

Impact of Sampling Rate on Deep Learning-based Human Activity Recognition Using Wearable Sensors

Nguyen Thi Hoai Thu, Dong Seog Han*

School of Electronic and Electrical Engineering, Kyungpook National University

thunguyen@knu.ac.kr, *dshan@knu.ac.kr

Abstract

In the wearable sensor-based human activity recognition (HAR) domain, it is crucial to select an appropriate sampling rate at which the sensor data would be captured before being forwarded to a classification model. This sampling rate needs to be selected carefully since sampling rates that are too high can require high storage capacity, wide transmission bandwidth, and high computational cost, while low sampling rates can reduce the classification accuracy. This study presents a statistical analysis of how sampling rates affect the performance of HAR systems, especially those whose classification methods are deep learning algorithms. With seven different sampling rates ranging from 100 Hz down to 20 Hz; and three advanced deep learning algorithms: multi-layer perceptron (MLP), convolutional neural network (CNN), and bidirectional long short-term memory network (BiLSTM), a series of experiments are carried out on the PAMAP2 benchmark dataset to find out the most effective sampling rate and determine which deep learning algorithm is best suited in handling low sampling rates.

I. Introduction

Wearable sensor-based human activity recognition systems (HAR) have been growing rapidly over the past decade, thanks to the advancement of microelectromechanical systems. With the advantages of protecting user privacy, wearable sensor-based HAR has dominated over the camera-based HAR approach and become a crucial part of the healthcare domain [1]. It can help users track their activities and health conditions, thereby promoting a healthier lifestyle. Some abnormal activities, such as freezing of gait from Parkinson's disease [2]. Various types of wearable sensors have been applied for the HAR systems to measure motions such as inertial measurement units (IMUs) and stretch sensors [3]. IMUs is one of the most broadly used sensors in HAR since they can capture human motion accurately. Therefore, this study will focus on the sampling rate of these sensors. The commonly used sampling rate of these sensors lies between 10 Hz and 100 Hz [1].

In a HAR system, the sensors capture the state changes at a fixed sampling rate and send this information to the processing unit for data preprocessing (filtering, windowing), feature extraction, and activity classification. Using a high sampling rate can provide more details on the motion of the user's body, thus helping to improve the accuracy of activity recognition. However, sampling sensor data at a high rate often requires consuming more energy, which is limited in wearable devices. Furthermore, to capture the data at a high frequency, high-quality sensors are often required, which can increase the production cost. On the other hand, using a low sampling rate can overcome the problems of power

consumption, storage capacity, and data transmission loss. However, sensors with a low sampling rate might not be able to capture all the body movements. According to the Nyquist-Shannon sampling theorem, the sampling rate should be greater than twice the Nyquist frequency for a lossless reconstruction of a particular signal. Therefore, some minor differences between activities that have high similarity, such as walking and walking downstairs or jumping and falling, can be neglected when using a low sampling rate, since they contain high-frequency components. In a nutshell, it is a trade-off between accuracy and efficiency when deciding to use either a high sampling rate or a low sampling rate. Therefore, it is important to find out the most effective sampling rate. In this paper, we want to find out how different sampling rates can affect the deep learning-based HAR system, and which deep learning model can handle low sampling rates.

II. Methodology

All the experiments in this study are carried out on the PAMAP2 dataset [4]. The dataset contains 18 types of daily-life, household, and sport activities performed by nine subjects wearing three IMUs and a heart rate monitor. All data are sampled at a rate of 100 Hz. The acceleration and angular velocity data from the three IMUs are used in this study. The sequential data of each IMU sensor can be expressed as $\mathbf{S}_i = [\mathbf{a}_x, \mathbf{a}_y, \mathbf{a}_z, \mathbf{g}_x, \mathbf{g}_y, \mathbf{g}_z]$. The data is collected at an original sampling rate of 100 Hz. To generate the sensor data at sampling rates of 80, 60, 50, 40, 30, 20 Hz, we use an FIR anti-aliasing low-pass filter and compensate the delay of the output signal. Finally, the sensor signals are split into fixed-length windows with a length of 2 seconds and an overlap of 50%.

Table 1. Detailed Architecture of three deep learning-based HAR models.

CNN	BiLSTM	MLP
Conv(3×3, 32, 'relu', same)	BatchNorm()	Dense(units=128, 'gelu')
Conv(3×3, 32, 'relu', same)	BiLSTM(units=128, 'concat')	Dense(units=128, 'gelu')
MaxPool(2,1)	BiLSTM(units=128, 'concat')	Dense(units=128, 'gelu')
Conv(3×3, 32, 'relu', same)	BiLSTM(units=128, 'concat')	Dense(units=128, 'gelu')
Conv(3×3, 32, 'relu', same)	Dense(units=18, 'softmax')	Flatten()
MaxPool(2,2)		
Conv(3×3, 32, 'relu', same)		
Conv(3×3, 32, 'relu', same)		
GlobalAveragePool()		
Dense(units=18, 'softmax')		

Three commonly used deep learning (DL) models are considered in this study, including convolutional neural network (CNN), bi-directional long short-term memory (BiLSTM), and multi-layer perceptron (MLP). The detailed architecture of these models is shown in Table 1. The CNN is constructed from a set of 2D convolutional layers with (3×3) kernels and pooling layers. In the BiLSTM model, we perform batch normalization on the raw sensor data as a regularization mechanism. Three BiLSTM layers with concatenation merge mode are then deployed for further feature extraction. The MLP model used in this study contains four hidden layers, each has 128 hidden nodes and a GELU activation function.

The recognition accuracies of the three deep learning algorithms with seven different sampling rate values are illustrated in Fig. 1. It can be easily seen that the CNN-based system gains the best performance out of the three deep learning models in all different sampling rates. It outperforms the other two models with big gaps of 3-4%. In the CNN-based system, it is surprising that even though the sampling rate is reduced fivefold from 100 Hz to 20 Hz, the system performance only decreases 1.6% from 97% to 95.35%. Therefore, CNN with 2D kernels can directly handle raw sensor data with low sampling rates without any additional steps. In contrast, the MLP-based HAR system has better performance at low sampling rates than high sampling rates, as it obtains the highest accuracy at $F_s = 20, 30$ Hz, and the lowest accuracy at a sampling rate of 60 Hz. Similarly, although the BiLSTM model gains the highest accuracy at $F_s = 100$ Hz, there is not much difference compared to other sampling rate values. These results show that a higher sampling rate does not always provide higher accuracy, especially when the deep learning model is applied directly to the raw sensor signal. One possible reason is that long input sequences resulting from a high sampling rate can hamper the model in extracting and maintaining important features.

III. Conclusion

In this paper, experiments on different sensor sampling rates and different deep learning algorithms are carried out to find out the impact of sampling rate on DL-based HAR system performance. Experimental results from three deep learning algorithms and seven sampling rate values show that CNN is the best model for handling raw sensor data with low sampling

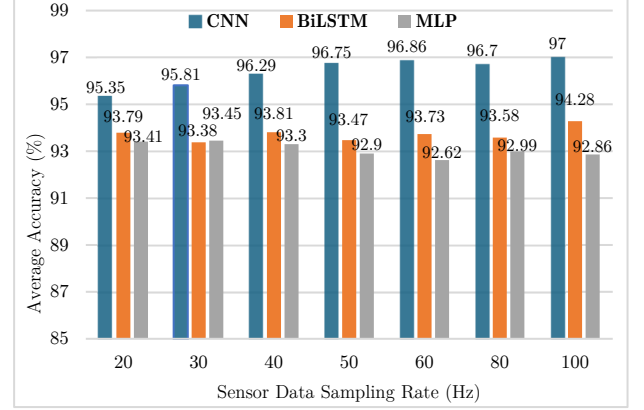


Fig 1. Performance comparison of three deep learning-based HAR systems on different sampling rates.

frequencies. One interesting finding is that higher sampling rates with more detailed sensor signals do not always provide better classification results due to some limitations in feature extraction.

ACKNOWLEDGMENT

This work was supported by the IITP (Institute of Information & Communications Technology Planning & Evaluation)-ITRC (Information Technology Research Center) grant funded by the Korea government (Ministry of Science and ICT) (IITP-2025-RS-2020-II201808).

References

- [1] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Communications Surveys and Tutorials*, vol. 15, no. 3, pp. 1192–1209, 2013.
- [2] N. T. H. Thu and D. S. Han, "Freezing of gait detection using discrete wavelet transform and hybrid deep learning architecture," in *2021 Twelfth International Conference on Ubiquitous and Future Networks (ICUFN)*. IEEE, 2021, pp. 448–451.
- [3] N. T. H. Thu and D. S. Han, "An investigation on deep learning-based activity recognition using IMUs and stretch sensors," in *2022 International Conference on Artificial Intelligence on Information and Communication (ICAIIIC)*. IEEE, 2022, pp. 377–382.
- [4] A. Reiss and D. Stricker, "Creating and benchmarking a new dataset for physical activity monitoring," in *Proceedings of the 5th International Conference on Pervasive Technologies Related to Assistive Environments*, 2012, pp. 1–8.