

# Activity Classification With Empirical RF Propagation Modeling in Body Area Networks\*

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## ABSTRACT

Mobile sensor-based systems are emerging as promising platforms for remote healthcare monitoring. One popular application of these systems is to track the real-time body movements of a patient by analyzing and classifying the physiological signals collected by the video sensors or the body-mounted mechanical sensors. However, the existing motion monitoring infrastructures are inconvenient to be carried with the patient. In this paper, we explore the potential of using the inexpensive off-the-shelf inertial sensors that embedded in the smart phones to identify the body movements. In our proposed system, variance, energy, and frequency domain entropy of linear acceleration and rotating orientation are extracted from the inertial sensors to form the feature vector. To enhance the performance of the system, quantitative metrics of RF propagation characteristics: level crossing rate, Doppler Spread, coherence time, Root Mean Square (RMS) Doppler bandwidth and variation of Path Loss are also investigated to provide new descriptors to the feature space. These features are imported and tested by four most commonly used machine learning algorithms: Backpropagation network (BP), Probabilistic Neural Network (PNN),  $k$ -Nearest Neighbor algorithm ( $k$ -NN) and Support Vector Machine (SVM) algorithm. Results show that using features from both RF sensor and inertial sensor would greatly improve the classification accuracy.

## Categories and Subject Descriptors

J.3 [LIFE AND MEDICAL SCIENCES]: Health; I.5.4 [Pattern Recognition]: Applications

## General Terms

Algorithms

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## Keywords

Activity Classification, Backpropagation network, Probabilistic Neural Network,  $k$ -Nearest Neighbor algorithm, Support Vector Machine

## 1. INTRODUCTION

In recent years, there has been a growing interest in Body Area Networks (BANs) for a variety of healthcare applications. Many current and future medical devices are wearable, using human body as a conduit for wireless communication, which implies that human body serves as a crucial part of the transmission medium in BANs. Implantable medical devices are designed to provide patients with timely monitoring and clinical diagnostic tools to detect physiological abnormalities. Body-mounted devices are investigated for use in providing a ubiquitous monitoring environment and emergency treatment. As more and more elders suffer from heart attack, stroke, Parkinson's syndrome or paralysis, remote healthcare monitoring systems become of increasing importance as a means to notify and update physicians about the current status of their patients. Patients could receive treatment immediately in emergency situations. For instance, patients with heart disease are often required a continuous monitoring of their movements. Therefore, accurately recognizing their movements will be extremely useful to the caregiver. For out-hospital applications, there are also needs for activity recognition, such as tracking people's daily steps, distance walked, calories burned, and hours slept and stairs climbed. Localization services in navigation systems would also be improved with real-time tracking and updating locations. Moreover, human body motion detection is appealing for application in the entertainment environment.

Traditionally, activity classification is achieved via video or body mounted sensors. Related work using computer vision has deployed to detect human body movements, e.g., Microsoft Kinect. Physical activities could also be recognized with acceleration data collected from multiple locations on the body. A lot of human activity recognition methods and algorithms with machine learning techniques are researched and developed for better performance in accuracy and complexity. These algorithms fall into two categories: unsupervised learning method and supervised learning method which deal with unlabeled and labeled data respectively. Unsupervised learning method e.g. Hidden Markov Model (HMM) are used to model simple activities [1]. Supervised learning algorithms are used for activity classification in-

clude a probabilistic approach (Naive Bayes, Gaussian Mixture Model, Logic classifier), a geometric approach (Support Vector Machine, Nearest Neighbor, multilayer perceptron) or a binary decision approach (C4.5 Binary Decision Tree).

Though a considerable amount of prior research has been devoted to activity classification with accelerometers, little work has been considered to differentiate human body activities using features extracted from channel propagation characteristics. In BANs, temporal variations of on-body channels [2] are related to body conditions, body motions, antenna positions, frequency bands and the surrounding environment. The general characterization of on-body fading channels can best be analyzed thoroughly in a scenario-based approach [3]. Among all the influenced factors mentioned above, the human body motion is a key factor leading to a greater variation of these dynamic channels.

A measurement campaign has been performed to understand RF propagation characterization with regard to fading effects caused by different human body motions. Studies of statistical characterization for dynamic channels have been done in indoor environments at frequencies around 400 MHz [4], 868 MHz [5, 6], 2.4 GHz [7, 8], and 5 GHz [9, 10, 11, 12]. Measurements related to dynamic channels were conducted in an anechoic chamber, office room and hospital room using either a channel sounder in wideband experiment or a Vector Network Analyzer (VNA) in narrowband experiment [13, 14, 15, 16, 17]. Some previous researches analyzed on-body fading effects, including the modeling of Path Loss (PL) model for various scenarios [18]. Other papers are concentrated on the analysis of temporal statistics [17] by evaluating fading rate, fading duration etc.

The characterization of on-body to on-body communication, induced by continuous human body motions are measured and investigated for the purpose of activity classification [19, 20]. The propagation model effectively quantizes three human body motions: standing, walking and jogging. Advances in miniaturization of mechanical devices have made inertial sensors and RF sensors embedded in the smart computing devices come true. Data are collected and processed offline from inertial sensors with smart devices and RF sensors with VNA. Pattern recognition algorithms are applied to classify human body motions. This paper compared and evaluated performance of Backpropagation network (BP), Probabilistic Neural Network (PNN),  $k$ -Nearest Neighbor algorithm ( $k$ -NN) and Support Vector Machine (SVM) which are considered as potential solutions to the activity classification problem with improved detection accuracy.

The rest of this paper is organized as follows: Section II describes empirical RF propagation modeling of three human body motions in BANs. In section III, the features extracted from build-in inertial sensors are described and analyzed. In section IV, we present four state-of-the-art machine learning algorithms: BP Network, PNN,  $k$ -NN and SVM to solve the activity classification problem. Performance evaluation is given in Section V to evaluate the detection accuracy and feasibility of the presented algorithms. Finally, conclusion and future work are summarized in section VI.

## 2. ACTIVITY CLASSIFICATION

Human body activity classification has tremendous application in medical, entertainment, security, etc. For instance, patients with obesity or diabetes are often required to follow an amount of regular exercises as part of their treatment; patients with heart attack diseases need to be remotely monitored in case of accident. The recognition of human activities could be approached with assistance of wearable sensors, RF and inertial sensors. Extracted features are mostly from user's movements described by acceleration, environmental variables with temperature sensor or physiological signals such as Electrocardiogram (ECG). With wearable accelerometers, human body activities could be classified with Hidden Markov Models (HMMs) [21]. As the smart computing device is becoming more powerful, a variety of activity recognition applications are also evolved [22, 23, 24, 25].

These activity classification problems could be solved by machine learning algorithms, which have a training stage and an evaluation stage. The training stage generates an activity recognition model from the attributes extracted from measured time series data sets. The evaluation stage is to test unknown data sets with the prior trained learning model.

- Collect raw data from RF and inertial sensors.
- Extract features from data: time domain features and frequency domain features.
- Trained learning models with known data sets.
- Evaluate unknown data sets by the learning model.

For the laboratory experiment, raw data are collected and processed from RF sensors and inertial sensors separately in this experiment. The RF data are collected by VNA with a transmitter antenna and receiver antenna from narrowband experiments. The receiver antenna is placed at right hip, which is usually considered as the center of Body Area Network. The transmitter antennas are placed at back, left wrist, left ankle and right ankle. Extracted RF data includes level crossing rate, Doppler spread, coherence time, RMS Doppler bandwidth, variance of Path Loss and Path Loss range, described in section III. The acceleration and orientation are collected with built-in inertial sensors from smart devices. Four smart devices are also placed at back, left wrist, left ankle and right ankle. The variance, energy and entropy features are obtained from accelerometer and orientation sensor in smart devices. In the future work, RF data could also be collected with body mounted smart phones via Bluetooth.

## 3. EMPIRICAL RF PROPAGATION MODELING OF HUMAN BODY MOTIONS

Though a considerable amount of prior research has been devoted to the channel modeling and motion detection in BANs, little work describes dynamic channels caused by human body motions in a quantitative manner. Based on an empirical approach, characterization of on-body to on-body channel model induced by continuous human body motions are measured and analyzed with VNA in the shielded room [19, 20]. Doppler spread spectrum, RMS Doppler bandwidth, coherence time, level crossing rate and Path Loss

are processed to quantitatively describe three human body motions. Doppler spread is the width of received spectrum when a single tone waveform has been transmitted, which provides information about the fading rate induced by relative movements. Applied the Fourier transform to the time domain data  $H(f_c; t)$ , Doppler spread  $D(\lambda)$  could be calculated as the width in frequency domain for a given threshold, where  $D(\lambda) = \int_{-\infty}^{+\infty} H(f_c; t)e^{-j2\pi\lambda t} dt$ . For the standing scenario, Doppler spread is always below 1 Hz. Walking motion has the Doppler spread around 3 Hz, while jogging has a Doppler spread greater than 6 Hz. RMS Doppler bandwidth is used to describe the spectral distribution of the power, defined as

$$f_N = \sqrt{\frac{\int \lambda^2 V(\lambda) d\lambda}{\int V(\lambda) d\lambda}} \quad (1)$$

where  $V(\lambda)$  is the Fourier transform of the complex autocorrelation function of  $H(f_c; t)$ . Coherence time, which is an alternative description of Doppler spread in the frequency domain, is analyzed in time domain. Channel coherence time is typically defined as the time duration over which normalized autocorrelation coefficients of time domain data above 50%,

$$\rho(m) = \frac{\sum_{n=1}^{N-|m|} \{x(n+m) - m_x\} \{x^*(n) - m_x^*\}}{|r(n+m)| \times |r(n)|} \quad (2)$$

where  $m_x = \frac{1}{N} \sum_{n=1}^N x(i)$  and  $|r(n)| = \sqrt{\frac{1}{N} \sum_{n=1}^N [x(n) - m_x]^2}$ .

The coherence time is usually below 90 *ms* for jogging motion, around 100 *ms* for walking motion and more than 200 *ms* for the standing scenario. Additionally, Path Loss from time domain data behaves differently for three human body motions.

The propagation model effectively quantizes different body motions. Path Loss variations, level crossing rate and coherence time in time domain are used as feature metrics to classify three human body motions, as well as Doppler spread, RMS Doppler bandwidth in frequency domain.

## 4. FEATURES EXTRACTED FROM INERTIAL SENSORS

Tremendous development of the mechanics has embedded inertial sensors into mobile devices. These small, high computation and low cost sensors interact with people in a sensor pervasive environment. Assisted with smartphones, caregivers could continuously monitor patients' location, movements and various environmental conditions based on relatively accurate data.

We attached four Samsung Exhibit II device on the same positions as receiver antennas: back, left wrist, left ankle and right ankle to collect data and model three human body motions: standing, walking, and jogging. This Samsung Exhibit II has an Android operating system with a 2.3.3 API level. There are more than seven build-in sensors: GP2A Proximity Sensor, AK8975 Magnetic Field Sensor, AK8975 Orientation sensor, BMA222 Acceleration Sensor, GP2A Light Sensor, etc. We use the variance, energy and frequency domain entropy of the linear acceleration and orientation as

the feature metrics to classify people's activities, along with extracted RF features discussed in section III.

### 4.1 Mean and Variance

Based on the collected data, statistical characterization of acceleration and orientation are discussed and analyzed with mean and variance in this part. These metrics are important features to distinguish between three possible motions. The DC component is the mean acceleration and orientation values of the signal over the sampling window. The variance of acceleration and orientation is reflective of the intensity of human body movements.

### 4.2 Energy

The energy [26] metric is defined as the sum of the discrete Fast Fourier Transformation (FFT) component magnitudes of the signal, normalized by the number of samples. Additionally, the DC component of the signal is excluded in the calculation. The energy feature is defined as

$$E = \frac{\sum_{i=1}^n |FFT(x_i)|}{n} \quad (3)$$

where  $n$  is the number of samples and  $x_i$  is the  $i$ -th signal amplitude.

### 4.3 Frequency-domain Entropy

The frequency-domain entropy [26] measures the information of the uncertainty associated with each sample in the data stream. It represents the expected value of information contained in the discrete FFT component of the reported signal. The frequency-domain entropy is calculated as the entropy of the normalized signal strength.

$$H(X) = \sum_{i=1}^n P(x_i) I(x_i) = \sum_{i=1}^n P(x_i) * \log \frac{1}{P(x_i)} \quad (4)$$

where  $P(x_i) = \frac{|FFT(x_i)|}{\sum_{i=1}^n |FFT(x_i)|}$ . And the DC component should also be excluded from this calculation.

## 5. ACTIVITY CLASSIFICATION ALGORITHM-S

Activity classification problem could be solved with machine learning algorithms, which requires a training stage and an evaluation stage. We compared and evaluated four machine learning algorithms: BP Network, PNN,  $k$ -NN and SVM with feature metrics extracted from RF sensor and inertial sensor.

### 5.1 Backpropagation Network

Backpropagation network was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. The scale conjugate gradient algorithm [1] is applied to the train data set to generate a function approximate to learn the behavior of Backpropagation network. The propagation network architecture is shown in the Fig.1. The training data set goes into Input. Weight  $\omega$  and  $b$  are iteratively adjusted to minimize the mean square error for feed forward networks, which is represented by the squared error between the network outputs and the target outputs.

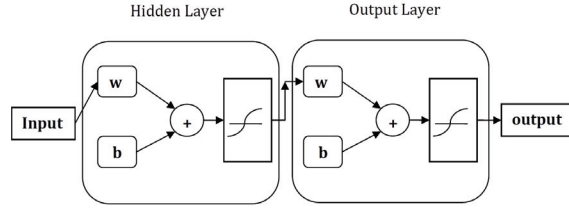


Figure 1: Propagation Network Architecture.

## 5.2 Probabilistic Neural Network

Probabilistic Neural Network (PNN) [27, 28] was first proposed by Donald F. Specht in 1988 to be used for the human body activity classification problem. There are four units in the PNN: input unit, pattern unit, summation unit and output unit. The input unit feeds input data to the pattern unit and does not perform any computation functionalities. In the pattern units, the exponentiation activation function is used to estimate the differentiation between target and input patterns. Each pattern neuron forms a product of the input vector  $x_k$ :

$$\varphi_{ai} = \frac{1}{(2\pi d)^{d/2}} \exp\left[-\frac{(x - x_{ai})^T(x - x_{ai})}{2\sigma^2}\right] \quad (5)$$

where  $x_{ai}$  is the  $i$ -th training vector from category  $a$ ,  $d$  is the dimension of the input feature vector,  $\sigma$  is the smooth factor. Smooth factors would have different effects on the estimated PDF.

The summation unit would accumulate and average the inputs from the pattern units which correspond to the same activity class.

$$f_a = \frac{1}{m} \sum_{i=1}^m \varphi_{ai} \quad (6)$$

where  $m$  denotes the number of training vectors in category  $a$ . Assuming an equal priori probability for each category, the classification of each pattern vector is made according to the Bayes' Rule:

$$c(x) = \arg \max\{f_a(x)\} \quad a = 1, 2, \dots, n \quad (7)$$

The output units represent the results of activity classification.

## 5.3 $k$ -Nearest Neighbor

The  $k$ -Nearest Neighbor algorithm ( $k$ -NN) [29] solves the activity classification problem by selecting the closest training sets in the feature space. This algorithm is among the simplest of all machine learning algorithms: an object is assigned to the class most common among its  $k$  nearest neighbors, which finds the estimated class with local optimality. Therefore it would require large storage space and intensive computation to achieve high performance.

Like other learning algorithms, a decision boundary is computed through the training stage where the training sets are vectors in a multidimensional feature space labeled individually. In the classification procedure, an unlabeled vector

is classified by assigning the label which is most frequently among  $k$  training sets nearest to the query point, where  $k$  is a user-defined constant. The training set is defined as:

$$x = \{x_1, x_2, \dots, x_n\} \quad (8)$$

Each  $x_i$  is a vector containing  $a$  features,  $x_i = \{x_{1i}, x_{2i}, \dots, x_{ni}\}$ . The Euclidean distance is used as the distance metric to find the nearest point from training set  $x$  to the unlabeled vector.

$$d(y, x_i) = \sqrt{\sum_{k=1}^a (y_k - x_{ik})^2} \quad (9)$$

The count of each category  $k$  is accumulated as  $c(k)$ . Therefore, the unlabeled vector is classified by solving  $\arg \max(c(x_i))$  subject to  $\sum_{i=1}^a c(x_i) = k$ . In this paper, a 4-th order nearest neighbor approach is applied to classify the three human body motions in the algorithm.

## 5.4 Support Vector Machine

Support Vector Machine (SVM) [29] is commonly used for activity classification problem. In order to obtain an "optimal" boundary (the most distant hyperplane from both sets), a kernel function is used to project data sets to a higher dimensional space with the aim of finding a linear decision boundary to partition the data.

The boundary hyperplane is expressed as

$$\omega^T x + b = 0 \quad (10)$$

where  $\omega$  is the weight coefficient vector and  $b$  is a bias term. The optimal boundary maximizes the minimum of the distance between the training vector and the boundary and is formalized to an optimization problem as

$$\begin{aligned} & \text{minimize} && \omega^T \omega \\ & \text{subject to} && y_i(\omega^T x_i + b) \geq 1 \end{aligned} \quad (11)$$

where  $y_i$  is -1 when  $x_i$  belongs to one set, otherwise  $y_i$  is 1.

This optimization problem could be achieved by Lagrange's method of indeterminate coefficients. The Lagrange's equation is defined as

$$L(\omega, b, a_i) = \frac{1}{2} \sum_i \sum_j a_i a_j y_i y_j x_i^T x_j + \sum_i a_i \quad (12)$$

where  $a_i \geq 0$  are the indeterminate coefficients. By solving this conditional optimization problem with derivative of  $L(\omega, b, a_i)$ , we could reduce it to a quadratic programming problem which finds  $a_i$  to maximize

$$L(\omega, b, a_i) = -\frac{1}{2} \sum_i \sum_j a_i a_j y_i y_j x_i^T x_j + \sum_i a_i$$

, subject to  $\sum_i a_i y_i = 0$ , where  $a_i \geq 0$ .

Kernel method is used to find the nonlinear boundary by transforming the vector space to a higher dimensional space, so that a nonlinear separable data could be linearly separable after transformation. Let  $\phi$  denotes the transformation to higher dimensional space. The kernel function is defined to the distance in transformed space is related to the original distance in the low dimensional spaces.

$$K(x, \hat{x}) = \phi(x)^T \phi(\hat{x}) \quad (13)$$

Here we use Gaussian kernel function

$$K(x, \hat{x}) = e^{-\frac{\|x-\hat{x}\|^2}{\sigma^2}} \quad (14)$$

However, unlike previous three approaches, the described SVM above can only be applied to binary classification. For multiple class problems, the one-against-all approach [30] is used. This one-against-all SVM construct one SVM per class which is trained to differentiate samples of one class from remaining samples of other classes. And classification of an unknown test set is made according to the maximum output among all SVMs.

## 6. PERFORMANCE EVALUATION

Four machine learning algorithms are compared and evaluated with accuracy performance shown in Table 1. Three sets of features are applied. The first data set is composed with variance, energy and frequency domain entropy features extracted from inertial sensors. The second data set is made by the level crossing rate, Doppler spread, coherence time, RMS Doppler bandwidth and variance of Path Loss features from RF sensors. And the third data set is a combination of both the first data set and the second data set.

Generally speaking, applying RF feature metrics to existing activity classification systems with inertial sensors would yield a better and satisfactory performance. Performance of Backpropagation network on different data sets is shown in second column in Table 1, where the RF sensors can detect human body motions with an accuracy of 96.67%, better than classified with accelerometer and orientation sensor. The PNN algorithm assisted with RF sensors and inertial sensors provides an accuracy of 83.3%. Potentially, the detection accuracy of PNN algorithm would increase if more distinguished features are provided, since this algorithm essentially calculates the relevance between the target data set and the training data set by the kernel function. The detection accuracy with inertial and RF sensors is not higher than that with each individually because of small test data sets. A 4-th order nearest neighbor approach is applied to classify three human body motions. The accuracy with inertial sensors is 91.7%, not higher than that with RF or inertial sensors. The reason is that RF sensors provide only six features, far less than 72 features provided by inertial sensors.

More valuable feature metrics would provide higher accurate estimation with the Euclidean distance. Applied the one-against-all SVM algorithms, the accuracy can achieve 93.3% with RF characteristics. Yet, a lower accuracy of 68.3% is obtained with only acceleration and orientation.

## 7. CONCLUSION

This paper classified three different human body activities assisted with RF sensors and inertial sensors placed on back, left wrist, left ankle and right ankle of human body. Variance, energy and entropy extracted from time domain data of inertial sensors (acceleration and orientation) are used to classify body movements. The quantitative characteristics of channel modeling from RF sensors are also applied to solving activity classification problem. Four machine learning algorithms are compared and evaluated to classify human body activities with the proposed feature metrics: Backpropagation Network, Probabilistic Neural Network,  $k$ -Nearest Neighbor and Support Vector Machine algorithm. Applying the RF feature metrics would generally improve the activity classification accuracy.

In order to obtain a more accurate channel model, large empirical data set must be gathered and evaluated. Extensive data would enable more detailed characterization of the BAN channels and features to be utilized in machine learning algorithms. Moreover, the future work should also address the design of algorithms for activity classification, including study of a wider range of activity types, such as sitting, falling down, standing up, eating, and drinking.

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**Table 1: Comparison of Four Machine Learning Algorithms**

Sensors	Backpropagation	Neural Network	k-Nearest Neighbor	SVM
Inertial	75%	83.3%	91.7%	68.3%
RF	96.67%	75%	83.3%	93.3%
Inertial+RF	96.67%	83.3%	91.7%	85%

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