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Variance Based Pattern Detection for Inferring Activities of Daily Living

W. Ali[1], M.A. Azam[1], U. Naeem[2], M.A. Ghazanfar[1], A. Khalid[3] and Y. Amin[1]

[1]Faculty of Telecom & Information Engineering, UET Taxila, Pakistan

[2]School of Architecture, Computing and Engineering, University of East London, London, UK

[3]Computer Science Department, COMSATS, Wah Cantt., Pakistan

wiqijan2002@yahoo.com; awais.azam@uettaxila.edu.pk; u.naeem@ucl.ac.uk; mustansar.ali@uettaxila.edu.pk; yasar.amin@uettaxila.edu.pk

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ABSTRACT

Being able to recognize activities of daily living (ADLs) using non-intrusive devices is very much dependent on the ability to discover a range of patterns within captured datasets. Pattern recognition plays an important role as the presence of patterns in one instance and the absence in another presents an accurate means of classification. In this paper, we present a pattern recognition approach based on recognizing the emerging patterns for inferring ADLs. In order to validate this proposed approach, a series of activity datasets have been used for validation experiments.

1. Introduction

We currently live in a digital age where everything is governed by data, which is increasing at an exponential rate as shown by U. M. Fayyad et. al. in [1]. The need to bridge the gap between the volumes of data generated and the need to analyze the data remains a challenge. This also applies to the activity recognition domain, where variations of data streams are captured from devices such as video cameras, heart rate monitors, pedometers, accelerometers and Radio-frequency identification (RFID) sensors. The data captured from these devices are then analyzed in order to infer the activity that is being conducted. Data captured by video cameras can easily be classified by humans, however video based systems are not really feasible as continuous direct observation by humans can be tedious, expensive and time consuming as shown by U. Hinrichs [2].Hence this has led to a series of automated approaches for activity recognition using data captured from visual based systems. However, drawback of such approach is that it can be computationally expensive and invades user's privacy [3]. Therefore, the need to make use of data streams that are captured using non-intrusive sensors, has become a popular choice for activity recognition. The structure of this type of data can be used to apply the concept of variance, which measures the distance between the variance of data values within the captured sensor event streams. Data values that are spread out with zero variance indicate identical values and high variance is an indication of data values that are spread out. Low variance among similar activities combined with emerging patterns may serve as an excellent classifier.

Common techniques for finding patterns from datasets are clustering [4] and association classification [1, 5-7]. Patterns in the data can be represented in many different forms, such as classification rules, association rules and clusters [8-10]. Emerging Patterns (EPs) is a kind of knowledge pattern that describes significant changes (differences or trends) between two classes of data [11]. EPs are sets of items (conjunctions of attribute values) whose frequency varies significantly from one dataset to another. These can also be used to classify activities that are conducted by different people within the home environment. Classification is the process of finding a set of models that describe and distinguish between two or more data classes or concepts. This model works by analyzing a set of training data that has been explicitly labeled with the class that it belongs to. This is then applied to predict the category of objects whose class labels are unknown based on their sensor readings in the training data. Because EPs represent factors that distinguish two classes of data, the technique of EPs is well fitted to serve as a categorization model.

Demand for Activities of Daily Living (ADL) recognition has been on the increase within many areas, particularly within the area of health and wellbeing. In this paper, we present an approach that utilizes accelerometer data from sensors to recognize ADLs. The proposed approach for inferring ADLs is called Variance based Emerging Patterns for Recognition of Activities of Daily Life (VEPRADL), which is responsible for the classification of activities conducted in a sequential, concurrent and interleaved manner. Finding and discriminating between patterns from captured data is a challenging task. Jumping Emerging Patterns is a kind of emerging patterns technique that is proposed in this paper. It works on the deterministic factors present in different steps to perform an activity; the difference among these deterministic factors is used as an accurate means of classification. This approach was applied to the following data sets:

- A public dataset of accelerometer data for human motion primitives detection [12].
- Activity dataset collected from a single chest-mounted accelerometer [13].

The remainder of the paper is organized in different sections like an overview of the related literature in section 2, methodology which includes two sub algorithms and concept of emerging patterns in section 3, two validation datasets in section 4, Results are presented in section 5 while section 6 presents a comparison with other techniques. Section 7 presents results of other data sets. Section 8 presents comparison of VEPRADL with different techniques on data set and section 9 presents conclusion and future work.

2. Related Work

Activity recognition is based on recognizing the tasks and intentions of one or more users from a sequence of user's actions under certain conditions as shown by Wu [14]. Activity recognition has many applications, such as assisting the elderly and the disabled presented by Nasreen [15]. Home-based rehabilitation can also be provided to a person suffering from traumatic brain injury through automatically monitoring their activities presented by Pollack [16]. Activity recognition can be in many forms, such as plan recognition, goal recognition, intent recognition and behavior recognition, which can also infer locations and provide location-based services [17-19].

Activity recognition is performed at two levels in existing research. Firstly, there is atomic activity recognition, which is based on using machine learning techniques [20-22] and body sensors [23-25] that capture basic body motions and object usage. Secondly, there is complex activity recognition, which involves more than one activity being conducted that needs to be recognized. This type of recognition also makes use of machine learning techniques [23, 26, 27].One of the major challenges for activity recognition techniques is to detect activities that are in concurrent and interleaved fashion. The goal of VEPRADL is to target this challenge by recognizing activities not only in a sequential but also in concurrent and interleaved manner.

Bujari [28] has shown pattern recognition of movement through smart phones, it can be very useful when trying to detect a pedestrian stops or crosses street given in the traffic light signal [28]. Novel emerging patterns based approach to sequential, interleaved and concurrent activity recognition is dedicated sensor setup employed for Activity Recognition [29]. In this approach, only 532 instances are collected and tested. It lags in accuracy for interleaved and concurrent activities as compared to VEPRADL.

Gu [30] was able to recognize the activities of two volunteers with 420 instances and achieve an average accuracy of 89.72 using emerging Patterns based Multi User Activity Recognizer for Activities of Multiple User's (epMAR), while in VEPRADL more than 20000 instances are tested.

A pattern mining approach to sensor based human activity recognition shows activity recognition in sequential, interleaved and concurrent manner with an accuracy of 90.96 %, 88.1 % and 82.53 % respectively [31]. For more comprehensive data set for their study, they conducted their own trace collection through sensors. Trace collection was done in a smart home. The data were collected over a period of two weeks. They had four volunteers. This technique has better accuracy than VEPRADL only in a sequential manner.

Semantic reasoning has also become a popular choice for activity recognition in sequential, interleaved and concurrent manner [32, 33]. Study by Modayil [32] shows promising results on individual activities but in VEPRADL we have dealt with multiple activities at a time.

Factorial Conditional Random Field (FCRF) based algorithm was deployed for the recognition of complex activities of single user for concurrent activities [34]. This technique was not able to recognize interleaved activities and scalability was also an issue.

Singla [35] was able to carry out interleaved activity recognition based on Naïve Bayes classifier with average accuracy of 81 and a Hidden Markov Model with average accuracy of 71 using three-fold cross validation of 8 activities.

We believe that existing approaches have been able to recognize interleaved activities; however, the recognition rates are strictly acceptable and could be improved.

3. Methodology

For the work in this paper, we propose a novel approach based on EPs, which differs from traditional semi supervised classification techniques that require training data. This approach constructs knowledge patterns from sensor streams captured while activities are being conducted. Being able to extract patterns in datasets is seen as a major challenge in Knowledge Discovery in Databases (KDD) and this has been exploited for a range of application domains, where it has been applied to determine the differences [36].

- Edible and poisonous mushrooms
- Smokers and nonsmokers
- Heart disease patients in Australia and heart disease patients in China
- Customer purchasing behaviour in 1999 and customer purchasing behaviour in 2000.

Extraction of EPs can be very useful when trying to make informed decisions given a dataset. The definition of EP, with a working example is as follows:

Given two different classes of data sets D1 and D2, the growth rate of an item set X from D1 to D2 is defined as Growth Rate (X) = 0, if supp1(X) = 0 and supp 2(X) = 0, if supp1(X) = 0 and supp2(X) > 0

The concept of EPs was firstly introduced by Dong [11], whereas Jumping Emerging Patterns (JEP) first appeared in [37] and constrained EP in [38]. Study by Bailey et al. presents two techniques for significantly improving emerging pattern classifying power. The first strategy involves mining patterns, which have a more targeted description of their relative supports in each dataset. The second technique is to employ a pair wise classification strategy for situations where more than two classes are present. Novel mining algorithms are also presented which emphasize dataset partitioning as a crucial mechanism in reducing the complexity of the task. Classification by aggregating EPs was applied to datasets like hepatitis, Australian, German, Iris, Tic-Tac-Toe, Waveform, Breast, Cleve, Ionosphere, Mushroom taken from the UCI machine-learning repository [39].

In this paper, EPs have been applied to ADL data sets, which are composed of sensor readings captured from a range of accelerometers. The training dataset utilized for this work is very limited as it consists of 10 to 15 but not more than 30 instances. The main factor used to classify between activities measures the low variances observed within different sensor readings given an activity. Hence, the principle of the proposed VEPRADL algorithm is that low variance between sensor readings can differentiate one activity from another.

Below is a formal breakdown of the proposed algorithm, which is made up of two sub algorithms.

3.1 Sub Algorithm 1

In a first step, attributes and activity columns are differentiated. As the algorithm is bound to work on more than one activity, in this regard the presence of more than one activity is checked. If there is only one activity, then it will be displayed as an ambiguous absent patterns. If there is more than one activity, then potential determinants will be formed based on the condition of the global variance of attribute readings of activities. If formed, then candidate determinants will be formed on the condition of lowest local variance among the attributes of activities. Lastly, candidate determinants will be colored showing patterns among attributes.

Sub algorithm 1: To find patterns in Labeled Activities

Input: Stream of Sensor Readings S = {s1, s2, s3.} and Parameter of ±, ÷, × σ, σ^2, GM, HM___ with labeled activities

Output: Set of Unique Patterns in Senor Readings of Different Activities

1. Attributes and Goal Column Differentiation

3. Distinct Goal Set

2 for each $\left(\mathrm{Goal}\left(g_{m\,,\;n}\right)\right)$ // For every activity Candidate determinants

i. for each $\left(a_x\,, a_y \_\_\_\_\_\_\right)$ // For Every Attribute

If

ii. $\sigma_l\left(a_x,\ a_y(g_m)\right) < \sigma_g\left(a_x,\ a_y\right)$ // if a local variance of attribute a_x and a_y for g_m is less than global variance of a_x and a_y

iii. $\sigma_l\left(a_x, a_y(g_m)\right) < \sigma_l\left(a_{x\,,}a_y(g_n)\right)$ if a local variance of attribute a_x and a_y for g_m is less than local variance of a_x and a_y for g_n
$a_x, a_y(g_m) = \text{uniquely coloured}$

If

iv. $\sigma_l\left(a_x a_y(g_m)\right) = \sigma_l\left(a_x\ a_y(g_n)\right)$ // if local variance of a_x for g_m is equal to local variance of a_x for g_n

v. if n $(g_m) > n\ (g_n)$

vi. $a_x = g_m$ //if number of instance of g_m are greater, patterns will be formed for a_x for $g_m$return $\left(<\right.$ axgm,aygm___>∩<axgn,aygn__> // return g_m and g_n uniquely coloured with their attributes uniquelycoloured

3.2 Sub Algorithm 2

In a test set for every attribute reading, if there is a low variance among readings in a training dataset for a particular activity. Then that activity is assigned to a reading in a test set.

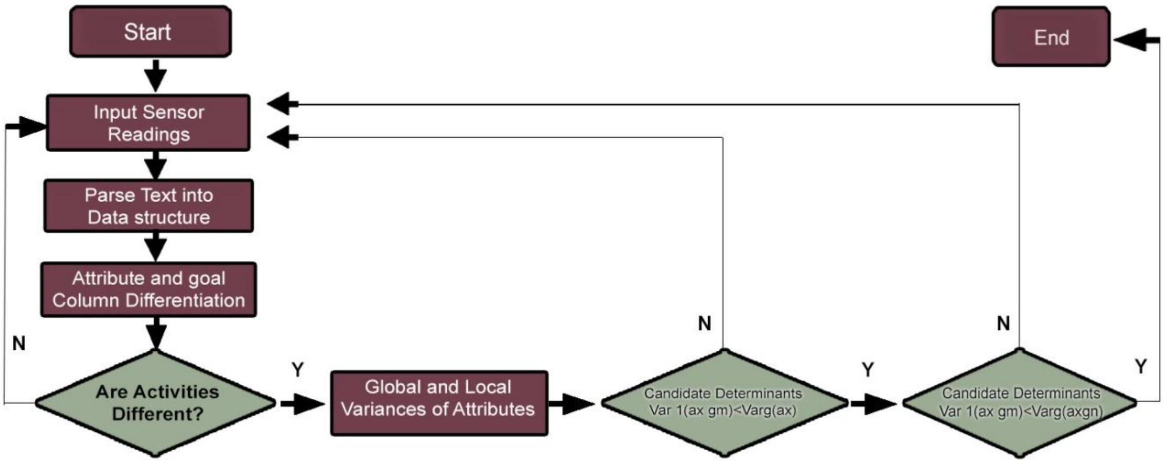

Fig. 1. VEPRADL algorithm block diagram

Sub algorithm 2: Classification of Activities

Input: Stream of Sensor Readings S = {s1, s2, s3}. Parameter of ±, ÷, × σ, σ^2, GM, HM___ without labels

Output: Labels Assigned to Sensor

1. File Parsing (Text to Data Structures, Dynamic Array)
2. Attributes and Goal Column Differentiationforeach$(a_x, a_y____)$ // For Every Attribute

If

$$\sigma_l(a_x a_y \_\_) == \sigma_l\left(a_x a_y \_\_ == (g_m)\right)$$
$$U \left(a_x a_y \_\_ == (g_n)\right)/*$$

For Every Attribute if there is a low variance among readings in training set */

then

$a_x a_y\_\_\_ = g_m \mho a_x a_y\_\_\_ = g_n$ // based on low variance activity gm or gn will be assigned to sensor readingsreturn$(g_m \mho g_m)$

The block diagram in Fig. 1 depicts the main functions of the proposed algorithm. Below the description of proposed Sub algorithm 1 and 2 is given.

4. Validation Datasets

VEPRADL algorithm is applied on two datasets, which were taken from the UCI machine learning repository
[12- 13].

1.1

4.1 Accelerometer Dataset for Human Motion Primitives Detection

This data set is a public collection of labeled readings of sensors to be used for the creation of systems to be used for activity recognition purpose. The dataset is composed of the recordings of selected Human Motion Primitives performed by 16 volunteers.

Basic information about the volunteers is reported in Table 1.

Table 1: Information of volunteers

Gender		Age			Weight		
M	F	Min	Max	Avg	Min	Max	Avg
11	5	19	81	57.4	56	85	72.7

Data is gathered by the tri-axial accelerometer, which is embedded in an ad-hoc sensing device (40 mm x 22 mm x 12 mm) that is attached at the right wrist of the user. Data transmission to the PC is wired, via a USB cable. Each file in the dataset follows the following naming convention shown in Table 2:

Table 2: File naming convention in aHmp dataset

START_TIME	Timestamp of the starting moment of the recording in the format [YYYY-MM-DD-HH-MM-SS]
HMP	name of the HMP performed in the recorded trial, following the naming convention specified in Section 2 of this manual
VOLUNTEER	identification code of the volunteer performing the recorded motion in the format [gN] where :- "g" indicates the gender of the volunteer (m -> male, f -> female)- "N" indicates the progressive number associated to the volunteer

Descriptions of the activities are presented in the Table 3.

4.2 Single Chest-Mounted Accelerometer Dataset for Activity Recognition

The dataset collects data from sensors placed on the chest. Un-calibrated Accelerometer Data are collected from 15 participants performing 7 activities. The dataset provides challenges for identification and authentication of people using motion patterns. The dataset collects data from a wearable accelerometer mounted on the chest. Sampling frequency of the accelerometer was 52 Hz. Accelerometer Data are un-calibrated and was saved in CSV (Comma Separated Values) format. The dataset was captured for the objective of making advancements in the area of activity recognition. Description of activities is presented in Table 4.

Table 3: Activity descriptions for accelerometer dataset of human motion primitives

Activities	Description
brush_teeth	To brush one's teeth with a toothbrush
climb_stairs	To climb a number of steps of a staircase
comb_hair	To comb one's hair with a brush
descend_stairs	To descend a number of steps of a staircase
drink_glass	To pick a glass from a table, drink and put it back on the table
eat_meat	To eat something using fork and knife
eat_soup	To eat something using a spoon
getup_bed	To get up from a lying position on a bed
Lie down_bed	To lie down from a standing position on a bed
pour_water	To pick a bottle from a table, pour its content in a glass on the table and put it back on the table
Sit down_chair	To sit down on a chair
standup_chair	To stand up from a chair
use_telephone	To place a telephone call using a fixed telephone (complete gesture)
Walk	To take a number of steps

Table 4: Activity descriptions for single chest-mounted accelerometer dataset for activity detection

Activities	Code
Working at Computer	1
Standing Up, walking and going up\ down stairs	2
Standing	3
Walking	4
Going up\ down stairs	5
Walking and talking with someone	6
Talking while standing	7

5. Results

This section presents the results in different scenarios

5.1 Results of Sequential Activities

Table 5 shows the accuracies of the activities performed in a sequential manner e.g. soup is taken before eating meat or going up stairs will be followed by down stairs. Combing hair and brushing teeth have low accuracy rate because sensors readings for these activities were very similar as they had low variance between them. This similarity makes it difficult to determine between two activities, which are performed in similar fashion, e.g. bending of the hand in both cases is very similar, which causes errors in classification when performed in a sequential manner. The remaining activities had greater accuracy rates because there was a significant difference between the variance within the sensor readings of these activities. Their sensor readings are different from one another, resulting in low variance between their sensor readings and additional attributes based on them, which results in improved classification.

5.2 Results of Concurrent Activities

Concurrent activities are very complex motions to detect and to classify between them. Concurrent activities are like making a telephone call while sitting, and making a telephone call while standing. These two situations present two different activities. Table 6 shows the activities that were carried out in a concurrent manner. These activities achieved high recognition rates, because the readings of sensors involve in making telephone are different from sensors involved in stand up chair and sit down chair.

Table 5: Recognition rates of activities performed in a sequential order

Activities	Accuracy (%)
Comb hair	72
Descend Stairs	92
Eat Meat	91
Stand up	86
Brush Teeth	91
Climb Stairs	93
Drink Glass	90
Eat Soup	90
Sit down	87

Table 6: Recognition Rates of Activities Performed Together in a Concurrent Manner

Activities	Accuracy (%)
Use Telephone with	92
Sit Down Chair	100
Use Telephone with	97
Stand Up Chair	95

5.3 Results of Interweaving Activities

'Eat Meat' and 'Drink Glass' activities can be explained as activities, because when a person eats a meal they would also drink water or beverage between the eat meal activity. Table 7 shows the activities performed in interweaved manner. The recognition rates of these activities were high because of the high variance of sensor readings between these activities when performed in interweaved manner.

Table 7: Recognition Rates of Activities Performed Together in Interweaved Manner

Activities	Accuracy (%)
Eat Meat	91
Drink Glass	90

6. Performance Comparison of the VEPRADL Algorithm

We performed an experiment that measured the performance of our proposed algorithm with the recognition techniques discussed in Human Motion Modeling and Recognition: a Computational Approach based on Gaussian Mixture Modeling and Regression [40].

In comparison to the VEPRADL Human Motion Modeling and Recognition: a Computational Approach based on Gaussian Mixture Modeling and Regression, only four activities were recognized which were “Climb Stairs”, “Drink Glass”, “Sit Down Chair” and “Stand Up Chair”. Hence, a comparison can only be done based on these four activities. A comparison of both approaches is shown in Table 8.

Table 8: Recognition rates comparison of VEPRADL with Gaussian Mixture Modeling (GMM) and Gaussian Mixture Regression (GMR)

Activities	VEPRADL Accuracy (%)	GMM and GMR Accuracy (%)
Climb Stairs	93	83.34
Drink Glass	90	93.34
Sit down Chair	87	60
Standup Chair	81	80

Table 8 shows that VEPRADL has a better recognition accuracy, then GMM and GMR except in case of Drink Glass activity, which in VEPRADL is performed in sequence and interweaved manner, while in Human Motion Modeling and Recognition it is checked with itself.

7. Results of Single Chest-Mounted Accelerometer Dataset for Activity Recognition

Before applying the algorithm on this particular dataset, the activities that were labeled with numbers needed to be replaced with actual names of activities and other features like sum, product, standard deviation of three features: x acceleration, y acceleration, z acceleration and Sum, product, product of x & y, y & z and z & x, division of x & y, y & z and z & x, variance, average, standard deviation, geometric mean, harmonic mean, average of absolute deviation of data points from their mean, square of average of absolute deviation of data points from their mean. After examining the activities we discovered there were a limited number of sequences, concurrencies and interweaving between activities. Hence, for this dataset only two activities at a time are validated with ground truth data. The recognition rates of the activities tested together are shown in Table 9. Note: Walking and Working at computer are multiple times because they are tested with other activities.

8. Performance Comparison of the VEPRADL Algorithm with other Recognition Approaches

A performance comparison of the proposed VEPRADL algorithm carried out with Random Forest classifier presented by Casale [41] and the Personalization and user verification system by Casale [13]. This comparison is based on five activities from the dataset is given in Table 10.

The first perception from the results in Table 10 shows that the Random Forest classifier and Personalization and User Verification System outperform VEPRADL but in these systems every activity is tested

Table 9: Recognition rates of activity recognition using single chest-mounted accelerometer dataset

Activities	Accuracy (%)
Working At Computer	90
Walking and talking with someone	70
Walking	79
Standing	98
Walking	92.5
Standing Up, walking and going up\ down stairs	77
Talking while standing	71
Working At Computer	85
Working At Computer	94
Going up\down stairs	80

Table 10: Recognition rates comparison of VEPRADL with other recognition approaches

Activities	VEPRADL accuracy (%)	Random forest classifier accuracy (%)	Personalization and user verification system accuracy (%)
Climbing stairs	80	89	94.26
Standing	98	88	72.53
Talking	70	92	84.96
Walking	79	95	97.65
Working	90	97	87.1

with itself, not in a sequential, interweaved and concurrent manner with other actions. As in VEPRADL every activity is tested with respect to other activities in sequential, interweaved and concurrent manner. Personalization and User Verification System is as its name suggests is not an activity recognition system. The dataset is intended for Activity Recognition research purposes. It provides challenges for identification and authentication of people using motion patterns.

Random forest classifier is applied on a wearable system, which is based on a new set of 20 computationally efficient features, which were gathered from sensor data that results in a higher classification of more than 90 %. All the results were validated by 5 fold cross validation. However, in VEPRADL it uses less than 1 fold cross validation, only few values in the training set and all other in test set. The highest confusion of 75% is between walking and going up/down stairs, which are same in a sense of motion, but in VEPRADL walking has an accuracy of 92.5 and up\down stairs has an accuracy of 80 % when tested together, showing effectiveness of VEPRADL against Random forest classifier.

5. Conclusion and Future Work

In this paper we proposed an algorithm for recognition of ADLs. Two datasets were used to validate the VEPRADL algorithm. Humans perform activity in a sequential, concurrent and interleaved manner, which makes unobtrusive ADL recognition a complex process. The work in this paper has addressed the challenges of providing a unified solution to solve complex issues that arise in recognizing sequential, interweaved and concurrent activities.

Around the world several patients reside in smart homes, hospitals, old care homes and their constant monitoring is causing burden on society. There is an immense need for their upkeep and rehabilitation, that mostly involve humans for this undertaking. Automated systems for this task are developed around the world to recognize activities done by patients in smart homes. Because of the complexity of the actions done by humans, there is no universal system for this determination. Humans perform activities in sequential, interleaved and concurrent manner. In this work, we applied our algorithm on different data sets for the purpose of classification to achieve promising results.

The focal point of this study was to recognize activities in sequential, interleaved and concurrent manner with a focus on two activities at a time.

In future, this will be scaled to more than two activities in scenarios, as multi user and group activities. VEPRADL will also be scaled for compound situations like groups and inter group and multi users performing activities in interleaved and concurrent manner.

References

[1] U.M. Fayyad, G.P. Shapiro and P. Smith, "From Data Mining to Knowledge Discovery in Databases", in Advances in knowledge discovery and data mining, American Association for Artificial Intelligence, AI Magazine vol. 17, No 3 pp. 1–34, 1996, Menlo Park, CA, USA.

[2] U. Hinrichs and S. Carpendale, "Making Sense of Wild Data: Using Visualization to Analyze in-the-wild Video Records", in Proceedings of the Designing Interactive Systems Conference, Research in the Wild workshop, Newcastle Upon Tyne, United Kingdom, June 11, 2012.

[3] B. Cvetkovic, M. Lustrek, B. Kaluza and M. Gams, "Semi-supervised Learning for Adaptation of Human Activity Recognition Classifier to the User", Proc. of Int. Joint Conf. on Artificial Intelligence, IJCAI, Barcelona, Catalonia, Spain, pp. 24–29, 2011.

[4] D. Perera, J. Kay, I. Koprinska, K. Yacef and O. R. Zaïane, "Clustering and sequential pattern mining of online collaborative learning data", IEEE Transaction on Knowledge and Data Engg., vol. 21, pp. 759 -772, 2009

[5] B. Liu, W. Hsu and Y. Ma, "Integrating classification and association rule mining", Proc. of the 4th Int. Conf. on Knowledge Discovery and Data Mining, New York, NY, August 27 – 31, 1998, pp. 80–86, 1998.

[6] W. Li, J. Han and J. Pei, "CMAR: Accurate and efficient classification based on multiple class-association rules", Proceedings of 1st International Conference on Data Mining, San Jose, CA, United States, Nov, 29 - Dec, 2, 2001, pp. 369–376, 2001.

[7] X. Yin and J. Han, "CPAR: Classification based on predictive association rules," in Proceedings of SIAM International Conference on Data Mining, San Francisco, CA, pp. 331–335, May 2003.

[8] R. J. Hilderman and H. J. Hamilton. Knowledge Discovery and Interestingness Measures: A Survey. University of Regina, Regina, Canada.[Online].Available: http:// www. cs.uregina. ca/Research/Techreports/2000-01.pdf.

[9] H. Lodhi, C. Saunders and J. Shawe-Taylor, N. Cristianini and C. Watkins, "Text classification using string kernels", J. Machine Learning Res, vol. 2, pp. 419–444, 2002.

[10] C. Leslie, E. Eskin and W. S. Noble, "The spectrum kernel: A string kernel for svm protein classification", Proc. of the Seventh Pacific Symposium on Biocomputing (PSB), Singapore, , pp. 564–575, 2002.

[11] G. Dong and J. Li, "Efficient mining of emerging patterns: Discovering trends and differences," Proceedings of Fifth ACM SIGKDD, Int. Conf. on Knowledge Discovery and Data Mining (KDD'99), San Diego, CA, USA, pp. 43– 52, Aug 15 - 18, 1999.

[12] B. Bruno, F. Mastrogiovanni and A. Sgorbissa, "UCI Machine Learning Repository", [https://archive.ics.uci.edu/ml/datasets/ Dataset+for+ADL+Recognition+with+Wrist-worn+Accelero

meter], School of Information and Computer Science, University of California, Irvine, CA, USA.

[13] P. Casale, O. Pujol and P. Radeva, "Personalization and user verification in wearable systems using biometric walking patterns". Personal and Ubiquitous Computing. [Online], vol. 16, no. 5, pp. 563-580, April, 2011, Available:https://www. researchgate.net/profile/Petia_Radeva2/publication/227192676_Personalization_and_user_verification_in_wearable_systems_using_biometric_walking_patterns/links/09e4150b71b8445558000000.pdf.

[14] Z. Wu, L. Wang, X. Tao and J. Lu, "Mining Emerging Patterns for Recognizing Activities of Multiple Users in Pervasive Computing", In Proceedings of Sixth Annual International Conference on Mobile and Ubiquitous Systems: Networking & Services, MobiQuitous, July, 2009, pp. 1-10.

[15] S. Nasreen, M. A. Azam, U. Naeem and M. A. Ghazanfar, "Inference of activities with unexpected actions using pattern mining", Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers, Osaka, Japan, September 07 - 11, pp. 1479-1488, 2015.

[16] M. E. Pollack, L. E. Brown, D. Colbry, C. E. McCarthy, COrosz, B. Peintner, S. Ramakrishnan and I. T. Samardinos, "Autominder : an intelligent cognitive orthotics system for people with memory impairment". Robotics and AutonomousSystems[Online], vol. 44, no. 3-4, pp.273-282, Available:http://www.math.ntua.gr/aarg/projects/Thalis_files/Tsamardinos_2.pdf.

[17] DHHu, S. J. Pan, V. W. Zheng and N. N. L, Q. Yang. "Real World Activity Recognition with Multiple Goals",In Proceedings of the Tenth International Conference on Ubiquitous computing Seoul, Korea, September 21 - 24, 2008, pp. 30-40.

[18] M.A. Azam, J. Loo, U. Naeem and M. Adeel, "Recognizing indoor/Outdoor Activities of Low Entropy People using Bluetooth Proximity and Object Usage Data", International Journal of Pervasive Computing and Communications, IJPCC, vol. 9, No. 4, pp. 346 – 366, 2013.

[19] M.A. Azam, J. Loo, S.K.A. Khan, U. Naeem, M. Adeel and W. Ejaz, "Behavioural Pattern Analysis of Low Entropy People Using Proximity Data", Journal of Wireless Mobile Networks, Ubiquitous Computing and Dependable Applications (JoWUA), vol. 3, No. 3, pp. 41 - 49, 2012.

[20] K. H. Schmitz, D. R. Jacobs, A. S. Leon, P. J. Schreiner and B. Sternfeld, "Physical Activity and Body Weight: Associations over Ten Years in the CARDIA Study", International Journal of Obesity, vol. 24, No. 11, pp. 1475-1487, 2000.

[21] M. Zhang and A. Sawchuk, "Motion primitive based human activity recognition using a bag-of-features approach", In Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium, Miami, Florida, USA, January 28 - 30, 2012, pp. 631–640.

[22] N. Kawaguchi, N. Ogawa, Y. Iwasaki, K. Kaji, T. Terada, K. Murao, S. Inoue, Y. Kawahara, Y. Sumi and N. Nishio, "Hasc challenge: gathering large scale human activity corpus for the real-world activity understandings", Proc. of 2nd Augmented Human International Conference, Article No 27, Tokyo, Japan, March 13 - 13, 2011.

[23] G.Z. Yang, B, Lo and S. Thiemjarus, Body Sensor Networks, 1st Edition, London,Springer Verlag London, 2006.

[24] F. Albinali, S. Intille, W. Haskell and M. Rosenberger, "Using wearable activity type detection to improve physical activity energy expenditure estimation", Proc. of the 12th ACM Int. Conf. on Ubiquitous Computing, Copenhagen, Denmark, pp. 311–320, Sept. 26 - 29, 2010.

[25] O. Chipara, C. Lu, T. Bailey and G.-C. Roman, "Reliable clinical monitoring using wireless sensor networks: experience in a step-down hospital unit", Proc. of the Eighth ACM Conf. on Embedded Networked Sensor Systems, Zürich, Switzerland, pp. 155–168, Nov. 03 - 05, 2010.

[26] H. Lu, W. Pan, N. Lane, T. Choudhury and A. Campbell, "SoundSense: Scalable sound sensing for people-centric sensing applications on mobile phones", Proc. of the 7th Int. Conf. on Mobile Systems, Applications and Services, Kraków, Poland, pp. 165–178, June 22 - 25, 2009.

[27] P. Zappi, C. Lombriser, T. Steifmeier, E. Farella, D. Roggen, L. Benini and G. Troster, "Activity recognition from on body sensors: Accuracy-power trade-off by dynamic sensor selection", Proc. of the 5th European Conf on Wireless Sensor Networks, Bologna, Italy, pp. 17–33, Jan. 30 – Feb. 01, 2008.

[28] A. Bujari, B. Licar and C. Palazzi, "Movement Pattern Recognition through Smartphone's Accelerometer", Proc. of IEEE Consumer Communications and Networking Conference, Las Vegas, NV, USA, pp. 502 – 506, 14 January-17 January, 2012.

[29] T. Gu, Z. Wu, X. Tao, P. K., and J Lu, "epSICAR: An emerging patterns based approach to sequential, interleaved and concurrent activity recognition", Proc. IEEE Int. Conf. on Pervasive Computing and Communications, pp. 1 – 9, March 9- March 13, 2009.

[30] T. Gu, Z. Wu, L. Wang, X. Tao and J. Lu, "Mining emerging patterns for recognizing activities of multiple users in pervasive computing", Proc. of the 6th Annual Int. Conf. on Mobile and Ubiquitous Systems: Networking Services, Toronto, Canada, pp. 13–16, July, 2009.

[31] T. Gu, L. Wang, Z. Wu, X. Tao and J. Lu, "A pattern mining approach to sensor-based human activity recognition", IEEE Transaction on Knowledge and Data Engineering, vol. 23, pp. 1359 - 1372, Sept. 2011.

[32] J. Modayil, T. Bai and H Kautz, "Improving the recognition of interleaved activities Research note", Proc. of the 10th Int. Conf. on Ubiquitous Computing, Seoul, Korea, pp. 40-43, 21- 24 Sept., 2008.

[33] L. Chen, C. D. Nugent and H. Wang, "A knowledge-driven approach to activity recognition in smart homes", IEEE Transaction on Knowledge and Data Engineering, vol. 24, pp. 961 -975, 2012

[34] T.Y. Wu, C.C. Lian and J.Y. Hsu, "Joint recognition of multiple concurrent activities using factorial conditional random fields", Proc. of Association for the Advancement of Artificial Intelligence Workshop Plan, Activity, and Intent Recognition, California, 2007.

[35] G. Singla and D. J. Cook, "Interleaved activity recognition for smart home residents", Proc. of the Fifth International Conf. on Intelligent Environments, Amsterdam, The Netherlands: IOS Press, pp. 145–152, 2009.

[36] L. Jinyan, "Mining emerging patterns to construct accurate and efficient classifier", Ph.D. dissertation, DCS &SE. University of Melbourne, Melbourne, January 2001.

[37] G. Dong, J. Li and X. Zhang. "Discovering jumping emerging patterns and experiments on real datasets", Proc. of 9th Int. Database Conf., Hong Kong, pp. 15–17, July, 1999.

[38] J. Bailey,T. Manoukian and K. Ramamohanarao, "Classification using constrained emerging patterns", 4th Int. Conf. on Web-Age Inf. Manage., Springer Verlag LNCS 2762. Chengdu, China, August, pp 226-237, 2003.

[39] G. Dong, X. Zhang, L. Wong and J. Li, "CAEP: Classification by Aggregating Emerging Patterns", Proc. of the 2nd Int. Conf. on Discovery Science, Springer-Verlag London, pp. 30-42, 1999.

[40] F. Mastrogiovanni, A. Sgorbissa , T. Vernazza , R. Zaccaria. "Human motion modeling and recognition: A computational approach", Proc. of IEEE Int. Conf. on Automation Science and Engineering, Seoul, South Korea, pp. 156-161, 20 - 24 August, 2012.

[41] P. Casale, O. Pujol and P. Radeva, "Human activity recognition from accelerometer data using a wearable device", Proc. of Iberian Conf. on Pattern Recognition and Image Analysis, Lecture Notes in Computer Science, vol. 6669, , pp. 289-296, 2001, Springer, Berlin, Heidelberg.