Activity Recognition Using Inertial Sensing for Healthcare, Wellbeing and Sports Applications: A Survey

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Abstract

This paper surveys the current research directions of activity recognition using inertial sensors, with potential application in healthcare, wellbeing and sports. The analysis of related work is organized according to the five main steps involved in the activity recognition process: preprocessing, segmentation, feature extraction, dimensionality reduction and classification. For each step, we present the main techniques utilized, their advantages and drawbacks, performance metrics and usage examples. We also discuss the research challenges, such as user behavior and technical limitations, as well as the remaining open research questions.

1 Introduction

In the last decade, human activity recognition has become an important emerging field of research within context-aware systems. Physical activity can be defined as "*any bodily movement produced by skeletal muscles result in energy expenditure above resting level*"[1]. The goal of activity recognition is to recognize the actions and goals of an agent or a group of agents from the observations of the agents' actions.

Traditionally, researchers used vision sensors for activity recognition[2][3]. However this type of activity recognition is intrusive and disruptive in some applications[4] and violates the privacy of the users in some cases[5]. With the advancements in microsensor technology, low-power wireless communication and wireless sensor networks (WSNs), inertial sensor systems[6] provide a low-cost, effective and privacy-aware alternative for activity recognition.

The most widely used inertial sensors are accelerometers and gyroscopes. An accelerometer consists of a mass suspended by a spring and placed in a housing. The mass inside the accelerometer moves depending on the acceleration of the sensor and displacement of the mass is measured as the difference of acceleration. A gyroscope sensor measures the angular velocity by using the tendency of vibration in the same plane as an object vibrates. There are various types of gyroscopes but advances in micro-machined electromechanical system (MEMS) technology enable the construction of small, inexpensive, reliable, and low power gyroscopes.

Although inertial sensor systems provide an ideal setting for activity recognition, there are still a number of challenges lying ahead. These challenges are related to human behavior[7] or technical issues[8].

Human Behavior Human behavior attributes present challenges for the recognition of activities. Usually people perform multiple tasks at the same time and this makes the recognition process more difficult. Besides this, differences between cultures and individuals result in variations in the way that people perform tasks. Changes in the sequence of activities and periodic variations can also produce wrong results.

Sensor Inaccuracy Most of the sensor network systems are closed-feedback loop systems and the reliability of the sensor data plays an important role in the overall recognition results.

Sensor Placement problem is caused by the wrong placement or orientation of sensors and changes in the position of sensors during motion.

Resource Constraints Power consumption is the main factor affecting the size of the battery and sensor nodes, accordingly. Besides this, sensor nodes should have enough memory space both for software components and data that needs to be stored, and they should be computationally sufficient while considering the power management.

Usability aims the sensor network systems to be easier to learn and more efficient to use. In order to achieve this, the system should be designed by keeping in mind the target groups' physiology and psychology.

Privacy Sensitive user information should be retrieved without invading users' private life and should be transmitted and stored with strong cryptography which requires computational power.

2 Applications

Advances in semiconductor industry, which also trigger the advancements in ultra-mobile devices, made it possible to build microprocessors that are smaller than a pin-head.

This evolution in todays' computing devices enables activity recognition systems to be widely used in our daily lives in forms of various applications ranging from medical to leisure.

2.1 Medical Applications

Traditional health care systems require patients to apply to the health care provider for a scheduled evaluation or in case of an emergency. Such clinical visits might either take a snapshot of patients' condition or be too late for any interventions[9]. In both cases, early indications of an illness might be missed. In addition to this lack in healthcare system, long term health care costs increase year-by-year[10][11]. Therefore, there is a rapid shift from a clinical setting to a patient or home centered setting with the help of wireless sensor network systems, which fill the gap in health care monitoring between clinical visits[12]. Continuous physical and physiological monitoring in any environment would shorten hospital stay for patients, improve both recovery and reliability of diagnosis[9] and improve patients' quality of life, as well.

Monitoring & Diagnosis Jiang et al.[13] present a remote health care service with movement and fall detection capabilities. Wu et al.[9] also propose a patient monitoring and medical diagnosis system in a similar manner. Wu et al. use physiological body-worn and contextual sensors located in the environment thus enable medical personnel to see the raw sensor data other than features extracted from sensors.

Rehabilitation Someren et al.[14] investigate the effect of medication on Parkinson patients and tremor duration after medication by using an actigraphy, which is a solid state recorder used for long-term continuous measurement of movement. Walker et al.[15] explore the activity and disability in patients with rheumatoid arthritis(RA) and Bartalesi et al.[16] suggest a system using kinesthetic wearable sensors for upper limb gesture recognition in stroke patients.

Correlation Between Movement and Emotions Picard et al.[17] propose a framework for emotion recognition in order to understand the correlation between intelligence and emotion in people and to build machines appearing more intelligent. In a similar way, Myrtek et al.[18] succeed in detecting the emotional activity by separating the metabolically induced heart rate from the emotionally induced heart rate.

Child & Elderly Care Children and elderly people constitute the most sensitive group in our society and they need continuous observation. Najafi et al.[19] propose a system for activity recognition and shows the results for classification of postural transitions in hospitalized elderly people and monitoring elderly people during their daily lives. Beside these, fall related hip fractures in elderly people are really dangerous and economic burden to the victim. Wu et al.[20] present a portable system which detects fall before the impact. In a similar manner, Busser et al.[21] propose an acceleromety-based ambulatory system for monitoring daily activities of children living under treatment or for diagnosis.

2.2 Home Monitoring and Assisted Living

Assisted living systems are used to provide supervision or assistance to the residents to ensure their health, safety and well-being. In order to accomplish this, assisted living systems provide services such as tracking, fall-detection, and security[22]. Some of these home monitoring and assisted living systems can be categorized as follows:

Tracking, Monitoring & Emergency Help Hou et al. [22] present an assisted living system providing services such as time-based reminder, vital sign measurement, human and object tracking, and fall detection and emergency help services.

Assistance for People with Cognitive Disorders Assisted living systems are also widely used for people with cognitive disorders. A person with cognitive disability is defined by DSM-IV[23] as someone who is "*significantly limited in at least two of the following areas: self-care, communication, home living, social/interpersonal skills, self-direction, use of community resources, functional academic skills, work, leisure, health and safety*". External assistive systems are used to remind people with cognitive disorders to accomplish daily activities and these systems range from paper-and-pencil methods[24] to specialized software applications[25]. Osmani et al.[26] present a scenario about activity recognition and reminding system composed of environmental and wearable sensors for a dementia patient. Dieter et al.[27] also propose an *adaptive prompter* system for Alzheimer patients which recognizes activities of the user by using various sensors and prompts appropriate messages verbally or visually.

Assistance for People with Chronic Conditions Besides physiological measurements, daily physical activity of chronic patients represents an important reflection of quality of their daily lives. Moreover, Berry et al.[10] investigate the economics of chronic heart failure and they emphasized the importance of reducing the rate of hospitalization. For this purpose, Davies et al.[28] present a lightweight sensor system in order to evaluate cumulative movement of limb for patients with chronic heart failure.

Marshall et al.[29] introduce a smart-phone application for self management of specific chronic diseases and they test the system for patients with chronic pulmonary disease(COPD). In a similar manner, Steele et al.[30] develop a system for monitoring daily activity and exercise in COPD patients. Bosch et al.[31] present a system for COPD patients that monitors and provides feedback to better manage their physical condition.

2.3 Sports and Leisure Applications

Body-worn WSNs can also be used for recognition of sportive and leisure activities in order increase the lifestyle quality of people. For this purpose, numerous activity recognition systems have been proposed:

Daily Sport Activities Ermes et al.[32] develop a method for daily activity recognition as well as sportive activity recognition such as cycling, playing football, exercising with a rowing machine, and running both for supervised and unsupervised data. Besides, Long et al.[33] present a system for computing daily energy expenditure for daily activities and sportive activities such as soccer, volleyball, badminton, table tennis, etc.

Martial Arts Detection of motion sequences in martial arts is also another application field for WSNs. Heinz et al.[34] use body-worn accelerometers and gyroscopes for motion sequences in Wing Tsun in order to increase interaction in video games of martial arts. It is also possible to use similar systems for martial arts education. Markus et al.[35] propose an interactive computerized toy ball for helping children in their Kung Fu education.

Automatic Video Annotation Activity recognition in sports could also be used for automatic sport video annotation and automatic generation of highlights by detecting specific events[36].

Performance Sports There are also some commercial systems for monitoring sportive activities. Nike presented a sensor called Nike+, which is to be placed inside a shoe, to keep track of running and jogging exercises while keeping the training history[37]. This sensor can be integrated with iPods or a SportBand, which is a product designed by Nike, and enables the user to set training goals or to challenge friends. Polar also develops various types of training and performance monitoring products for different types of activities, ranging from running and cycling to team sports[38].

3 Activity Recognition Process

There are many different methods for retrieving activity information from raw sensor data in the literature. However, the main steps can be categorized as *preprocessing*, *segmentation*, *feature extraction*, *dimensionality reduction* and *classification*[6]. Figure 1 summarizes the activity recognition process. In this section we present the most widely used algorithms and methods for each of these steps.

3.1 Preprocessing and Signal Representation

Due to the nature of inertial sensors, the acquired sensor data should first pass a pre-processing phase. Almost always, high frequency noise in acceleration data needs to be removed. Therefore, non-linear, low-pass median[39], Laplacian[40], and Gaussian filters[41] can be employed for removal of high-frequency noise. In some cases gravitational acceleration has to be extracted from accelerometer data in order to analyze only useful dynamic acceleration. For this purpose, high-pass filters can be used to distinguish body acceleration from gravitational acceleration[42].

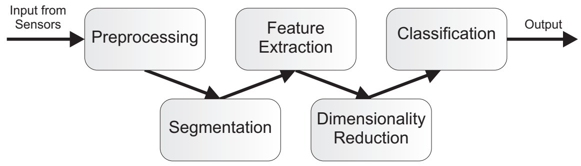

Figure 1: Steps for activity recognition process.

Representation of raw data while preserving useful information is the key to efficient and effective solutions[43] and it affects the overall performance and computation time of activity recognition systems.

Piecewise Linear Representation (PLR) is "*the approximation of a time series T, of length n, with K straight lines*"[43] where K is much smaller than n in general. Keogh et al.[43] present the usage of the PLR method in various segmentation algorithms.

Fourier Transforms (FTs) are capable of holding the primary information and they also reduce the dimensionality of data[44]. Discrete-FTs (DFTs) are a specific version of FTs that require discrete input functions like sensor samples[45]. A more efficient version of FTs, namely Fast-FT (FFT) was also proposed for mobile devices to extract primary information of data and reduce the dimension.

Wavelet Transforms (WTs) are similar to FTs but WTs can better represent functions with discontinuities and sharp peaks. Similar to DFTs, in Discrete-WT (DWT), wavelets are discretely sampled. Therefore, DWTs can be widely used for activity recognition applications[46, 47] and are shown to be a powerful method for recognizing transitions between postures while eliminating noise during activities such as walking and running[19, 40].

3.2 Segmentation

Retrieving important and useful information from continuous stream of sensor data is a difficult issue for continuous activity and motion recognition[6]. For this purpose, several segmentation methods for time series data have been proposed.

3.2.1 Sliding Windows

Sliding windows algorithms are simple, intuitive and online algorithms and therefore are popular for medical applications[43]. A sliding window algorithm starts with a small subsequence of time series and adds new data points until the fit-error for the potential segment is greater then the threshold which is defined by the user. Although they are simple and online, sliding window algorithms might cause poor results in some cases[48]. They work with a complexity of $O(nL)$, where L is the average length of a segment[49].

3.2.2 Top-Down

Top-down algorithms, which are well known in the machine learning and data mining communities as *iterative end-point fits*[50], are used to break time series data into many segments by splitting data at the best location. They start with halving the data into two parts and until all segments have approximation errors below the user defined threshold. These algorithms work recursively and their computational complexity is $O(n^2K)$ where K is the number of segments[49].

3.2.3 Bottom-Up

Bottom-up segmentation algorithms are natural complements to top-down algorithms. Therefore, they start the segmentation process with the finest possible approximation which is $n/2$ segments for n-length time series[43]. Then, they merge a pair of adjacent subsequences of time series to create larger segments and in the meanwhile they calculate the cost for this operation. This process continues until the cost value reaches a stopping criteria. Like sliding window algorithm, the computational complexity for this algorithm is also $O(nL)$[49].

3.2.4 Sliding Window and Bottom-Up (SWAB)

Keogh et al.[43] present the SWAB that combines sliding window and bottom-up segmentation, in order to provide the online behavior of sliding window algorithm and retain the superiority of bottom-up. SWAB applies a two level segmentation procedure to a time series. First, using sliding window algorithm, it creates a single segment. And then, this segment is moved into the pre-allocated buffer to apply bottom-up approach. This process continues as long as new data arrives. The complexity for SWAB is slightly higher than the bottom-up approach while the performance is as good as the bottom-up algorithm[49].

3.3 Feature Extraction

In general, features can be defined as the abstractions of raw data and the purpose of feature extraction is to find the main characteristics of a data segment that accurately represent the original data[6]. In other words, the transformation of large input data into a reduced representation set of features, which can also be referred as *feature vector*, is called feature extraction. The feature vector includes important cues for distinguishing various activities[42, 51, 52] and features are then used as inputs to classification algorithms[53]. Table 1 presents the most widely used features and their applications.

Type	Features	References
Time-Domain	Mean	[54, 55, 56, 57, 42, 52, 58, 59, 60]
	Variance, Std. Dev., Mean Abs. Dev.	[54, 51, 58, 42, 59, 52, 61, 62]
	RMS	[60, 59, 42]
	Cum. Histogram	[60]
	Zero or Mean Crossing Rate	[60, 54]
	Derivative	[59]
	Peak Count & Amp.	[51]
	Sign	[63]
Frequency-Domain	Discrete FFT Coef.	[52, 64]
	Spectral Centroid	[9]
	Spectral Energy	[55, 56, 57, 42, 52, 9]
	Spectral Entropy	[34, 55, 19]
	Freq. Range Power	[34]
Time-Frequency Dom.	Wavelet Coef.	[19, 65, 40, 66, 67, 68]
Heuristic Features	SMA	[39, 42]
	SVM	[39, 40, 57, 60]
	Inter-axis Corr.	[55, 56, 57, 52, 42]
Domain-Specific	Time-Domain Gait Detection	[69]
	Vertical or Horizontal Acceleration	[40, 69]

Table 1: The most widely used features and their applications.

3.3.1 Time-Domain Features

Time-domain features include basic waveform characteristics and signal statistics[8] and they are are directly derived from a data segment.

Mean The mean acceleration value of the signal over a segment is the DC component of the acceleration signal[55]. Ravi et al.[56] extract the mean value from each of the three axes of the accelerometer and Wang et al.[57] present the accuracy of the mean value feature for classification.

Variance Lombriser et al.[58] compute the variance of a 3 accelerometer components and a light sensor. Huynh et al.[52] also include the variance of a digital compass.

Root Mean Square (RMS) Ghasemzadeh et al.[59] include RMS feature in their application and present a formula for the RMS error computation. Maurer et al.[60] also consider the RMS feature.

3.3.2 Frequency-Domain Features

Frequency-domain features focus on the periodic structure of the signal, such as coefficients derived from Fourier transforms[8].

Spectral Energy Energy feature can be used to capture data periodicity of the acceleration data in the frequency domain and it can be used to distinguish sedentary activities from vigorous activities[42]. Huyn et al.[52] and Lombriser et al.[58] present classification algorithms employing energy features.

Spectral Entropy Wang et al.[57] calculate the frequency-domain entropy as the normalized information entropy of the discrete FFT component magnitudes of the signal which is assumed to help to discriminate the activities with similar energy values. Bao et al.[55]

also use entropy feature in their feature vector and several classifiers are tested with this feature vector.

3.3.3 Time-Frequency Domain Features

Time-frequency domain features are used to investigate both time and frequency characteristics of complex signals[8] and they generally employ wavelet techniques. They are mainly used to detect the transition between different activities[70].

Wavelet Coefficients Wavelet transforms divide the original signal into wavelet coefficients which enable the signal to be analyzed with a resolution matched to the resolution to the scale of coefficient[65]. Sekine et al.[66] and Nyan et al.[67] use this flexibility of wavelet coefficients and present walking pattern and gait detection applications respectively.

3.3.4 Heuristic Features

Heuristic features are the features which have been derived from a fundamental understanding of how a specific movement would produce a distinguishable sensor signal[53].

Signal Magnitude Area (SMA) SMA features are shown to be used effectively for identifying periods of daily activities[71]. Similarly, Karantonis et al.[39] use the SMA as the basis for identifying periods of activity. Yang et al.[42] use SMA to identify static and dynamic activities.

Signal Vector Magnitude (SVM) Mathie[72] defines SVM "*to be the sum of integrals of the moduli of the three acceleration signals, normalised with respect to time*". SVM is also used by Karantonis et al.[39] to detect falls since at least two consecutive peaks occur in the SVM above a defined threshold during a fall.

Inter-axis Correlation It is especially useful for discriminating between activities that involve translation in just one dimension[42]. Bao et al.[55] use the correlation between axes and achieve good results for distinguishing cycling from running.

3.3.5 Domain Specific Features

Most of the features presented so far are shown to perform poorly in real life scenarios[73]. Therefore, for real life scenarios we need more features which are tailored to specific applications[69].

Time-Domain Gait Detection Bieber et al.[69] use a time domain algorithm for gait detection in addition to the FFT and they achieve an accuracy of 95% accuracy for step detection. Bidargaddi et al.[40] also present a method used for walk detection using features of vertical acceleration signals.

3.4 Dimensionality Reduction

The goal of dimensionality reduction methods is to increase accuracy and reduce computational effort. If less features are involved in the classification process, less computational effort and memory are needed to perform the classification. In other words, if the dimensionality of a feature set is too high, some features might be irrelevant and do not even provide useful information for classification, and computation is slow and training is difficult as well[42]. Two general forms of dimensionality reduction exist: feature selection and feature transform[74].

3.4.1 Feature Selection Methods

Feature selection methods select the features, which are most discriminative and contribute most to the performance of the classifier, in order to create a subset of the existing features.

SVM-Based Feature Selection Although SVMs are powerful neural computing methods, their performance is reduced by too many irrelevant features[75]. Therefore, SVM-based feature selection methods are proposed. Wang et al.[57] consider an SVM-based feature selection aproach for better system performance. They perform some experiments to select several most important features and conclude that 5 attributes would be enough to classify daily activities accurately.

K-Means Clustering Clustering is defined by Huynh et al.[52] as "*a method to uncover structure in a set of samples by grouping them according to a distance metric*". They perform K-means clustering to rank individual features according to their discriminative properties and correspondance between the cluster precision and the recognition performance is presented.

Forward-Backward Sequential Search This method is a combination of forward and backward selection, which are described by Fukunaga[76]. Pirttikangas et al.[61] present an application of this method to select best features and their approach resulted with 19 features for accelerometer and heart-rate data.

3.4.2 Feature Transform Methods

Feature transform techniques try to map the high-dimensional feature space into a much lower dimension, yielding fewer features that are a combination of the original features. An important advantage of feature transform techniques is that they properly handle the situation in which multiple features collectively provide good discrimination, while they provide relatively poor discrimination individually.

Principal Component Analysis (PCA) PCA is a well known and widely used statistical analysis method and it is used by Yang et al.[42] to transform the original features into a lower dimensional space. Yoon et al.[77] also propose an unsupervised dimensionality reduction method based on the Common PCA (CPCA) method, which is generalized from PCA.

Independent Component Analysis (ICA) Mantyjarvi et al.[65] use ICA with PCA to reduce the dimensionality of the feature vector. They present the experimental results for the usage of PCA and ICA feature transform methods with wavelet transform. Their results revealed that the difference between PCA an ICA is negligible.

Local Discriminant Analysis (LDA) Ghasemzadeh et al.[59] apply LDA to a reduced feature set after they use PCA to reduce the dimension of the original feature set in order to increase the performance of LDA method. Ward et al.[51] also propose an LDA-based feature reduction method for audio data.

3.5 Classification and Recognition

The selected or reduced features that create feature sets are used as inputs for the classification and recognition methods. Table 2 presents a summary for the most widely used classification and recognition methods.

Classification Method		Ref.	Sensor Placement	Accuracy
Threshold-based		[34]	rear hip, neck, wrists, knees, and lower legs	NA
		[78]	waist	NA
		[40]	waist	89.14%
		[79]	waist	NA
Pattern Recognition	Decision Tables	[55]	wrist, upper-arm, waist, thigh, ankle	46.75%
		[56]	waist	46.67%
	Decision Trees	[55]	wrist, upper-arm, waist, thigh, ankle	84.26%
		[39]	waist	90.8%
		[80]	thorax	80%
	Nearest Neighbor	[56]	waist	49.67%
		[60]	wrist, belt, necklace, trousers pocket, shirt pocket, bag	NA
		[58]	wrist	91%
	Naïve Bayes	[34]	rear hip, neck, wrists, knees, and lower legs	NA
		[9]	knee	NA
		[81]	NA	83.97%
	SVM	[56]	waist	73.33%
		[57]	ext. objects	84.28%
		[44]	NA	87.36%
	HMMs	[82]	shoulder, waist, wrist	90%
		[83]	wrist, elbow	72%
		[63]	10 for right arm, 9 for left	87.36%
	GMMs	[84]	hip	88.76%
		[85]	waist	76.6%
Artificial Neural Networks		[86]	chest	84%
		[42]	wrist	95

Table 2: Categorization of related work on activity recognition according to the classification methods mostly used.

3.5.1 Threshold-Based Techniques

Threshold-based techniques are widely used to distinguish activities with various intensities. Mathie et al.[78] propose an activity recognition system using a single waist mounted accelerometer to discriminate dynamic activities by using energy features. In their latter study[79], they use a similar approach to recognize transition of motion. Bidargaddi et al.[40] present their results for the system used to distinguish walking activity from other high intensity activities like biking or rowing. Heinz et al.[34] also propose a threshold-based motion analysis and recognition system for Wing Tsun motion sequences.

3.5.2 Pattern Recognition Techniques

Decision Tables serve as a structure which can be used to describe a set of decision rules and record decision patterns for making consistent decision. Bao et al.[55] investigate the recognition of various daily activities and ambulation by using 5 sensors and present the performance of decision tables. Ravi et al.[56] also consider the performance of normal, boosted and banged versions of decision table classification for 4 different scenarios.

Decision Trees are decision support tools using a tree-like model of decisions and their outcomes, and costs. Caros et al.[80] present a basic decision tree approach to discriminate between standing/sitting and lying by using a sensor placed on the thorax of the subject.Karantonis et al.[39] also propose a basic decision tree method for a real-time classification application and achieve an accuracy of 90.8%.

Nearest Neighbor (NN) algorithms are used for classification of activities based on the closest training examples in the feature space. Maurer et al.[60] propose a multisensor (accelerometer and microphone) activity recognition platform worn on different body positions and examine the use of k-NN method for classification. Besides, Lombriser et al.[58] used k-NN algorithm for online recognition of activities.

Naïve Bayes is a simple probabilistic classifier based on Bayes' theorem. Wu et al.[9] present a patient monitoring system with various sensors located on the knee of a subject. They use a Naïve Bayes classifier for abnormal gait, "limb", detection. Dougherty et al.[81] employ the Naïve Bayes for activity recognition and they investigate the effect of discretization on Naïve Bayes classiers.

Support Vector Machines (SVMs) are supervised learning methods used for classification. Wang et al.[57] explain an SVM based activity recognition system using objects attached with sensors to recognize drinking, phoning, and writing activities and they achieve a performance of 72.17%, 84.28%, and 80.35%, relatively for each activity. He et al.[44] also present the effect of 3 different feature extraction methods over SVM classifier.

Hidden Markov Models (HMMs) are statistical models widely used for activity recognition[51, 87]. Lester et al.[82] and Ward et al.[83] suggest personal activity recognition systems by using HMMs. Similarly, Zappi et al.[63] propose a dynamic sensor selection system used for HMM based recognition of manipulative activities of assembly line workers.

Gaussian Mixture Models (GMMs) are parametric representations of probability density functions, based on a weighted sum of multi-variate Gaussian distribution[85]. Allen et al.[85] use a GMM based recognition approach to recognize the transitions between activities with an accuracy of 76.6%. Ibrahim et al.[84] also propose a system with a single sensor mounted on the hip of the subject and achieve an accuracy of 88.76% for discriminating different walking patterns.

3.5.3 Artificial Neural Networks

Jafari et al.[86] propose an artificial neural network based activity recognition system in order to determine the occurrence of falls. Their system works with single sensor placed onto the chest of the subjects and it achieves an accuracy of 84% for detecting falls. Yang et al.[42] adopt multilayer feedforward neural networks (FNNs) as activity classifiers and recognize 8 daily activities with an overall performance of 95%.

4 Discussion and Conclusion

In this paper, we surveyed the different approaches for activity recognition using inertial sensors, with a focus on applications from health care, well-being and sports. We first identified the main challenges and application directions, next we analyzed the related work according to the main steps of the activity recognition process: preprocessing, segmentation, feature extraction, dimensionality reduction, and classification.

As a general observation, we note that in almost all cases results reported in the literature are obtained by first gathering the sensory information on a central computer and then processing the data off-line. Performing activity recognition online and in a distributed manner (i.e. with each sensor having just a partial view of the overall situation) remains therefore an open research question.

However, distributed intelligence also creates new problems and these problems still remain unexplored. One of these problems is finding a way of reaching the best decision with minimum communication and power consumption. Similarly, finding a good way of doing distributed training and learning is still an open research question for distributed reasoning systems.

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