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IDENTIFICATION AND CATEGORIZATION OF HUMAN ACTIVITIES USING MACHINE LEARNING

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Abstract — activity recognition can be used by recommender systems to help the users track their daily physical activity and promote them to increase their activity level. With the recent progress in wearable technology, unobtrusive and mobile activity recognition has become reasonable. With this technology, devices like smartphones and smartwatches are widely available, hosting a wide range of built-in sensors, at the same time, providing a large amount of computation power. Overall, the technological tools exist to develop a mobile, unobtrusive and accurate physical activity recognition It contains data generated from accelerometer, gyroscope and other sensors of Smart phone to train supervised predictive models using machine learning techniques like SVM, Random forest and decision tree to generate a model. Which can be used to predict the kind of movement being carried out by the person which is divided into six categories walking, walking upstairs, walking down-stairs, sitting, standing and laying. MLM and SVM achieved accuracy of more than 99.2% in the original data set and 98.1% using new feature selection method. Results show that the proposed feature selection approach is a promising alternative to activity recognition on smart phones.

INTRODUCTION

The human activity recognition model can be implemented with the use of camera module which captures the raw data that serves as an input to the recognition system. By creating different frames of such input data categorization of activity is done after feature

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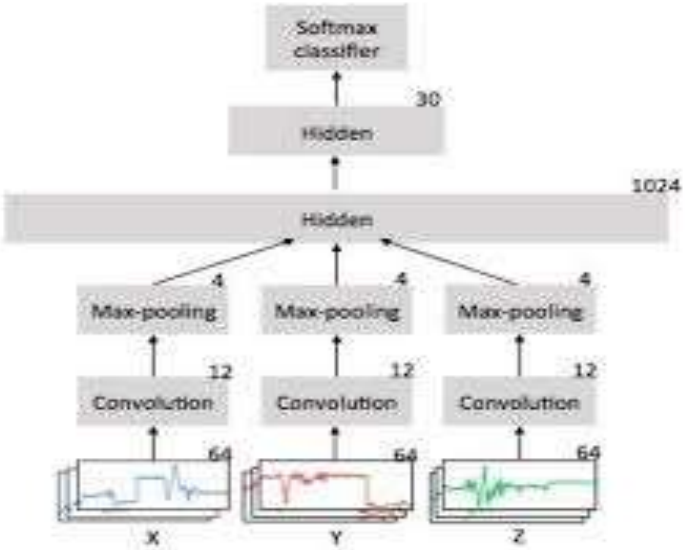
extraction. Such activity is then identified as normal or suspicious and immediate alert is sent to the authority. Human Activity Recognition is an active field of research and scientific development in which various models have been proposed using different methods for identification and categorization of activities using Machine Learning. The features of image or video data set are extracted using different kinetic models associated with spatial or temporal feature leaning. Also, many deep layer trained models have been successfully used in this field to reach the fundamental goal of this model which is recognition and categorization of activity taking place. These activities can be of different varying nature such as day to day activities like running, jogging, eating, sitting, etc. There can be numerous types of activities in different fields like healthcare, childcare, security or work safety. Human Activity Recognition has a very significant role in different fields like human computer interaction, video surveillance system, robotics, daily monitoring, wildlife observation, etc.



PROPOSED SYSTEM

EXISTING SYSTEM

- Several investigations have considered the use of widely available mobile devices. Ravi et. al. collected data from only two users wearing a single accelerometer-based device and then transmitted this data to the phone carried by the user (Ravi et al.,2005).
- Lester et. al. used accelerometer data from a small set of users along with audio and barometric sensor data to recognize eight daily activities (Lesteret al., 2006). However, the data was generated using distinct accelerometer-based devices worn by the user and then sent to the phone for storage.
- Some studies took advantage of the sensors incorporated into the phones themselves. Yang developed an activity recognition system using a smart-phone to distinguish between various activities (Yang, 2009).
- However, stair climbing was not considered and their system was trained and tested using

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data from only four users. Brezmeset. al. developed a real-time system for recognizing six user activities (Brezmeset al., 2009). In their system, an activity recognition model is trained for each user, i.e., there is no universal model that can be applied to new users for whom no training data exists.

- Bayat et al. gathered acceleration data from only four participants, performing six activities. (Bayat et al., 2014) Shoaib et al. evaluated different classifiers by collecting data of smart-phone accelerometer, gyroscope, and magnetometer for four subjects, performing six activities. (Shoaib et al., 2013).

PROPOSED SYSTEM

- The purpose of being able to classify what activity a person is undergoing at a given time is to allow computers to provide assistance and guidance to a person prior to or while undertaking a task.
- The difficulty lies in how diverse our movements are as we perform our day-to-day tasks.
- There have been many attempts to use the various machine learning algorithms to accurately classify a person's activity, so much so that Google have created an Activity Recognition API for developers to embed into their creation of mobile applications.

LITERATURE SURVEY

1. Andrej Karpathy, Sanketh Shetty, Thomas Leung, Rahul Sukhtankar, George Toderici, Li Fei-Fei)

In this proposed model the study of performance of convolutional neural networks is done in large-scale video classification. As the performance of model is not entirely sensitive to details of architecture, the slow fusion model perform much better than early and late fusion. A mixed resolution architecture is also identified which contains low resolution context and high resolution fovea stream which is very effective in speeding up CNN without any harm to the accuracy.

Videos are very variable in nature due to their temporal extent and therefore requires complex procedure for processing. So in this model each video is treated as a bag of short and fixed sized clips to make the further procedure of categorization and classification more convenient. By doing such a task the spatio-temporal features can be learnt by extending the connectivity of network in time dimension. Here, 3 categories of broad connectivity are used which are Early Fusion, Late Fusion and Slow Fusion. Later a multi resolution architecture is described to address the computational efficiency.

The datasets used in this model are UCF-101 and Sports- 1M.

2. Learning hierarchical invariant spatio-temporal features for action recognition with independent subspace analysis.

   (Will Y Zou, Serena Y Yeung, Quoc V Le, Andrew Y Ng)

   In this paper they have implemented a method which learns the features from spatiotemporal data with the use of independent subspace analysis. A standard processing pipeline has been used through which the observation has been made that many state-of-the-art methods are outperformed by their simple method. They have used a single method using same parameters across all datasets and have proved to be consistently better than variety of combination of different methods.

   Using their method the feature extraction of activity is very fast and efficient as hand designed features. They have also compared the speed of their method with HOG3D algorithm and concluded that using one layer their method is faster than HOG3D but if two layers are used the algorithm is slower. It has also been said that as this method uses matrix vector product and convolutions, its implementation can be done on GPU in an efficient manner.

   Various experiments in this model are carried out on datasets such as KTH, Hollywood2, UCF sport action and YouTube in which standard processing pipeline is used.

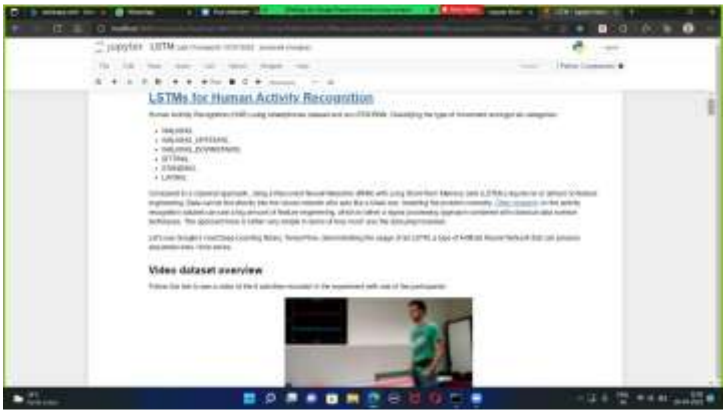
3. Bao, L. and Intille, S. S. (2004). Activity recognition from user-annotated acceleration data. In Pervasive computing, pages 1–17. Springer.

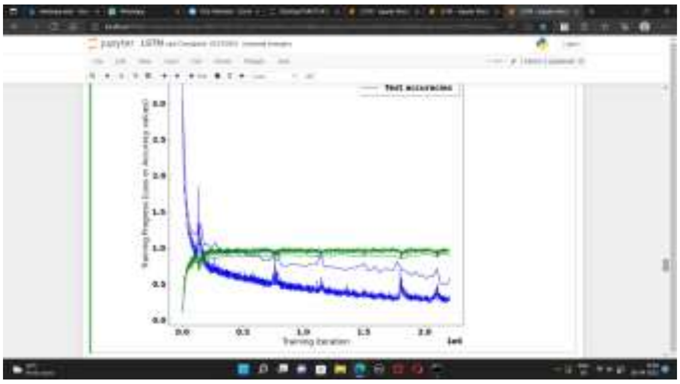
In this work, algorithms are developed and evaluated to detect physical activities from data acquired using five small biaxial accelerometers worn simultaneously on different parts of the body. Acceleration data was collected from 20 subjects without researcher supervision or observation. Subjects were asked to perform a sequence of everyday tasks but not told specifically where or how to do them. Mean, energy, frequency-domain entropy, and correlation of acceleration data was calculated and several classifiers using these features were tested. Decision tree classifiers showed the best performance recognizing everyday activities with an overall accuracy rate of 84%. The results show that although some activities are recognized well with subject-independent training data, others appear to require subject-specific training data. The results suggest that multiple accelerometers aid in recognition because conjunctions in acceleration feature values can effectively discriminate many activities. With just two biaxial accelerometers – thigh and wrist – the recognition performance dropped only slightly. This is the first work to investigate performance of recognition algorithms with multiple, wire-free accelerometers on 20 activities using datasets annotated by the subjects themselves.

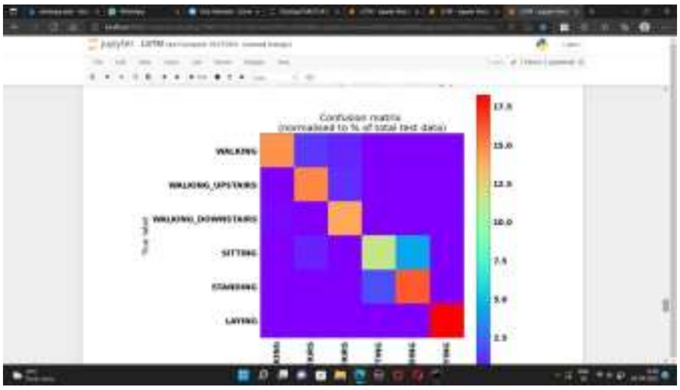
RELATED WORK

Human Activity Recognition can benefit various applications in fields like smart home monitoring, healthcare services, security surveillance, childcare etc. In future we can update this application by using object activity recognition in which activities performed by objects can also be tracked and analyzed. Application of integrated large datasets can be done to identify the activity taking place as slower rate of time. Even very subtle or minute variations should be recognized by the system. The data of actor performing the anomalous activity can be stored and identification of actor can be done if not caught in the first place. Activities that are of reoccurring manner should be stored to save time and space during recognition process. Implementation of such model can also be done in Government authority section. Much more developments for improvisation in accuracy and dealing with issues related to optical identity and background clutter of image can be done.

SAMPLE SCREENSHOTS







CONCLUSION

In this project, a platform to combine sensors of smartphones and smartwatches to classify various human activities was proposed. It recognizes activities in real-time Moreover, this approach is light-weight, computationally inexpensive, and able to run on handheld devices. The results showed that there is no clear winner, but naive Bayes performs best in our experiment in both the classification accuracy and efficiency. The overall accuracy lies between 84.6% and 89.4%, at which the differences are negligible. Thus, this platform is able to recognize various human activities. However, all of the tested classifiers confused walking and using the stairs activities. The second conclusion is that adding the smartwatch's sensor data to the recognition system improves it's accuracy with at least six percentage point. Finally, it is computations that the best sampling frequency is in the field of 10 Hz. Some questions still require to be answered. Most important is the conducting of larger experiments with more people in order to perform more robust evaluation to clarify if indeed one method is better than the other, or whether, any off-the-shelf method can do well in this classification task. This work could be further extended by incorporating more sensors (e.g. heart rate sensor), recognizing high-level activities (e.g. shopping or eating dinner) or extrapolating these trained classifiers to other people.

REFERENCES

1. Moez Baccouche, Franck Mamalet, Christian Wolf, Christophe Garcia, and Atilla Baskurt Asa, (2011). Sequential Deep Learning for Human Action Recognition Retrieved from: https://link.springer.com/content/pdf/10.1007%2F978-3-642-25446- 8_4.pdf

2. Shikhar Sharma, Ryan Kiros & Ruslan Salakhutdinov, (2016 February). Action Recognition using Visual Attention Retrieved from: http://www.shikharsharma.com/publications/pdfs/action- recognition-using-visual-attention-nips2015.pdf

3. Mohamad Hanif Md Saad, Aini Hussain, Liang Xian Loong , Wan Noor Aziezan Baharuddin, Nooritawati Md Tahir, (2011). Event Description From Video Stream For Anomalous Human Activity and Behavior Detection Retrieved from: https://ieeexplore.ieee.org/document/5759931

4. Ishan Agarwal, Alok Kumar Singh Kushwaha, Rajeev Srivastava, (2015). Weighted Fast Dynamic Time Warping Based Multiview Human Activity Recognition Using a RGB-D Sensor Retrieved from: https://ieeexplore.ieee.org/document/7490046

5. Murat Cihan Sorkun, Ahmet Emre Daniman, Ã–zlem Durmaz ncel (2018). Human Activity Recognition With Mobile Phone Sensors: Impact Of Sensors And Window Size Retrieved

from:
https://ieeexplore.ieee.org/document/840 4569

6. Neslihan KÃ¤se, Mohammadreza Babaee, Gerhard Rigoll, (2017).

   Multi-view human activity recognition using motion frequency

   Retrieved from:

   https://sigport.org/sites/default/files/docs /ICIP_PaperID1443_Final.p df

7. Hui Huang, Xian Li, Ye Sun, (2016 August). A triboelectric motion sensor in wearable body sensor network for human activity recognition Retrieved from:

8. https://www.researchgate.net/publication /303876425_A_Triboelectri c_Motion_Sensor_in_Wearable_Body_S ensor_Network_for_Human_Activity_R ecognition

9. Shuiwang Ji, Wei Xu, Ming Yang, Kai Yu, (2012). 3D Convolutional Neural Networks for Human Action Recognition Retrieved from: https://ieeexplore.ieee.org/document/616 5309

BIOGRAPHIES

Ch. V. Murli Krishna is an Associate Professor and the head of the CSE (Data Science) department at NRI Institute of Technology. He has over 20 years of experience in engineering academics and has taught both undergraduate and postgraduate courses. He has also guided many B. Tech, M. Tech, and MCA projects as part of the academic curriculum. In addition to his teaching responsibilities, he has been involved in various administrative tasks like NBA, NAAC, ICT, and IQAC. He has organized several workshops, faculty development programs, and Tech Fests. He is a member of IAENG, IFERP, and INSC. He completed his M. Tech. in Computer Science & Engineering in 2009 and is currently pursuing a Ph.D. in Computer Science & Engineering at GITAM (Deemed to be University), Vizag.

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