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# IMU-Based Robust Human Activity Recognition using Feature Analysis, Extraction, and Reduction

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***Abstract*—In recent years, research investigations on recognizing human activities to assess the physical and cognitive capability of humans have gained importance. This paper presents the development of a robust recognition system for Human Activity Recognition under real-world conditions. The activities considered are walking, walking upstairs (walk-up), walking downstairs (walk-dn), sitting, standing and sleeping. The proposed system consists of 3 main elements - a feature extraction from an IMU (Inertial Measurement Unit) based on the spectral and temporal analysis; a feature dimensionality reduction techniques to reduce the high dimensional feature representation, and; various model training algorithms to recognize the human activities. Different methods for feature extraction based on time and frequency domain signal properties are evaluated. The high dimensionality of extracted features results in complex model training and suffers from the curse of dimensionality. Therefore, we evaluated feature selection and transformation algorithms to improve robustness without decreasing the prediction accuracy. Our results finding shows that Random forest feature selection method, when used with Ensemble bagged classifier, provides an accuracy of 96.9% with 15 features compared to the current benchmark system that employs 561 features. We further obtained a less complex activity recognition system via Neighborhood component analysis along with Ensemble bagged classifier that yields a classification accuracy of 96.3% with only 9 features.**

***Index Terms*—IMU-based Activity recognition, Feature extraction, Feature selection, Dimensionality reduction, Generalization**

## I. Introduction

There has been a tremendous increase in the research of Human activity recognition (HAR) in recent years due to its potential application in the fields of video surveillance systems, health care, human-computer interaction, multimedia annotation [1]. HAR is the ability to interpret human body motion via sensors and determine human activity/action [2].

RGB camera, depth sensors and wearable sensors are the technologies widely used for HAR [3]. RGB camera uses real-time images for classification which is simple but has low efficiency. It requires high image processing and performance is affected due to the presence of large data [4]. Privacy concern is present when using a RGB camera for HAR. Depth sensor based HAR system is robust, lighter and cheaper compared to RGB camera-based system but is limited by sensor viewpoint and occlusion issues. Wearable IMU sensors are non-intrusive, lightweight and portable measuring devices which overcome the sensor viewpoint and occlusion issues. They can be easily mounted on the subject, after which activities can be detected in a non-hindering manner [3], [5], [6]. After preprocessing of the motion for activity recognition, discriminative features are then derived from time and/or frequency domain representation of the motion signals [7] and used for activity classification [8]. While developing an IMU-based human activity recognition system, model cost and complexity is an important parameter governing the number of features and type of classifier used. The high number of features increases the building time of the recognition models and when trained, they suffer from curse of dimensionality and poor generalization [9]. In our work, we explored and evaluated feature selection and dimensionality reduction algorithms in conjunction with various classification models to design a high accuracy model with a compact and robust discriminative feature space. Our results demonstrated that our proposed HAR system were comparable with the state of the art systems while generating a more compact discriminative space.

## II. Related study

Researchers in human activity classification have employed various pattern recognition techniques but almost all follow the subsequent computation. Initially, a window is applied to sensor data to reduce the effect of noise. Following which characteristic features are extracted from the aforementioned windowed data. Upon potential reduction in the number of feature vectors, a classification algorithm is appointed to label the data [10].

Fleury, M. Vacher and N. Noury, in SVM-Based Multimodal Classification of Activities of Daily Living in Health Smart Homes: Sensors, Algorithms, and First Experimental results, classify daily activities using an SVM. They classified the activities of sleeping, preparing to have breakfast, dressing and undressing, resting, hygiene activities, bowel movement and communication. Classification accuracy achieved were 75% when a polynomial kernel was used, while 86% when Gaussian kernel with an adapted parameter was used [11].

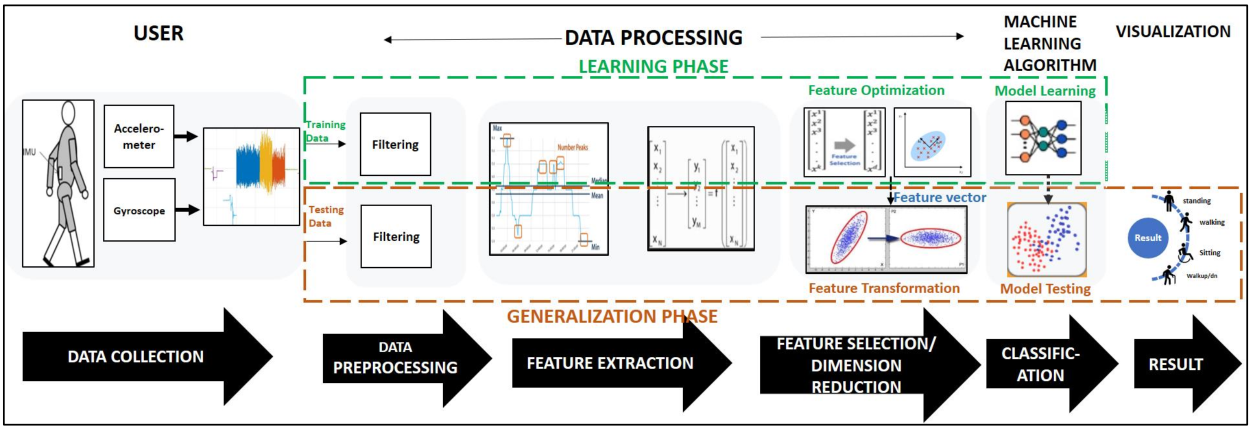


Fig. 1: Framework for IMU- based human activity recognition system

Paul and T. George, in their paper An effective approach for human activity recognition on smartphone, have studied the classification of activities (standing, walking, running and sitting) using KNN versus Clustered KNN algorithm. Results indicated that clustered KNN proved to be better than KNN with an overall accuracy of 92% [12]. Girija Chetty and Matthew White, in their paper Body sensor networks for human activity recognition have used information theory based feature ranking algorithms and compared the recognition accuracy using classifiers- random forests, ensemble and lazy learner on standard UCI HAR dataset. Using Random forest an accuracy of 96.3% is achieved with 561 features and 94.29% with 128 features [13]. Stephen J. Preece et.al in A Comparison of Feature Extraction Methods for the classification of Dynamic Activities from Accelerometer Data comparison between feature extraction methods are studied. Frequency-based features performed better than wavelet-based features and provided recognition accuracy of 95% with 60 features [7]. Doewes, Afrizal, Edi Swasono, Sri and Harjito, Bambang in Feature Selection on Human Activity Recognition Dataset using Minimum Redundancy Maximum Relevance obtained an accuracy of 95% with 201 features and 96.54% with 480 features on standard HAR system dataset [14]. The objective of this study is to obtain discriminating features from the dataset and find an optimal technique to reduce the features and improve the performance of the recognition system.

## III. Methodology

### A. Data Acquisition

Data used for the project is the public domain dataset from the UCI Machine learning repository. A group of 30 volunteers with ages ranging from 19 to 48 years were selected for this task. The volunteers performed the activities with an IMU sensor strapped to their waist. Each subject performed the protocol twice: on the first trial, the IMU was fixed on the left side of the belt and on the second it was placed by the user himself as preferred. The activities were video recorded to generate labels. The tasks were performed in laboratory conditions but volunteers were asked to perform freely the sequence of activities for a more naturalistic dataset [15].

### B. Framework-IMU-based human activity recognition system

Figure 1 illustrates the framework for an IMU- based system used to recognize human activity. The first step involves collecting relevant data through the user. In the learning phase, relevant features are extracted from the time- series raw data. Model complexity is reduced by applying Feature selection/Dimension reduction technique. Recognition model is created from the dataset of selected features. This model is then used in the testing phase to evaluate raw signal and create an activity label. The model is integrated with visualization units for user interface [16].

## IV. Feature Extraction

Feature extraction is a process of obtaining useful features for classification [17]. Here the accelerometer and gyroscope signals are analyzed to remove redundancy and obtain distinguishing features for classifying activities. Human activities are performed over a longer time duration when compared to sensor sampling rate (which is 50Hz). Thus, a single sample at a specific time instant does not provide sufficient information to define an activity [18]. So, time windowing is used to extract quantitative measures to compare signals. As seen in Figure 2 and 3 irrespective of the position in the time domain, the amplitude signals from the accelerometer and gyroscope conclude that central tendency can be used as a distinguishing feature to classify activity of laying from the rest. Similarly, the standard deviation of sitting, standing and laying is lower compared to the walking activities. But signal statistical measures are not enough to distinguish activities such as walking from walking upstairs / downstairs. Hence, examining the signal variation over time is necessary. Acceleration signal is highly fluctuating and is composed of 2 components- the fast-varying component due to physical activities and the slow-varying one due to gravitational force acting on the body. Using high pass filter the body component of acceleration is separated. Analyzing

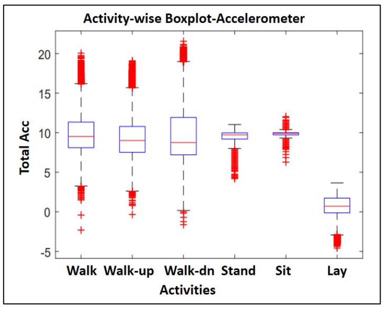


Fig. 2: Accelerometer amplitude

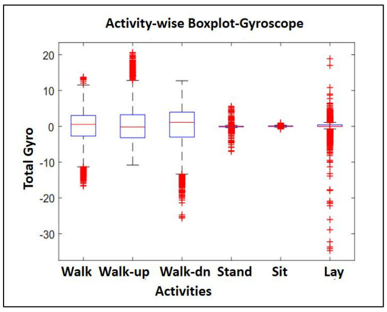


Fig. 3: Gyroscope amplitude

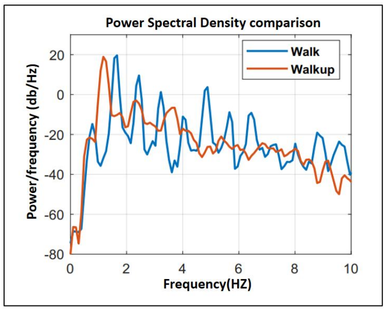


Fig. 4: PSD- walking & walk-up

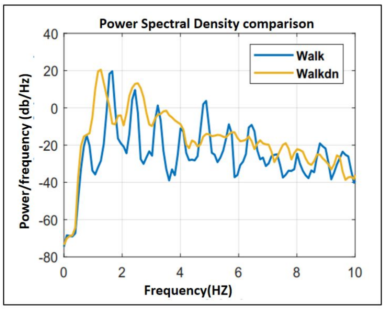


Fig. 5: PSD- walking & walk-dn

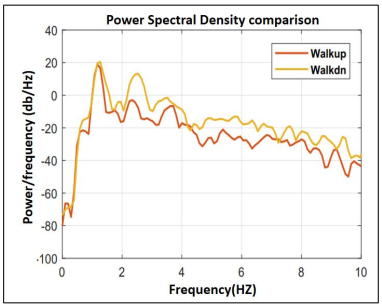


Fig. 6: PSD-walk-up & walk-dn

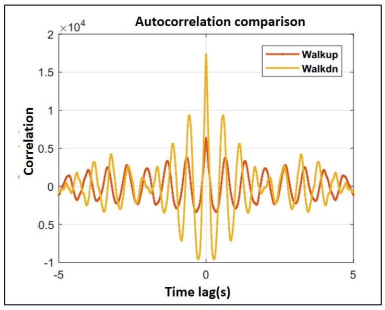


Fig. 7: Autoco-walk-up & walk-dn

the body component of acceleration for each activity, we see an irregular periodicity. Thus, power spectral density (PSD) has the potential to differentiate between activities. PSD estimates the power of the signal in the frequency domain [19]. Welch method of spectral averaging is used by dividing the time period into K equal segments. The K spectral series are averaged point by point that reduces the variance of the spectral estimate and provides a smooth appearance of the spectrum [20].

From the PSD plots in Figure 4 and 5, it can be validated that for the activity of walking compared to walking up or down has a difference in the amplitude and position of peaks. But as seen in Figure 6 walking up and walking down cannot be easily distinguished by the PSD function. So, we explore the autocorrelation (Autoco) function that is a strong frequency estimation feature that helps in identification of low pitch fundamental frequencies [21]. As seen from Figure 7 autocorrelation provides differentiating features with respect to amplitude between walking up and walking down activities.

Mathematical explanation for some of the extracted features is as follows:

1.PSD using Welch's method [22]:

$$y_j(t) = y((j-1)K + t) \tag{1}$$

where $t = 1, ...., M$ and $j = 1, ...., S$. $y_j(t)$ denotes the $j^{th}$ data segment and $(j-1)K$ is the start point for the $j^{th}$ sequence of the sample. We have considered 50% overlap so we have $K = M/2$ and hence $S = 2M/N$ data segments.Here $N$ is the total no. of observations.

The windowed periodogram for $y_j(t)$ is as follows:

$$\phi_j(\omega) = \frac{1}{MP} |\sum_{t=1}^{M} v(t) y_j(t) \exp^{-jwt}|^2 \tag{2}$$

Where P is the power of the temporal window $v(t)$ given by

$$P = \frac{1}{M} \sum_{t=1}^{M} |v(t)|^2 \tag{3}$$

And the PSD is calculated by averaging the windowed periodogram in equation 2

$$\phi_W(\omega) = \frac{1}{S} \sum_{j=1}^{S} \phi_j(\omega) \tag{4}$$

2.Autocorrelation [23]: It measures the correlation between $y_t$ and $y_{t+k}$, where $k = 0, ..., K$ and $y_t$ is a stochastic process. so autocorrelation for a delayed k is given by

$$r_k = \frac{c_k}{c_o} \tag{5}$$

Where $c_k$=$\frac{1}{T}\sum_{t=1}^{T-k}(y_t - \bar{y})(y_{t+k} - \bar{y})$ and $c_o$ is the sample variance of the time series.
A total of 137 features are extracted from the windowed accelerometer and gyroscope signal. Table1 provides the summary of the feature extraction methods applied.

## V. Dimensionality reduction & feature selection

In a high-dimension space, estimation of density is difficult due to the scarcity of training data. Thus the system accuracy is impacted when unseen data is tested [1]. Also, a large number of features results in complex classification algorithm,

TABLE I: Summary of extracted features

| No. of features | Description of the feature | Mathematical explanation |
|---|---|---|
| 6 | Mean | $\mu = \frac{1}{N}\sum_{i=1}^{N} A_i$ |
| 6 | RMS | $x_{rms} = \sqrt[2]{\frac{1}{N}\sum_{n=1}^{N} \lvert x_n \rvert^2}$ |
| 18 | Autocorrelation(height of the main peak and height,position of 2nd peak) | From equation(5) |
| 72 | Spectral peak(height and position) | From equation(4) |
| 30 | Spectral power | |
| 1 | Resultant accelerometer vector | $a_v = \sqrt[2]{a_{xi}^2 + a_{yi}^2 + a_{zi}^2}$ |
| 1 | Resultant gyroscope vector | $g_v = \sqrt[2]{g_{xi}^2 + g_{yi}^2 + g_{zi}^2}$ |
| 3 | Angle between accelerometer axis and accelerometer vector | $\theta_{axis} = cos^{-1}(\frac{a_{axis}}{a_v})$ |

increase in learning time and curse of dimensionality. Before discussing the different feature space reduction technique,t-SNE (t-Stochastic Neighbor Embedding) is used to obtain a 2D view of the high dimension of feature extracted by converting it to a matrix of pairwise similarities. t-SNE captures most of the local structure of the high dimensional data and reveals the presence of clusters [24]. Figure 8 shows that the extracted features, when viewed in 2D space segregates the cluster of laying activity completely. The walking activities are chaotic and standing and sitting activities clusters are not well separated.

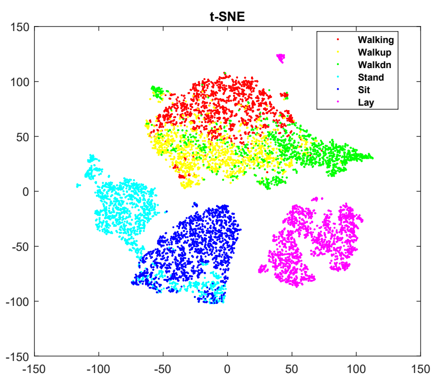


Fig. 8: 2D visualization of high dimensional feature space

## A. Dimensionality reduction

PCA(Principle component analysis) and Kernel PCA (KPCA) are discussed in this work. PCA builds a low-dimension representation of the features that describe the maximum variance in the features. This is fulfilled by finding the linear basis of reduced dimensionality for the features, in which the variance is maximal [25]. As the size of the covariance matrix is directly proportional to the dimensionality of data points, in the presence of very high dimension data, the computation of eigenvectors might not be possible. This is the major drawback of PCA.

KPCA is a modification of PCA in the high-dimension space build using kernel function. It computes the principal eigenvectors of kernel matrix instead of the covariance matrix. KPCA has the property of building nonlinear mapping. Figure 9 provides a detail flowchart for dimensionality reduction using PCA and KPCA techniques.

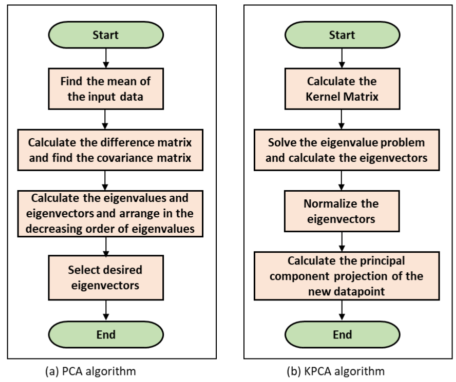


Fig. 9: Flowchart-Algorithm for dimension reduction[26][27]

## B. Feature selection

Feature selection techniques are broadly divided into 3 categories: Filter method in which the features are evaluated independently and ranked to select the best K features. The wrapper method uses a classifier to obtain optimal feature sets. The embedded method searches for an optimal feature set while creating a classifier. Filter methods are simpler and faster whereas the accuracy of wrapper methods are generally higher and more computationally expensive [28].

ReliefF: Is a filter-based feature selection method used for very large datasets. In this method for each sample, k nearest neighbors having a different class label is selected. Neighbor class label same as the sample is called nearest hit and others is the nearest miss. Weights of the features are computed by considering the k nearest hits and misses between classes [28].

Random Forest feature selection method (RF): It is an embedded method in which each feature is permuted to verify its impact on the model accuracy. The permutation of unimportant features have no impact on model accuracy whereas if important features are permuted the accuracy decreases significantly [29].

Feature selection by neighborhood component analysis (fscnca): It is a wrapper method in which it learns the feature weights using a diagonal adaptation of NCA (Neighborhood Component Analysis). NCA uses distance metric to find a linear transformation of features to maximize the average leave-one-out classification accuracy. Here transformation matrix $A$ is obtained by differentiating objective function for$A$ and use of iterative solver. In this work, Stochastic gradient descent (sgd) solver is used. Initially, regularization parameter$\lambda$ values

Input: for each training instance a vector of attribute values and the class values.
Output: the vector W of estimation of the qualities of the attributes
1. Set all weights W[A]: =0;
2. for i: = 1 to m do begin
3. randomly select an instance $R_i$;
4. find k nearest hits $H_j$;
5. for each class C ≠ class ($R_i$) do
6. from class C find k nearest misses $M_j$(C);
7. for A: = 1 to a do
8. $W[A] = W[A] - \sum_{j=1}^{k} diff(A, R_i, H_j) l(m * k) + \sum_{C \neq class(R_i)} [\frac{P(C)}{1-P(class(R_i))} \sum_{j=1}^{k} diff(A, R_i, H_j(C))] l(m * k)$
9. end
10. Apply stopping criteria for tree model W
11. end;

Fig. 10: ReliefF algorithm [28]

Input: T: training sample with $x_i$ feature vector and $y_i$ class label ;
1. Choose the number of trees m to build
2. **for** i := 1 to m **do begin**
3. select a sample from training observations;
4. sample is trained to build a tree;
5. **for** each split **do**
6. choose random k features from original features P;
7. choose the best features from the k features and partition the data;
8. **end**
9. apply stopping criteria for tree model without pruning;
10. **end;**

Fig. 11: RF Algorithm [29]

**Input: T: training sample with $x_i$ feature vector and $y_i$ class label, $\alpha$: initial step length, $\sigma$: kernel width, $\lambda$: regularization parameter, $\eta$: small positive constant;**
1. **Initialize: w (0) = (1,1,….,), ε (0)=-∞, t=0 and repeat**
2. **for i= 1,….N do**
3. **compute $p_{ij}$ and $p_i$ using $w^t$ ;**

$$p_i = \sum_j y_{ij} p_{ij} \qquad p_{ij} = \begin{cases} \frac{\kappa(D_w(x_i, x_j))}{\sum_{k \neq i} \kappa(D_w(x_i, x_k))}, & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases} \qquad D_w(x_i, x_j) = \sum_{l=1}^{d} w_l^2 |x_{il} - x_{jl}|$$

4. **for l=1,…,d do**
5. $\Delta_l = 2\left(\frac{1}{\sigma}\sum_i \left(p_i \sum_{j \neq i} p_{ij}|x_{il} - x_{jl}| - \sum_j y_{ij} p_{ij} |x_{il} - x_{jl}|\right) - \lambda\right) w_l^{(t)}$
6. **t=t+1**
7. **$w^{(t)}=w^{(t-1)} + \alpha\Delta$**
8. **$\varepsilon^{(t)}=€(w^{(t-1)})$**
9. **if $\varepsilon^{(t)} > \varepsilon^{(t-1)}$ then $\alpha$=1.01$\alpha$ else $\alpha$=0.4$\alpha$**
10. **until $|\varepsilon^{(t)}-\varepsilon^{(t-1)}| < \eta$**
11. **$w=w^{(t)}$; return w**

Fig. 12: NCA Algorithm [27]

are tunned by cross-validation to produce minimum classification loss. Features weights are obtained by fitting the NCA model using the best $\lambda$ value and sgd solver. The feature set is obtained by applying the threshold on weight [30]. Figure 10 to 12 provides a detail pseudo code for feature selection methods using ReliefF, Random forest and Neighborhood Component Analysis techniques.

## VI. Results and Conclusion

### A. Results

Evaluation using 137 extracted features: Based on the 'No free lunch theorem', any particular classifier cannot be considered superior to the others. So the best classifier for a particular activity is task dependent. In order to build a robust recognition system for human activity classification, we have compared the performance of the features extracted using Decision tree, KNN, SVM, Neural network and Ensemble bagged classifier. As seen in Figure 13 Ensemble bagged classifier with 10 fold cross-validation provides an accuracy of 96.8% in human activity detection using 137 features. Evaluating performance only based on accuracy is not adequate when the data is imbalanced i.e. when the number of positive cases is much greater than the negative cases or vice versa. So in this study, we have also analyzed the measure of precision and recall. Precision gives the relevant instances out of the retrieved instances and recall gives information about the relevant instances that are retrieved over the total amount of relevant instances. The precision and recall results showed consistency with the accuracy result. As seen from confusion matrix of fscnca method using Ensemble bagged classifier in Figure 14 , the precision and recall are around 96% and classifier accuracy is 96.3% suggesting a good classification outcome.

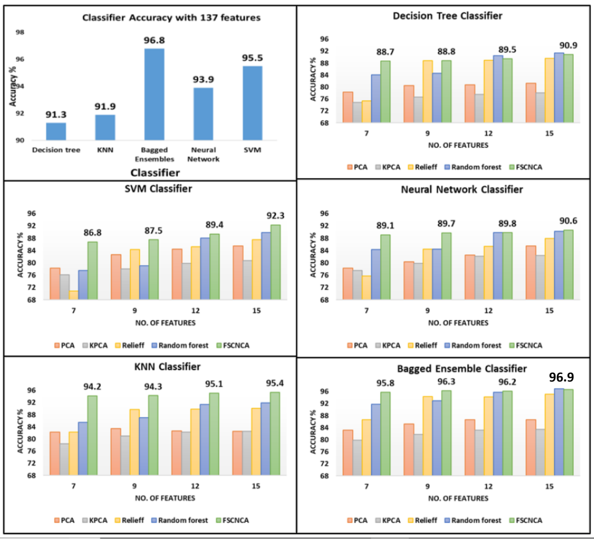


Fig. 13: Accuracy Metric: Comparison across classifiers and feature reduction methods with respect to no. of features

| | | Predicted Class | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Walking | Walking-up | Walking-Dn | Standing | Sitting | Laying | Recall% |
| True class | Walking | 1660 | 26 | 35 | | 1 | | 96 |
| | Walking-up | 33 | 1481 | 29 | 1 | | | 96 |
| | Walking-Dn | 55 | 60 | 1291 | | | | 92 |
| | Standing | | 1 | | 1703 | 73 | | 96 |
| | Sitting | 1 | | | 65 | 1840 | | 97 |
| | Laying | | | | 1 | | 1943 | >99 |
| | Precision% | 95 | 94 | 95 | 96 | 96 | 100 | 96.3 |

Fig. 14: Confusion matrix: fscnca-9 features

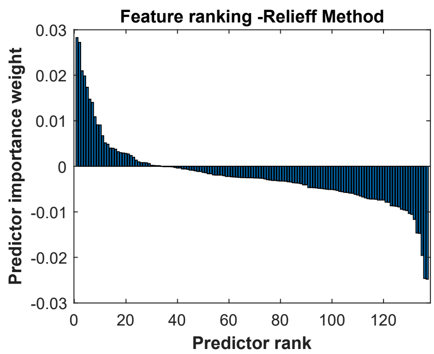


Fig. 15: Feature ranking for feature selection

Evaluation using reduced feature set: ReliefF method computes the rank and the weight of the features and as seen in

Figure 9, the importance of features for prediction reduces exponentially. Selecting more than 30 features for classification is redundant as the feature importance weight reduces to zero and goes negative. A threshold of 0.01 is considered for predictor weight which suggests using more than 15 features for classification is redundant. Hence the performance of classifiers is evaluated by reducing the features/dimension between 7 to 15. Using random forest feature selection method an accuracy of 96.9% is achieved using ensemble bagged classifier and 15 features which is comparable to accuracy achieved with 137 features. Curse of dimensionality and complexity of the model can be reduced by reducing the number of features and still maintain the performance of the classifier. In this study, an accuracy of 96.3% is achieved with only 9 features using the feature selection method by neighborhood component analysis and ensemble bagged classifier. The precision and recall are above 96%. The state-of-art classification accuracy is 97%, achieved on this data set. However, this accuracy is achieved on a 561-D high dimension feature space whereas The results discussed in this work achieved very similar classification accuracy by using a much more compact discriminative feature space of 15-D features via spectro-temporal feature extraction and reduction.

### B. Conclusion

In this study, we designed an IMU based activity recognition system that accurately and robustly identifies among 6 different activities. We achieved the state of the art accuracy of $\approx$ 97% by generating a compact 15-D discriminative space, via exploring feature extraction and reduction and discriminative analysis of the resulting space. With negligible tolerance on accuracy down to 96.3%, we were able to further reduce the feature space down to 9-D space for more robust generalization of predictive model.

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