

# Jump-Rope Technique Classification and Counting: A Technique-Independent Jump Segmentation Approach

Satoshi Ido, Shigemi Ishida, Hiroshi Inamura

Graduate School / School of Systems Information Science, Future University Hakodate, Japan  
{g2125004, ish, inamura}@fun.ac.jp

**Abstract**—We propose a wearable-based method to automatically segment jump intervals and classify jump rope techniques using 6-axis inertial data. By extracting single jump segments through a dynamic thresholding algorithm, the system classifies multiple techniques using a single classifier. Leave-One-Subject-Out cross-validation demonstrates the method's capability to achieve high user-independent accuracy for specific techniques, while identifying remaining challenges in accommodating individual variations in movement.

**Index Terms**—Wearable devices, movement recognition, jump rope.

## I. INTRODUCTION

In recent years, the use of wearable devices to visualize physical activity and provide feedback has garnered significant attention as a means of establishing exercise habits and maintaining motivation.

Among various forms of exercise, jump rope is widely enjoyed as a convenient and effective form of aerobic exercise; however, existing commercial smartwatches are limited to detecting a single type of jump and are insufficiently capable of distinguishing between multiple advanced techniques such as forward jumps, backward jumps, side-to-side jumps, and cross jumps.

In this paper, we report on a method that uses 6-axis IMU data from a wrist-worn device to accurately extract a *single jump* regardless of individual habits or the type of technique, and automatically classify and count these four types of techniques.

## II. RELATED WORK

Automatic jump counting for jump rope activities is broadly categorized into vision-based and sensor-based approaches. Vision-based methods analyze video footage to detect jumps, leveraging foot takeoff and landing identification [1] or skeleton estimation algorithms [2]. Conversely, sensor-based methods utilize wearable or equipment-mounted devices, such as 6-axis inertial sensors to capture rope rotation [3] or magnetic sensors embedded in the handles to measure rotation speed [4].

However, existing methods primarily focus on basic forward jumps and remain insufficient for classifying advanced techniques, e.g., cross jumps, double jumps, or handling multi-technique scenarios simultaneously. Furthermore, they lack the flexibility to adapt to variations in individual jumping forms and movement intensities. Therefore, a robust system capable of adaptively classifying and counting diverse jump rope techniques is required.

## III. PROPOSED METHOD

Our key idea is to accurately segment a single jump using 6-axis data obtained from wearable devices. If we can segment the data into individual jump intervals using a unified processing method for all techniques, we can extract distinct features including variations between techniques from the data within those intervals, making it possible to classify multiple techniques.

To accommodate individual differences in jumping styles, we dynamically determine the threshold for each subsequent jump based on the ratio of positive to negative peak amplitudes in the IMU data. Specifically, using the peak amplitudes from the immediately preceding jump, we normalize the values so that the sum of the absolute amplitudes equals 1, and apply these normalized values as multipliers for the next threshold. For example, if the positive amplitude of the preceding jump is 60 and the absolute negative amplitude is 40, the multipliers for the next threshold calculation are set to 0.6 for the positive side and 0.4 for the negative side.

Figure 1 shows an overview of the proposed method. This method consists of data acquisition, data segmentation, feature extraction, and technique classification blocks. In the data acquisition block, acceleration and angular velocity data along the XYZ axes are acquired from wearable devices. In the data segmentation block, jumps are detected in the acquired data, and the data is segmented into individual jumps. The feature extraction block derives a feature vector for each segmented data to classify jump-rope techniques in the classification block.

Figure 2 illustrates a specific example of the data segmentation. Sensor data is segmented based on the Y-axis angular velocity. From the Y-axis angular velocity data sequence, we first extract positive and negative peaks. For each peak, we calculate a scaled peak point represented by the green and orange solid circles in Fig. 2 by multiplying the peak amplitude by the corresponding multiplier. All the positive scaled peaks are then smoothed using a low-pass filter, resulting in a dynamic positive threshold. A dynamic negative threshold is also calculated using the negative scaled peaks. In Fig. 2, the positive and negative dynamic thresholds are shown as green and orange dotted lines, respectively. Finally, we segment the data into intervals defined as a *single jump*, spanning from the moment the value falls below the negative dynamic threshold to when it rises above the positive dynamic threshold. In the feature extraction block, various statistical measures are

This is the author's version of the work.

© 2026 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

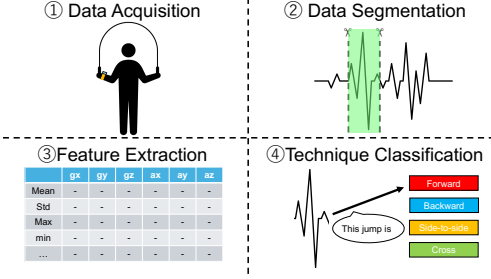


Fig. 1. System Overview

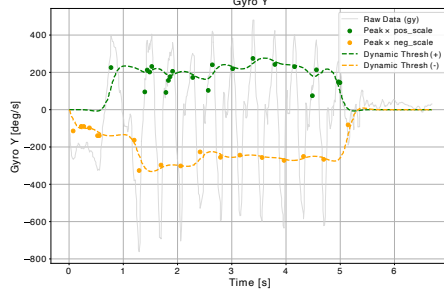


Fig. 2. Example of angular velocity along the Y-axis

|              | Side-to-side | Cross | Forward | Backward |
|--------------|--------------|-------|---------|----------|
| Side-to-side | 0.56         | 0.32  | 0.09    | 0.03     |
| Cross        | 0.10         | 0.69  | 0.04    | 0.18     |
| Forward      | 0.27         | 0.14  | 0.46    | 0.13     |
| Backward     | 0.12         | 0.10  | 0.01    | 0.78     |

Fig. 3. Technique classification result

extracted as features from the data samples within a single jump to classify jump techniques using a supervised learning algorithm in the classification block.

#### IV. EVALUATION

##### A. Experiment Setup

To evaluate the impact of individual differences on classification accuracy, four participants (two males and two females in their 20s) performed rope-jumping tasks using an ASICS Clear Jump Rope. Each participant executed 50 jumps for four distinct techniques: forward, backward, side-to-side, and cross jumps. During the trials, acceleration and angular velocity data were collected at a sampling frequency of 100 Hz using an M5StickC Plus2 worn on the right wrist.

##### B. Technique-Classification Accuracy

To evaluate the proposed method, technique classification was conducted using Leave-One-Subject-Out (LOSO) cross-validation with a Random Forest classifier. Jump segments were automatically extracted from the IMU data of four subjects. For each segment, a 48-dimensional feature vector was constructed by calculating eight statistical measures, i.e., mean, standard deviation, maximum, minimum, RMS, zero-crossing count, and Hilbert envelope mean and maximum, across all six axes. Since the number of extracted segments varied across subjects due to automated segmentation, the dataset was balanced by standardizing the jump count per subject to the minimum. Finally, the confusion matrices from each fold were normalized and averaged to visualize the overall classification trends as a heatmap.

Figure 3 shows the averaged confusion matrix. While Backward (0.78) and Cross (0.69) achieved higher accuracies, performance declined for Side-to-side (0.56) and Forward (0.46), with Forward frequently misclassified as Side-to-side (0.27). Frequent mutual confusion among these techniques indicates substantial individual variations in movement patterns among subjects, highlighting the inherent difficulty of user-independent classification under the Leave-One-Subject-Out evaluation.

While the proposed method classifies specific techniques user-independently with high accuracy, performance for other techniques remains sensitive to individual variations. Therefore, there is room for further improvement in designing robust features and exploring personalized model optimization.

##### C. Jump-Counting Accuracy

In addition to technique classification, we evaluated the accuracy of the proposed segmentation method in counting the number of jumps. Counting accuracy was defined as  $1 - |N_{\text{det}} - N_{\text{gt}}|/N_{\text{gt}}$ , where  $N_{\text{det}}$  is the number of automatically detected jump segments and  $N_{\text{gt}} = 10$  is the known number of jumps performed in each recorded trial. Averaged over all 80 trials from the four participants, the proposed method achieved a mean counting accuracy of 84.7%, with technique-wise accuracies of 89.0% (Forward), 88.0% (Backward), 88.5% (Cross), and 73.5% (Side-to-side). The lower counting accuracy for Side-to-side jumps is consistent with its lower classification accuracy, suggesting that segmentation errors for this technique propagate into misclassification. These results were obtained from only four participants, which is insufficient to fully validate the method's adaptability to individual differences across a broader population; expanding the participant pool and collecting multi-session data for each subject are important directions for future work.

#### V. CONCLUSION

This paper proposed a method to automatically segment jump rope intervals and classify multiple techniques using wearable devices. By developing a dynamic thresholding algorithm based on preceding peak amplitudes, the system effectively extracted features from individual jumps. Leave-One-Subject-Out cross-validation demonstrated that the method achieves high user-independent accuracy for specific techniques, although addressing individual variations in other techniques remains a subject for future improvement.

#### REFERENCES

- [1] X. Li and J. Wang: "Video-based rope skipping repetition counting with ResNet model", *Int. J. Engineering and Computer Science*, **10**(11), pp. 25413–25419 (2021).
- [2] J.-W. Kim, J.-W. Shin, and S.-H. Choi, "Jump rope exercise assistance program," *IEEE Access*, **12**, pp. 169149–169162 (2024).
- [3] M. Shang, C. de Bleecker, et al., "A seq-to-seq temporal convolutional network for volleyball jump monitoring using a waist-mounted IMU," *IEEE Access*, **13**, pp. 42986–42996 (2025).
- [4] Xiaomi, "Xiaomi Smart Jump Rope FAQ," Xiaomi Global Support. <https://www.mi.com/global/support/faq/details/KA-517101/> (accessed on Jun. 4, 2026).