ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 5, Issue 10, October 2020

Device Free Human Activity Recognition for the Elderly Using Passive RFID

[1] Jothe Krishnan, [2] Priyavarshini S, [3] Saadhana Sainath, [4] Dr.S.Chitrakala
[1] [2][3][4] Anna University

Abstract: - **Activity recognition is one of the most promising research topics in pervasive computing applications. In general, activity recognition techniques mainly focus on the direct observation of people and their behaviors with the help of cameras or wearable sensors. Recently, device-free activity recognition has drawn much attention since it does not require subjects to wear any devices. An RFID based, device-free activity recognition system is developed by leveraging off-the-shelf, pure passive RFID tags and exploiting easy-to-obtain RSSI signal. The common issues related to RFID such as sensitivity to environment and false negative readings are taken care of in this system. The proposed system interprets the activity performed by a person by deciphering the signal fluctuations obtained from the RFID tags using machine learning algorithms. A dictionary-based approach is devised to learn a compact set of dictionaries for the activities. This system achieves efficient and robust activity recognition via a more compact and robust representation of activities. With recent advances in embedded sensors and wireless technologies, it has become possible to develop a wide range of applications such as surveillance, ambient assisted living, remote health monitoring and intervention, fall detection and ambulatory monitoring.**

Keywords: Activity recognition, compressive sensing, dictionary learning, feature selection

INTRODUCTION

The population is aging worldwide because of increasing life expectancy and low birth rate. With the recent developments in low-cost sensor devices and networking technologies, we have seen a wide range of activity recognition applications for remote health observation and intervention and behavior analysis. Existing approaches in this field have several significant issues such as privacy (using video camera to monitor people), practicality (a person cannot always remember to wear the device) and maintenance (replace batteries regularly). ***An RFID-based, device-free activity recognition system*** overcomes these issues. Machine learning algorithms are employed for the effectiveness of the system. Radio Signal Strength Indicator (RSSI) is exploited to match the signal fluctuation of each activity. Dictionary learning approach is proposed to understand the structural information between RSSI signals of different activities by compact and discriminative dictionaries learnt separately for each activity. Sparse co-efficients of the learned dictionaries are exploited to extract the embodied information to appropriately classify the activity. The system aims at deciphering the activity performed by a subject by analyzing the signal fluctuations using Radio Frequency technology and machine learning algorithms. In general, this system offers several advantages such as easy to deploy, maintenance free, low cost, and lightweight in computational cost. Human activity recognition system holds the potential to support independent living of elder people.

PROPOSED SYSTEM

The proposed system interprets the activity performed by a person by deciphering the signal fluctuations obtained from the RFID tags using machine learning algorithms. The overall architecture of our proposed system is shown in Fig.1.

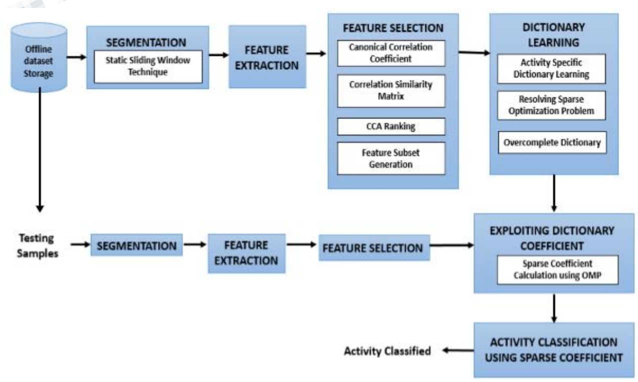


Fig 1: Overall Architecture for Activity Recognition

The whole process consists of three main stages:

- The noisy RSSI raw signal is obtained from the various RFID tags. Signal fluctuations occur if the subject is within the reading range of the tags. The obtained signals are then processed as individual segments. The low-level statistical features are then extracted from each of the individual segments.

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 5, Issue 10, October 2020

- A salient subset of features is selected. The dependency between the features is considered. A compact and discriminative dictionary is then learnt for each activity.
- Given a new streaming signal, the activity recognition problem is equivalent to finding the dictionary from the learned activity dictionaries that best approximates the testing sample.

The system generates an activity label for the given query sample based on the training done earlier. The dataset contains data that were collected from 6 different subjects. The technical details of these stages and the algorithms are discussed in the rest of the sections.

MODULE DESCRIPTION

SEGMENTATION

The first major task is to divide the continuous sequence of RSSI data stream into a set of individual segments **S = {S_1, S_2, ……, S_n}** where each segment corresponds to a specific activity. Each segment is generated by a sliding-window based method. Selection of window length plays an important role in the performance of classification. Here ***the window length is chosen as 6***. The output for each input sample is the statistic over the window of the current sample and the previous sample. Segmentation helps the classifier better understand the underlying activity and compresses the streaming data.

FEATURE EXTRACTION

The extraction process transforms information by extracting seven statistical feature vectors from each segment. This process yields a total of **n** feature vectors **O = {o_l, o_2, …., o_s}** where **$O \in R^n$** and **n = 7 x t** where t is the number of tags. The seven statistical features that are extracted are listed below in table I along with their descriptions.

Table I Statistical features

No.	Feature	Description
1	Min	Minimal value of S_i.
2	Max	Maximal value of S_i
3	Mean	Average value of S_i
4	Variance	The square of the standard deviation of S_i
5	Root Mean Square	The quadratic mean value of S_i
6	Standard Deviation	Measure of the spread of S_i
7	Median	The median of S_i

Algorithm 1. Feature Extraction

Input: Individual segment S = {S_1, S_2, …., S_n}
Output: Feature vectors O = {o_1, o_2, …., o_s}
Step 1: Initializing vector for each feature
f = (size of data stream - 1) x 12
Step 2: Applying feature vector function on data segment.
Step 3: **do**
Step 2 for each segment
while (segment! = NULL)
END

These extracted feature vectors are sent for feature selection to refine the large set of feature vectors into significant feature vectors.

FEATURE SELECTION

We assess and identify the most important features by studying the correlations between features using ***filter-based unsupervised Canonical Correlation Analysis (CCA) algorithm***. The feature subset is generated by using a simple forward selection greedy algorithm.

We compute the canonical correlation for each pair of features and generate feature subsets using a greedy algorithm based on computed pair-wise canonical correlations. For each pair of feature vectors **{oi, oj}**, which can be linearly mapped into $\boldsymbol{O_i \to W_{o_i}^T O_i}$ and $\boldsymbol{O_j \to W_{o_j}^T O_j}$ the correlation coefficient can be obtained by maximizing (1):

$$\rho_{ij} = \frac{W_{o_i}^T o_i \, W_{o_j}^T o_j}{\sqrt{W_{o_i}^T o_i \, W_{o_j}^T o_j}} \tag{1}$$

Algorithm 2. Feature Selection

Input: Feature vectors O = {o_1, o_2, …., o_s}
Output: Feature Subset

Step 1: Find the most relevant feature
Step 2: Sort the sensors based on this feature in descending order.
Step 3: For every activity, select the first 1…n sensors.
Step 4: Check the quality of features.
Step 5: Choose sensors that deliver the highest gain.
END

International Journal of Science, Engineering and Management (IJSEM)
Vol 5, Issue 10, October 2020

After CCA is applied to all the feature pairs, an initial ranking can be generated based on the correlation coefficient. A higher rank is assigned to the weakly correlated features and a lower rank is assigned to the redundant, strongly correlated features. Forward Selection is used to generate the feature subset from the pair-wise rankings. The algorithm begins with an empty set of features and keeps adding features that gives the best rank. This process continues until the predefined dimensionality of the features is reached or all the features are already considered. The ranked features are displayed in Fig 2.

Selected_avg	[7;2;3;9;4;10;12;5;11;8]
Selected_max	[7;10;2;4;9;12;5;11;8;6]
Selected_med	[7;2;3;9;4;8;10;11;12;6]
Selected_min	[2;7;5;9;12;11;3;4;8;6]
Selected_rms	[7;2;3;9;4;10;12;11;5;8]
Selected_var	[10;4;7;2;8;6;3;5;1;12]
Std_selected	[10;7;3;5;4;2;12;9;1;6]

Fig 2: Ranking of Selected features

DICTIONARY LEARNING

A dictionary is learnt for each activity, which is formed by a set of basis vectors learned by solving a sparse optimization problem. Each basis vector can effectively capture part of the key structural information of the training data from each activity. The dictionary for each activity is learned from a collection of training samples via solving a l1-norm optimization problem. To learn and encode the information of the testing samples belonging to an activity class, we first construct an overcomplete dictionary D_k for each class C_k. The training samples for the k^{th} activity is represented as $\mathbf{O^k = \{O_1^k, O_2^k, \ldots, O_n^k\}}$. We intend to learn a dictionary matrix D_k over which O^k has a sparse representation $\mathbf{X^k = \{X_1^k, X_2^k, \ldots, X_n^k\}}$.

The optimization problem can be formalized as given below in (2):

$$min_{\boldsymbol{D},\boldsymbol{X}} \, ||\boldsymbol{O} - \boldsymbol{DX}||_2^2 \; , s.t \; ||\boldsymbol{x_i}||_0 \le \tau_0 \qquad (2)$$

Algorithm 3. Dictionary Learning using K-SVD

Input: Signal set O, initial dictionary D_0, target sparsity S, No. of iteration L.

Output: Dictionary D and sparse matrix X such that O≈DX.

Step 1: Initialize D = D_0

Step 2: Find best coefficient matrix,

$$\min_{\mathbf{D},\mathbf{x}_i} ||\mathbf{o}_i - \mathbf{D}\mathbf{x}_i||_2^2, \quad \text{s.t.} \quad ||\mathbf{x}_i||_0 \le \tau_o$$

where τ_0= no. of non-zero columns

Step 3: Use an approximate solving method like Orthogonal Matching Pursuit (OMP) to solve the above sparse coding problem.

Step 4: Compute Error Matrix.

$$\mathbf{E}_j \leftarrow [\mathbf{o}_|, \ldots, |\mathbf{o}_N] - \sum_{i \ne j} \mathbf{d}_i \mathbf{x}_\tau^i$$

Step 5: Apply SVD to the error matrix to obtain $\mathbf{E}_j^R = \mathbf{U\Delta V}$. Update d_i with the first column of U and x_i with the first column of V.

Step 6: Update D column by column in the same fashion to complete the dictionary.

Step 7: Goto **Step 1** and initialize D = D^+ and follow the other steps until stopping rule is reached.

END

The ***K-SVD*** algorithm is adopted to solve this problem which performs two steps iteratively. Initially, ***Sparse Coding Stage*** where D is kept fixed and the co-efficient matrix X is computed by orthogonal matching pursuit (OMP) algorithm. Followed by, ***Dictionary Update stage*** where the dictionary D is updated sequentially. Once the optimization problem is solved, dictionaries per activity class are created.

EXPLOITING DICTIONARY COEFFICIENTS

After learning K individual activity-specific dictionaries, any new incoming test RFID signal can be represented in terms of its dictionary basis from the learned dictionaries. To calculate the sparse coefficients of an input RFID sample w.r.t a given dictionary, we use ***orthogonal matching pursuit***.

The several strategies that can be used to exploit the learned sparse coefficients are listed below in Table II with their descriptions:

Table II Methods to exploit learned sparse coefficients

Technique	Description	Formula
Reconstruction error (RE)	Activity label is associated with the training sample with least reconstruction error.	$\boldsymbol{l_{o^*} = l(arg\ min\ e_k\ )}$
Maximal Coefficient (MC)	Activity label is associated with the	$\boldsymbol{l_{o^*} = l(arg\ max\ d_k^i\ )}$

IFERP connecting engineers... developing research

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 5, Issue 10, October 2020

	training sample with maximum value of absolute coefficient.	
Maximal mean of coefficients (MMC)	Activity label is the top label with the maximal mean of coefficients	$l_{o^*} = l(arg\,max \sum_i {d_k^i}/{m})$
Maximal sum of coefficients (MSC)	Activity label is the top label with the maximal mean of coefficients	$l_{o^*} = l(arg\,max \sum_i d_k^i)$
Concatenate coefficients (ConSVM)	Learned coefficients are transformed into a feature vector. This is fed into SVM for classification.	SVM classifier

Algorithm 4. Exploiting Dictionary Coefficients

Input: Sensor Samples of K activities, Testing Signal Samples of K activities.

Output: Computed sparse co-efficient

Step 1: Extract feature vectors of signal samples for each activity

Step 2: Compute sparse representation using constructed dictionary

Step 3: Project testing sample using Orthogonal Pursuit Matching.

Algorithm (OMP)

Step 1: Initialize the residual $r_0 = y$ and initialize the set of selected variable $X(c_0) = \emptyset$. Let the iteration counter = 1

Step 2: Find the variable X_{t_i} that solves the maximization problem $\max_t X_t' r_{i-1}$ and add the variable X_{t_i} to the set of selected variables. Update $c_i = c_{i-1} \cup \{t_i\}$.

Step 3: Let $P_i = X(c_i)\left(X(c_i)'X(c_i)\right)^{-1} X(c_i)'$ denote the projection onto the linear space spanned by the elements of $X(c_i)$. Update $r_i = (I - P_i)y$.

Step 4: If the stopping condition is achieved, stop the algorithm. Otherwise, set i=i+1 and return to Step 2.

END

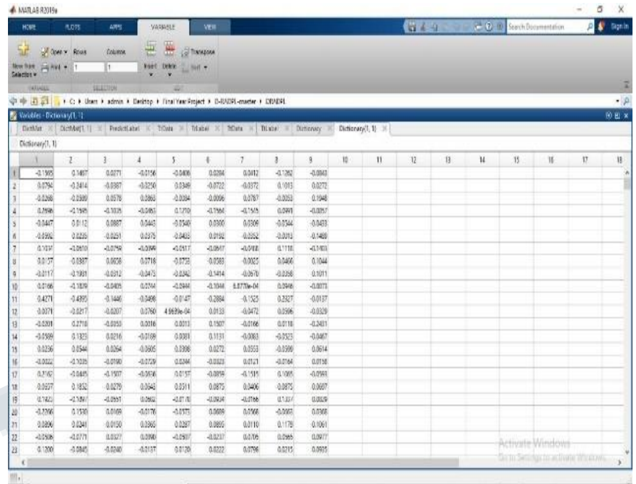


Fig 3: Dictionary Coefficients for activity "Sitting"

ACTIVITY CLASSIFICATION

Given a new streaming signal, the activity recognition problem is equivalent to finding the dictionary from the learned activity dictionaries that best approximates the testing sample.

Algorithm 5. Dictionary specific Activity Classification

Input: Sensor samples of K activities, testing signal samples of K activities.

Output: Activity label for the testing signal samples.

Step 1: Extract feature vectors of signal samples for each activity.

Step 2: Perform feature selection on the feature vectors using CCA.

Step 3: Compute sparse coefficients from the selected features.

Step 4: Compare the computed coefficients with that of already defined dictionaries.

Step 5: Output is activity label of the existing sparse coefficient matrix that matches the computed matrix of testing data.

END

The activity label for the activity "Sitting" is displayed in Fig 4.

IFERP
connecting engineers... developing research

ISSN (Online) 2456 -1304

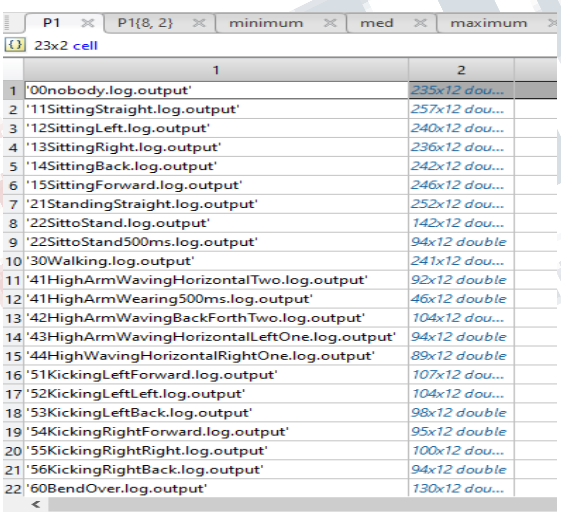
International Journal of Science, Engineering and Management (IJSEM)
Vol 5, Issue 10, October 2020

Fig 4: Activity label for "Sitting"

EXPERIMENTAL RESULTS

DATASET DESCRIPTION

The dataset consists of signal samples that were collected from six different subjects. Each subject was asked to perform the set of 23 activities and the signal fluctuations were recorded. For the training phase, the data collected from five subjects were fed into the system. For the testing phase, the left-out subject's data was fed. The dataset has been illustrated in Fig 5.



P1 | P1{8, 2} | minimum | med | maximum

23x2 cell

	1	2
1	'00nobody.log.output'	235x12 dou...
2	'11SittingStraight.log.output'	257x12 dou...
3	'12SittingLeft.log.output'	240x12 dou...
4	'13SittingRight.log.output'	236x12 dou...
5	'14SittingBack.log.output'	242x12 dou...
6	'15SittingForward.log.output'	246x12 dou...
7	'21StandingStraight.log.output'	252x12 dou...
8	'22SittoStand.log.output'	142x12 dou...
9	'22SittoStand500ms.log.output'	94x12 double
10	'30Walking.log.output'	241x12 dou...
11	'41HighArmWavingHorizontalTwo.log.output'	92x12 double
12	'41HighArmWearing500ms.log.output'	46x12 double
13	'42HighArmWavingBackForthTwo.log.output'	104x12 dou...
14	'43HighArmWavingHorizontalLeftOne.log.output'	94x12 double
15	'44HighWavingHorizontalRightOne.log.output'	89x12 double
16	'51KickingLeftForward.log.output'	107x12 dou...
17	'52KickingLeftLeft.log.output'	104x12 dou...
18	'53KickingLeftBack.log.output'	98x12 double
19	'54KickingRightForward.log.output'	95x12 double
20	'55KickingRightRight.log.output'	100x12 dou...
21	'56KickingRightBack.log.output'	94x12 double
22	'60BendOver.log.output'	130x12 dou...

Fig 5: Dataset containing 23 activities

The signal fluctuations for each activity were recorded with the help of twelve RFID tags. The values obtained from these tags for the activity "Sitting" are shown in Fig 6.

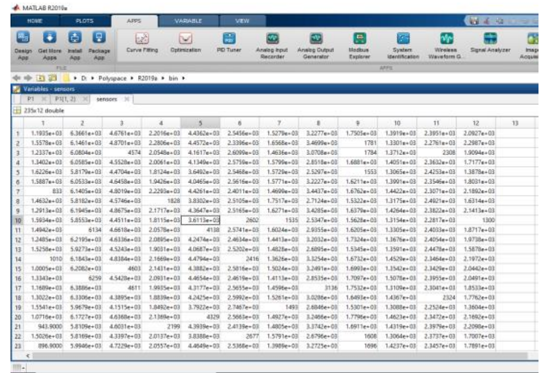


Fig 6: Sampled signals obtained from RFID tags

FINAL OUTPUT

Given a new testing signal, the signal is processed as individual segments. The low-level features are then extracted from each segment. The salient subset of features is then selected from the extracted features. This feature subset along with learned dictionaries can assign an activity label to the given testing sample. The entire process is shown in Fig 7.

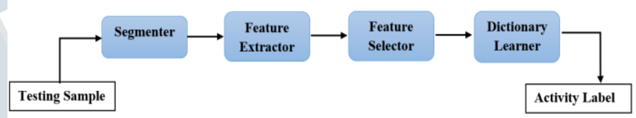


Fig 7: Activity Recognition

PERFORMANCE EVALUATION

Precision

The equation for calculating precision is given below in (4).

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{4}$$

Table III lists the individual activities with their respective precision values.

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 5, Issue 10, October 2020

Table III Precision Values

Activity	Precision	Percentage
SS	1.00	100%
SL	1.00	100%
SR	1.00	100%
SB	1.00	100%
SF	1.00	100%
St	0.91	91%
StS	1.00	100%
W	0.91	91%
WH	1.00	100%
WBF	1.00	100%
WL	0.91	91%
WR	0.82	82%
KLF	0.73	73%
KLL	1.00	100%
KLB	1.00	100%
KRF	1.00	100%
KRR	0.91	91%
KRB	0.82	82%
BO	0.91	91%
CTS	0.91	91%
FF	0.91	91%
FL	0.55	55%
FR	0.64	64%

The bar graph shown in Fig 8 represents the Precision values for each of the activities.

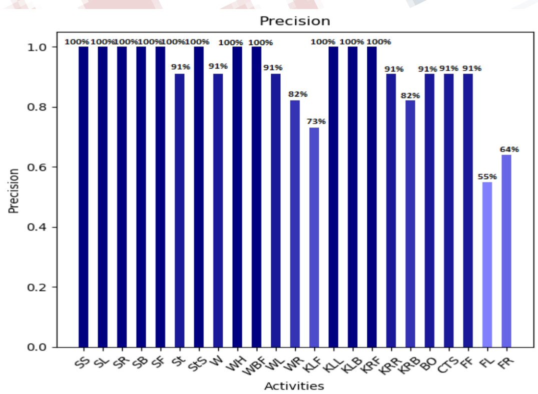


Fig 8: Precision Bar Graph

Recall

The equation for recall is given below in (5).

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \qquad (5)$$

Table IV lists the individual activities with their respective Recall values.

Table IV Recall values

Activity	Recall	Percentage
SS	1.00	100%
SL	1.00	100%
SR	1.00	100%
SB	1.00	100%
SF	0.91	91%
St	1.00	100%
StS	0.91	91%
W	0.77	77%
WH	0.84	84%
WBF	1.00	100%
WL	0.91	91%
WR	0.82	82%
KLF	0.73	73%
KLL	0.80	80%
KLB	0.91	91%
KRF	1.00	100%
KRR	0.84	84%
KRB	1.00	100%
BO	0.90	90%
CTS	0.91	91%
FF	0.83	83%
FL	1.00	100%
FR	1.00	100%

The bar graph shown in Fig 9 represents the Recall values for each of the activities.

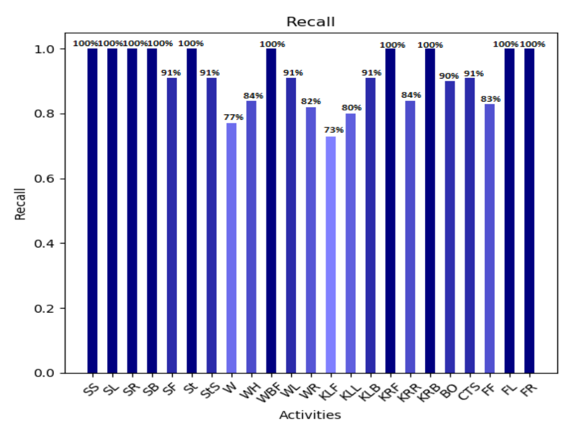


Fig 9: Recall Bar Graph

F1-Score

The F1 score conveys the balance between the precision

International Journal of Science, Engineering and Management (IJSEM)
Vol 5, Issue 10, October 2020

and the recall. The equation for calculating F1-score is given below in (6)

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (6)$$

Table V lists the individual activities with their respective F1-Score values.

Table V F1-Score Values

Activity	F1-Score	Percentage
SS	1.00	100%
SL	1.00	100%
SR	1.00	100%
SB	1.00	100%
SF	0.95	95%
St	0.95	95%
StS	0.95	95%
W	0.83	83%
WH	0.91	91%
WBF	1.00	100%
WL	0.91	91%
WR	0.82	82%
KLF	0.72	72%
KLL	0.88	88%
KLB	0.95	95%
KRF	1.00	100%
KRR	0.87	87%
KRB	0.90	90%
BO	0.90	90%
CTS	0.91	91%
FF	0.86	86%
FL	0.70	70%
FR	0.78	78%

The bar graph shown in Fig 10 represents the F1-Score values for each of the activities.

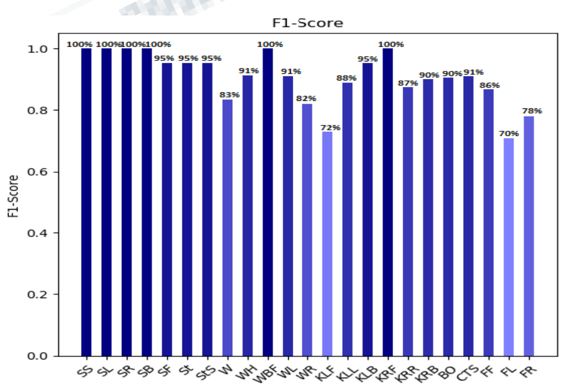


Fig 10: F1-Score Bar Graph

Confusion Matrix

A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm. The confusion matrix for our system is illustrated in Fig 11.

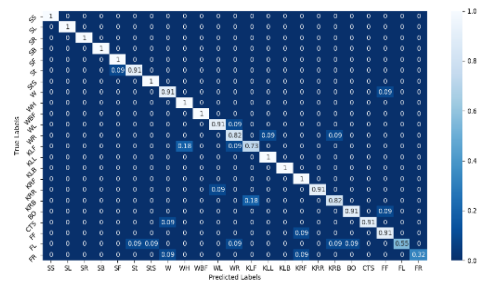


Fig 11: Confusion Matrix

CONCLUSION

The technical details of a device-free, unobtrusive human activity recognition system that holds the potential to support independent living of older people is proposed which is a critical research and development area. We explored sparse representation over RSSI and understood how to learn signal strength fluctuation to improve system robustness and effectiveness. We particularly investigated a dictionary-based approach for sparse representation of noisy and unstable radio frequency identification (RFID) streaming signals. We have also investigated the way of extracting robust features from raw signal strength stream by designing a simple but highly rank-based feature selection method. Our approach is the very first to explore sparse dictionary learning. Moreover, several applications can be benefitted from our system.

REFERENCES

[1] S. Mennicken, J. Vermeulen, and E. M. Huang, “From today’s augmented houses to tomorrow’s smart homes: New directions for home automation research,” in Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput., 2014, pp. 105–115.

[2] E. Kim, S. Helal, and D. Cook, “Human activity recognition and pattern discovery,” IEEE Pervasive Comput., vol. 9, no. 1, pp. 48–53, Jan.– Mar. 2010.

[3] C. Xin and M. Song, “Detection of PUE attacks in cognitive radio networks based on signal activity pattern,” IEEE Trans. Mobile Comput., vol. 13, no. 5, pp. 1022–1034, May 2014.

[4] J. Tung, H. Snyder, J. Hoey, A. Mihailidis, M. Carrillo, and J. Favela, “Everyday patient-care technologies

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 5, Issue 10, October 2020

for alzheimer's disease," IEEE Pervasive Comput., vol. 12, no. 4, pp. 80–83, Oct.–Dec. 2013.

[5] Y. Lee, S. Lee, B. Kim, J. Kim, Y. Rhee, and J. Song, "Scalable activity- travel pattern monitoring framework for large-scale city environment," IEEE Trans. Mobile Comput., vol. 11, no. 4, pp. 644–662, Apr. 2012.

[6] J. K. Aggarwal and M. S. Ryoo, "Human activity analysis: A review," ACM Comput. Surveys, vol. 43, no. 3, 2011, Art. no. 16.

[7] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman, "Activity recognition from accelerometer data," in Proc. 17th Conf. Innovative Appl. Artif. Intell., 2005, pp. 1541–1546.

[8] W. Zhu, J. Cao, Y. Xu, L. Yang, and J. Kong, "Fault-tolerant RFID reader localization based on passive RFID tags," IEEE Trans. Parallel Distrib. Syst., vol. 25, no. 8, pp. 2065–2076, Aug. 2014.

[9] S. Sigg, M. Scholz, S. Shi, Y. Ji, and M. Beigl, "RF-sensing of activities from non-cooperative subjects in device-free recognition systems using ambient and local signals," IEEE Trans. Mobile Comput., vol. 13, no. 4, pp. 907–920, Apr. 2014.

[10] N. C. Krishnan and D. J. Cook, "Activity recognition on streaming sensor data," Pervasive Mobile Comput., vol. 10, pp. 138–154, 2014.

[11] H. Abdel Nasser, M. Youssef, and K. A. Harras, "Wigest: A ubiquitous Wi-Fi-based gesture recognition system," in Computer Communications (INFOCOM), 2015 IEEE Conference on. IEEE, 2015, pp. 1472–1480.

[12] Mohammed A.A. Al-qaness "Device-free human micro-activity recognition method using Wi-Fi signals," Geo Spatial Information Science, Volume-22, 2019. Issue 2: Special Issue: Ubiquitous Positioning, Indoor Navigation and Location-Based Services (UPINLBS)

[13] Liyao Li, Rui Bai, Binbin Xie, Yao Peng, Anwen Wang, Wei Wang, Bo Jiang, Jian Liang, And Xiaojiang Chen, "R&P: An Low-Cost DeviceFree Activity Recognition for E-Health" volume 6 – 2018.

[14] Z. Zhou, L. Shangguan, X. Zheng, L. Yang, and Y. Liu, "Design and implementation of an rfid-based customer shopping behavior mining system," 2017.

[15] K. Ali, A. X. Liu, W. Wang, and M. Shahzad, "Keystroke recognition using Wi-Fi signals," in International Conference on Mobile Computing and Networking. ACM, 2015.

[16] M. Zhao, F. Adib, and D. Katabi, "Emotion recognition using wireless signals," in International Conference on Mobile Computing and Networking. ACM, 2016.

[17] Y. Wang, K. Wu, and L. M. Ni, "Wifall: Device-free fall detection by wireless networks," 2017.

[18] D. Zhang, J. Zhou, M. Guo, J. Cao, and T. Li, "TASA: Tag-free activity sensing using RFID tag arrays," IEEE Trans. Parallel Distributed Syst., vol. 22, no. 4, pp. 558–570, Apr. 2011.

[19] J. Han, et al., "Twins: Device-free object tracking using passive tags," in Proc. IEEE Int. Conf. Comput. Commun., 2014, pp. 469–476.

[20] S. Wagner, M. Handte, M. Zuniga, and P. J. Marr_on, "On optimal tag placement for indoor localization," in Proc. IEEE Int. Conf. Pervasive Comput. Commun., 2012, pp. 162–170.

[21] Z. Yang, Z. Zhou, and Y. Liu, "From RSSI to CSI: Indoor localization via channel response," ACM Comput. Surveys, vol. 46, no. 2, 2013, Art. No. 25.

[22] B. Wei, W. Hu, M. Yang, and C. T. Chou, "Radio-based device-free activity recognition with radio frequency interference," in Proc. 14th Int. Conf. Inf. Process. Sensor Netw., 2015, pp. 154–165.

[23] Lina Yao, Quan Z. Sheng, Xue Li, Tao Gu , Mingkui Tan, Xianzhi Wang Sen Wang, and Wenjie Ruan, "Compressive Representation for Device Free Activity Recognition with Passive RFID Signal Strength", IEEE transactions on mobile computing, vol. 17, no. 2, february 2018.

[24] Mathews, S. M., Kambhamettu, C., & Barner, K. E." Centralized class specific dictionary learning for wearable sensors based physical activity recognition". 2017 51st Annual Conference on Information Sciences and Systems (CISS).