known as the Pulse Integration Index (PII), is selected as 15 here. Higher PII leads to better SNR. A PII of 15 will integrate $2^{15} = 32,768$ scans providing an SNR improvement of 45 dB [2].

The output received from the radar is logged as a range time data (like Raster scan [18]), as shown in Fig. 3 . Each of the scan data in 480 samples corresponds to a particular distance in m (from 0 to 3.51m, where 0 m is the position of antennas). Every single scan data vector forms a row of our 2D matrix, called as fast time axis. Therefore, the fast time sampling occurs every t_f seconds leading to f_{fast} given by Eq. 3.

$$\begin{aligned} t_f &= b_s \times t_b \approx 61\,ps \\ f_{fast} &= 1/t_f = 16.4\,GHz \end{aligned} \tag{3}$$

[1]For detailed procedure on setting up the radar module and how the parameters impact the working of given radar please refer to [16]

[2]Meaning and significance of each parameter is available in the instruction guide of the module

This process is repeated after certain interval for a given number of times, where N (480 in our case) number of samples are recorded forming a row each time. The slow time interval, t_s is selected as $t_s = 139\ ms$.

These generated rows are stacked one after the one in a column-wise manner, giving the slow time axis. This leads to a slow time sampling rate of $t_s^{-1} = 7.19Hz$

Hence, The data along the slow time indicates the average time for which the data was collected while fast time indicates the range around the radar for which data was captured.

Thus a range time data (2D matrix), like raster scan, is produced which is shown as intensity plot in the Fig. 3. Let the 2D matrix is represented by $[X_{i,j}]_{n\times 480}$, where n^3 is the numbers of scans performed. Each sample entry in the 2D matrix is denoted by $I_{i,j}$ which corresponds to intensity of radar return at the corresponding distance ($j \times 0.0091$ m) for i^{th} scan [12]. The range axis as shown in Fig. 3 corresponds to the fast time axis of 480 samples. Each sample is associated with a particular distance with resolution of 0.0091 m [16]. Each row of the 2D matrix (R_i) corresponds to an individual scan vector, and each column (C_j) corresponds to intensity return for that particular distance.

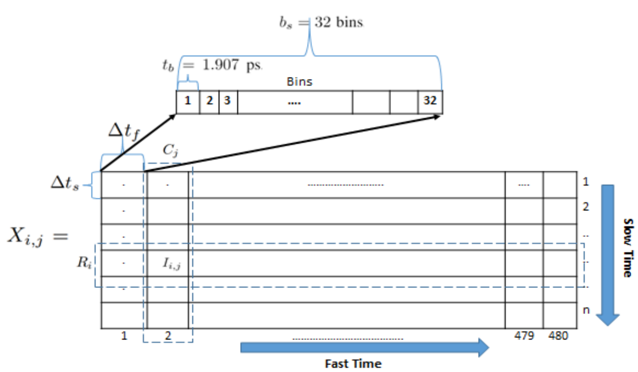

Fig. 3. Range Time 2D matrix

A. Data Pre-processing

The 2D raw data matrix is first filtered [16]. The filters are run across a single scan along the fast time axis. Following algorithm is carried out on each received raw data matrix:

- Band pass filtering is carried out using 3^{rd} order IIR filter, with bandpass in the radar operating frequency range of 3.1 GHz to 4.8 GHz.
- Motion filtering of the received data is carried out using second order difference filter.
- The envelope of the motion filtered scans is extracted. Input and output of these steps are shown in Fig. 4. The absolute of the obtained envelope corresponding to each activity is used for further processing.

Output of this algorithm obtained for investigated activities(A1-A4) are shown in Fig. 5. Distinction among these activities is apparent from these images.

[3]n is configured differently for each activity type according to the time taken to perform them

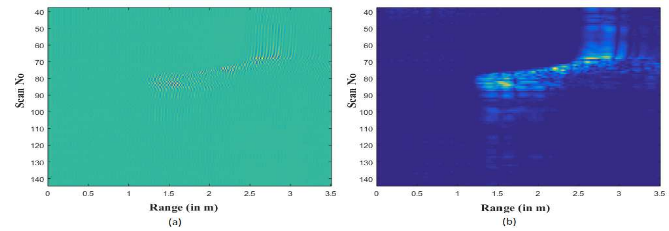

Fig. 4. Range Time data as intensity plot of UWB radar (a) Motion filtered data (b) Envelope detected intensity plot

TABLE II
BASIC STATISTICS OF ACTIVITY DATA

Activity	Time Span (in sec)			Spatial Span (in m)		
	Min	Max	Mean	Min	Max	Mean
A1	3.6	6.6	5.1	2.38	2.92	2.65
A2	1.2	3.3	2.1	1.45	2.62	1.73
A3	1.3	8.6	2.3	1.32	2.44	1.65
A4	6.2	9.5	7.7	2.45	3.20	2.80

B. Activity Data Extraction

Let I_{R_i} denotes the average intensity at i^{th} row and similarly I_{C_j} denote the average intensity at j^{th} column.

For each row R_i,

$$I_{R_i} = \frac{\sum_{j=1}^{N}(I_{i,j})}{N}, \forall j = 1, 2, ...N \ \&\ i^{th}row$$

For each column C_j,

$$I_{C_j} = \frac{\sum_{i=1}^{n}(I_{i,j})}{n}, \forall i = 1, 2, ...n \ \&\ j^{th}column$$

Hence the probability along the fast and slow time axis is

$$\begin{aligned} P(R_i) &= \frac{I_{R_i}}{\sum_i I_{R_i}} \\ P(C_j) &= \frac{I_{C_j}}{\sum_j I_{C_j}} \end{aligned} \tag{4}$$

We have assigned a probability given in Eq.4, which is proportional to the average intensity of the corresponding row or column. All the rows and columns that fall within mid 90% (excluding initial 5% and last 5%) are taken for further processing. This is done as the excluded part has very low intensity and does not have information related to the activity.

For all activities basic analysis is done to find the time (in sec) and spread (in m) taken to complete the activity. The selected activity's slow time axis will give the time taken taken to complete it, while the portion's fast time will give the spatial range in which the subject was performing the activity. Following table summarizes our analysis.

From the table II, it is seen maximum time taken by one of the subject to complete a activity is 9.5 sec for fall (A4). Similarly the maximum span is also noted in the case of fall (A4) with spread of 3.2 m. This has been done with an intention to detect the vital signs of the subject even after the fall. Although, in this work we have restricted to activity detection only, but in future we would implement vital sign computation in cases of fall recognition.

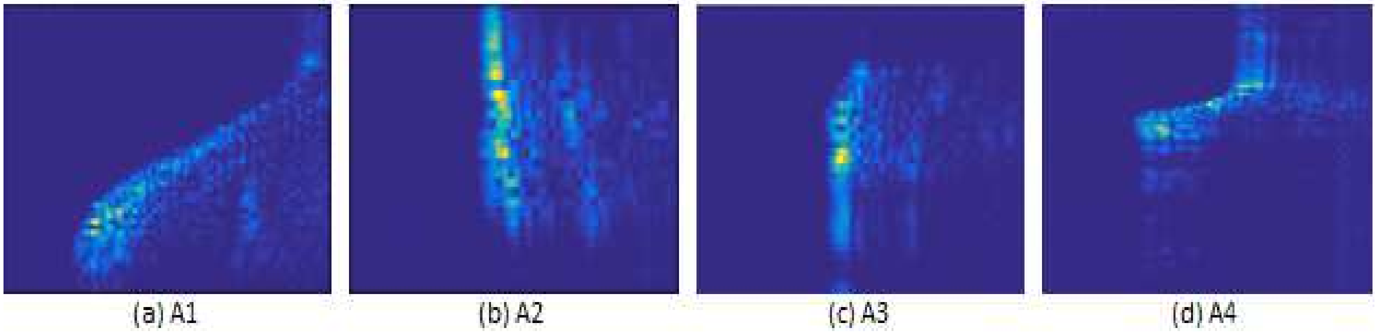

Fig. 5. Range time plots for 4 activities. (a) A1: Walking (b) A2: Sit Down(c) A3: Stand up (d) A4: Simulated Frontal fall

C. *Adaptive Feature Extraction Using 2D2DPCA*

Two-dimensional Two-directional Principal Component Analysis (2D2D-PCA) [13] is well known technique in image processing. This uses a 2-D image data in matrix form without prior vectorization of the image like PCA. 2D2D-PCA operates on matrix data by maximizing generalized total scatter criterion as given in [13]. We have chosen 2D2D PCA to operate on 2D radar data and obtain features. This technique operates in column as well as row direction, capturing information along both axes, thus is suitable for use in our range time data.

However, this requires all data to be in same size in form of 2D matrix. The data after discarding unnecessary segments, is thus resized to a common size using interpolation.This is done to fit the same dimension requirement of 2D2D PCA.This is an important part as it makes all the activity data (range time) aligned irrespective of the activity start time, duration or distance from radar at which activity was performed. Proposed pipeline was initially tried for different image size and we empirically selected that input data size should be 20×60 as this preserves basic nature of shapes in intensity plot.

Let number of principal components chosen for row and column dimensions is denoted by P_r and P_c. Row and column dimensions are chosen so that they explain 80% (or 90%) variance. Then using those dimensions referred as P_r and P_c we obtain a $P_r \times P_c$ matrix of computed features. This matrix is vectorized before classification. Seifert et.al. [13] gives a good explanation of 2D2D PCA based feature selection.

Analysis is performed using dimensions chosen corresponding to 80% and 90% variance explained for row as well as column. Not much variation in accuracy is observed for the classifiers mentioned in section III-D. For 90% variance case maximum 93% accuracy ia achieved while that for 80% variance gives 95% accuracy. So for the proposed pipeline number of components are chosen according to 80% variance explained. In training phase the algorithm is trained on data and classifier is configured. In test phase output of radar is passed through the pipeline proposed in Fig. 2 to perform activity detection.

Finally, for a new data after preprocessing stage we obtain a 20×60 matrix (resized). This is given as input for pretrained 2D2D PCA based feature computation module to obtain features.

D. *Classification*

The extracted feature set are classified using various classifiers viz. Subspace kNN, Bagged Tree [19], Cubic SVM [20], Quadratic SVM [20] and Fine kNN [15], on 10 fold cross validation. Accuracy, Area Under Curve (AUC) Receiver Operating Characteristics(ROC) [21], Precision, Recall [22] for these classifiers are summarized in Table III.

TABLE III
CLASSIFIER COMPARISON

Classifier	Accuracy (%)	AUC ROC	Precision	Recall
Subspace kNN	94.9	0.99	0.95	0.95
Bagged Tree	89	0.99	0.89	0.88
Cubic SVM	86	0.99	0.87	0.86
Quadratic SVM	86	1.0	0.86	0.86
Fine kNN	91.2	0.96	0.92	0.91

In terms of accuracy, precision and recall Subspace kNN outperforms every other classifier and in terms of AUC ROC this is at par with others. Based on these results given in Table III Subspace kNN is chosen as best classifier and in used for further analysis.

IV. RESULTS AND DISCUSSIONS

Experimentation is designed to obtain performance measure for unknown person's activity detection. Towards that goal 2 subjects (out of 7) were randomly selected as test subjects and remaining 5 as training set. 5 such random trials are performed (Experiment E1, E2,..., E5). Thus results obtained for this case can be marked as test results on unseen and unknown person's activity detection.

Accuracy obtained from each Experimental trial is promising, with values falling in the range (91.6% - 98%) for training and (75% - 97.5%) for testing. Both testing and training accuracy is shown in Fig. 6. Obtained average percentage accuracy (together with standard deviation) for training and testing are 91.4 ± 1.6 and 86.4 ± 5.2respectively.

For evaluating performance of a classifier, apart from accuracy and activity specific precision and recall values are important indicator. Precision [22], also known as positive predictive

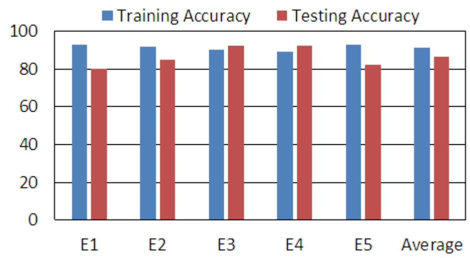

Fig. 6. Training and testing accuracy for different experiments

value defines the portion of the dataset the model says was relevant are actually relevant while recall (or sensitivity) [22] expresses the ability of the model to identify all the correct instances in a dataset. Tables IV and IV gives detailed result for activity wise precision and recall.

Lowest value of average precision and recall is 0.79 and 0.75 for A3. Highest value of average precision and recall is 0.94 and 0.93 for A2 and A4 respectively. Standard deviation of both precision and recall of fall detection is 0.06. Thus, proposed method is effective for fall detection also.

TABLE IV
PRECISION TABLE FOR ACTIVITIES

Activity	Precision					Average	σ
	E1	E2	E3	E4	E5		
A1	0.67	0.91	1.0	1.0	0.78	0.87	0.12
A2	1.0	0.8	1.0	0.9	1.0	0.94	0.07
A3	0.71	0.86	0.83	0.82	0.73	0.79	0.05
A4	0.91	0.83	0.9	1.0	0.83	0.89	.06

TABLE V
RECALL TABLE FOR ACTIVITIES

Activity	Recall					Average	σ
	E1	E2	E3	E4	E5		
A1	0.92	1.0	0.9	1.0	0.7	0.9	0.1
A2	0.6	0.8	0.9	0.9	0.8	0.8	0.1
A3	0.46	0.6	1.0	0.9	0.8	0.75	0.18
A4	0.84	1.0	0.9	0.9	1.0	0.93	0.06

V. CONCLUSION AND FUTURE WORKS

Methodology for detecting activity using UWB radar range scan data is proposed. Devised approach is light weight, unobtrusive and works well for unknown person's activity recognition. This method is suitable for identifying activities in real time and can be part of a big IoT infrastructure due to its high scalability. Accuracy of $86.4(\pm 5.2)\%$ is achieved for unknown person's activity detection. The average precision and recall obtained in this is $0.87(\pm 0.06)$ and $0.84(\pm 0.08)$ respectively, proving the detection scheme to be effective.

Thus it can be said that UWB radar due to its inherent high resolution is able to capture signature of an activity very well. Such a potential can be exploited in future for identifying person from individual gait. We also aim to incorporate vital sign detection using UWB radar together with activity detection so that a holistic elderly care facility can be build.

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