Journal of Theoretical and Applied Information Technology
30th June 2018. Vol.96. No 12

ISSN: **1992-8645** www.jatit.org E-ISSN: **1817-3195**

RECOGNITION OF COMPLEX HUMAN ACTIVITY USING MOBILE PHONES: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Using mobile phones for Human Activities Recognition (HAR) is very helpful in providing a personalized support system for healthcare management and general wellbeing of the user. Many studies have been published which have investigated the HAR with the help of mobile phones. But, in these studies, the researchers briefly mentioned the complex HARs and did not provide any discussion or comparison with the models used. In our study, we have carried out a systematic review of the currently used models in the Complex HAR. We have been carrying out an automatic search in 4 digital libraries since 2012, to address four research questions in our study. We found 11 primary studies after applying the included - excluded criteria. Further studies need to be carried out in this area, especially for solving the issue of a trade-off between the recognition accuracy and the computational load.

Keywords: *Complex Activity Recognition, Mobile Phone Devices, Systematic Literature Review, Composite Activity, Interleave Activity, Concurrent Activity.*

1. INTRODUCTION

The Human Activities Recognition (HAR) with the help of mobile phones provides an important and essential context-aware data with regards to the kind of activities or routines performed by any individual within a particular time frame by leveraging the sensory data present on the currently available sensor-rich, portable and inexpensive mobile devices. This helps in using the mobile phones for providing a personalized support for the healthcare and general wellbeing along with making a significant contribution in the fields of security, robotics and military domains.

The simple (atomic) human activities could be recognized using current recognition methods. But, the nature of human activity is complex and this is a challenge for the recognition methods specially with using mobile phones. One human activity may composite several atomic activities occurring concurrently or interleaving and they may have different structure and temporal dependencies. It is a computationally expensive to retraining the model for several variances of complex activity and to increase the range of temporal dependencies between states using current recognition methods. So, we should deal with these lacks when we recognize complex activities using limited resource devices such as mobile phones. Finding solutions for those problems will help in increase the usage of mobile phones for actual applications like in smart environments.

Number of reviews were done in HARs using mobile devices. However, all these reviews briefly considered the complex human activities recognition and also provided no discussion and comparison between the models used. In our study, we have investigated the currently used models for recognizing the complex activities using a mobile phone. Our study is a comprehensive systematic review of the primary guidelines which were proposed earlier (Kitchenham et al., 2009) [1].

Our study focus in primary searches that propose a recognition model and combine both keywords the recognition of complex activities; and using mobile phone sensors. So it was excluded the papers that does not using mobile phone sensors for activity recognition such as the papers [2, 3], [4, 5, 6, 7], [8, 9, 10, 11, 12], and [13, 14, 15] from ScienceDirect, Springer, ACM and IEEE respectively. There are papers used mobile phone sensors but for the recognition of simple activities such as [16, 17, 18, 19], [20, 21, 2, 22], [23, 24, 25, 26, 27], and [28, 29] from ScienceDirect, Springer, ACM and IEEE respectively. Those also were excluded from our study. Finally, excluded the papers that discuss the activity recognition for group of subjects simultaneously such as [30, 31, 32, and 33].

We have described the details of the systematic review of the published reports, used in our study as follows. In Section 2, we reviewed the related published studies. In Section 3, we have described the methodology used, while in Section 4, we have addressed 4 research questions. Finally, Section 5 contains the results and in Section 6, our conclusions and the outline for future works have been presented.

2. RELATED WORK

Several sensors have been investigated for extracting the useful activity-related data. Some of these sensors include: vision-based sensors which track the movement of the people and the objects based on the images captures on the video (Aggarwal and Ryoo, 2011) [34], wearable and ambient sensor-based devices (Chen et al., 2012) [35] or the mobile phone-based sensors. The ambient sensors refer to those sensors which are present in the static areas in the environment, while the wearable sensors refer to those which are either worn or are present on the individual's body (Lara and Labrador, 2013) [36].

Many studies have reviewed the activity recognition with the help of mobile phones (Incel et al., 2013; Su et al., 2014; Shoaib et al., 2015) [15, 37, 38]. Though these studies have investigated the complicated activities recognition, in brief, they have not discussed and compared the different models used. Furthermore, they used conventional methods for reviewing the literature.

In their study, Incel et al., (2013) [15] provided the taxonomy for the existing studies in activity recognition with the help of mobile sensors and also discussed the open issues present in the literature. They noted that the majority of the studies applied the offline training and classification, which was primarily focused on recognizing the simple locomotory actions; and the studies were also user-dependent.

Su et al., (2014) [37] described a traditional review of the techniques used for activity recognition which used the mobile phone sensors, its applications and limitations in this technology. The authors stated that the use of the complex activity recognition leads to added issues for the different recognition models. They also argued that the HMM classifier was an effective solution for recognizing the complex activities.

In their study, Shoaib et al., (2015) [38] concentrated primarily on the online activity recognition with the help of smartphone sensors wherein the data collection, its pre-processing and the classification processes were implemented on the mobile phones in real-time. The researchers observed the problems while comparing the studies as different techniques were used for activity recognition. Hence, they made some recommendations for the future design recognition systems. Their recommendations, with some modifications, have been used in our SLR for a quality assessment of general and not restricted to the online studies.

In our study, we have extensively studied

the currently-used models for recognizing the complex activities using mobile phones. We analyzed all primary reports based on the type of sensors, complex activities and the classifiers used in every study, and also presented our results, quality and the drawbacks of every study.

3. RESEARCH METHODOLOGY

In this study, we will examine the currently-used models for recognizing the complex human activities using a mobile phone. We have carried out this study as the literature review according to the guidelines published earlier (Kitchenham et al., 2009) [1] which consists of 3 stages, viz.: planning, conducting and reporting. All details about the systematic literature review have been provided in the following sections.

3.1 Research Questions

In previous reviews, the authors have studied the reports which have used the smartphone sensors for monitoring simple human activities; however, it must be noted that the human activities are very complex. Recognizing such complex activities helps in using the smartphones in many actual applications. In our study, our main goal was reviewing the complex activity recognition with the help of mobile phones. In this SLR, the following questions were addressed;

RQ1. How many studies were carried out for complex human activity recognition, since 2012?

RQ2. Which models have been applied?

RQ3. What is the performance of the models and the quality of the research studies?

RQ4. What are the drawbacks of the current studies?

In our study, we wish to determine the extent to which the smartphone sensors have been used for recognizing the complex human activities (RQ1). In the RQ2, we have considered the different models used for recognizing the complex activities, such as the type of activities studied, different sensors in the phone, presence of additional sensors, classification techniques, performance and usage of the resource in these models. For RQ3, we investigated the quality of the initial search, like the experimental details, model validation and its effect on the resources and the generalization of the experimental environment. Finally, RQ4 discussed the limitations in the current studies which have to be improved for future research.

3.2 Search Strategy

We carried out an automated search for research papers and conference studies since 2012, in the chosen online repositories of IEEE, Springer, Science Direct, and ACM. We selected these online repositories as they contained high impact research studies. We constructed our terms based on the definition of the complex activities happening concurrently or interleaving.

In our review, we have focused on the studies which include terms like (composite, complex, concurrent, interleave, activity recognition, mobile phones), and the study title must include (activity recognition) and the remaining content consists of (complex, concurrent, interleave, mobile phones). We also checked for general words and their synonyms like (composite, complex, concurrent, interleave) having a Boolean "OR" between these terms to search for a maximal number of results. Appendix A presents the details of this search string which has been used in every online repository.

3.3 Study Selection

We searched for every term from the inclusion criterion in the full-text of the resulting studies before selecting the primary reports, which would be further used. Thereafter, we checked the different sections of the paper like the abstract, the introduction, and conclusions of the selected reports using the first step of the inclusion/ exclusion criterion for validating their selection amongst the primary studies. We selected the papers that have been published between 1st Jan 2012 – 31st Aug 2016, for the following research topics:

Complex HAR using mobile phones.

We excluded the papers published on the topics below:

a) Did not use the English language.
b) Did not propose a recognition model like surveys or was a book with abstract papers such as [39, 40, 41, 42, 43, 44, and 45].
c) It reviewed and recognized group activities for several subjects simultaneously.
d) Complex HARs using ambient sensors, camera sensors, environmental sensors, or the wearable sensors.
e) Simple HAR with the help of mobile phones such as [46, 47, 48, 49].

3.4 Data Extraction And Analysis

We categorized the data extracted according to the general research topics with respect to all selected reviews and applied the Activity Recognition Cycle (ARC) stages (Bulling et al., 2014) [50], which was followed by a majority of the pattern recognition systems. The extracted data included: References, Setting (position or orientation, the number of participants, mobile), Definitions and Activities, Features, Sensor and Sample Rates, Window size, Classifier and Personalization, Evaluation methodology and its

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Performance, Resource consumption analysis, and the limitations. Thereafter we analyzed the 11 primary studies with respect to their Experimental Settings, Activities, Sensor, Segmentation, Features, Classifier, Evaluation, and limitations. Table 4 presents the summary of the results.

3.5 Study Quality Assessment

We evaluated every primary study with the help of a roadmap (Shoaib et al., 2015) [38] for carrying out a comparative research on online activity recognition using smartphones. Though the following criteria are mainly for online research, they can be applied for any HAR using the mobile phones, but we added that the study must be a peer-review paper. These criteria include:

Reproducibility: Have the authors provided the experimental details for ensuring its reproduction? This "Detail" criterion must be answered as "Yes" if the paper could fulfil 4 out of the 8 points for the extracted data in the data collection section.

Proper validation: Has the experiment been validated using a proper number of different users and a reasonable amount of time? We have stated that the "Evaluation" criterion must be "Yes" if the study was evaluated properly.

Resource consumption analysis: Have the authors provided a resource consumption analysis for their experiments? With regards to the "Consumption analysis" criterion, it must be "Yes" if the paper has determined the computational complexity or the resource usage for the system.

Personalization: Has the author used online training for the system? With regards to the "Online training" criterion it must be answered "Yes" when study trained the system online or "No" when trained in real time.

Position-independence: Can the users place the sensor anywhere on their body? The "Independent" criterion is answered "Yes" if the user can apply the sensor anywhere on the body.

Comparing classifiers: Has the author compared multiple classifiers for the same experiment environment? The "Compare classifiers" is answered "Yes" if the author compared the performance of the work using various classifiers.

3.6 Validity Threats

We carried out the whole study in a transparent and reliable manner, and justified and documented all the details and also saved the raw data for any further analysis. We used some synonyms of the terms like (complex, composite, concurrent, interleave) having an "Or" to separate the main keywords for covering a maximum number of results. We based our study according to the guidelines laid down by Kitchenham [1] for decreasing the bias which could occur in the primary search' findings and an automated search was applied for the widely-used higher quality online repositories. For validating the data, the authors carried out the primary study selection and data extraction. First author searched for the various inclusion criteria within the full texts of every study for selecting the primary papers and also checked the various sections like Abstract, Introduction and the Conclusions against the inclusion/ exclusion criteria for validating their selection as the primary studies. Thereafter, the data was extracted from the studies. The other authors carried out random checks for the selection and the data extraction by determining the search results obtained, extracting relevant data from the initial search, comparing the obtained results with those obtained and solving the resulting conflicts.

4. RESULTS

After analyzing the search results, 11 were selected, which included 7 conference proceedings, and 4 articles, as described in Fig. 1. Out of these, 4 were published in 2015, 3 in 2013 1 study was published in 2016, as shown in Fig. 2. A majority of these were published by IEEE (i.e. 6 studies) as presented in Fig. 3. Thereafter, we extracted the data from the SLR and reported it here for addressing the various questions.

Journal of Theoretical and Applied Information Technology
30th June 2018. Vol.96. No 12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

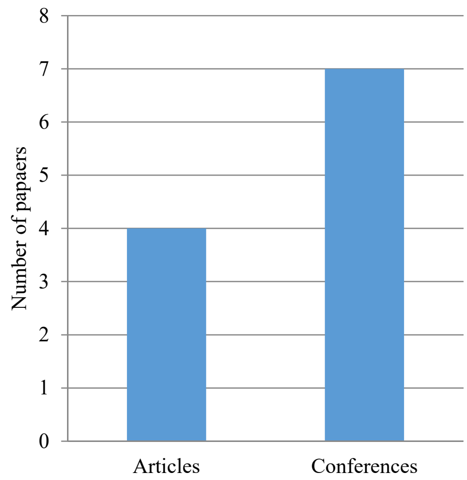

Figure 1: Type of articles in primary searches.

4.1. The Number Of Researches Published In Selected Databases (Addressing RQ1):

• We searched 4 databases: Science Direct, Springer, ACM, and IEEE, with the help of a search string, specified above. We determined 1045 relatable studies.

In Table 1, we have shown the number of the selected papers in every database, while Fig. 4 showed their percentage values.

• After applying the Inclusion and Exclusion criteria, we selected 12 studies which satisfied the

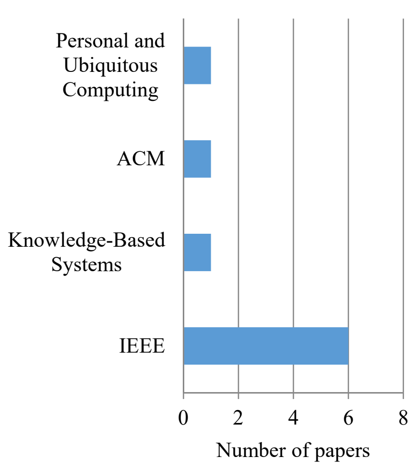

Figure 2: The publishers of primary searches.

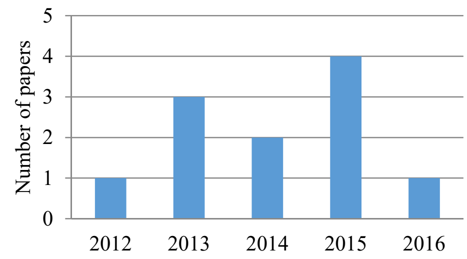

Figure 3: Publishing years of primary searches.

Table 1: Number of Papers in each Database.

Database	Number of papers
ScienceDirect	105
Springer	51
ACM	216
IEEE	673
Total	1045

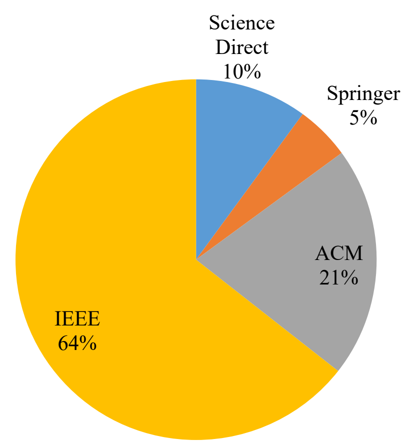

Figure 4: Percentage of Papers in each Database.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

criteria as shown in Table 2. One of these included studies (Dynamic sensor event segmentation for real-time activity) was present in 2 of the databases studied (i.e., Springer and ACM). In Fig. 5, we have shown the percent values of the included papers versus the excluded papers. Table 3 and Fig. 6 show the number and the percent values of the included vs. the excluded papers in every criterion.

Table 2: Number of included and excluded papers.

Included/Excluded	No
Excluded Papers	1033
Included Papers	12
Total	1045

4.2. The Models Used By the Researches to Recognize the Complex Activities (Addressing RQ2):

• We analyzed 11 of the included papers with regards to their Experiment Settings, Activities, Sensors, Segmentation, Features, Classifier, Evaluation, and limitations. Table 4 summarizes all the results.

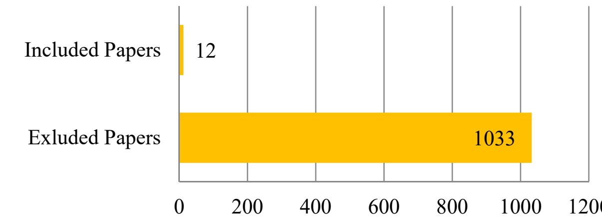

Figure 5: Percentage of included and excluded papers

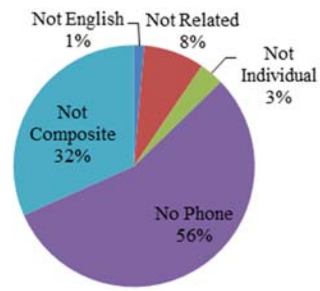

Figure 6 :Percentage of included papers vs. excluded related to each criteria.

4.2.1. Standalone smartphone's sensors approach (PS6)

In their study, Dernbach et al., (2012) [51] studied the capability of the mobile phone sensors for recognizing the complex human activities. They used the accelerometer and the gyroscope from the smartphones for recognizing the complex activities as follows: cooking, cleaning, washing hands, sweeping, medication, watering plants etc. They tested 6 classifiers (Multi-layer Perceptron, Best-First Tree, and Bayesian network, Naïve Bayes, Decision Table and K-star) for investigating the capacity of the mobile phone sensors as a standalone for recognizing the complex human activities.

Table 3: Number of included papers vs. excluded related to each criteria.

Database	Included /Excluded	English	Related	Individual	Phone	Composite	Total
ScienceDirect	No	0	7	0	67	28	102
	Yes	3	3	3	3	3	3
	Total						105
Springer	No	0	2	1	32	15	50

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Database	Included /Excluded	English	Related	Individual	Phone	Composite	Total
	Yes	1	1	1	1	1	1
	Total						51
ACM	No	0	3	26	115	70	214
	Yes	2	2	2	2	2	2
	Total						216
IEEE	No	14	73	7	359	214	667
	Yes	6	6	6	6	6	6
	Total						673

The authors noted a poor performance of the mobile phone sensors as a standalone for recognizing complex human activities; however, the smartphones could be used for collecting data regarding the recognition of the complex activities.

4.2.2. Histogram approach for long term activities (PS5)

In their study, Garcia-Ceja and Brena (2013) [52] built the activity model with a histogram, and then extracted the features from this histogram and applied a simplified threshold. They used the triaxial accelerometer from the smartphone for recognizing five long-term human activities like working, commuting, shopping household activities exercising. Then, the K-Nearest Neighbours test was used and they obtained an accuracy of 92.5%.

4.2.3. Big dataset (PS9)

In their study, Çelenli et al., (2014) [53] collected a dataset of more than100 people to determine to what extent the smartphones could recognize the human activities. They recognized 7 basic and one complex activity (getting in or out of the car). They also used the gyroscope and the accelerometer of the smartphone. Furthermore, they used 6 classifiers like the Classification via Regression, Multilayer Perceptron, Bayesian Network, K-Star, Bagging and the Logistic Model Tree and obtained a recognition accuracy of 98%. However, the authors tested only one complex human activity in their study.

4.2.4. Time series shapelets approach (PS1, PS2)

In one study, (Liu et al., 2016) [54], the authors used the mobile phone sensors for recognizing the complex human activities in the day-to-day life and sports with the help of the time series shapelets. They used the accelerometer and the gyroscope of the mobile phone for recognizing normal activities (e.g., relaxing, meeting, office work, eating, and physical exercises) and the activities involved in playing basketball (walking, jumping, running, standing, bouncing ball, throwing ball, passing the ball or raising hands). The researchers used the sensor event-based window approach for data segmentation, whereas another study (Liu et al., 2015) [55] used 10 different window sizes (ranged between 50 -500). The Time series shapelets approach as the data classifier had the ability to recognize the human complex activities efficiently; however, it is very time-consuming.

4.2.5. Hybrid approach using CDAT (PS4)

In one study, Saguna et al., (2013) [56] used the hybrid approach involving the data and the knowledge approaches, for recognizing 16 complex human activities and noted an accuracy of 95.73%. The smartphone accelerometer, GPS, Wi-

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Fi and Bluetooth RFID tags were applied for recognizing the 16 complex human activities like going to work, cooking, watching online videos, and jogging on the treadmill in a gym. In their study, the researchers used the decision tree classifier along with the concepts of situation and weighting. By the situation concept, they meant that the context data like time, temperature, and location that was not obtained by the sensors could restrict the number of the recognized human activities. They also used weights for determining the presence of the key atomic activities. They noted a high recognition accuracy, as they used an HMM classifier, which was a heavy computational software for complex HAR.

4.2.6. Hybrid model using Machine learning (PS8)

In their study, BakhshandehAbkenar and Loke (2014) [57] suggested the use of a hybrid model for carrying out mobile activity recognition and it used the machine learning process along with the ontological representation of the different activities. They implemented this model using the Continuous SPARQL (C-SPARQL) for conducting queries for recognizing the different human activities. 3 complex human activities were detected by the model like Commuting, Commuting on a bus, and Exercise Program, with the help of the Accelerometer data and the mobile GPS. They observed a (1+R)s of lag time as the total response time, wherein R was dependent on the used network. Further experimentation is needed for validating the complex HAR.

4.2.7. Hybrid framework using Graph Pattern approach (PS7)

In one study, the authors (Meditskos et al., 2013) [58] interpreted the high-level activities with the help of the hybrid framework from the OWL ontology and the SPARQL CONSTRUCT graph pattern. The authors described the basic SPACT capabilities applying the use case. However, they did not provide any details for checking or validating the framework.

4.2.8. Hierarchical approach (PS11)

In their study, Filios et al., (2015) [59] applied two levels of the feature extraction technique. They obtained the motion and the environmental data from the sensors at the lowest level and then detected the activity at a higher level. The authors also used 2 forms of sensors, i.e., motion and sound sensors, for recognizing five motions, like Lying, Sitting etc., and the sounds like those made by different modes of transportation, the supermarket cash desk noises etc., while the complex activities recognized included: Shopping, standing in a queue etc. They applied 4 different machine learning algorithms like the J48 LMT, FT (from tree algorithms) and IBk (from lazy algorithms), and obtained an accuracy of 94.574 %. Though they obtained high recognition accuracy, they had to deal with a high computational load.

4.2.9. Dynamic segmentation approach (PS3)

In a study, Wan et al., (2015) [60] presented the dynamic (real time) sensor segmentation approach which incorporated the concepts of both the sensor and the time correlation. In this study, the researchers validated the process in 2 phases, where the Phase I was applied to the dataset, which the researchers had collected, whereas Phase II represented the benchmark dataset. In Phase I; 42 sensors like PIR, light sensors etc. were applied, while Phase II consisted of 39 sensors like door and temperature sensors. The activities like cooking (breakfast, lunch or dinner), preparing food etc. was recognized by 5 classifiers: Bayesian network, Naıve Bayes, C4.5 decision tree, HMM, and Naıve Bayes Tree (NBT), and they obtained a recognition accuracy of 98.22%. However, their approach might not be reasonable for segmenting of the concurrent or coinciding events.

4.2.10. Pervasive middleware approach (PS10)

A study by Vaka et al., (2015) [61] was called as Pervasive Middleware for Activity Recognition (PEMAR) which combined: activity modelling, recognition and mobile layers. They used the sensors like the SensorTag, TI Chronos Watch, remote Wii systems, and mobile phones for recognising 25 gestures using the K-means algorithm and the HMM classifiers. The authors applied the PEMAR as the applicable middleware for determining the different human motions and mapping them in various types of gaming application. The authors noted an accuracy of 95%;

however, they did not make any mention of the performance showed by their approach for recognizing complex human activities.

4.3. The Resource Consumption Analysis, Evaluation Method, Performance And Quality Score For The Researches (Addressing RQ3):

• In our plan, we have cited the quality of the selected papers, with regards to the specific criteria. In Table 5, all the results have been presented, while in Fig. 5, we have shown the percent value for every satisfied criterion. We have noted that the manner in which the experiments must be implemented and the evaluation of the study are some of the highest criteria fulfilled in our review, whereas online training and independence had the least attention.

4.4. The Limitations Of Current Researches (Addressing RQ4):

• Table 4 lists the limitations.

5. DISCUSSION

Here, we have discussed the results and compared them to other published studies on complex HAR and mobile HAR. We have discussed the results obtained based on the following points of view: activities studied, sensors and the inferring techniques used, resource usage and the performance. All results have been discussed based on a common category of the related reviews.

5.1. Activities

We have noted a difference while considering the definition of simple and complex activities. However, the works agree that the complex human activities are a set of some basic activities (composite) which have a different sequence and can be carried out either as interleaved or concurrently.

The different complex activities studied are classified as:

Day-to-day activities: Washing hands, watering plants, cleaning, Cooking, eating, sweeping, shopping, medication.

Health activities: Exercising and playing basketball.

Working activities: Relaxing, working, meeting.

In these works, many more complex activities were discussed as compared to the simple locomotory activities have been studied in the mobile phone-related literature like sitting, walking, standing, walking upstairs / downstairs, driving, running and biking (Incel et al., 2013) [15].

The studies (Dernbach et al., 2012; BakhshandehAbkenar, and Loke, 2014; Çelenli et al., 2014; Wan et al., 2015) [51 ,57 ,53, 60] distinguished between recognizing the simple and the complex human activities and this was similar to the recommendations made by (Saguna et al., 2013) [56], which stated that the complex activities had a different duration and sequences, and hence, must be disconnected from the simple activities which are atomic with a shorter time duration. This was compared to the studies (Garcia-Ceja and Brena, 2013) [52] that studied the duration of complex activities. Furthermore, (Filios et al., 2015) [59] employed the sound context data for recognizing the complex activities.

5.2. Sensors

The common smartphone sensors were used are accelerometer and gyroscope (Dernbach et al., 2012; Çelenli et al., 2014; Liu et al., 2015) [51, 53, 55]. Employing the 2 sensors for recognizing the activities was a similar tactic to an earlier study (Shoaib et al., 2015) [38], which recommended the use of the 2 sensors for recognizing various activities like walking upstairs and downstairs. It must be noted that the study by (Dernbach et al., 2012) [51] showed that the mobile phone sensors alone poorly recognize the complex activities. In one study, (Roy et al., 2016) [62], the authors observed that the recognition accuracy increased when the ambient sensors were used along with the smartphone sensors (Saguna et al., 2013; Wan et al., 2015) [56, 60]. In some other study, (Wan et al., 2015) [60], several sensors (around 42) were used for recognizing the activity data. However, (Liu et al., 2015) [55] observed that using many sensors created many issues in the real-world, and he suggested using a smaller set of sensors which were strategically placed.

5.3. Classifier

We observed that many studies had used a different technique for classifying the complex activities. In one study, (Saguna et al., 2013) [56] the authors used the decision tree for recognizing the simple activities using a mobile phone. They noted that the decision tree had a lower accuracy and could not handle the differences with regards to the sequences and the concurrent or the interleaved nature of the complex human activities.

Another study, (Saguna et al., 2013) [56], applied the knowledge driven approach and obtained a higher accuracy as compared to other studies. Garcia-Ceja and Brena (2013) [52] employed the constraints from the context data and obtained an increase in accuracy. These results were similar to those observed earlier in the literature, and it can be concluded that using the context helps in increasing the accuracy of the complex HAR (Saguna et al., 2013) [56]. All these studies provide very useful background knowledge and a context-related data for improving the precision of the complex HAR.

The published studies of Liu et al., (2015; 2016) [54, 55] used the time series shapelet for recognizing the complex human activities, and they obtained a recognition accuracy of 77%. They faced a time complexity when recognizing the complex human activities using the time series. Some studies used more than 1 classifier (Dernbach et al., 2012; Çelenli et al., 2014; Filios et al., 2015; Wan et al., 2015) [51 ,53 , 59, 60]. In the study by Wan et al., (2015) [60], the Naïve Bayes Tree (NBT) classifier showed 98.22% accuracy, but it consumed a lot of time and memory. 93% accuracy was noted when the Multi-layer Perceptron was used (Dernbach et al., 2012) [51], while k-star showed an accuracy of 98% (Çelenli et al., 2014) [53], but it recognized only 1 complex activity; whereas 94.5% was obtained using FT (Filios et al., 2015) [60].

Studies were also published which used a hybrid framework which combined the knowledge and the data approaches like (Meditskos et al., 2013; BakhshandehAbkenar and Loke, 2014) [58, 57] , however, they did not state how they have assessed their data.

5.4. Performance and Resource Usage

We have observed a general recognition accuracy of 50-92% as compared to the mobile simple human activity recognition accuracy (80 - 97 %) (Incel et al., 2013) [15]. There are studies with a higher accuracy, but they had certain other issues. In their study, Wan et al., (2015) [60] obtained 98% accuracy, but their technique consumed a lot of resources. Furthermore, k-star (Çelenli et al., 2014) [53] showed 98%, but it recognized only one complex human activity. Also, there was a false prediction and confusion arose between some of the similar human activities (Liu et al., 2015) [42], when we tried to identify complex activities. Hence, there must be many sensors having a high sampling rate for identifying the differences between the activities (Liu et al., 2015) [55] and the boundaries must be well-defined between the activities for avoiding confusion between them.

The most commonly used performance criteria include the recognition accuracy, however, (BakhshandehAbkenar and Loke, 2014) [57] used the criteria of the total response time, in their study. Many other studies made no mention of the manner in which they assessed their technique (Meditskos et al., 2013; Vaka et al., 2015; Wan et al., 2015) [58 , 61 , 60], while many authors did not validate the complex human activities properly (BakhshandehAbkenar and Loke 2014; Çelenli et al., 2014) [57,53]. Three of the studies (BakhshandehAbkenar and Loke, 2014; Filios et al., 2015; Liu et al., 2015) [57, 59, 55] made the consumption analysis, while one of them (Filios et al., 2015) [59] carried out online data training.

Finally, we state that there was a need to develop better complex HAR processes which can deal with duration and sequence variations of the complex human activities and employ a light computation method for use in the smartphones with keeping of the higher recognition accuracy.

6. IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

Based on our search results, we found that there are few studies done in complex HARs using mobile devices. Further studies need to be carried out in this area, especially for solving the issue of a trade-off between the recognition accuracy and the computational load. Therefore, we highlight number of current findings to be directions for future research studies.

- The complex activities have various durations and sequences so should be separated from simple activities that atomic and have short duration. One way was used is organizing the human activities into hierarchical levels, the atomic in low level, and complex ones in high and composite of set of atomic activities (Saguna et al., 2013) [56].
- The mobile phone sensors alone poorly recognize the complex activities (Dernbach et al., 2012) [51]. However, it was observed that the recognition accuracy increased when the ambient sensors were used along with the smartphone sensors (Roy et al., 2016) [62].
- Background knowledge and a context-related data improve the accuracy of complex activity recognition (Garcia-Ceja and Brena, 2013; Saguna et al., 2013) [52, 56].
- Should be used set of sensors which are strategically placed and having a high sampling rate for identifying the differences between the activities (Liu et al., 2015) [55] and the boundaries must be well-defined between the activities for avoiding confusion between them.
- There are studies used a hybrid framework to recognize the complex activities. The hybrid framework combines the knowledge and the data approaches to solve the main two problems of complex activities those long term temporal dependencies and structure. Data driven approach can recognize the temporal dependencies of sequential and concurrent activities. While, knowledge driven approach can recognizing different levels of activities with high classification accuracy. However, the authors did not state how they have assessed their results.

The findings from our review will open this area of research to more research opportunities and practically will help to build more useful and real world mobile applications using human activity recognition. The improvement in recognition of complex human activity using mobile phone could be extended to other fields. For example, increase the performance recognition of complex activities will lead to conduction of extensive studies in human-robot interaction, human computer interfaces, and smart homes. Also, figuring out lightweight method to recognize human activities will help in other devices that have limited energy resource as wireless sensor networks (WSN) that have important military and security applications.

7. CONCLUSION AND FUTURE WORK

In our systematic literature review, we analyzed the currently-used models with respect to their ability to identify the complex activities using a smartphone sensor. We have been carrying out an automated search, since 2012, using 4 digital libraries for answering the research questions. After applying the inclusion and the exclusion criteria, we were able to select 11 primary studies; however, using the mobile phones for the real-world applications requires the recognition of complex human activities. Furthermore, the authors also noted that the details regarding the experimental implementation and evaluation of the work were the highest criteria fulfilled in these primary studies, whereas online data training and independence garnered the least attention. To the best of our knowledge, this is a first review which has extensively analyzed the complex HAR with the help of a smartphone and presented some open issues in the area, which would assist the researchers to further investigate them. Finding solutions for some of these issues would help in using the smartphones for real world applications. The most probable limitation of our review could be a probable bias during the search, selection or data extraction. We have followed various processes for decreasing the bias like the fact that the review has been carried out by different authors, in various stages and proper guidelines were followed. In future, a thorough study must be carried out in this area, especially for addressing the problem related to trade-off between the recognition accuracy and a high computing load.

APPENDIX A: SEARCH STRING

In our review, the authors have focused on studies with the following terms (complex, composite, interleave, concurrent, activity recognition, mobile phone). The title of the paper must contain words like (activity recognition), whereas the text must contain terms like (complex, interleave, concurrent, mobile phone).

Science Direct:

TITLE (activity recognition) or TITLE-ABSTR-KEY (complex, interleave, concurrent, mobile phone) and pub-date > 2011 [All Sources (Computer Science)]

SpringerLink:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The title contains activity recognition, with at least one of the words as (complex, OR interleave, OR concurrent, OR mobile OR phone) in the area of Computer Science Articles, dated between 2012 and 2016, include preview only content.

IEEE:

(("Document Title": activity recognition) OR In Full text metadata: complex, interleave, concurrent, mobile phone) and refined by Publisher: IEEE? Content Type: Conference Publications Journals and Magazines? Year: 2012-2017

ACM:

"query": {acmdlTitle: (+activity+recognition) AND content. ftsec: (complex, interleave, concurrent, mobile phone)}

"filter": {"publicationYear":{ "gte":2012 }}, ()

APPENDIX B: LIST OF PRIMARY STUDIES

PS1 - Liu, L., Peng, Y., Wang, S., Liu, M., & Huang, Z. (2016). Complex activity recognition using time series pattern dictionary learned from ubiquitous sensors. Information Sciences, , 340, 41-57.

PS2 - Liu, L., Peng, Y., Liu, M., & Huang, Z. (2015). Sensor-based human activity recognition system with a multilayered model using time series shapelets. Knowledge-Based Systems, 90, 138-152.

PS3 - Wan, J., O'Grady, M. J., & O'Hare, G. M. (2015). Dynamic sensor event segmentation for real-time activity recognition in a smart home context. Personal and Ubiquitous Computing, 19(2), 287-301.

PS4 - Saguna, S., Zaslavsky, A., & Chakraborty, D. (2013). Complex activity recognition using context-driven activity theory and activity signatures. ACM Transactions on Computer-Human Interaction (TOCHI), 20(6), 32.

PS5 - Garcia-Ceja, E., & Brena, R. (2013). Long-term activity recognition from accelerometer data. Procedia Technology, 7, 248-256.

PS6 - Dernbach, S., Das, B., Krishnan, N. C., Thomas, B. L., & Cook, D. J. (2012, June). Simple and complex activity recognition through smart phones. In Intelligent Environments (IE), 2012 8th International Conference on (pp. 214-221). IEEE.

PS7 - Meditskos, G., Dasiopoulou, S., Efstathiou, V., & Kompatsiaris, I. (2013, March). Sp-act: A hybrid framework for complex activity recognition combining owl and sparql rules. In Pervasive Computing and Communications Workshops (PERCOM Workshops), 2013 IEEE International Conference on (pp. 25-30). IEEE.

PS8 - BakhshandehAbkenar, A., & Loke, S. W. (2014, April). Myactivity: cloud-hosted continuous activity recognition using ontology-based stream reasoning. In Mobile Cloud Computing, Services, and Engineering (MobileCloud), 2014 2nd IEEE International Conference on (pp. 117-126). IEEE.

PS9 - Çelenli, N., Seviş, K. N., Esgin, M. F., Altundağ, K., & Uludağ, U. (2014, September). An unconstrained activity recognition method using

Journal of Theoretical and Applied Information Technology
30th June 2018. Vol.96. No 12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 4:Comparison of Selected Papers.

No	Ref	Setting	Activities	Sensors	Window size	Features	Classifier	Evaluation	Limitation
1.	PS 1	- Ten subjects -Mobile in left leg pocket -For eight work days.	-Daily living: unwind, attend meeting, office work, lunch/dinner and physical exercise. -Basketball playing: walking, running, standing, jumping, throwing ball, bouncing ball, passing ball and lifting hands.	-Accelerometer and gyroscope of smartphone -Sampling rate of 20 Hz.	-Employed the sensor event-based windowing	- Statistical, - Time and frequency: Auto-correlation etc. -Structure: FFT etc. - Peak and segment: Intensity etc. - Coordinate : Radial etc.	Time series shapelets.	- Accuracy level is 77.78%. -Quick and simultaneous energy efficiency	-It is time consumption.
2.	PS 2	- Ten subjects -Mobile in left leg pocket -For eight work days.	-Daily living: unwind, attend meeting, office work, lunch/dinner and physical exercise. -Basketball playing: walking, running, standing, jumping, throwing ball, bouncing ball, passing ball and lifting hands.	-Accelerometer and gyroscope of smartphone -Sampling rate of 20 Hz.	-10 window sizes (ranging from 50 to 500)	- Statistical, - Time and frequency: Auto-correlation etc. -Structure: FFT etc. - Peak and segment: Intensity etc. - Coordinate : Radial etc.	Time series shapelets.	- Accuracy is 77%	
3.	PS 3	-Two distinct datasets. - Dataset I for a 6-months . - Dataset II for 10 months.	-Phase II : six basic categories: eating, bathing etc. -Phase II : includes Cooking (for breakfast, lunch and dinner), Preparing simple food etc.	-Phase I: 42 sensors such as PIR , light sensors etc. -Phase II: In addition, 39 sensors such as door	- A dynamic segmentation that incorporates the notions of both sensor and time correlation.		-an ontological approach. -Also, classifiers: Nai¨ve Bayes, Bayesian network, C4.5 decision tree , HMM. In addition, a	- The average recognition accuracy was at over 98.22% .	-This approach may not be feasible in segmenting concurrent or overlapping events.

No	Ref	Setting	Activities	Sensors	Window size	Features	Classifier	Evaluation	Limitation
				sensors and temperature sensors			hybrid algorithm, Naı¨ve Bayes tree (NBT).		
4.	PS 4	- On the user's waist. - Two subjects for the duration of 21 days.	-16 complex activities such as: cooking, going to work, watching videos online, jogging at the gym	- Accelerometer of smartphones/ Mulle v3. -GPS, Wi-Fi, and Bluetooth RFID tags.	-The algorithm finds the start atomic activity and then sets a time window of the size of the lifespan TL for each matched AS ∨ CS belonging to a CAk.		Decision tree.	-The recognition accuracy was 95. 73%.	-It was used HMM classifier that is a heavy computing for complex activity recognition.
5.	PS 5	- The cellphone was placed in the user's Belt. - The data was collected by one user.	- 5 long-term activities: commuting, working, at home, shopping and exercising.	- a triaxial accelerometer of smartphone. - The sample rate was set at 50Hz.	- The moving average filter. - Using a window length of 15 with an overlap of 33%. - Also set the simple activity window length to 2, 4 and 10 seconds .	-14 Features. - The statistical features: mean, standard deviation etc.	- K-Nearest Neighbors.	- The accuracy was 92.5%	
6.	PS 6	-The location and orientation of the phone was	-Simple : Cycling, climbing stairs, driving, lying down, running,	- Accelerometer and gyroscope of a smart phone.	- Experimented with one, two, four, eight, twelve and sixteen	-Mean, Min, Max, Standard Deviation, Zero-Cross, Correlation.	-Six were examined: Multi-layer Perceptron, Naïve Bayes,	- The accuracy is 50% for smartphone as a standalone scheme	

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

No	Ref	Setting	Activities	Sensors	Window size	Features	Classifier	Evaluation	Limitation
		not standardized - Ten undergraduate students . The subjects repeated execution of these complex activities four times	sitting, standing and walking. -Complex: cleaning, cooking, medication, sweeping, washing hands, watering plants.	- The sampling rate is the fastest which can reach a maximum of 80 Hz.	seconds time windows. -Windows always overlapped by one half of the window length.		Bayesian network, Decision Table, Best-First Tree, and K-star.		
7.	PS 7						- SP-ACT, a hybrid framework defines a combination of OWL ontologies and SPARQL CONSTRUCT graph patterns.	- They illustrate the basic capabilities of SPACT through a use case.	- No details to check or validation method.
8.	PS 8	- The device always must be in a certain pocket	- Six atomic activities including OnBus, Walking, Running, Stationary, OnTrain, and Cycling. - Three types of complex	- Accelerometer data and GPS.		- Typical statistical values were computed.	- The approach is hybrid, uses Decision tree classifier for basic activities, and then using higher level	- Implemented a cloud-hosted framework called MyActivity using Continuous SPARQL (C-SPARQL) to run	-More experimentation is required to verify complex activity recognition.

No	Ref	Setting	Activities	Sensors	Window size	Features	Classifier	Evaluation	Limitation
			activities have been defined to be realized in our model: 'Commuting', 'CommutingOnTheBus', and 'ExerciseProgram'				reasoning with ontologies for more complex activity recognition. - Offline, fed the data into the classifiers.	queries in order to recognize human activities. - Total response times: Approximately (1+R)s of lag time. R depends on the network.	
9.	PS 9	- More than 100 subjects . - Did not specify orientation of the phone. - But the Phone should remained in the subject's pocket .	-Seven basic actions (walking, running, jumping, standing, ascending stairs, descending stairs, and standing up and sitting down as one action) and a complex action (getting in and out of a car).	- Accelerometer and gyroscope of phone. - 100Hz was the sampling rate.	-Tested window sizes of 1, 2, 4 and 6 seconds. - With Overlapped half the size of a window.	- From accelerometer: Minimum, Maximum etc. - From gyroscope: Mean and standard deviation etc.	- Six classifiers : Bayesian Network, Multilayer Perceptron, K-Star, Classification via Regression, Bagging and Logistic Model Tree.	- 98% recognition accuracy	-Just one complex activity is tested.
10.	PS 10	- More than 50 people.	- Total of 25 gestures.	- SensorTag, TI Chronos	- Low pass filter -High pass		- K-means algorithm and HMM.	- The accuracy is 95%. -The Pervasive Middlewar	-Not mention the performance of

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

No	Ref	Setting	Activities	Sensors	Window size	Features	Classifier	Evaluation	Limitation
				Watch, remote Wii systems, and smart phones	Filter -Idle state filter (iv) Motion detect filter - The segmentation of the acceleration calculated from its axes.			e for Activity Recognition (PEMAR) is implemented as an applicable middleware for understanding human motion and mapping it to other forms of gaming applications.	complex .
11.	PS 11	- The position of the phone is not specified. -From 13 people	- 5 motions: Lying, Sitting etc. - The sounds: means of transportation, supermarket cash desks etc. -complex daily activities: Shopping, Waiting in a queue etc.	- Sensor's sampling period is 60 seconds - Audio sampled at 16 bit with a sampling rate of 16 kHz.	- Sensors' windows of 2 seconds. -Windows of 1 minute to get the complex activity. -for sound: 32ms windows with 50% overlapping. -Sound filters: Hamming filter, the Mel-frequency cepstral	- Motion features: the mean value, the standard deviation value etc. -for the sound: Max and min value and coefficient of variation etc.	- 4 machine learning algorithms : J48 LMT, FT (from the tree algorithms) and the IBk (from the lazy algorithms).	-The accuracy is 94.5736 %.	-It has a big computation load.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

No	Ref	Setting	Activities	Sensors	Window size	Features	Classifier	Evaluation	Limitation
					coefficients (MFCC).				

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 5: Quality of included papers.

Ref	Independent	Article	Online training	Evaluation	Consumption analysis	Compare	Detail	Total Yes (From 7)
PS1	No	Yes	Yes	Yes	Yes	Yes	Yes	6
PS2	No	Yes	Yes	Yes	Yes	Yes	Yes	6
PS3	Not mention	Yes	Not mention	Yes	No	Yes	Yes	4
PS4	No	Yes	Not mention	Yes	No	Yes	Yes	4
PS5	No	No	No	Yes	No	No	Yes	2
PS6	Yes	No but cited 120 times.	Not mention	Yes	No	Yes	Yes	4
PS7	Not mention	No	Not mention	No	No	No	No	0
PS8	No	No	No	Yes	Yes	No	Yes	3
PS9	No	No	Not mention	Yes	No	Yes	Yes	3

PS10	Not mention .	No	No	Yes	No	No	Yes	2
PS11	Yes	No	No	Yes	Yes	Yes	Yes	5
Total	2	4	2	10	4	7	10	

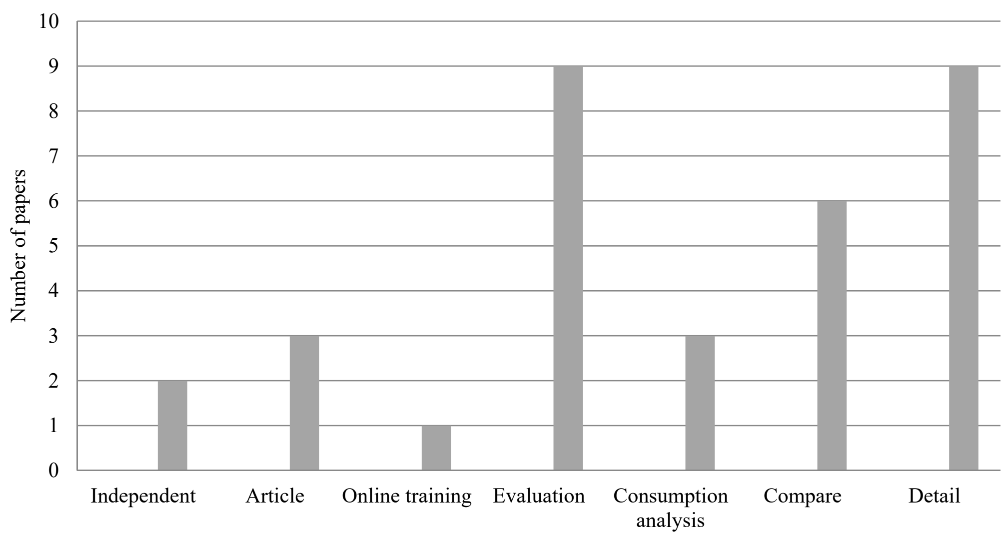

Figure 7:Number of Each Satisfied Criteria.

smart phones. In Biometrics Special Interest Group (BIOSIG), 2014 International Conference of the (pp. 1-7). IEEE.

PS10 - Vaka, P., Shen, F., Chandrashekar, M., & Lee, Y. (2015, March). PEMAR: A pervasive middleware for activity recognition with smart phones. In Pervasive Computing and Communication Workshops (PerCom Workshops), 2015 IEEE International Conference on (pp. 409-414). IEEE.

PS11 - Filios, G., Nikoletseas, S., Pavlopoulou, C., Rapti, M., & Ziegler, S. (2015, December). Hierarchical algorithm for daily activity recognition via smartphone sensors. In Internet of Things (WF-IoT), 2015 IEEE 2nd World Forum on (pp. 381-386). IEEE.

ACKNOWLEDGEMENT

This research was funded by the Research University Grant (20H38) of Universiti Teknologi Malaysia.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

REFERENCES

[1] Kitchenham, B., Brereton, O. P., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering–a systematic literature review. Information and software technology, 51(1), 7-15.

[2] Ignatov, A. D., & Strijov, V. V. (2016). Human activity recognition using quasiperiodic time series collected from a single tri-axial accelerometer. Multimedia tools and applications, 75(12), 7257-7270.

[3] Okeyo, G., Chen, L., & Wang, H. (2014). Combining ontological and temporal formalisms for composite activity modelling and recognition in smart homes. Future Generation Computer Systems, 39, 29-43.

[4] Bai, L., Li, K., Pei, J., & Jiang, S. (2016). Main objects interaction activity recognition in real images. Neural Computing and Applications, 27(2), 335-348.

[5] Ertuğrul, Ö. F., & Kaya, Y. (2016). Determining the optimal number of body-worn sensors for human activity recognition. Soft Computing, 1-8.

[6] Saito, Y., & Nishiyama, H. (2015). Design of a collaborative method with specified body regions for activity recognition: generating a divided histogram considering occlusion. Artificial Life and Robotics, 20(2), 129-136.

[7] Vital, J. P., Faria, D. R., Dias, G., Couceiro, M. S., Coutinho, F., & Ferreira, N. M. (2016). Combining discriminative spatiotemporal features for daily life activity recognition using wearable motion sensing suit. Pattern Analysis and Applications, 1-16.

[8] Eliseev, V., & Shabalin, Y. (2015, September). Dynamic response recognition by neural network to detect network host anomaly activity. In Proceedings of the 8th International Conference on Security of Information and Networks (pp. 246-249). ACM.

[9] Gayathri, K. S., Elias, S., & Ravindran, B. (2015).
Hierarchical activity recognition for dementia care using Markov Logic Network. Personal and Ubiquitous Computing, 19(2), 271-285.

[10] Xiao, F., Xie, X., Zhu, H., Sun, L., & Wang, R. (2015, November). Invisible Cloak Fails: CSI-based Passive Human Detection. In Proceedings of the 1st Workshop on Context Sensing and Activity Recognition (pp. 19-23). ACM.

[11] Yokota, T., & Hashida, T. (2016, October). Hand Gesture and On-body Touch Recognition by Active Acoustic Sensing throughout the Human Body. In Proceedings of the 29th Annual Symposium on User Interface Software and Technology (pp. 113-115). ACM.

[12] Ye, H., Shao, W., Wang, H., Ma, J., Wang, L., Zheng, Y., & Xue, X. (2016, October). Face Recognition via Active Annotation and Learning. In Proceedings of the 2016 ACM on Multimedia Conference (pp. 1058-1062). ACM.

[13] Avci, U., & Passerini, A. (2014). Improving activity recognition by segmental pattern mining. IEEE Transactions on Knowledge and Data Engineering, 26(4), 889-902.

[14] Banerjee, T., Keller, J. M., Skubic, M., & Stone, E. (2014). Day or night activity recognition from video using fuzzy clustering techniques. IEEE Transactions on Fuzzy Systems, 22(3), 483-493.

[15] Incel, O. D., Kose, M., & Ersoy, C. (2013). A review and taxonomy of activity recognition on mobile phones. BioNanoScience, 3(2), 145-171.

[16] Gao, X., Chen, Z., Tang, S., Zhang, Y., & Li, J. (2016). Adaptive weighted imbalance learning with application to abnormal activity recognition. Neurocomputing, 173, 1927-1935.

[17] González, S., Sedano, J., Villar, J. R., Corchado, E., Herrero, Á., & Baruque, B. (2015). Features and models for human activity recognition. Neurocomputing, 167, 52-60.

[18] Reyes-Ortiz, J. L., Oneto, L., Sama, A., Parra, X., & Anguita, D. (2016). Transition-aware human activity recognition using smartphones. Neurocomputing, 171, 754-767.

[19] Yin, J., Tian, G., Feng, Z., & Li, J. (2014). Human activity recognition based on multiple order temporal information. Computers & Electrical Engineering, 40(5), 1538-1551.

[20] Cvetković, B., Janko, V., Romero, A. E., Kafalı, Ö., Stathis, K., & Luštrek, M. (2016). Activity Recognition for Diabetic Patients Using a Smartphone. Journal of medical systems, 40(12), 256.

[21] Guo, J., Zhou, X., Sun, Y., Ping, G., Zhao, G., & Li, Z. (2016). Smartphone-Based Patients' Activity Recognition by Using a Self-Learning Scheme for Medical Monitoring. Journal of medical systems, 40(6), 1-14.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[22] Kong, Q., & Maekawa, T. (2014). Reusing training data with generative/discriminative hybrid model for practical acceleration-based activity recognition. Computing, 96(9), 875-895.

[23] Baldominos, A., Saez, Y., & Isasi, P. (2015, July). Feature set optimization for physical activity recognition using genetic algorithms. In Proceedings of the Companion Publication of the 2015 Annual Conference on Genetic and Evolutionary Computation (pp. 1311-1318). ACM.

[24] Guo, H., Chen, L., Peng, L., & Chen, G. (2016, September). Wearable sensor based multimodal human activity recognition exploiting the diversity of classifier ensemble. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (pp. 1112-1123). ACM.

[25] Hauber, M., Bachmann, A., Budde, M., & Beigl, M. (2013, December). jActivity: supporting mobile web developers with HTML5/JavaScript based human activity recognition. In Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia (p. 45). ACM.

[26] Li, X., Zhang, Y., Li, M., Marsic, I., Yang, J., & Burd, R. S. (2016, October). Deep neural network for RFID-based activity recognition. In Proceedings of the Eighth Wireless of the Students, by the Students, and for the Students Workshop (pp. 24-26). ACM.

[27] Ye, J., Fang, L., & Dobson, S. (2016, September). Discovery and recognition of unknown activities. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct (pp. 783-792). ACM.

[28] Gjoreski, H., Kozina, S., Gams, M., Lustrek, M., Álvarez-García, J. A., Hong, J. H., ... & Patwari, N. (2015). Competitive live evaluations of activity-recognition systems. IEEE Pervasive Computing, 14(1), 70-77.

[29] Tao, D., Jin, L., Yuan, Y., & Xue, Y. (2016). Ensemble manifold rank preserving for acceleration-based human activity recognition. IEEE transactions on neural networks and learning systems, 27(6), 1392-1404.

[30] Abkenar, A. B., Loke, S. W., Rahayu, W., & Zaslavsky, A. (2016, March). Energy Considerations for Continuous Group Activity Recognition Using Mobile Devices: The Case of GroupSense. In Advanced Information Networking and Applications (AINA), 2016 IEEE 30th International Conference on (pp. 479-486). IEEE

[31] Benmansour, A., Bouchachia, A., & Feham, M. (2016). Multioccupant activity recognition in pervasive smart home environments. ACM Computing Surveys (CSUR), 48(3), 34.

[32] Gordon, D., Hanne, J. H., Berchtold, M., Shirehjini, A. A. N., & Beigl, M. (2013). Towards collaborative group activity recognition using mobile devices. Mobile Networks and Applications, 18(3), 326-340.

[33] Gordon, D., Scholz, M., & Beigl, M. (2014, September). Group activity recognition using belief propagation for wearable devices. In Proceedings of the 2014 ACM International Symposium on Wearable Computers (pp. 3-10). ACM.

[34] Aggarwal, J. K., & Ryoo, M. S. (2011). Human activity analysis: A review. ACM Computing Surveys (CSUR), 43(3), 16.

[35] Chen, L., Hoey, J., Nugent, C. D., Cook, D. J., & Yu, Z. (2012). Sensor-based activity recognition. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 42(6), 790-808.

[36] Lara, O. D., & Labrador, M. A. (2013). A survey on human activity recognition using wearable sensors. IEEE Communications Surveys & Tutorials, 15(3), 1192-1209.

[37] Su, X., Tong, H., & Ji, P. (2014). Activity recognition with smartphone sensors. Tsinghua Science and Technology, 19(3), 235-249.

[38] Shoaib, M., Bosch, S., Incel, O. D., Scholten, H., & Havinga, P. J. (2015). A survey of online activity recognition using mobile phones. Sensors, 15(1), 2059-2085.

[39] Cicirelli, F., Fortino, G., Giordano, A., Guerrieri, A., Spezzano, G., & Vinci, A. (2016). On the design of smart homes: A framework for activity recognition in home environment. Journal of medical systems, 40(9), 200.

[40] Cook, D., Feuz, K. D., & Krishnan, N. C. (2013). Transfer learning for activity recognition: A survey. Knowledge and information systems, 36(3), 537-556.

[41] Feng, A., Gardner, M., & Feng, W. C. (2017). Parallel programming with pictures is a Snap!. Journal of Parallel and Distributed Computing, 105, 150-162.

[42] Haescher, M., Matthies, D. J., Trimpop, J., & Urban, B. (2015, June). A study on measuring heart-and respiration-rate via wrist-worn accelerometer-based seismocardiography

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

(SCG) in comparison to commonly applied technologies. In Proceedings of the 2nd international Workshop on Sensor-based Activity Recognition and Interaction (p. 2). ACM.

[43] Woznowski, P., Kaleshi, D., Oikonomou, G., & Craddock, I. (2016). Classification and suitability of sensing technologies for activity recognition. Computer Communications, 89, 34-50.

[44] Wu, J., Cheng, B., & Wang, M. (2016, June). Energy minimization for quality-constrained video with multipath TCP over heterogeneous wireless networks. In Distributed Computing Systems (ICDCS), 2016 IEEE 36th International Conference on (pp. 487-496). IEEE

[45] Xing, T., Fang, D., Chen, X., Jin, M., Zheng, X., & Zhao, K. (2015, November). Doppler Effect based Moving Target Detection Adaptive to Speed. In Proceedings of the 1st Workshop on Context Sensing and Activity Recognition (pp. 41-46). ACM.

[46] Abdallah, Z. S., Gaber, M. M., Srinivasan, B., & Krishnaswamy, S. (2015). Adaptive mobile activity recognition system with evolving data streams. Neurocomputing, 150, 304-317.

[47] Deng, W. Y., Zheng, Q. H., & Wang, Z. M. (2014). Cross-person activity recognition using reduced kernel extreme learning machine. Neural Networks, 53, 1-7.

[48] Li, A., Qin, Z., Chen, M., & Liu, J. (2014, June). ADAutomation: An Activity Diagram Based Automated GUI Testing Framework for Smartphone Applications. In Software Security and Reliability, 2014 Eighth International Conference on (pp. 68-77). IEEE.

[49] Xie, F., Song, A., & Ciesielski, V. (2014, July). Genetic programming based activity recognition on a smartphone sensory data benchmark. In Evolutionary Computation (CEC), 2014 IEEE Congress on (pp. 2917-2924). IEEE.

[50] Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. ACM Computing Surveys (CSUR), 46(3), 33.

[51] Dernbach, S., Das, B., Krishnan, N. C., Thomas, B. L., & Cook, D. J. (2012, June). Simple and complex activity recognition through smart phones. In Intelligent Environments (IE), 2012 8th International Conference on (pp. 214-221). IEEE.

[52] Garcia-Ceja, E., & Brena, R. (2013). Long-term activity recognition from accelerometer data. Procedia Technology, 7, 248-256.

[53] Çelenli, N., Seviş, K. N., Esgin, M. F., Altundağ, K., & Uludağ, U. (2014, September). An unconstrained activity recognition method using smart phones. In Biometrics Special Interest Group (BIOSIG), 2014 International Conference of the (pp. 1-7). IEEE.

[54] Liu, L., Peng, Y., Wang, S., Liu, M., & Huang, Z. (2016). Complex activity recognition using time series pattern dictionary learned from ubiquitous sensors. Information Sciences, 340, 41-57.

[55] Liu, L., Peng, Y., Liu, M., & Huang, Z. (2015). Sensor-based human activity recognition system with a multilayered model using time series shapelets. Knowledge-Based Systems, 90, 138-152.

[56] Saguna, S., Zaslavsky, A., & Chakraborty, D. (2013). Complex activity recognition using context-driven activity theory and activity signatures. ACM Transactions on Computer-Human Interaction (TOCHI), 20(6), 32.

[57] BakhshandehAbkenar, A., & Loke, S. W. (2014, April). Myactivity: cloud-hosted continuous activity recognition using ontology-based stream reasoning. In Mobile Cloud Computing, Services, and Engineering (MobileCloud), 2014 2nd IEEE International Conference on (pp. 117-126). IEEE.

[58] Meditskos, G., Dasiopoulou, S., Efstathiou, V., & Kompatsiaris, I. (2013, March). Sp-act: A hybrid framework for complex activity recognition combining owl and sparql rules. In Pervasive Computing and Communications Workshops (PERCOM Workshops), 2013 IEEE International Conference on (pp. 25-30). IEEE.

[59] Filios, G., Nikoletseas, S., Pavlopoulou, C., Rapti, M., & Ziegler, S. (2015, December). Hierarchical algorithm for daily activity recognition via smartphone sensors. In Internet of Things (WF-IoT), 2015 IEEE 2nd World Forum on (pp. 381-386). IEEE.

[60] Wan, J., O'Grady, M. J., & O'Hare, G. M. (2015). Dynamic sensor event segmentation for real-time activity recognition in a smart home context. Personal and Ubiquitous Computing, 19(2), 287-301.

[61] Vaka, P., Shen, F., Chandrashekar, M., & Lee, Y. (2015, March). PEMAR: A pervasive middleware for activity recognition with smart phones. In Pervasive Computing and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Communication Workshops (PerCom Workshops), 2015 IEEE International Conference on (pp. 409-414). IEEE.

[62] Roy, N., Misra, A., & Cook, D. (2016). Ambient and smartphone sensor assisted ADL recognition in multi-inhabitant smart environments. Journal of ambient intelligence and humanized computing, 7(1), 1-19.