Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 15, Issue. 1, No.10 : 2024
ISSN : **1906-9685**

HUMAN ACTIVITY RECOGNITION

Ms. T. Jhansi , MCA Student, Department of Master Of Computer Applications,

Vignan;s Institute of Information Technology(A), Visakhapatnam-530049.

Abstract

Human activity recognition (HAR) is a diverse research domain focused on discerning specific movements or actions of individuals based on sensor data. This data can be acquired remotely through various means such as video, radar, or wireless technologies. It encompasses information gathered from sensors like accelerometers, gyroscopes, and others embedded in smartphones. These datasets are utilized to train supervised predictive models employing machine learning algorithms like Support Vector Machines (SVM), Random Forest, and Decision Trees to construct predictive models. These models are adept at predicting the type of activity being performed by individuals, which are typically categorized into six main classes: walking, walking upstairs, walking downstairs, sitting, standing, and laying down.

In the original dataset, both SVM and MLM algorithms achieved remarkable accuracies exceeding 99.2%. Additionally, employing a novel feature selection technique led to a slightly reduced but still impressive accuracy of 98.1%. These findings underscore the efficacy of the proposed feature selection methodology as a viable approach for activity recognition on smartphones.

Keywords

- Machine Learning,
- Accelerometer,
- Gyroscope,
- Supervised Predictive Model,
- SVM, Random Forest, Decision Tree.

Introduction

The importance of physical activity for maintaining a healthy lifestyle is widely recognized by the public, prompting researchers to delve deeper into its relationship with overall health. Accurately documenting physical activities is essential for advancing this research (Bauman et al., 2006). Such data serves as a foundation for developing activity recognition systems, which offer a means for healthcare professionals to monitor their patients' recovery progress automatically and continuously (da Costa Cachucho et al., 2011). The sedentary lifestyles prevalent in today's modern world, characterized by reduced physical demands in both work and leisure activities, have raised concerns (Gyllensten, 2010). Numerous studies have established connections between physical inactivity and various common diseases (Preece et al., 2009). Consequently, activity recognition systems can be integrated into recommendation systems to assist users in tracking their daily physical activities and encourage them to increase their activity levels. Advancements in wearable technology have made it feasible to develop mobile, unobtrusive, and accurate activity recognition systems. Devices such as smartphones and smartwatches, equipped with an array of built-in sensors and ample computational power, facilitate this progress. Consequently, the ability to recognize individuals' physical activities during their daily routines is now achievable. However, there remains a gap in research concerning the utilization of lightweight devices for activity recognition. Key requirements for an activity recognition system include real-time recognition capabilities, necessitating computable features for classification and the use of short window durations to avoid delayed responses. Additionally, classification schemes should be simple, lightweight, and computationally efficient to enable their execution on handheld devices.

Literature Survey

Human activity recognition has been a subject of extensive research over the years, with various methodologies proposed to address this complex challenge. These approaches typically leverage either vision sensors, inertial sensors, or a combination of both. Machine learning algorithms and threshold-based techniques are commonly employed for classification. While machine learning methods tend to yield more accurate and reliable results, threshold-based algorithms offer speed and simplicity. In the realm of vision-based approaches, one or more cameras are utilized to capture and identify body postures (references [8] and [9]). On the other hand, inertial sensors such as accelerometers and gyroscopes, affixed to different body positions, represent another prevalent solution (references [10]-[13]). Some strategies amalgamate both vision and inertial sensors to enhance accuracy and robustness (reference [14]).Data processing plays a pivotal role in the efficacy of these algorithms, as the quality of input features significantly impacts performance. Prior efforts have focused on extracting relevant features from time series datasets, often employing analyses in both the time and frequency domains (reference [15]).Active learning, a technique utilized in various machine learning domains to mitigate the time and labor expenses associated with labeling samples, has also garnered attention. Applications of active learning span diverse domains such as speech recognition, information extraction, and handwritten character recognition (references [18]-[20]). Notably, this technique has yet to be extensively explored in the context of human activity recognition.

Conclusion

The public widely acknowledges the significance of physical activity in maintaining good health, prompting researchers to delve into its correlation with overall well-being. Accurate documentation of physical activities is pivotal for advancing such research endeavors (Bauman et al., 2006). This data serves as the bedrock for the development of activity recognition systems, which offer healthcare professionals a means to autonomously and continuously monitor their patients' recovery progress (da Costa Cachucho et al., 2011). The prevalence of sedentary lifestyles in modern society, characterized by reduced physical demands in both occupational and leisure pursuits, has sparked concerns (Gyllensten, 2010). Numerous studies have established links between physical inactivity and various common diseases (Preece et al., 2009). Consequently, integrating activity recognition systems into recommendation platforms can aid users in tracking their daily physical activities and motivating them to enhance their activity levels. Advancements in wearable technology have made the development of mobile, inconspicuous, and precise activity recognition systems feasible. Devices like smartphones and smartwatches, equipped with an array of embedded sensors and substantial computational power, facilitate this advancement. Consequently, the ability to identify individuals' physical activities during their daily routines is now within reach. However, there exists a gap in research concerning the use of lightweight devices for activity recognition. Essential requirements for an activity recognition system include real-time recognition capabilities, necessitating features that are computable for classification and the utilization of brief window durations to prevent delays in response. Furthermore, classification methodologies should be straightforward, lightweight, and computationally efficient to enable deployment on handheld devices.

References

[1] H.Wang,A .Klaser,C.Schmid and C-L.Liu, “Action recognition by dense trajectories ,” in Proc. IEEE Conf. Comput. Vis.Pattern Recog.,Jun. 2011,pp 3169-3176.

[2] H.Wang and C Schmiid , “Action recognition with improved trajectories,” in Proc.IEEE Int. Conf.Comput. Vis., Dec 2013,,pp 3551- 3558.

[3] Y-G Jiang,Q.Dai,X.Xue,W.Liu and C-W Ngo. “Trajectory-based modeling of human actions with motion reference points,” inProc. Eur.Conf .Comput.Vis.,Oct 2012,Vol 7576,pp.425-438.

[4] M. D. Rodriguez, J. Ahmed, and M. Shah, “Action MACH: A spatiotemporal maximum average correlation height filter for action recognition,”in Proc. IEEE Conf. Comput. Vis. Pattern Recog., Jun. 2008,pp. 1–8.

[5] Y. Hu, L. Cao, F. Lv, S. Yan, Y. Gong, and T. S. Huang, “Action detectionin complex scenes with spatial and temporal ambiguities,” in Proc. IEEE Conf. Comput. Vis. Pattern Recog., Sep.– Oct. 2009, pp.128–135.

[6] T. Lan, Y. Wang, and G. Mori, “Discriminative figure-centric models for joint action localization and recognition,” in Proc. IEEE Int. Conf. Comput. Vis., Nov. 2011, pp. 2003– 210.

[7] M.Raptis, I.Kokkinos and S.Soatto,” Discovering discriminative action parts from mid-level

video representations” ,in Proc ,IEEE Conf.Comput.Vis,.Pattern Recog.,Jun 2012,pp.1242-1249.

[8] W. Brendel and S. Todorovic, “Learning spatiotemporal graphs of human activities,” in Proc. IEEE Int.Conf. Comput. Vis., Nov. 201.

[9] M.Jain,J.van Genmert,H.Jegou ,P.Bouthemy and C.Snoek ,”Action localization with tubelets from motion” ,in Proc IEEE Conf, Comput.Vis.Pattern Recog. Jun 2014 pp 740-747.