Optimizing On-Body Sensor Placements for Deep Learning-Driven Human Activity Recognition

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Abstract. The effective positioning of sensors and the appropriate data merging play a crucial role in advancing systems for recognizing human activities (HAR) using deep neural networks. This study thoroughly evaluates five well-known deep learning structures designed for HAR based on smartphone multi-position sensors. During various activities, the research analyzed data from accelerometers and gyroscopes placed in five different locations on the body. Convolutional neural network (CNN), Long short-term memory (LSTM), Bidirectional LSTM (BiLSTM), Gated recurrent units (GRU), and Bidirectional GRU models were assessed for the classification of activities, considering different sensor combinations across various positions. The study's main findings confirm that achieving accuracy and F1-scores exceeding 99% for the leading BiLSTM, GRU, and BiGRU models is possible by utilizing multi-modal data from well-suited sensor configurations across wrists, arms, pockets, and belts. These recurrent networks consistently outperform CNN and standard LSTM models, which depend on bimodal inputs. Notably, the wrist offers additional motion-sensing capabilities from both the accelerometer and gyroscope, thereby enhancing the fidelity of recognition across multiple positions. The insights derived contribute guidelines for designing robust sensor placements and strategies for fusing data to optimize HAR driven by deep learning, especially on common smartphones. Applications in various domains, such as automated fitness tracking, patient monitoring, and context-aware computing, can benefit from these on-body sensor-based deep models tailored to specific device locations.

Keywords: Human activity recognition · Sensor fusion · Sensor placement · Deep learning · Wearable sensors

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O. Gervasi et al. (Eds.): ICCSA 2024, LNCS 14814, pp. 327–338, 2024.
https://doi.org/10.1007/978-3-031-64608-9_21

1 Introduction

Wearable devices show great potential in health and fitness monitoring applications, assisted living technologies, and context-aware computing [10,22]. The primary objective of human activity recognition (HAR) is to automatically identify individuals' physical activities through the analysis of data from on-body sensors, including inertial measurement units and accelerometers [4,8,11]. The continuous monitoring of activities has become feasible due to the widespread use of consumer-grade activity trackers and smartwatches. Nevertheless, the accuracy of inferred activities is heavily influenced by the placement of sensors on wearable devices [13].

Earlier research has conducted experimental examinations into the impact of placing wearable sensors on activity recognition effectiveness using traditional machine learning methods [15,19]. Repeatedly, the torso and wrist positions have been identified as offering the highest accuracy for classifiers, including decision tree, k-nearest neighbor, and support vector machine models. However, recent advancements in deep learning, particularly the progress of convolutional neural networks (CNN) and recurrent networks, have elevated results on benchmark datasets for HAR [17]. Deep models can acquire robust feature representations from multimodal sensor data in an end-to-end fashion. This shift in approach necessitates a fresh examination of suitable strategies for positioning wearable sensors.

The strategic arrangement of sensors and integration of data from various on-body locations play a crucial role in developing HAR systems using deep learning. Despite this importance, there needs to be a thorough examination that assesses strategies for placing sensors specifically designed for deep neural networks. This study aims to establish guidelines for the optimal configuration of wearable sensors, specifically tailored to the analysis of human activities driven by deep learning.

This study explores data from accelerometers and gyroscopes at five locations on the body: wrists, arms, belts, right pockets, and left pockets. During the investigation, participants engage in routine activities like walking, sitting, standing, and jogging. We evaluate five notable deep-learning structures to classify these activities across multiple positions through sensor fusion. The architectures under assessment include CNNs, long short-term memory (LSTMs), bidirectional LSTMs (BiLSTMs), gated recurrent units (GRUs), and bidirectional GRUs (BiGRUs).

The primary results confirm that integrating data from accelerometers and gyroscopes at specific wrist, arms, belt, and pocket locations improves accuracy and F1-score, surpassing 99% for the top-performing BiLSTM, GRU, and BiGRU recurrent networks. These recurrent networks consistently outshine CNN and regular LSTM models. Notably, the wrist plays a crucial role in providing essential signals for motion sensing from both modalities, enhancing recognition capabilities across various positions.

The remaining sections of this document are structured as outlined below. Section 2 reviews existing research on the analysis of sensor positions in HAR

and the progress made in deep learning. Section 3 details our framework based on deep CNNs, along with the experimental setup and evaluation metrics used for analysis. The presentation of quantitative results, diagnostic inferences, and critical observations is covered in Sect. 4. Lastly, Sect. 5 provides concluding remarks and outlines directions for future works.

2 Related Works

2.1 Deep Learning for S-HAR

Recent significant investigations into HAR [25] have brought to light issues linked with traditional machine learning methods that impact the capability to identify human activities. The constraint is around opting for manually crafted features, a decision-making process heavily reliant on the expertise of the individual making the choices [27]. Deep learning has emerged as a viable alternative to tackle these limitations effectively in only a few years.

In recent years, there has been extensive exploration of advanced learning models to address challenges in classifying time-series data related to recognizing human activities. Researchers have scrutinized different complex structures on standard datasets to assess their effectiveness in accurately recognizing activities. Among the popular methodologies, CNNs [16] and LSTM networks [14] have demonstrated promising outcomes in HAR tasks involving data from smartphone sensors. These sophisticated models offer suitable assessment metrics for measuring performance in identifying periodic time-series signals. Encouraged by their proven capabilities, our study delves into applying CNN and LSTM models to classify hand gestures using motion data from smartwatches. We gauge the efficiency of both models in solving the hand movement recognition challenge based on pertinent evaluation criteria, providing insights into their suitability for HAR applications driven by wearable sensors.

In 1997, Schuster and Paliwal introduced the BiLSTM [23] to expand the knowledge capacity within the LSTM network. The BiLSTM is connected to two hidden layers operating in opposite directions, enabling it to gather information from preceding and succeeding sequences simultaneously. Unlike unidirectional models, the BiLSTM does not require any reconfiguration of input data and can incorporate future inputs while maintaining its current state. In their work on sensor-based HAR (S-HAR), Alawneh et al. [1] conducted a comparative analysis of unidirectional and bidirectional LSTM models. The findings revealed that the BiLSTM surpasses the unidirectional technique regarding recognition efficiency.

While LSTM has effectively mitigated the vanishing gradient problem associated with RNNs, the memory cells within its architecture result in increased memory consumption; in 2014, Cho et al. [5] introduced the GRU network as a new model based on RNNs. The GRU is a simplified version of LSTM, lacking a distinct memory cell in its structure [6]. Within the GRU network, update and reset gates are responsible for adjusting the modification degree of each hidden state. These gates determine the knowledge that should be transferred to the next state and what should not be transferred [20,21]. Addressing the S-HAR

problem through data augmentation, Okai et al. [18] established a robust deep learning model based on the GRU network. In comparisons within this study, the GRU model outperformed and demonstrated greater resilience than the LSTM models.

An inherent drawback of this network lies in its unidirectional nature, meaning the output at a given time step relies solely on past information from the input sequence, excluding the current input. In specific scenarios, it could prove advantageous to consider the past and future when making predictions [12]. To address this, Alsarhan et al. [2] introduced a BiGRU model for HAR. The outcomes demonstrated that employing the BiGRU model for recognizing human actions through sensor data is also highly effective.

2.2 Position-Aware HAR

The recognition of on-body device positions has been a relatively neglected aspect of research. Initially, scholars delved into recognizing activities without considering the device's location [9]. However, they discovered that the recognition rate varies significantly based on the location. Subsequent experiments focused on the device's position and its impact on the recognition rate, indicating that this information enhances activity recognition accuracy. However, opinions on its impact remain divided [7]. A critical examination of their findings highlights that differing viewpoints may arise from the specific positions and activities considered. Notably, studies have yet to comprehensively explore all relevant on-body positions in everyday physical activities, leaving uncertainty about the accuracy of detecting each pertinent position for different activities.

In the broader context of recognizing activities, the positioning of sensors holds significant importance, prompting numerous researchers to explore the impact of various locations on activity performance [26]. These investigations reveal that seven distinct body locations — forearm, head, shin, thigh, upper arm, waist, and chest - exhibit varying behaviors in activity recognition. Subdividing these body parts into smaller regions does not yield improved accuracy. Moreover, additional research indicates that the optimal placement of sensors depends on the specific activity under consideration [3]. Consequently, the value of position information and the feasibility of deducing device positions from an accelerometer has been firmly established.

3 The Sensor-Based HAR Framework

This study employs a HAR system that is conscious of the positioning, encompassing four primary stages: 1) the collection of raw data from sensors, 2) the pre-processing of the gathered data, 3) the creation of processed features and samples, and 4) the training of machine learning models on the processed data and the assessment of their performance in classifying activities. Figure 1 depicts the comprehensive workflow involving these four phases.

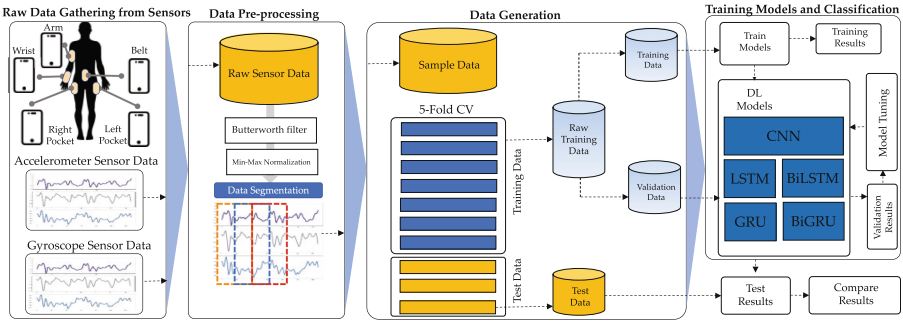

Fig. 1. The position-aware HAR framework based on smartphone sensors used in this work.

3.1 Pervasive Dataset

The dataset utilized for evaluating HAR, known as the Pervasive benchmark dataset [24], utilizes smartphone sensors to collect data on seven physical activities: walking, running, sitting, standing, jogging, biking, walking upstairs, and walking downstairs. These fundamental daily movements are commonly employed in similar research investigations. The data gathering process involved ten male participants aged between 25 and 30, each engaging in every activity for 3–4 minutes, with biking conducted outdoors. Indoor walking and running occurred in a university building corridor, while stair walking tasks were performed in a 5-floor building with stairs.

Five smartphones were strategically placed on each participant to capture motion data simultaneously from various on-body positions — right and left jeans pocket, belt area near right leg, upper right arm, and right wrist. Accelerometer samples were recorded at a rate of 50 samples per second across all devices and positions for the entire duration of each activity. Previous studies have affirmed the adequacy of this sampling frequency for recognizing fundamental human activities [28].

3.2 Data Pre-processing

Before extracting features, the initial sensor data underwent a pre-processing stage that involved denoising and normalization. Denoising was performed to filter out any noise artifacts, preventing contamination of the signals. Normalization was applied to standardize all sensor readings to a standard scale, ensuring consistency. The pre-processed data streams were then segmented into fixed-length portions using a sliding window approach. The segmentation utilized overlapping windows of 5-second durations, with a 50% overlap between consecutive windows. This process allowed for extracting distinctive time-series features from each window, facilitating subsequent activity classification. The inclusion of overlap ensures seamless transitions between the segmented data chunks.

3.3 The Deep Learning Model

This study assesses five well-known deep learning structures – CNNs, LSTMs, BiLSTMs, GRUs, and BiGRUs – for the task of recognizing human activities across various positions.

CNNs utilize a layered structure comprising convolutional layers for extracting features, pooling layers for achieving scale-invariant representations, flattened and fully connected layers for reducing dimensionality, and an output layer for classification. They excel at capturing local dependencies in data.

LSTMs tackle the vanishing gradient challenge in standard recurrent neural network models by explicitly modeling long-range context using specialized memory cells and gated operations. This allows for effective temporal modeling of extended time-series data.

GRUs offer a streamlined alternative to LSTMs, delivering competitive performance across various applications. Bidirectional versions of both LSTMs and GRUs enhance context modeling by considering information from both past and future time steps.

This comparative evaluation provides valuable insights into practical deep-learning approaches for addressing the multi-position activity recognition challenge.

3.4 Hyperparameter Tuning by Bayesian Optimization

In this research, Bayesian optimization served as an automated method for adjusting the hyperparameters of neural network architectures. This approach offers an effective way to optimize complex functions that lack explicit mathematical representations. By creating a probabilistic surrogate model of the target function, Bayesian optimization steers the search process toward global optima through iterative sampling.

Given the computational intensity and challenging gradient derivation in assessing neural networks, Bayesian treatment facilitates the efficient tuning of non-linear performance objectives. Unlike grid or random search methods, it reduces the necessary trial iterations, thereby reducing training expenses. Bayesian optimization proves particularly useful for optimizing intricate structures of deep neural networks, such as CNN, LSTM, and GRU, where multiple interconnected hyperparameters are involved.

The primary optimization objective is identifying the highest value at the sampling point for an unknown function f.

$$x^{+} = \arg\max_{x \in A} f(x) \tag{1}$$

where A denotes the search space of x.

4 Experiments and Research Findings

Within this segment, we elucidate the experimental setup and present the results of our experiments conducted to assess the performance of five deep learning models in HAR, considering smartphone sensor data.

4.1 Experimental Environment

For this study, the experimental setup utilizes Google Colab Pro+ as a cloud-based notebook environment featuring Tesla V100 GPUs to expedite computations. All code is written in Python 3.6.9, employing widely used machine learning libraries. TensorFlow 2.2.0 is used for constructing models, Keras 2.3.1 for high-level neural network APIs, Scikit-Learn for training pipelines, Numpy 1.18.5 for numerical processing, and Pandas 1.0.5 for manipulating data structures.

This optimized configuration in Colab, coupled with established Python data science tools, streamlines the process of quickly prototyping and evaluating deep learning architectures for recognizing human activities across various sensor positions.

4.2 Experimental Results

In assessing the effectiveness of deep learning models in recognizing activities across positions, we applied a 5-fold cross-validation technique on the Pervasive dataset. This method ensures a balanced distribution of activity classes in each validation fold, mitigating sampling bias. The dataset was segmented into five stratified bins or folds, with four folds (80% data) allocated for training and one bin (20% data) for testing the model in each iteration. This process was iterated five times, each fold acting as the test set once. Consequently, every data point was included in both the training and evaluation stages throughout the cross-validation procedure.

The experiments involved testing five deep neural networks – CNN, LSTM, BiLSTM, GRU, and BiGRU – that underwent optimization using Bayesian hyperparameter tuning for recognizing activities based on smartphone sensor data from multiple positions. Performance in recognizing activities was compared among the models based on accuracy and F1-score. The results of the experiments are detailed in Tables 1 – 2, showcasing benchmark scores on important evaluation metrics for each network architecture. This enables a thorough examination of differences in the models' capabilities in classifying human activities across various positions.

The outcomes in Table 1, illustrating the accuracy of deep learning models on sensor data from various on-body positions, lead to the following key insights:

1. Accelerometer data analysis:
   - The BiLSTM and GRU models consistently achieve the highest accuracy across all sensor positions – left pocket, right pocket, belt, arm, and wrist.

Table 1. Accuracies of the deep learning models using sensor data from different positions.

Sensor	Model	Accuracy				
		Left Pocket	Right Pocket	Belt	Arm	Wrist
Accelerometer	CNN	99.53%	99.42%	99.04%	98.11%	96.70%
	LSTM	99.66%	99.66%	99.52%	98.27%	99.08%
	BiLSTM	99.86%	99.78%	99.70%	98.59%	98.88%
	GRU	99.80%	99.84%	99.60%	98.96%	99.20%
	BiGRU	99.78%	99.88%	99.82%	98.80%	99.08%
Gyroscope	CNN	94.72%	94.36%	95.20%	92.81%	98.27%
	LSTM	84.07%	78.33%	80.22%	82.51%	99.04%
	BiLSTM	84.88%	83.63%	80.98%	88.73%	99.32%
	GRU	86.27%	86.59%	86.61%	88.17%	99.24%
	BiGRU	88.29%	87.39%	88.31%	96.41%	99.38%
Accelerometer + Gyroscope	CNN	99.62%	99.50%	98.98%	98.21%	98.27%
	LSTM	99.58%	99.80%	99.56%	97.95%	99.04%
	BiLSTM	99.94%	99.90%	99.72%	98.47%	99.32%
	GRU	99.94%	99.92%	99.64%	99.16%	99.24%
	BiGRU	99.88%	99.88%	99.82%	99.46%	99.38%

  - The BiLSTM attains the top accuracy of 99.86% on the left pocket, while the GRU reaches the peak score of 99.88% on the right pocket data.
  - The CNN model, although slightly less accurate than BiLSTM and GRU on accelerometer data, still demonstrates competitive accuracy ranging from 96.7% to 99.53% across positions.
2. Gyroscope data analysis:
  - The BiGRU model attains maximum accuracy, peaking at 99.38%, specifically on wrist data. The wrist position consistently yields the highest gyroscope accuracy for all models, indicating its suitability for rotational motion sensing.
  - The LSTM and BiLSTM architectures exhibit noticeably lower gyroscope accuracy, ranging between 78–88%, and they are outperformed by other models, notably on non-wrist positions.
3. Combined accelerometer and gyroscope data analysis:
  - Utilizing accelerometer and gyroscope data further enhances accuracy across the models, reaching 99.94% for GRU and BiGRU networks.
  - Sensor fusion proves beneficial in augmenting overall recognition capability.

Here are the notable findings derived from the F1-score of deep learning models on sensor data from diverse positions, as illustrated in Table 2:

1. Accelerometer data F1-score analysis:

Table 2. F1-score of the deep learning models using sensor data from different positions.

Sensor	Model	F1-score				
		Left Pocket	Right Pocket	Belt	Arm	Wrist
Accelerometer	CNN	99.52%	99.42%	99.04%	98.10%	96.66%
	LSTM	99.66%	99.66%	99.52%	98.26%	99.08%
	BiLSTM	99.86%	99.78%	99.70%	98.58%	98.88%
	GRU	99.80%	99.84%	99.60%	98.96%	99.20%
	BiGRU	99.78%	99.88%	99.82%	98.80%	99.08%
Gyroscope	CNN	94.69%	94.31%	95.19%	92.77%	98.25%
	LSTM	80.28%	73.13%	76.44%	79.10%	99.04%
	BiLSTM	81.25%	80.10%	78.36%	88.01%	99.32%
	GRU	83.33%	83.66%	83.91%	87.33%	99.24%
	BiGRU	86.78%	85.42%	86.70%	96.39%	99.38%
Accelerometer + Gyroscope	CNN	99.62%	99.50%	98.98%	98.20%	98.25%
	LSTM	99.58%	99.80%	99.56%	97.94%	99.04%
	BiLSTM	99.94%	99.90%	99.72%	98.46%	99.32%
	GRU	99.94%	99.92%	99.64%	99.16%	99.24%
	BiGRU	99.88%	99.88%	99.82%	99.46%	99.38%

  - The F1-scores exhibit patterns closely mirroring the accuracy results detailed in Table 1.
  - The BiLSTM, GRU, and BiGRU designs achieve the highest F1-score, surpassing 99%, on accelerometer data from multiple positions.
  - The CNN model achieves highly competitive F1-score, comparable to GRU's performance, reaching up to 99.52% on left pocket data. However, BiLSTM and BiGRU outperform CNN by slight margins.
2. Gyroscope data F1-score analysis:
  - Parallel to accuracy trends, gyroscope sensor F1-score are notably lower than accelerometer scores, except for the wrist position, where all models attain over 98% F1-score. This underscores the wrist's efficacy in sensing rotational motions.
  - LSTM and BiLSTM models demonstrate considerably lower F1-score, ranging between 73–86%, for classifying activities using gyroscope data from positions other than the wrist. Their ability to capture rotational motion needs to be improved.
3. Combined accelerometer and gyroscope data F1-score analysis:
  - The fusion of accelerometer and gyroscope data further amplifies the F1-score, reaching up to 99.94% for the BiLSTM architecture, leveraging the benefits from both motion modalities.

5 Conclusion and Future Works

This study thoroughly assessed deep learning methods for recognizing human activities across multiple positions, employing smartphone sensors. Five models, namely CNN, LSTM, BiLSTM, GRU, and BiGRU, underwent evaluation with data from accelerometers and gyroscopes at five on-body locations. The results confirm that combining sensor data and utilizing multiple positions improves accuracy and F1-score across all models.

Notably, the BiLSTM, GRU, and BiGRU models attain scores exceeding 99% with combined data from appropriate wrist, arm, belt, and pocket positions. These models consistently surpass the CNN and standard LSTM networks. Additionally, the wrist accelerometer and gyroscope offer complementary motion-capturing capabilities, enhancing the overall fidelity of activity recognition. These results guide effective deep learning design and strategic sensor placement strategies in position-aware HAR applications using smartphones. Practical applications in domains such as fitness tracking, health monitoring, and context-aware computing can benefit from these neural approaches customized for on-body device locations.

For future considerations, additional experiments with more extensive datasets can enhance the general applicability of the findings and identify an appropriate level of complexity for multimodal HAR using deep neural networks. Furthermore, assessing the models on data from alternative wearable gadgets such as smart glasses, rings, shoes, etc., positioned on different body parts, presents an avenue for further exploration.

Acknowledgments. This research project was supported by Thailand Science Research and Innovation Fund; University of Phayao under Grant No. FF67-UoE-214; National Science, Research and Innovation Fund (NSRF); and King Mongkut's University of Technology North Bangkok with Contract no. KMUTNB-FF-67-B-10.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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