A Survey on Human Activity Recognition based on Temporal Signals of Portable Inertial Sensors

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Related Work

Sensors locations and count are very important issues that have to be taken into consideration while designing an accelerometer-based HAR system. As seen in Table 1, many settings have been studied through the previous work.

-Several kinds of activities have been considered by HAR systems. These include: ambulation activities, daily activities, fitness activities, and industrial activities. However, most of the studied HAR systems concentrate on ambulation activities as shown in Table 2.

- to measure the similarity between acceleration time series, preprocessing have to be applied first to extract more informative features which can substitute the raw data. Table 3 summarizes the selected features for our related work.

Table 1

Reference	Used Sensors A	M	G	No. of Sensors	Sensors Location	Sampling Rate (HZ)	Learning Method/Algorithm	No. of Activities	Accuracy (%)
[29]	X			2	Hip left and right sides	256	Multilayer perceptron	4	90
[27]	X		X	2	Waist, front trouser pocket	5	Threshold-based	5	86.7
[36]	X			1	Waist	50	Multiple classifiers	8	84
[19]	X			1	Waist	45	Threshold-based	12	90.8
[31]	X			6	Wrist, waist, necklace, trouser pocket, shirt pocket, bag	50	Decision Trees Naive-Bayes	6	88
[18]	X			12	Ankles, knees, elbows,shoulders, wrists, hip left and right sides	92	Multiple Eigenspaces combined with SVM	8	88.3
[17]	X			1	different locations (clothes pocket, waist belt,and trouser pocket)	100	SVM	4	97.21
[37]	X			1	Waist	14	Multilayer perceptron	9	95.5
[11]	X			1	Chest	50	Threshold-based	3	81.25
[23]	X			3	Hip, dominant ankle, non-dominant thigh	50	AdaBoost, SVM, RLogReg	7	88.2
[16]	X			1	Trouser pocket	100	SVM	4	97.5
[47]	X			2	Foot, waist	150	Feed forwarn NN, HMM	4	89.7
[22]	X			1	Wrist	100	KNN	5	92.2
[46]	X			1	Waist	1	SVM	6	82.8
[20]	X			1	Chest	20	Feed-forwarn NN	15	97.9
[24]	X			1	Trouser pocket	20	Decision trees (J48), logistic regression, neural network	6	91.7
[28]	X			1	Thigh	250	SVM	5	99
[9]	X			1	Wrist	33	C4.5, neural network	5	94.1
[13]	X		X	9	Wrists, arms, thighs, ankles, waist	50	Hierarchical clustering, K-means, decision trees	25	93.3
[48]	X			1	Right thigh	20	Feed Forwarn NN, HMM	8	85
[25]	X			1	Chest	50	C4.5	3	92.6
[43]	X			1	Waist	100,50, 16,5	J48 adaptive decision tree	10	87
[33]	X			1	Torso	40	Threshold-based	6	100
[10]	X			2	Dominant wrist, ankle	30	K-NN probabilistic neural network	7	96
[42]	X		X	7	Waist, wrists, right arm, left thigh, ankles	30	Bayesian Sparse representation-Based	14	87.7
[3]	X			1	Waist	50	MC-HF-SVM	6	89
[45]	X		X	1	Waist	100	K-NN, naive Bayes, SVM	9	95.2
[2]	X			1	Waist	80	Stochastic Approximation classifier	2	94.5
[38]	X			3	Chest, right thigh,left ankle	25	HMM	12	91.4
[8]	X			1	Right wrist	32	GMM, GMR	8	68.7
[39]	X			1	Trouser pocket	1	Hierarchical-SVM	4	98.5
[4]	X			1	Trouser pocket	20	KNN	6	99.4
[14]	X			2	Abdomen,right thigh	50	Threshold-based, Random Forest	4	98.85
[32]	X	X	X	1	Right shoe	100	KNN	20	77
[6]	X			3	Wrist, chest, foot	100	Neural network	14	89.7
[7]	X		X	3	Chest, left crus, right thigh	50	Neuro-fuzzy classifier	7	97.2
[40]	X			1	Back mounted	50	KNN	5	95.6
[21]	X			1	Wrist	32	Neural network	7	91
[30]	X			1	Wrist	20	Template-matching-based	22	80
[41]	X			3	Chest,dominant wrist, dominant ankle	100	Back propagation neural network	12	93.7
[15]	X		X	1	dominant wrist	50	Random forests	14	80
[5]	X		X	1	dominant wrist	50	LSTM	31	97

Introduction

-A wide range of computer applications depend mainly on human activity recognition (HAR) in their work such as monitoring patients and elderly people, surveillance systems, robots learning and cooperating, and military applications.

-The idea of automatic HAR system depends on collecting measurements from some appropriate sensors which are affected by selected human motion attributes. Then, depending on these measurements, some features are extracted to be used in the process of training activity models, which in turn will be used to recognize these activities later

-Based on the data acquisition paradigm, HAR systems can be divided into two categories: surrounding fixed-sensor systems and wearable mobile-sensor systems.

-During the recent few years, there has been a tremendous evolution in the manufacturing of mobile devices. Particularly mobile phones, tablet PCs, and smart watches.

-Smart phones have also become more and more popular. Recent statistics show that the total number of smartphone subscribers reached 3:9 billion in 2016 and is expected to reach 6:8 billion by 2022 [1].

-Therefore, the disadvantages of wearable mobile-sensors of being intrusive, uncomfortable, and annoying have vanished to a great extent, making this method of on-board sensing from smart devices very suitable for HAR data acquisition.

-Among all wearable sensors, accelerometers are considered as the most used sensors in HAR systems [12].

-Being small-sized, inexpensive, and embedded in most of smart mobile devices has encouraged many researchers to use acceleration in their work

-Compared to cameras, accelerometers are more suitable for HAR systems, it is very difficult to fix a camera to monitor a user everywhere;

Conclusion

- A review of HAR systems which uses temporal signals generated from portable inertial sensors has been introduced. Types of HAR systems according to data acquisition paradigms, types of attributes, and sensors' types, counts and locations have been presented. Moreover, various machine learning algorithms which are used with HAR systems have been stated. Finally, some important related proposed systems are illustrated.

Table 2

Ref.	Walking	Stairs (Up/Down)	Sitting	Standing	Running	Lying	Jumbing	Other
[29]	X	X						X
[27]	X	X	X	X				
[36]	X	X		X	X			X
[19]	X		X	X		X		X
[31]	X	X	X	X	X			
[18]	X	X	X	X				X
[17]	X				X		X	X
[37]	X		X	X	X	X		X
[11]	X				X			X
[23]	X	X	X	X	X	X		X
[16]	X				X		X	X
[47]	X	X			X			
[22]								X
[46]	X		X	X		X		X
[20]	X	X	X	X	X	X		X
[24]	X	X	X	X	X			
[28]	X		X	X	X			X
[9]	X		X	X	X	X		
[13]	X	X	X	X		X	X	X
[48]	X		X	X		X		X
[25]	X		X		X			
[43]	X	X	X	X				X
[33]	X	X				X		
[10]	X	X	X	X	X			X
[42]	X		X	X		X	X	X
[3]	X	X	X	X		X		
[45]	X	X	X	X	X		X	
[2]	X				X			
[38]	X	X	X	X		X		
[8]	X	X	X	X				X
[39]	X		X	X	X			
[4]	X	X	X	X	X			
[14]			X			X		X
[32]	X				X			X
[6]	X	X	X	X	X	X	X	X
[7]	X	X	X	X	X	X		
[40]	X				X		X	X
[21]	X	X	X	X				X
[30]	X				X			X
[41]	X	X	X	X	X	X		X
[15]	X	X	X	X		X		X
[5]	X	X	X	X	X			X

Table 3

Ref.	Time Domain: Mean	Standard Deviation	Correlation	Variance	RMS	Mean Crossing Rate	Zero Crossing Rate	Normalized Signal Magnitude Area (SMA).	Interquartile Range	Minimum	Maximum	Median	Frequency Domain: Energy	Entropy	Other
[29]															X
[27]		X													X
[36]	X	X	X										X		
[19]								X							X
[31]	X	X		X	X	X	X								X
[18]	X			X											
[17]															X
[37]															Raw data
[11]	X							X							
[23]	X		X	X									X	X	
[16]															X
[47]	X														
[22]	X	X	X							X	X	X			X
[46]										X	X				
[20]	X	X	X					X							
[24]	X	X													X
[28]	X			X					X			X			X
[9]	X	X	X	X						X			X	X	X
[13]	X	X			X										X
[48]	X			X											
[25]	X	X	X	X	X								X		X
[43]	X			X									X	X	X
[33]	X										X				X
[10]		X											X	X	X
[42]	X	X	X	X	X	X	X		X			X			X
[3]	X	X	X					X						X	
[45]	X	X	X	X	X	X	X	X				X	X	X	X
[2]	X	X	X	X	X	X	X		X			X			X
[38]															Raw data
[8]															Raw data
[39]					X										X
[4]	X	X	X		X			X	X	X	X	X		X	X
[14]															X
[32]	X														
[6]	X	X										X	X	X	X
[7]	X	X					X					X	X	X	X
[40]															X
[21]	X			X		X									X
[30]	X			X	X					X	X		X	X	
[41]															X
[15]			X												
[5]													X		X

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