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THE IMPACT OF DATA NORMALIZATION AND DATA AUGMENTATION ON THE TRANSFERABILITY OF ACTIVITY RECOGNITION MODELS ACROSS DIFFERENT ACCELEROMETERS

This study analysed the impact of data processing methods on the transferability of human activity recognition models across different accelerometers. Data were collected from four sensors for three types of activity: walking, running, and standing. The model was trained on data from a single sensor and then evaluated on the others. Four approaches were compared: no normalization, global normalization, window-based normalization, and window-based normalization with rotation-based extension. The results show that window-based normalization significantly improves transferability between sensors. Rotation-based extension further increases resistance to sensor orientation, which additionally improves the model's transferability, although its effect is smaller and depends on the data.

WPŁYW NORMALIZACJI ORAZ SZTUCZNEGO ROZSZERZANIA DANYCH NA PRZENOŚNOŚĆ MODELI ROZPOZNAWANIA AKTYWNOŚCI POMIĘDZY RÓŻNYMI AKCELEROMETRAMI

Artykuł bada wpływ metod przetwarzania danych na możliwość przenoszenia modeli rozpoznawania aktywności człowieka między urządzeniami wyposażonymi w różne modele akcelerometrów. Dane zebrano z czterech czujników, dla trzech rodzajów aktywności fizycznej: chodzenia, biegania oraz stania. Model został wytrenowany na danych z jednego czujnika, a następnie oceniony na pozostałych. Porównano cztery podejścia: brak normalizacji, normalizacja globalna, normalizacja dla okna czasowego oraz normalizacja dla okna czasowego z rozszerzeniem opartym na obrocie wokół osi. Wyniki pokazują, że normalizacja dla okna czasowego znacznie poprawia przenoszalność między czujnikami. Rozszerzenie oparte na obrocie dodatkowo zwiększa odporność na orientację czujnika, co dodatkowo wpływa na przenośność modelu, chociaż jego wpływ jest mniejszy i zależy od danych.

1. INTRODUCTION

Accelerometers are one of the sensors commonly used in measurement systems, especially for monitoring physical activity. The use of artificial intelligence (AI) methods to identify the type of physical activity on wearable and other IoT devices based on data from accelerometers is a well-documented problem [1]. However, the transferability of the model across different types of accelerometers and users remains a significant challenge [2]. In practice, different accelerometers have different characteristics, such as signal offsets or spatial orientations [3]. Due to this, a model trained on data from one sensor often performs worse on data from another device.

The aim of this study is to analyse the impact of data processing methods on a model's ability to generalize across different types of accelerometers and to identify the key factors influencing model transferability. The following chapters provide information on the system's characteristics, the methodology used, the experiments conducted, the results, and the conclusions.

2. SYSTEM CHARACTERISTICS

The study used four types of accelerometers: BMI270, ADXL345, LIS2DW12, and LSM6DS3TR-C. All the sensors were set up in the same way, using the same measurement range (±4g) and sampling frequency of 50 Hz. Data were collected on three types of physical activity: standing, walking, and running, with measurements taken separately for each sensor.

The data was stored as time series containing acceleration values along the x, y, and z axes. The entire dataset consists of 12 sessions, each containing 9,000 rows in the following format: *label, sensor, ts_ms, sensor_ax, sensor_ay, sensor_az*, resulting in a total of 108,000 data records. In addition, the data was recorded with sensors in various initial orientations, which made it possible to simulate conditions similar to real-world applications where the device's position may change.

To prepare the data for AI model training, the signal was segmented into 2-second time windows with 50% overlap, corresponding to 100 samples. This method of preparing the data allows for the capture of characteristic movement patterns within a short time interval [4].

The following section describes the methods used to process the collected data in order to improve the model's transferability across different sensors.

3. METHODOLOGY

The input data obtained can be used to train the model immediately after it has been collected, organized, and grouped. However, it is worth considering various pre-processing methods to achieve better final results. In this particular scenario, the following methods were utilized.

3.1. Normalization methods

One method is normalization [5]. This article examines two approaches to data normalization. The first was global normalization, which involves calculating the mean and standard deviation for the entire training set and applying the same parameters to all data [5]. This approach assumes that data from all sensors have a similar statistical distribution. This was followed by per-window normalization. This type involves normalizing each time window independently which means a separate mean and standard deviation are calculated for each window [5]. This method eliminates the effects of signal offset and differences in measurement scale between sensors.

3.2. Data augmentation

To improve the model's robustness to sensor orientation, data augmentation based on random 3D rotations was applied [6]. Each sample was transformed using rotation matrices defined by random angles around the X, Y, and Z axes within a range of ±45°, corresponding to realistic changes in sensor orientation. For each training sample, additional rotated versions were generated, which increased the size of the training dataset. This operation changes the orientation of the reference frame without altering the nature of the motion.

3.3. Classification model

Based on the collected data, a machine learning (ML) model was developed for activity classification. A one-dimensional convolutional neural network (1D CNN) was selected due to its suitability for processing time series data [7]. The model processes input windows of size (100, 3), corresponding to 100 time samples and three acceleration axes. Its architecture consists of two convolutional layers, followed by a fully connected classification layer with a softmax activation function.

4. EXPERIMENTS

This paragraph describes the experiment that was conducted. The dataset was divided into a training set and a test set in an 80/20 ratio. The model was trained exclusively on data from a single sensor, while its performance was evaluated using data from the other sensors.

Four experimental variants of model training were performed: no normalization (raw data), global normalization, per-window normalization and per-window normalization with rotational augmentation.

The same model architecture and identical training parameters were used in all experiments, and only the data used to train the model was modified, ensuring the comparability of the results. The model was retrained from scratch after each stage of the experiment, and all results were recorded.

Model performance was evaluated using classification accuracy as well as precision, recall, and F1-score [8]. For the reference sensor 1, the metrics were computed on a separate test subset. For the remaining sensors 2–4, the model was evaluated on their full datasets to assess cross-sensor transferability. The following section presents the results of the experiment.

5. RESULTS

The results of the experiment were recorded in two formats: numerical data and graphs. The first and most important results are presented in Table 1. This table consists of 5 columns, where the first "setup" column indicates every step in the experiment, while the other columns show the specific results obtained by specific sensors.

Tabele 1. Model accuracy results for each stage of the experiment

setup	Sensor 1 BMI270 (reference)	Sensor 2 ADXL345	Sensor 3 LIS2D	Sensor 4 LSM6D
raw	0.998	0.663	0.730	0.801
global_normalization	0.991	0.663	0.670	0.727
per_window_normalization	0.991	0.787	0.974	0.955
per_window_rotation	0.972	0.919	0.933	0.951

Table 1 and Figure 1 show that the model trained on raw data shows limited transferability across sensors. However, its performance varies depending on the target device and the activity class.

The use of global normalization does not lead to a significant improvement in results, indicating that data from different sensors do not meet the assumption of a common statistical distribution.

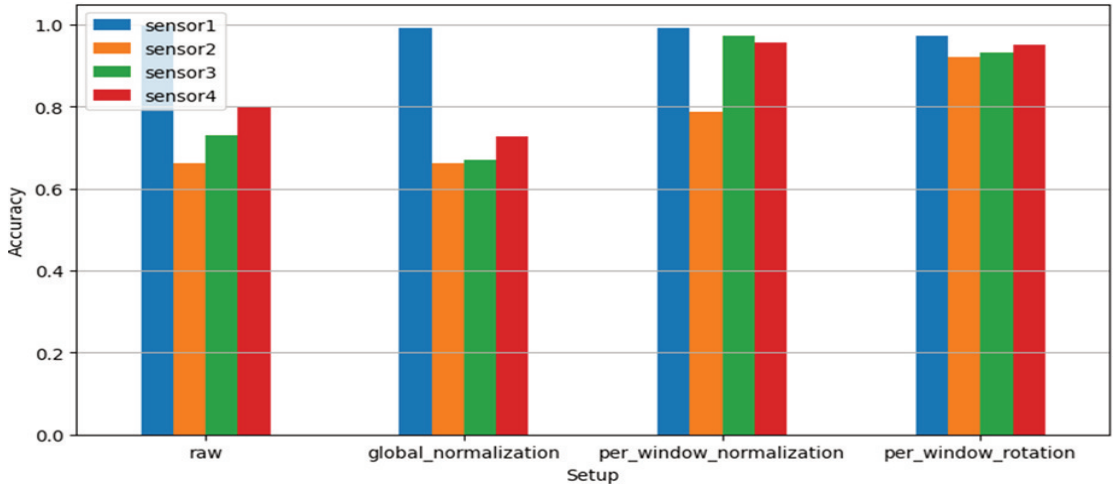


Figure 1. Accuracy comparison of pre-processing and augmentation stages

The greatest improvement was achieved through per-window normalization, which significantly increases classification accuracy for all sensors, especially 3rd and 4th. This result indicates that eliminating local signal variations is crucial for improving model generalization.

The introduction of rotational data augmentation leads to further changes in the results, although its impact is not the same for all sensors. A significant improvement was observed for sensor 2, while sensors 3 and 4 showed a slight decrease in performance. This suggests a redistribution of classification performance among the sensors rather than a uniform improvement. As a result, the model achieves a more balanced level of accuracy across the sensors, as illustrated by the bars corresponding to the *per_window_rotation* configuration in Figure 1.

Further analysis of precision, recall, and F1-score reveals differences in performance across activity classes. The most challenging class is "standing", which is often misclassified without appropriate normalization due to sensitivity to sensor orientation and the gravitational component. The "running"

class achieves the best performance, while "walking" shows intermediate results and is more prone to confusion with other activities. Per-window normalization significantly improves the recognition of "standing" and leads to more balanced performance across classes. Rotational augmentation further modifies the error distribution and can improve robustness to orientation changes, although its effect is not consistent across all sensors.

6. CONCLUSION

The results show that the main limitation in recognizing cross-sensor activity lies in how the input data is represented, rather than in the model itself. Differences between sensors, such as signal offset, scale, and orientation, have a significant impact on classification performance.

Per-window normalization proved to be the most effective method for reducing these differences and ensuring consistent performance across multiple devices. Rotational transformation can further improve robustness to orientation changes, but its effect is not uniform and depends on the specific sensor.

From a practical point of view, appropriate data pre-processing is essential when applying ML methods in measurement systems that use heterogeneous sensors.

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