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Human Activity Recognition: Challenges and Process Stages

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ABSTRACT: With the wide range of applications in vision based intelligent systems, the attention of researchers in the computer vision field have attracted by image and video analysis technologies. Despite the diversity of computer vision researches, few literature reviews have been proposed to monitor people and recognize their activities. This paper focus in the literature reviews on the generic process stages of Human Activity Recognition (HAR) which include: data acquisition from the sensor, Preprocessing, Segmentation, Feature extraction and, training and classification. The challenges corresponding with activity recognition also will be listed.

KEYWORDS: Human activity recognition (HAR), Activity recognition process, Wearable sensors, Video sensors, Kinect, Preprocessing, Segmentation, Feature extraction, classification.

I. INTRODUCTION

Computer vision (CV) is one of the computer sciences fields. And it aims to build smart applications to understand the contents of images and videos as the human understanding. One of the main tasks of the CV are detection and recognition. Detection and recognition applications are various and used for different purposes. One of these purposes is to monitor people to recognize their physical activities.

Monitoring peoples to recognize their physical activities either if they are with or without disabilities to help them in carrying out their daily tasks or prevent emergencies is included under the core building block called Human Activity Recognition (HAR). And according to [1], HAR refers to "automatic recognition of physical activities". And it is an important area of computer vision and pattern recognition research and applications. And according to [2], the first works on human activity recognition (HAR) date back to the late ’90s.

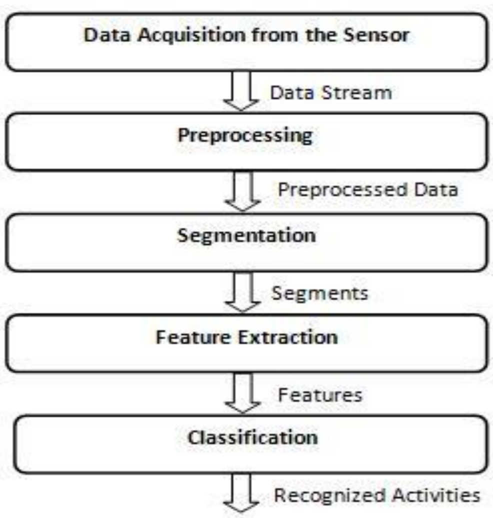

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Figure 1: Steps for Activity Recognition Process.

HAR is one of the most important research topics of computer vision. To design and evaluate any HAR system, we have to follow specific steps or stages for retrieving activity information from the sensor. These steps called Activity Recognition Process [3] (see Fig. 1). And it includes: data acquisition from the sensor, preprocessing, segmentation, feature extraction and, training and classification. And the performance of literature HAR methods has been affected by the chosen techniques of these steps. In any monitoring system, the performance will be affected by the sensor chosen as the start until classification the activities.

In this paper, we will present two basic sections corresponding with activity recognition. First, the challenges that face the activity recognition systems developers. Second, the studies that investigate each stage of the activity recognition process which any monitoring and recognition system will go through.

II. ACTIVITY RECOGNITION CHALLENGES

There are still many issues and challenges that motivate the development of new activity recognition techniques to improve the accuracy under more realistic conditions. Challenges corresponding with activity recognition have been discussed in researches [1-5]. A number of these challenges are:

•Human behavior: performing multiple tasks at the same time makes the recognition process more difficult [3–5].
•The definition of physical activities: develop a clear understanding of the definition of the activities under investigation and their specific characteristics [1].
•Intraclass variability: the same activity may be performed differently by different individuals [1].
•Intraclass similarity: classes that are fundamentally different, but that show very similar characteristics in the sensor data [1,5].
•Selection of attributes and sensors: the selection of the attributes to be measured and the sensors that measure it plays an important role in recognition performance [1, 2].
•Sensor inaccuracy: the sensor data play an important role in the overall recognition results [3].
•Sensor placement: the wrong placement or orientation of sensors could be causing a problem or effect the recognition performance [3, 4].
•Resource constraints: power consumption is the main factor affecting the size of the battery and sensor nodes (if using inertial sensor) [2–4].
•Usability: the systems should be easier to learn and more efficient to use [3].
•Privacy: sensitive user information should be not invading users' private life [3].
Subject sensitivity: The accuracy of activity recognition is heavily affected by the subjects participated in training and testing stages [4].
•Obtrusiveness: HAR systems should not require the user to wear many sensors nor interact too often with the application [2][4].
•Data collection: collection of training data under realistic conditions [1][2].
•Flexibility: the flexibility to support new users without the need of re-training the system [2][4].
•Processing: where the recognition task should be done, whether in the server or in the integration device [2].
•Tradeoffs in HAR: the tradeoff between accuracy, system latency, and processing power [1].
•Multiple residents: More than one resident can be present in the same environment [1].
And offcourse there is another challenges corresponding to the application domain itself, but we present the common and the most popular.

III. ACTIVITY RECOGNITION PROCESS

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Activity recognition process steps are different from research to another. Bulling et al. [1] used a general-purpose framework which called Activity Recognition Chain (ARC). This framework has specific stages which are data

Acquisition, signal preprocessing and segmentation, feature extraction and selection, training, and classification. While Avci et al. [3] survey applications of using inertial sensors under five main HAR steps: preprocessing and signal representation, segmentation, feature extraction, dimensionality reduction and classification. In other hand, Lara et al. [2] show the general structure of HAR, which contain only two main stages: training and testing (also called evaluation). Next, we will introduce the HAR process steps as ARC framework [1] which present in Fig 1. And we will introduce these steps in details and provide some of the most popular references and methods for each step.

3.1. Sensor Data Acquisition:
The sensor is the source that we need to collect data in the activity recognition systems [4]. So raw data are acquired using sensors. Different sensors produce different types of data. For example, data collected from most wearable sensors such as the accelerometer or gyroscope are in the form of time series, ambient sensors such as motion sensors produce numerical or categorical data, and cameras and thermographic devices record image/video data [6]. So Data acquisition varies from one sensor to multiple sensor and from one fixed camera to multiple cameras and moving cameras [5].
The types of these sensors are different and the classifications of it are various between articles [2]–[4]. However they are the same sensors at the end. Su et al. [4] classify the sensors in three basic categories: video sensors, environmental-based sensors and wearable sensors (smartphones sensors). While Avci et al. [3] and Lara et al. [2] classify them into only two categories. In [3], the sensors classes are vision and inertial sensors, but in [2] they approached external and wearable sensors as the two types of sensors used in HAR. Next, the most two types used in HAR: wearable and vision sensors will be presented.
Wearable sensors are the mobile sensors that are in small size and designed to be worn on the human body in daily activities. Most of the mobile sensors are equipped on smartphones [4]. Including accelerometers, GPS, light sensors, temperature sensors, gyroscope, barometer, etc. And these sensors were used in various systems [1], [7]–[14], to recognize different activities. Those systems are summarized in Table 1 (The abbreviations and acronyms are defined in Table A in the Appendix).

Table A: List of Abbreviations and Acronyms.

ACC	Accelerometers	**LR**	Logistic Regression
ADL	Activities of Daily Living	**LSM**	LibSVM classifier
AMB	Ambulation activities	**MAG**	Magnetometer
ANN	Artificial Neural Networks	**MLP**	MulitlayerPerceptron classifier
ARC	Activity Recognition Chain	**NB**	Naïve Bayes
BN	Bayesian Network classifier	**PHO**	Activities related to phone usage
CV	Computer Vision	**PT**	Playing Tennis
DA	Discriminative Analysis	**RFIS**	Recurrent Fuzzy Inference System
DT	Decision Tables	**SI**	Subject Independent
GMMs	Gaussian Mixture Models	**SMA**	Signal Magnitude Area
GYR	Gyroscope	**SVM**	Signal Vector Magnitude

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HAR	Human Activity Recognition	**SVM**	Support Vector Machine classifier
HMM	Hidden Markov Models	**SW**	sliding window
IB1	IB1 (KNN with K=1)	**TR**	Transitions between activities
IBL	Instance based learning	**UAV**	Unmanned Aerial Vehicle
JB	Joint Boosting classifier	**UB**	Upper body activities
KNN	K-nearest neighbor	**VS**	Vital sign sensors
LDA	Linear Discriminant Analysis	**WEKA**	Waikato Environment for Knowledge Analysis

Vision or video sensors are basically a camera, which is classified as an external sensor because it is attached to the fixed place or point. It is suitable for interactive application (e.g. as an input device without using the keyboard or mouse) and security applications (e.g. Crimes detections) [2]. The most important example to the vision sensors is Kinect camera [15–17], which is the one of its type and the one that we will use.
Kinect camera is providing full-body 3D motion capture, facial recognition, and voice recognition capabilities [18]. And this sensor was the main concern for several of researches [16]–[20]. Some researchers were explained the characteristics of Kinect [15], and how it is working [17]. And other focused on comparisons between it and other vision sensors [20]. While other contain both its work methods and comparison [17].
In work [18], the article shows the component of Kinect sensor. And how it works in skeletal tracking, head-pose and facial expression tracking, and teleimmersive conferencing. This article focuses on the vision aspect of the Kinect sensor. And in [17], the authors present a description of the Kinect camera device and the active technique that it uses to extract the 3D information from the scene.

Reference	Year	Execution	Activities	Sensors	Obtrusive	Learning
Bulling et al. [1]	2014		ADL (12), PT(3), NULL Class	3 ACC (upper arm, lower arm, wrist)	High	DA,NB, SVM, HMM, JB, KNN.
Shoaib et al. [7]	2012		AMB (7)	ACC, GYR and MAG, (4 phones)on (pocket, arm, belt, wrist)	High	WEKA (NB, LSM,MLP,LR,IB1, DT,J48)
Khan et al. [8]	2010		AMB, TR (15)	ACC(chest)	Medium	ANN
Lara et al. [9]	2011		AMB (5)	ACC and VS (chest)	Medium	ALR, Bagging, C4.5, NB, BN
Vinh et al. [10]	2011		AMB, ADL (21)	ACC (wrist, hip)	Medium	SMCRF
Cheng et al. [11]	2010		UB (11)	Electrodes (neck)	High	LDA
Lara et al. [12]	2012		AMB (3)	ACC and VS (chest)	Medium	C4.5

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Berchtold et al. [13]	2010		AMB, PHO	ACC (phone)	Low	RFIS
Riboni et al. [14]	2011		AMB, ADL (10)	ACC (watch, phone), GPS	Low	COSAR

Then, they provide multiple applications which use the Kinect sensor in the fields of Unmanned Aerial Vehicle (UAV), ground robot and medical. Wu et al. [17] show as a result of their comparison, that the Kinect has been yet the first camera which combines the RGB color camera with structure-light depth camera into one single camera. And in comparing to RGB cameras, they show that the Kinect is the highest resolution of an off-the-shelf RGB camera and it is lenses are more accurate than a typical webcam. And in comparing to laser scanner, they show that the Kinect is a real-time sensor which running on 30Hz and it does not need to scan the scene row-by-row or column-by column to extract the 3D information like a laser scanner to get the depth. And it is also safer to use in human because it is using type 2 infrared light. Not like most of the laser scanners which use the type 1 laser which is dangerous to eyes. Finally, they list other of it is advantages and disadvantages.

Depending on Kinect characteristics [15], and advantages [17], Kinect camera was very useful in various works especially in human-machine interaction for human gesture recognition. Gesture recognition allows people to interact with machines in a natural way without the use of I/O devices.

Works [16] and [19] provide different techniques for different gesture recognition using Kinect sensor and the first used also its SDK and toolkits. In 2011, Biswas et al. [19] propose a mechanism to recognize eight of hands and head gestures (e.g. Clap, Call, Greet, Wave, No, Yes, Clasp, Rest). And the training data were created with five subjects. While in 2014, Giuroiu et al. [16] came with a more general system that can be recognize each kind of dynamic and static gestures a person can make. And only two subjects create the training data, but every value used as input is normalized so the system works regardless of the body size and shape. Those important works summarized in Table 2 (The abbreviations and acronyms are defined in Table A in the Appendix).

Table 2. Summary of Gesture Recognition Systems using Kinect.

Reference	Year	Activities	Sensors	Obtrusive	Flexibility	Subjects	Classifiers
Giuroiu et al. [16]	2015	Dynamic and Static gestures	v.1 Kinect, SDK	Low	SI	2	DTW, Bayesian
Biswas et al. [19]	2011	Hand and Head (8)	Kinect	Low	SI	5	SVM

3.2. Pre-processing:

The Preprocessing or signal representation is the second stage of ARC. We do it after we collect the data from sensors and before we make any other calculations. The purposes of preprocessing the data is and to prepare the acquired data for feature extraction [1]. It's different, but most of systems use it to reduce the noise from the users [7], or the sensors themselves [4].

The work [19] proposes a mechanism to recognize eight of hands and head gestures by using Kinect sensor. They start with preprocessing step which used after Kinect depth camera produce depth image that represent the subject. They remove the background by using auto thresholding on the depth histogram. After that, using histogram equalization to detect the position of hand with respect to the rest of the body. While in work [7], evaluate and compare the role of three smartphone sensors. Four smartphones attached to the participant body. Preprocessing was done in two stages. First to remove the noise caused by removing the smartphones from the participants after they perform the activities to

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stop them. Second to add the four dimension called magnitude for each sensor, i.e., (x, y, z, magnitude) because the magnitude is orientation-insensitive unlike other three axis of an accelerometer and a gyroscope.

The method for data representation must choose carefully because it will affect the performance and accuracy of the system.

3.3. Segmentation:

The segmentation is the third stage of human activity recognition. And some research, such as [7], assume this stage as a part of preprocessing stage. This stage identifies segments of the preprocessed data streams which likely to contain information about activities. Also called activity detection or spotting [1].

Retrieving useful information from continuous streams of sensor data is a difficult issue for continuous activity and motion recognition [3].And for this purpose we have used segmentation methods like Sliding Window (SW) [1], [3], [7], energy-based segmentation, rest-position segmentation, additional sensors and contextual Sources [1], top-down, bottom-up segmentation, Sliding Window and Bottom-Up (SWAB) [3].

SW is the most popular segmentation method. And have been used in various activity systems. In this method, extract a data segment by moving a window over the time series data to use these segments in the other ARC stages. But the size or length of this window ( ) is affecting the accuracy of the recognition [1]. Bulling et al. [1] and Shoaib et al. [7], both using wearable sensors and SW segmentation in their systems. System in [3] was to recognize twelve of Activities of Daily Living (ADL). While the system in [14] was to recognize seven of ambulation activities. Yes, they both using window segmentation. But they choose different W_S. In work [1], they try different values of which is = 0.1,0.25,0.5,1,2,3,4,5,6,7,8s. They find that increasing leads to a decrease of recall. And they also find that precision reaches a maximum at =1s. And that was the value they used in their system. But in [7], they used =2s based on previous studies such as [11] and others.

However, having short windows may enhance the feature extraction performance, but would have higher overhead due to the recognition algorithm being triggered more frequently. Besides, short time windows may not provide sufficient information to fully describe the activity performed. On the other hand, if having too long windows, there might be more than one activity within a single time window [2]. And information on activity segments is very useful in a lot of purpose like classification and when no activity is sensed, it's useful to turn off the ARC to save power [1].

3.4. Feature Extraction:

This feature extraction stage also called selection stage. The purpose of this stage is reduced the signals into features that are discriminating for the activities [1]. Avci et al. [3] define feature extraction as the conversion of big input data into a reduced representation set of features, which can also be referred as feature vectors. The feature vector used for distinguishing different activities and then features used as inputs to classification algorithms. Features may be derived based on expert knowledge or automatically calculated.

The features in activity recognition are different and wide. Research [1], [3], [4], introduce the most popular features that used in activity recognition. Bulling et al. [1] classify features in four categories: signal-based features, body model features, event-based features and multilevel features. Avci et al. [3] classify features in five categories: time-domain features, frequency-domain features, time-frequency domain features, Heuristic features and domain specific features. For feature computation in Su et al. [4], they extract feature in both time and frequency domain. Time-domain features such as mean, max, min, correlation and SMA. Frequency-domain features such as energy, entropy, time between peak and binned distribution.

The feature space is the total numbers of extracting features from the data. In the feature space, the more clearly the ability of separated each activity, the higher recognition accuracy or performance can be achieved. A large number of features may improve recognition performance but also increases computational complexity. In the real time systems, we should use the minimum number of features that give us accurate activity recognition because we need to achieve goals like minimize memory, computational power, and bandwidth requirements [1]. If less features are concerned in the classification process, less memory and computational effort are needed to do the classification. So to increase

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accuracy and reduce computational effort we used a sub-stage called dimensionality reduction. For this sub-stage, two general forms of dimensionality reduction be existent: feature selection and feature transform [3].

3.5. Training and Classification

The models need to be trained before operating. Training is performed using training data with feature vectors. The selected features that create feature sets are used as inputs for the classification and recognition methods [3]. And the classification stage performs two separate stages. In the first stage using a trained model, each feature vector is referred to a set of class labels with corresponding scores. In a second stage, the calculated scores can be used by the end application to make a decision whether to trust the system's output [1].

Classifiers, which also called learning approaches are different and reviewed in many research [1]–[4]. Lara et al. [2] cover learning approaches in terms of supervised and semisupervised learning. Avci et al. [3] presented three methods of Classification: Threshold-Based Techniques, Pattern Recognition Techniques and Artificial Neural Networks (ANN). In [4], they review popular classifiers whether it is Base-level classifiers or Meta-level classifiers. The rest of the classifiers with the references of the studies that use them can be shown in the Table 3.

Table 3: Summary of the Classifiers with their References.

Classifiers	References
Decision Tree (DT)	[2]–[4], [10], [13]
Decision Tables	[3], [4]
Bayesian	[1]–[3], [10]
k-Nearest Neighbors (KNN)	[1], [3], [4]
Artificial Neural Networks (ANN)	[3], [9]
Support Vector Machines (SVM)	[1]–[4], [19]
Hidden Markov Models (HMM)	[3], [4], [7]
Instance based learning (IBL)	[2]
Gaussian Mixture Models (GMMs)	[3]
Discriminative Analysis (DA)	[1]
Joint Boosting (JB)	[1]
Classifier ensembles	[2], [10]
Weka Toolkit	[4], [7]

There are some facts about some classifiers such as C4.5 classifier (DT) generates models easy to understand by humans which make it the most widely used decision tree classifier. And the high cost in terms of computation and storage, makes IBL models not convenient to be implemented in a mobile device because each new instance to be classified needs to be compared to the entire training set. Also the topology construction issue in Bayesian Networks, as it is necessary to make assumptions about the independence among features. Finally, the high computational cost and the need for large amount of training data are two common drawbacks of neural networks [2]. The NB Classifier suited when the dimensionality of the inputs is high. Despite the simplified assumptions, in many complex real situations NB performs very well. The big advantage of this type of classification is that it can use very little training data to estimate the parameters [14]. And finally, the selected classifier is an important factor which affects the recognition performance [7].

IV. Conclusion

As we have seen above, we present some latest and important works on HAR in general and process stages in specific. We present all the five stages of the HAR process which any monitoring system should go through in details and its literature studies. We also present a list of the challenges that any activity recognition systems developer should take care about and put it into consideration.

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We see how the chosen sensor or approach changes the performance and results. And how different sensors produce different types of data. Chosen of the sensor always depending on the application and it is objectives. And chosen the approach depending on the developer and how he want his system to work.

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