Latest Trends in Human Activity Recognition and Behavioral Analysis using Different Types of Sensors

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Abstract*— *Human behavioral analysis (HBA) is an active area of research centered on analyzing the principles of physical and psychological human behavior. Activity recognition using sensors is already implemented through wearable devices and smartphones, while many studies are being carried out to further improve and strengthen the accuracy and precision of data gathered from different type of sensors. One of the biggest potential large-scale implementations of HBA could be more self-adaptive smart homes. The aim of this paper is to summarize 20 papers from the past 5 years (2013-2018). These papers used a spectrum of sensors to further improve human activity recognition (HAR) performance, while some try to bridge the gap between physical and psychological recognition (HBA). Results demonstrated that the smartphone is the most used device for the potential increase in the accuracy of behavior classifications. Additionally, accelerometers and gyro-scopes are the most common choice of sensors for tracking human activities.

***Index Terms*— Human Activity Recognition, Human Behavioral Analysis, Emotion Recognition, Activity Sensors**

I. INTRODUCTION

An activity sensor is essentially a device that detects and tracks physical movements, while recording and often responding to the input i.e. movements in a set form. Human activity recognition (HAR) utilizes various sensors such as accelerometers [2], gyroscopes [19], heart rate monitors [14] with novel machine learning techniques to transform low-level collected data and provide rich contextual information in a real-life application. HAR has a plethora of implementations and benefits in various everyday situations, i.e. fitness, healthcare, smart homes being some of the most common uses today [3]. While human activity recognition focuses more on motion and physical movements, HBA goes further in depth to bridge a relation between physical movements and psychological states. HBA aims to incorporate physical movements observed by sensors and use them to analyze the subject's emotions at the given time. Jekauc and Brand [8] stated that while there have been studies carried out to hypothesize the relation between affective states and physical activity, not enough evidence has been gathered for the relation to become a research focal point as yet. In this area, various studies are emerging to gather stronger evidence on the correlation as well as new techniques to utilize the link to introduce smarter systems using activity recognition devices. One such study carried out by Quiroz, Yong and Geangu [18], makes use of data collected from smartwatch accelerometers to predict a user's emotion based on their gait tracked via smartwatches. Similarly, Kanjo, Younis and Sherkat [11] present the first attempt at fusing and modeling data from environmental and physiological sources collected from sensors in a real-world setting. While Kakarla and Reddy [10] focus on facial recognition for emotion detection.

HAR on the other hand has been a major focal point of research, however it is still a controversial topic due to the diverse qualities of human activities and their tracking methods [7]. Currently, the most common choice of sensors for activity recognition are smartphone accelerometers and gyroscopes. However, Chen, Zhu, Soh and Zhang [3], raised the issue of a degradation in accuracy of activity recognition data due to the flexibility of smartphone us-age. On a similar note, Murao, Mogari, Terada, and Tsukamoto [15] noted that while thorough research has been carried out to observe and gather the best sensor(s) placement, not enough consideration is given toward device or sensor wearability.

This paper reviews different types of sensors, datasets, classification and analysis methods applied in human activity detection. The main contribution of this study is detailed evaluation and analysis of recent research articles in activity detection and behavioral analysis using sensors. The aim is to analyze the current implementations addressed by the research articles as well as the out-comes of each of the papers in relation to the issues raised by them.

The rest of this paper is organized as follows: Section II presents details the review approach and flow adaptation. Section III provides a tabular summarization followed by discussion on the visualization from the evaluated papers. And finally, Section IV concludes the paper.

II. REVIEW METHOD

The review process of this paper covers publications from 2013 until 2018. The main flow of the review process was adopted from the study of Pak and Teh [17]. There are 20 evaluated articles from peer-reviewed journals and conferences. The detailed evaluation of these articles is in Section III. A column by column breakdown is presented below in Table 1, in order to make the evaluation clear. The first column indicates the reference of the articles. The next column is the publication year of the evaluated articles. The following column covers the description of the evaluated article. Each study applies different classification or analysis methods, for instance Support Vector Machines, Neural Network model, Random Forest etc. To detail this, the fourth column represents the analysis method or classifier evaluated in the respective study. The next column includes the type of sensor the respective researchers used in their study. The second last column covers the type of device used in their study. Lastly, the seventh column represents the dataset used in the evaluated papers.

III. RESULTS

Table 1: Summarization of Evaluated Research Articles

Ref	Year	Description	Classification or Analysis Method	Type of Sensor	Type of Devices	Dataset
[22]	2013	Hidden Markov Model (Hmm) based Tri-training algorithm in human activity recognition with smartphone	HMM based Tri-training algorithm	Smartphone- tri-axial accelerometer	Smartphone-android	Collected data
[15]	2013	Evaluation function of sensor position for activity recognition considering wearability	Activity recognition algorithm	3-axis wireless accelerometers	Wearable sensor	Collected data
[12]	2013	Sensor-embedded teeth for oral activity recognition	C4.5 Decision Three (DT) Multivariate Logistic Regression (MLR) Support Vector Machine (SVM)	Tri-axial accelerometer	Oral sensory unit	Collected data
[23]	2014	Wearable sensor-based human activity recognition from environmental background sounds	Haar-like sound feature with hidden Markov model (HMM)	Power-aware sensor node consisting of embedded sound acceleration, IR sensor Other sensors with a size of an ID card	Wearable device	Collected data
[10]	2014	A real time facial emotion recognition using depth sensor and interfacing with second life based virtual 3d avatar	Facial Action Code Systems (FACS) and Facial Animated Parameters (FAP)	Kinect depth sensor	Kinect camera	N/A
[5]	2014	Recognizing Human Activities from Smartphone Sensor Signals	Support Vector Machines J48 decision trees Random forests	Accelerometer Gyroscope Microphone	Smartphone	Collected data
[24]	2015	Smartphone-based human activity recognition in buildings using Locality-constrained Linear Coding (LLC)	Support Vector Machines (SVM) KNN Kernel-Extreme Learning Machine Sparse Representation Classifier	Smartphones-accelerometer Gyroscope	Smartphone	Collected dataset
[19]	2015	Devices are different: assessing and mitigating mobile sensing heterogeneities for activity recognition	C4.5 trees SVMs k-NN learners random forests	Accelerometer Gyroscopes	Smartphone (Android and iOS) Smartwatch Tablet	Collected dataset
[9]	2015	Human activity recognition using wearable sensors by deep convolutional neural networks	Deep Convolutional Neural Networks	Accelerometers Gyroscopes	Smartphone Smartwatche s Sport bracelets	Three public datasets: UCI USC SHO

[13]	2015	Recognizing lifestyle activities of diabetic patients with a smartphone	Classifiers trained with machine learning	Smartphone microphone Wi-Fi signal-location GPS receiver Accelerometer Respiration-rate	Smartphone	Collected dataset
[1]	2016	Multi-modal audio, video and physiological sensor learning for continuous emotion prediction	SVM Baseline Neural network model Convolutional Neural Network	Physiological sensor modalities	Audio recording and video devices	Remote Collaborative and Affective Interactions (RECOLA) database
[6]	2016	HASC-PAC2016: large scale human pedestrian activity corpus and its baseline recognition	Baseline	Accelerometer Gyroscope Magnetometer Location Barometric pressure Proximity Wi-Fi	Smartphone	ASC corpora HASC-IPSC
[21]	2016	Performance Evaluation of Classifiers on WISDM Dataset for Human Activity Recognition	Machine learning classifier algorithms (LibSVM, J48 and Random Forest decision tree algorithms IBK instance-based J-RIP rule induction Bagging and Logistic Regression)	Accelerometer	Smartphone	Dataset WISDM group
[2]	2017	Performance analysis of smartphone-sensor behavior for human activity recognition.	Nearest Neighbors (NN) Random Forests SVM	Accelerometer Gyroscope	Smartphone	Collected dataset
[16]	2017	Classification of human activity based on smartphone inertial sensor using support vector machine.	Multiclass SVM linear kernel Polynomial kernel	Smartphone on the waist	Smartphone	Collected dataset UCI Machine Learning Respiratory
[3]	2017	Robust human activity recognition using smartphone sensors via coordinate transformation and principal component analysis and online SVM	SVM NN KNN Decision tree (DT)	Smartphone placed in pants' pocket, shirt's pocket, and backpack	Smartphone-android	Collected dataset
[20]	2017	Human activities recognition in android smartphone using Support Vector Machine	SVM	Smartphone-acceleration Gyroscope Accelerometer	Smartphone-android	Collected dataset
[4]	2017	Full model for sensors placement and activities recognition	Feature selection technique	Six-axis accelerometer/gyroscop e	Wearable sensor	Collected dataset
[14]	2017	Convolutional neuronal networks-based sensor fusion techniques for multimodal human activity recognition	Deep learning method Random Forest (RF)	Heart rate monitor Wrist sensor	Wearable devices	Real-world multimodal dataset (PAMAP2)
[11]	2018	Towards unravelling the relationship between on-body, environmental and emotion data using sensor information fusion approach	Statistical correlation, covariance and multiple regression analysis SVM Random Forest (RF) KNN Naive Bayes (NB)	On-body and mobile multi- sensors (Heart Rate Body Temperature Breathing Motion Electrodermal Activity EEG Headsets Muscle contraction Blood Volume pulse)	Microsoft band Android phone	Collected data

Table 1 above briefly summarizes and organizes the 20 articles evaluated in the area of Human Activity Recognition and Human Behavioral Analysis. Moving to a more detailed discussion, we look at the different types of sensors, methods and devices used in the studies as well as some of the limitations or drawbacks raised and/or addressed by the respective studies.

While HAR is a major research focal point, there is still a common limitation of degradation or lack of accuracy and precision in readings. Chen, Zhu, Soh, and Zhang [3] note that while sensors embedded within smartphones are a less intrusive and more convenient choice of device for HAR data collection, their flexibility of use enables degradation in recognition accuracy due to orientation, placement, and subject variations. To tackle this issue, they proposed a more robust HAR system which takes the respective factors into account. They present an online independent support vector, which utilizes principal component analysis (CT-PCA) to rule out the effect of orientation variations, thus improving the accuracy of activity recognition. In a similar earlier study, Zhu, Chen, and Soh [24] stated that most of the activity recognition data collected via smartphones did not take feature selection into account, directly feeding features from both the time and frequency domains to the machine learning algorithms. This oversight results in a decrease in accuracy of system performance. Addressing this issue, they propose a Locality-constrained Linear Coding (LLC) feature selection approach to increase HAR performance. Experiments showed an improved accuracy of around 90% with the LLC approach as a result of a more efficient dictionary for feature representation and gyroscope signals. Xie and Wu [22] introduce a Hidden Markov Model (HMM) based tri-algorithm using tri-axial smartphone accelerometer data to explicitly reduce the amount of noise introduction into classifier groups and make the output state stream connect more smoothly by getting rid of unlabeled and abnormal samples in the training dataset. Also taking the HMM approach, Zhan and Kuroda [23] to introduce a novel low-level calculation one-dimensional (1-D) Haar-like sound feature with Hidden Markov Model to recognize background environmental sounds. This approach was introduced to address the limitations of sound recognition algorithms (SRA) i.e. limited resources and the power consumption requirement. The proposed method showed an accuracy of 96.9% when tested with 22 regular environmental sounds applicable to daily activities. Currently this method outperforms similar commonly used SRAs with respect to both, the accuracy and the power consumption.

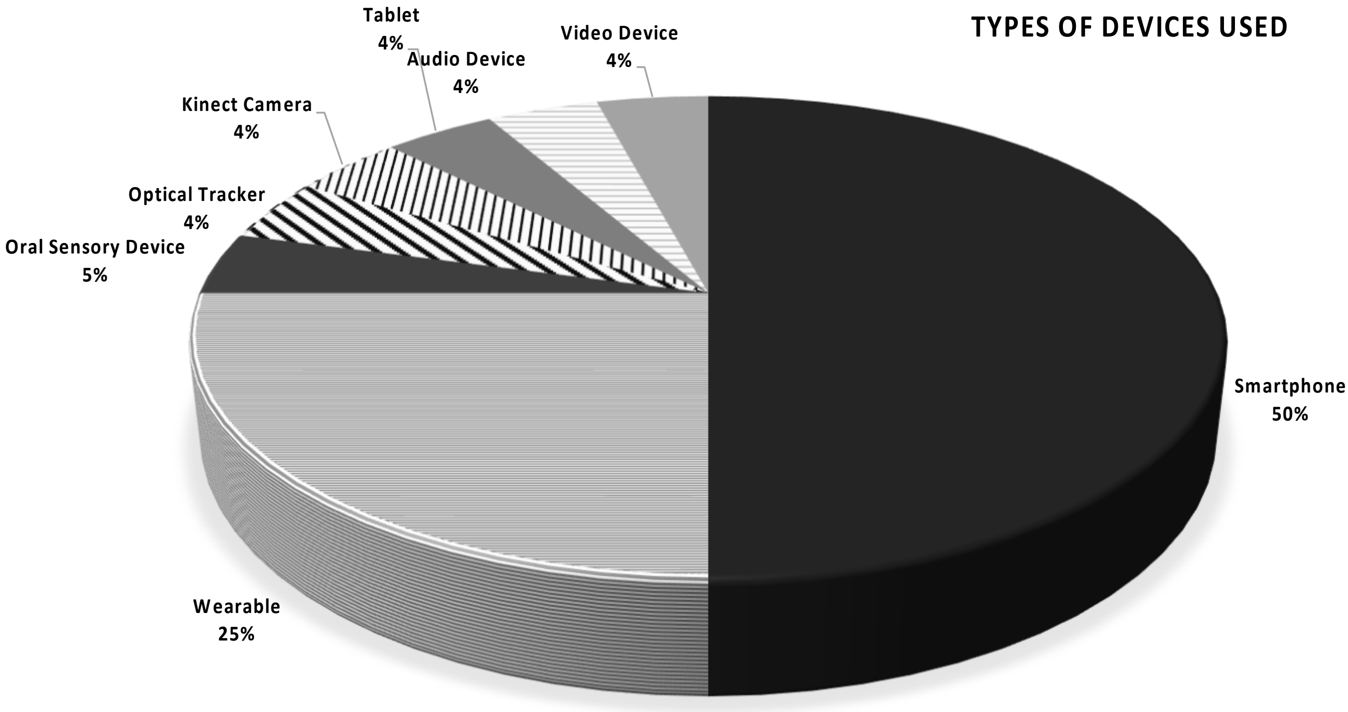

Fig. 1: Types of devices used (%)

The figure above (Fig. 1), illustrates a summary of all the devices that have been used in the evaluated research articles. As can be seen, smartphones and wearables are two of the most common choice of device. The accelerometer and gyroscope found in smartphones and wearables are thus, two of the most common type of sensors being used in HAR research. That being said, when various sensors are deployed through multiple devices, the performance accuracy of HAR systems is vastly diminished due to discrepancies in training, device hardware and operating system features [19]. The study evaluated 13 device models from different manufacturers with nine users and various common classification techniques to determine the effect of on-device sensors and sensor handling heterogeneities on HAR performance. The study showed that on-device sensors and sensor handling heterogeneities significantly hinder HAR performance with an added effect on the results, depending on variations in devices and types of techniques used. They proposed and tested mitigation techniques such as preprocessing to decrease in heterogeneity-caused losses in accuracy. One such technique proposed was the clustering of devices based on their heterogeneity properties, allowing classifiers to train on specific device clusters. Murao, Mogari, Terada and Tsukamoto [15] raised the fact that although thorough research is being carried out to determine the most suited sensor placement for context aware systems, not enough consideration is giving toward device wearability and user comfort. Hence the paper proposed an evaluation function that rates sensor placement taking into account its accuracy and wearability through 20 sensors placed on the test subject's body with 30 variations of physical activity, mostly being exercises such as yoga and weight training. Through survey questionnaires, the study resulted in finding the best sensor combination whose wearability meets the accuracy tolerance indicated by the test subject. Addressing the challenges of smartphone variety as well as overall accuracy of in-built device sensors, Chen and Shen proposed an HAR system with a higher recognition accuracy. They presented three classification models, one personalized model and two generalized models to evaluate activity recognition performance from smartphone motion sensors. They tested their approach of 27,681 samples with various multi-class classifiers (RF, SVM - linear kernel, SVM RBF kernel and k Nearest Neighbor), concluding that the approach resulted in improvements of the accuracy in sensor-based activity recognition. The performance was tested on different variations of smartphone placements, user spaces, and involvement of sensors. The personalized model reached an F-score of 95.95% while the generalized models reached an F-score of 96.26%.

Further on classifier performance, Walse, Dharaskar and Thakare [21] use the WISDM HAR public domain dataset to evaluate various machine learning classifiers to prove the efficiency of smartphone collected activity data in determining daily activities despite the device being in the user's pocket. They observed that with the correct classifier, the recognition accuracy for most activities can be as high as 96%. Other researchers on this area carried out experiments using the Multilayer Perceptron classifier (MLP) and Random Forest (RF) classifiers, resulting in a 91.7% accuracy for MLP and 75.9% for the RF classifier. In comparison, the results of the study in this case had a much higher accuracy of 98.09% using the RF classifier with activities also being classified much faster. Jiang and Yin [9] make use of Deep Convolutional Neural Networks (DCNN) to achieve improved recognition accuracy with a low computational cost by using novel activity images as the inputs for the DCNN. The DCNN is designed to study low-level to high-level features from the activity image leading to activity recognition. The proposed method was tested on three public domain datasets and showed to have outperformed state-of-the-arts in terms of recognition accuracy and computational cost. Münzner, Schmidt, Reiss, Hanselmann, Stiefelhagen and Dürichen [14] use CNN's on real-world multimodal datasets (RBK and PAMAP2) to determine whether data specific normalization is necessary, how to ideally fuse multimodal sensor data and how dependent the efficiency of some current HAR approaches is on their training dataset. The study showed that sensor specific normalization is necessary for increased recognition accuracy. They presented a novel method for pressure focused normalization with showed to have increased the F1 score by approximately 4.5% when tested on the RBK dataset. They also found that the CNN based on a shared filter approach had a lower dependency on readily usable training data in comparison to other fusion approaches. Nurhanim, Elamvazuthi, Izhar and Ganesan [16] study the performance of different classification kernels of the SVM for classifying various daily activities. Test subjects performed various physical activities such as sitting, climbing stairs, and laying down which were tracked and measured using inertial sensor signals. The collected data was processed using signal processing methods and multiple features of time and frequency domain. The selected classification techniques were evaluated on the following performance criteria: precision, recall, and correct accuracy classification rate percentages using 10-fold validation. Their proposed One Versus All Multiclass Support Vector Machine (OVA MC-SVM) Polynomial kernel method provided the highest classification performance of 98.57%. Also making use of SVM, Tran and Phan [20] presented a completed system which covers feature extraction, data acquisition, training and recognition of human activity, with some limitations such as low recognition percentage for certain activities. The accuracy of their system is dependent on feature selection and model training quality. The Android system was tested with 248 features, with a result of 89.59% recognition accuracy. Ichino, Kaji, Sakurada, Hiroi and Kawaguchi [6] mention that current research utilizes a rather small number of test subject data, mostly created within a test lab. To address this current obstacle, they held the HASC Challenge to collect activity recognition data over a span of 5 years. The data collected consisted of indoor pedestrian data with an equal ratio of age and gender. To aid in HAR research and accuracy optimization studies they combined the challenge data into a publicly available single corpus (HASC-PAC2016).

Luštrek, Cvetkovic, Mirchevska, Kafali, Romero, and Stathis [13] make use of smartphones to aid in better tracking of daily lifestyle activities of diabetes patients, which could be beneficial for physicians as well the patients themselves. The proposed approach consisted of three steps as follows, first, GPS data was collected from the smartphone as well as Wi-Fi coordinates and accelerometer data. Following this the trained classifiers were used to determine the user's activity and then passed through machine learning and symbolic reasoning. Machine learning was applied to take on large quantity difficult-to-interpret data using multiple classifiers in an appropriate hierarchy. This approach strengthened the recall for eating activities through applied heuristics and showed a classification accuracy of 0.88.

Moving to a different approach to activity recognition Li, Chen, Chen, Huang and Chu [12]focus on oral activity recognition (OAR). The study was carried out using an oral wearable system and tested on various oral activities such as drinking, coughing, chewing and speaking. The evaluation was conducted in a lab with 8 test subjects. The study calculated a 59.8% F-measure of oral activity recognition with a person-independent SVM classifier and a 93.8% through a person-dependent SVM classifier. The study was carried out using 10-fold cross-validation with SVM, decision tree (DT) and multilayer perceptron (MLP). SVM results (93.8%) outperformed DT (52.2%) and MLP (60.5%) by a large gap for person-dependent data. Person-independent classification has a lower F-score however SVM (59.8%) remained the most robust classifier with DT getting a 40.8% F-measure and MLP achieving a 55.9% F-measure.

Branching towards bridging the gap between physical and psychological HAR, Kakarla and Reddy [10] use facial recognition to detect a person's emotion. Using a Kinect Sensor, they track facial activity in real-time to identify specific points of interest using mesh on the test subject's face for feature extraction. They implemented a FACS trained algorithm based on real-time emotion recognition using a Kinect Depth Sensor. Kanjo, Younis and Sherkat [11] carried out a real-world study with mobile and on-body sensors through 40 test participants walking. The study was conducted to evaluate the relationship between environmental, on-body and emotion data through sensor fusion. Multiple regression showed a visible correlation between heart rate and exposure to environmental noise. Aside from noise, air pressure was shown to have had the greatest effect on changes in motion and body temperature. Emotion data was collected through online self-reporting. To predict emotions, they use a multi-learner approach based on the stacking algorithm. Using the physiological and environmental datasets, they use stacking with SVM, RF, KNN, and Naive Bayes (NB). The results showed an F-measure of 0.84 and an accuracy of 86% in emotion prediction using on-body sensors. More on emotion prediction Brady et al. [1] address the current challenges in emotion detection from audio, video and physiological sensors. They discuss The Audio Video Emotion Challenge (AVEC) which adopts fusion and multi-learning on all available modalities. The study presents the development of novel high- and low-level features for modeling emotion in the audio, video, and physiological channels and notes the importance of using the time-series characteristics of valence and arousal states. The resultant system outperformed baseline systems when evaluated with a test set, achieving a Concordant Correlation Coefficient (CCC) of 0.687 for valence and 0.770 for arousal.

IV. Conclusion

This paper presents a summarization of 20 research studies from the past 5 years (2013-2018), carried out in the area of Human Activity Recognition (HAR). Some of these papers attempt to bridge the gap between physical and psychological recognition i.e. Human Behavioral Analysis (HBA) through proposed classifiers and algorithms. The studies carried out in the articles contributed to improving HAR performance accuracies as well as propose new methods addressing certain limitations or obstacles in current HAR research. One of the main potential implementations of HBA could be more advanced self-adaptive smart homes as well as more independent health care applications in hospital and patient care. Results showed that accelerometers and gyroscopes are the most opted for choice of sensors, with smartphones and wearables are two of the most common choice of devices for HAR and activity tracking.

V. References

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