

## A Review of Physical Human Activity Recognition Chain Using Sensors

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### ABSTRACT

In the era of Internet of Medical Things (IoMT), healthcare monitoring has gained a vital role nowadays. Moreover, improving lifestyle, encouraging healthy behaviours, and decreasing the chronic diseases are urgently required. However, tracking and monitoring critical cases/conditions of elderly and patients is a great challenge. Healthcare services for those people are crucial in order to achieve high safety consideration. Physical human activity recognition using wearable devices is used to monitor and recognize human activities for elderly and patient. The main aim of this review study is to highlight the human activity recognition chain, which includes, sensing technologies, preprocessing and segmentation, feature extractions methods, and classification techniques. Challenges and future trends are also highlighted.

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## 1. INTRODUCTION

Physical activity (PA) and sports are highly associated with health [1-3]. Hazardously, physical inactivity is considered as the fourth risk factor for mortality in the world [4]. Scientific evidences consider physical activity and sports are key elements of health and wellbeing [5, 6]. Moreover, regular PA has physical and mental health benefits such as [7-10]:

- Decreasing the risk of chronic diseases such as diabetes, cardiovascular, stroke, depression, anxiety, high blood pressure, heart disease, many types of cancer, hypercholesterolemia, and arthritis.
- Controlling the weight and obesity.
- Enhancing cognitive performance.
- Improving the mood and solving sleep difficulties.
- Building healthy muscle, bones, and joints.

Nowadays, improving lifestyle, encouraging healthy behaviors, and decreasing the chronic diseases are urgently required [11, 12]. Importantly, the use of advanced technology and computer capabilities in healthcare industries [13] has gained a vital role of our daily lives [14, 15]. However, tracking and monitoring elderly and patients are challenges [16]. Healthcare services for those people are vital in order to achieve high safety living [17-19]. Wearable devices are now highly used for human activity recognition. They are used as a predictor for any abnormal health cases [20, 21]. Figure 1 shows human activity monitoring using wearable sensors.

The main aim of this review study is to present the importance of modern technologies for improving the healthy behavior and lifestyle of the humans. Moreover, physical human activity recognition chain using wearable sensors is highlighted.

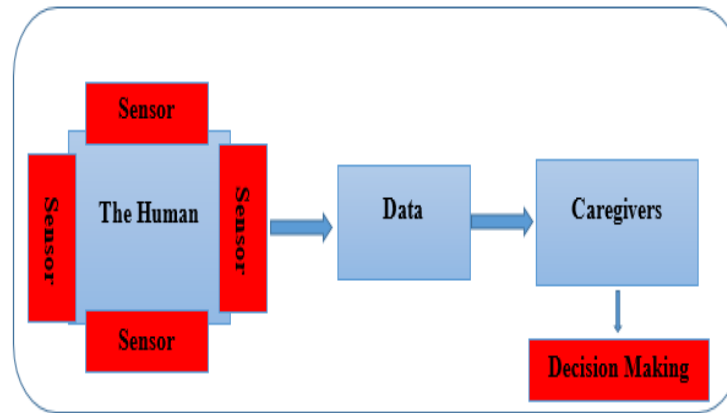


Figure 1. Human activity monitoring using wearable sensors

## 2. HUMAN ACTIVITY RECOGNITION

The analysis of human activity data is crucial [22]. However, data obtained by sensors can be used as a predictor of health status. Basically, the recognition of activities can be divided into two categories, external sensors and wearable sensors [23]. A main example of external sensors is smart homes [24, 25] which have the ability to recognize complex activities [26] such as preparing a meal and answering a phone call. Nowadays, in computer vision and machine learning fields, human activity recognition using wearable sensors has become one of the state-of-the-art research areas, where Figure 2 shows human activity recognition chain [27].

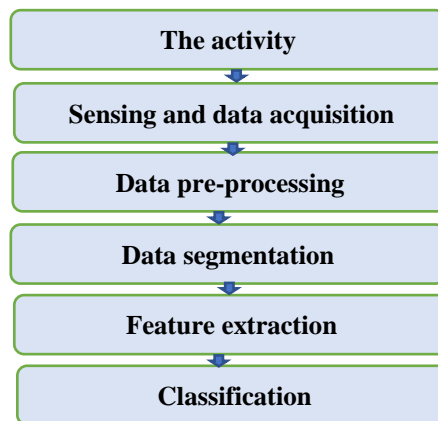


Figure 2. Human activity recognition chain.

Initially, to make the data suitable for analysis, obtained sensor's data are preprocessed [28] before it goes through the rest of the chain. As example, signals have to be filtered firstly. In order to remove high frequency components, low pass filters are used. In addition to filtering technique, data conversion, calibration, normalization, and cleaning may be used in this stage. The main aim of the segmentation stage [29] is to seek the segments, which contain a valuable data about activities, and to reduce the amount of processed data. Sliding window techniques are the common example of the segmentation stage [30]. Feature extraction stage [31-34] is used to find a high resolution of data representation for each segment. Extracted features can be divided into four main categories: time domain, frequency domain, learning techniques, and other techniques. Tables 1 and 2 summarize the time and frequency domain-based techniques, respectively. Table 1 summarizes time domain based techniques. Moreover, Table 2 summarizes frequency domain based techniques, while Table 3 summarizes intelligent learning based techniques and Table 4 summarizes intelligent learning based techniques.

Table 1. Physical human activity recognition feature extraction and selection techniques based on time domain techniques

The technique	References
Statistical values: mean, variance, skewness and kurtosis	[35]
Maximum and minimum values	[36]
Fourier transform	[37]
Wavelet transform	[38]
Entropy	[39]
Mean Absolute Deviation (MAD)	[40]
Signal magnitude area	[41]
Zero crossing rate	[42]
Interquartile range	[43]
Hidden conditional random fields	[44]

Table 2. Physical human activity recognition feature extraction and selection techniques based on frequency domain techniques

The technique	References
Discrete Fourier Transform (DFT)	[45]
Discrete Cosine Transform (DCT)	[46]
Spectral centroid	[47]
Principal frequency	[48]
Frequency domain entropy	[49]
Maximum frequency	[50]
Fast Fourier Transform (FFT)	[51]
FFT energy	[52]
FFT mean and standard deviation	[53]
Mel-Frequency Cepstrum	[54]
Perceptual Linear Predictive Cepstrum	[55]

Table 3. Physical human activity recognition feature extraction and selection techniques based on intelligent learning

The technique	References
Artificial Neural Networks	[56, 57]
Hidden Markov Fields (HMF)	[58, 59]
Dynamic Bayesian Networks (DBN)	[60]
Codebook approach (CB)	[61]
Convolutional Neural Network (CNN)	[62]
Hand-crafted features (HC)	[63]
Multi-Layer-Perceptron (MLP)	[64]
Long Short-Term Memory network (LSTM)	[65]
Autoencoder (AE)	[66]

Table 4. Physical human activity recognition feature extraction and selection techniques based on other learning

The technique	References
Autoregressive Model (AR)	[67]
Multi-class Linear Discriminant Analysis (MLDA)	[68, 69]
Principal Components Analysis (PCA)	[70]
HAAR filters	[71]
Shape analysis	[72]
Bag-of-Words	[73]
Linearly Dependent Concept	[74]

In the classification stage, the classifier (classification algorithm/technique) uses the extracted features to differentiate between different human activities [75, 76]. Table 5 summarizes different classification algorithms.

Table 5. Classifiers used for physical human activity recognition

Classification technique	References
Autoregressive Model (AR)	[77, 78]
Linear regression	[79, 80]
Logistic regression	[81, 82]
Markov Models	[83, 84]
Random Forest	[85, 86]
Boosting and Bagging	[87, 88]
Sequential Minimal Optimization	[89-91]
Fuzzy Logic	[92-94]
Relevance vector machines	[95, 96]
Support Vector Machines	[97, 98]
Least Squares Support Vector Machines	[99, 100]
Adaptive minimum distance	[101, 102]
Gaussian Mixture Model (GMM)	[103, 104]
Naive Bayes	[105, 106]
Gaussian naive bayes	[107, 108]
Bernoulli naive bayes	[109, 110]
Multinomial naive bayes	[111, 112]
Bayesian Networks	[85, 113, 114]
K-nearest neighbors	[115, 116]
Zero rule	[116, 117]
One rule	[103, 118]
Decision tree	[119, 120]
Fisher's linear discriminant	[121, 122]
Decision stump	[123, 124]
Stochastic gradient descent	[125, 126]
Linear discriminant analysis	[127, 128]
Quadratic discriminant analysis	[129-131]
Boosted tree	[132, 133]
Conditional Random Fields	[134, 135]
Skip Chain	[136, 137]
Codebook	[138, 139]
Linear Predictive Coding	[140, 141]
Neural Network: Multilayer Perceptron	[142, 143]
Neural Network: Basic radial function	[144-146]
Multilayer Neural Networks	[144-146]
Deep Learning: Convolutional Neural Networks (CNNs)	[139, 147-153]
Deep Learning : Deep Belief Networks (DBNs)	[154-156]
Deep Learning: Autoencoder	[157-161]
Deep Learning: Sparse Coding	[162-164]
Deep Learning: Recurrent Neural Network (RNN)	[165-168]
Deep Learning: Boltzmann machine	[169-172]
Deep Learning: Feedforward Neural Network (FNN)	[173-175]

### 3. WEARABLES AND SENSING TECHNOLOGY

Currently, wearable devices and sensors [176-180] (such as pulse monitors, mobile phones, smart watches, and smart glasses) are used in many modern applications such as industry, medical field, and security [181-183]. In the medical applications, the main purpose of these devices and sensors is to obtain a reliable data to use them in monitoring/tracking people's activities and behaviors [184]. However, signs of humans' body such as brain signals, blood pressure, temperature, heart rate, motion, spinal posture, sweat rate, respiration rate and glucose level can be monitored [185]. Moreover, with the help of wearable devices and sensors [186], healthcare providers can continuously and remotely monitor all signs and activities [187-190]. As an example of remote activity monitoring, sensors can be used to track subject's motion and unexpected activities, such as fall detection [191].

In the PA and sports, activity recognition [192-194] can be used to obtain physical activities such as running, driving, jumping, swimming, dancing, playing sports, walking, lying, standing, sitting, hiking, and

jogging [195, 196]. Several studies have applied activity recognition for patients, physically or mentally disabled people, children, and elderly [197]. Thus, wearable computing and sensing technology will positively enhance health and medical technology [198]. This leads to reduce medical cost, cure at home, redefine the doctor-patient relationship, and enhance medical services [199, 200]. Several types of sensors are developed and applied for the monitoring of activities and physiological parameters [201]. Table 6 summarizes available market sensors used in physical human activity monitoring [34, 202, 203].

Table 6. Available market sensors used in physical human activity monitoring

Sensor	Application
Piezoresistive Sensor [204]	Force or pressure measurement
Sweat rate sensor [205]	Sweat measurement
Inertial sensors [206, 207]	Linear and angular accelerations measurements
Accelerometers [208]	Acceleration measurement
Shoe monitor sensor [209]	Locomotion measurement
ElectroCardiogram (ECG) sensors [210]	Rate and regularity of the heart beats measurement
Body temperature sensor [211]	Skin temperature measurement
Blood pressure sensor [212]	Blood pressure measurement
Pulse oximetry sensor [213]	Oxygen saturation level in blood measurement
Glucose sensor [214]	Glucose rate measurement
Smart phones [215, 216]	Several messurments
Cameras [217]	Recognition of activities and gestures from video sequences
GPS [218, 219]	Human's movment
Spirometer, Electrooculography (EOG), and galvanic skin [220]	Physiological sensor
Electroencephalogram (EEG) [221, 222]	Brain signals
Magnetic field sensor [223]	Inertial sensor

#### 4. CHALLENGES AND FUTURE TRENDS

This section summarizes human activity recognition challenges and future trends [76, 224-239]:

- Diversity of physical activities: definition of the activities and their specific characteristics is challenging task.
  - Activity variation: certain activity may lead to multiple different styles of human motion.
  - Outdoor/ uncontrolled environment: background noise may affect human activity recognition algorithms.
  - Data collection and unavailability of big datasets.: intelligent algorithms for human activity recognition needs sufficient and big training data. Most available datasets are laboratory datasets.
  - Feature extraction: knowledge expert- driven feature extraction methodes have to be extensively discussed. However, time and frequency methodes do not have the ability to deal with dynamic nature of human activities.
  - Computational time: new feature extraction processes need more computational time.
  - Performance and accuracy: multiple sensors or multiple classifiers have to be used
  - Intra-class variability and inter-class similarities: Humans act differently.
  - Performance evaluation: false negative state must be reducing.
  - Complex activities: complex and multitasking activities are diffecult to recognize.
  - The NULL Class: required activities may interfere with activities that have similar behaviour/patterns but that are irrelevant to the scope.
  - Class imbalance: the number of instances of one class far exceeds the other.
  - Flexibility: the HAR system must be flexible to add new users without needing to re-train the system.
  - Privacy and security: threats maybe occure due to highly sensitive information.
  - Safety: touchable batteries maybe dangerous.
  - Wearable sensors placement: how and where the wearable sensors can placed and attached to related locations in the body.
- Design of wearable sensors: the sensor must be easy and comfortable for the users.

- Single sensor modalities: information fusion strategies have to be discussed more.
- Energy efficiency: online continuous sensing is energy consuming.
- The size: size of the sensor must be reduced.
- Obtrusiveness: human does not able to wear many sensors.
- Ergonomics: wearable devices must be comfortable for the users.
- Sealing: wearable devices must be protected from water and sweat.
- Noise: various noise levels for the same modality may occur.

## 5. CONCLUSION

In the IoMT era, analysis of human activity data is vital and represents the future of healthcare industry. Signs of humans' body such as brain signals, blood pressure, temperature, heart rate, motion, spinal posture, sweat rate, respiration rate and glucose level can be monitored. Data obtained by sensors can be used as a predictor of health status. Thus, this literature has covered the physical human activity recognition chain using wearable sensors. Initially, in order to make the data suitable for analysis, obtained sensor's data are preprocessed and segmented. Feature extraction stage is used to find a high resolution of data representation for each segment. Extracted features can be analyzed by four main methods: time domain, frequency domain, learning techniques, and other techniques. The classifier (classification algorithm/technique) uses the extracted features to differentiate between different human activities. Importantly, this review paper may be used as a report of all algorithms used in human activity researches.

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