2026 IEEE/SICE International Symposium on System Integration (SII)
January 11-14, 2026. Cancún, México

A Dynamic Noise Correction Method for Person Recognition Using 3D Point Clouds According to Sprint Speed of Short Distance Runners

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Abstract— **Accurately recognizing objects is crucial for ensuring the safety of automobiles and autonomous robots. However, fast movements, such as sprinting, cause motion blur, which complicates detection tasks. In this study, we developed an algorithm to enhance the accuracy with which 3D point clouds recognize individuals in sprinting motion. Data were collected using LiDAR sensors, which are commonly employed in autonomous driving technology. Our previous research explored methods for removing and correcting motion blur by adjusting the reference values for noise removal based on sprinting speed. Initial results showed that addressing dynamic noise significantly improved recognition accuracy compared to the original data. One challenge encountered during the prior investigation, however, was the excessive correction of lateral and vertical body movements. To tackle this issue, we proposed a refined method targeting motion blur specifically caused by sprinting. This method detects inter-frame blur in three dimensions. By comparing the proposed approach with the prior investigation's results, we confirmed further improvements in recognition accuracy.**

I. INTRODUCTION

In recent years, technologies for sprint motion analysis have been advancing rapidly, driven by growing interest in both sports science and performance enhancement. Among these, motion capture technology has played a central role [1]. This technology employs multiple cameras to acquire accurate three-dimensional positional data, enabling detailed analysis of biomechanical factors such as joint angles, stride patterns, and the timing of leg movements. Such capabilities have made motion capture a valuable tool in both research and practice. However, despite its precision, the system requires the subject to wear reflective markers or inertial sensors. These attachments can interfere with natural movements and potentially affect athletic performance [2]. In sprinting in particular—where motions are fast and sensitive to small disturbances—even the subtle weight and placement of wearable devices can influence the running form. Moreover, the usage of motion capture is generally limited to controlled indoor environments, such as laboratories or motion analysis studios. This makes it hard to collect data outdoors, where environmental factors and real-world constraints may affect performance. In addition, motion capture systems involve high installation and operating costs, and they require careful environmental preparation to ensure accurate measurement. Similarly, camera-based measurement methods, which are sometimes applied in competitive settings, are fundamentally limited to two-dimensional data acquisition. When multiple cameras are deployed to capture more comprehensive information, issues such as distance limitations, calibration requirements, and occlusion effects present further challenges. As an alternative, Light Detection and Ranging (LiDAR) has recently attracted increasing attention for its potential application in sports motion analysis [3]. Unlike conventional camera-based systems, LiDAR has the capability to directly capture three-dimensional data of the surrounding environment by emitting laser light and detecting its reflection. LiDAR has already demonstrated strong utility in fields such as autonomous driving and robotics [4]–[7], and these advantages highlight its promise for motion analysis in dynamic sports contexts. To analyze human movements using LiDAR, however, it is essential to extract time-varying motion data from the raw point cloud sequences associated with the target cluster. A key difficulty arises from the presence of noisy data when the target is in motion. This phenomenon, commonly referred to as motion blur, occurs because the sensor scans sequentially over time, and discrepancies arise between the scanning process and the rapid motion of the target object. Motion blur poses a significant obstacle to accurate data acquisition, as it distorts the true shape and trajectory of the moving subject. The degree of motion blur depends largely on the scanning time of the sensor and the relative velocity between the target and the scanning beam. Consequently, in the case of sprinting motion—where athletes move at high speeds and acceleration plays a major role—motion blur becomes especially pronounced. Therefore, addressing motion blur is an essential requirement for ensuring reliable and robust three-dimensional object detection in short-distance running analysis. By effectively correcting this phenomenon, it becomes possible to leverage the advantages of LiDAR to achieve accurate, field-ready motion analysis that is less constrained by the limitations of conventional systems.

Point cloud processing of dynamic objects is influenced by motion blur resulting from their movement, necessitating appropriate noise reduction techniques. The effect of dynamic noise, including rapid movements of arms and legs, is particularly noticeable in the recognition of a person in high-speed motion, such as a sprinter. In this study, we focused on motion blur, which is blur caused by sprinting. The target is a person in sprinting motion, and the goal is to improve the recognition accuracy of the person in class classification by effectively removing the noise caused by the sprinting motion. By achieving this goal, we expect not only

*This work was supported by MEDIA ROBOTECH INC

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to improve the accuracy of object recognition for autonomous mobile robots, but also to improve the performance of athletes by elucidating their sprinting motion.

In this paper, we first present previous studies and our past research. Then, we present a proposed method for correcting dynamic noise. Next, we describe the experimental method and evaluation results, including comparisons with original data and previous studies. Finally, a summary and future work are provided.

II. RELATED WORK

Several studies have addressed the issue of motion blur when capturing dynamic objects [8]–[11]. These studies have demonstrated the effectiveness of motion blur correction techniques, showing that appropriate processing can substantially improve the reliability of motion analysis. However, they also highlight several limitations. For example, many existing approaches necessitate the integration of LiDAR with camera-based systems, requiring the use of multiple measurement devices. This increases system complexity and raises concerns about sensor synchronization. Furthermore, integrating multiple sensing modalities significantly increases the volume of acquired data, thereby imposing a heavier computational burden during processing. These requirements can reduce the practicality of the system, especially in outdoor sports scenarios, where simple, portable, and efficient measurement systems are preferred.

To address these issues, our previous research proposed a noise correction method designed for sprinting motion using a LiDAR sensor [12]. In that study, the LiDAR device was positioned behind the starting line of a subject sprinting in a straight line, and point cloud data of the motion was collected. The acquired data were segmented on a frame-by-frame basis, and noise correction was performed based solely on displacement in the forward direction. This approach successfully improved recognition accuracy by suppressing motion blur along the primary axis of movement. However, several limitations became apparent. Since the method relied solely on forward displacement, excessive correction occurred in the other two components relative to the forward direction. Furthermore, this method was not applicable when the forward direction itself varied, such as when athletes deviated slightly from a straight path while sprinting.

The objective of the present study is to address the limitations of our earlier work, particularly the inability to handle variability in the forward direction, while simultaneously aiming to enhance recognition accuracy further. Building upon the previous method's foundations, we propose an improved approach that introduces directional constraints in all three dimensions. This new approach is more robust against variations in motion.

III. PROPOSED METHOD

A. Proposal Dynamic Noise Correction

In this study, we propose a correction method for motion blur removal that utilizes the centroid of local point clouds. The core idea is to replace noisy or distorted points with more stable representative values computed from their local neighborhood, thereby improving both the geometric consistency and the robustness of recognition. First, for each point $P_i = (x_i, y_i, z_i)$, the point cloud is projected onto a spherical surface, as illustrated in Fig. 1. This spherical projection provides a convenient framework for defining local neighborhoods, since points that lie within a certain angular and radial distance can be grouped together naturally. A correction region (indicated by the black frame in Fig. 1) is then determined by specifying a sphere of radius r_t around the target point, together with threshold values for the y and z axis components. These thresholds are introduced to restrict the correction region in the lateral and vertical directions, ensuring that only points in close spatial proximity contribute to the correction. The correction process replaces the original point P_i with the centroid of the neighboring points located within the correction region. The centroid, denoted as $P_i' = (x_i', y_i', z_i')$, is calculated according to (1), where n represents the number of neighboring points (depicted as blue points in Fig. 1). This process mitigates the influence of outliers and local distortions caused by motion blur. In cases where no valid neighboring points exist within the correction region, the original point P_i is retained in order to preserve the continuity of the overall object shape. By applying this operation to all points, the method achieves noise reduction and geometric correction in the point cloud.

$$P_i' = \left(\frac{\sum_{j=1}^{n} x_j}{n}, \frac{\sum_{j=1}^{n} y_j}{n}, \frac{\sum_{j=1}^{n} z_j}{n} \right) = \frac{1}{n} \sum_{j=1}^{n} P_j \tag{1}$$

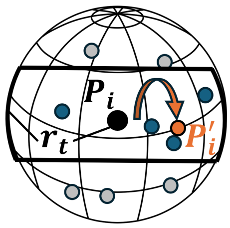

Fig. 1. Proposal Dynamic Noise Correction

In this study, the x-axis is defined as the direction of motion, the y-axis as the lateral direction of the body, and the z-axis as the vertical direction. These axis definitions are used consistently throughout this paper, unless otherwise noted. When using this method, it is important to determine the specified area. The following section explains how to calculate the radius r_t and threshold values for the y- and z-components.

1) How to Determine Radius r_t: To determine the radius r_t, we first derived a function that represents the distance traveled by the subject within each frame over time, as illustrated in Fig. 2. In the derivation of the traveled distance, each data point in the plot corresponds to the frame-by-frame displacement. This displacement was calculated from the difference in the directional components between consecutive frames at the centroid of the point cloud representing the segmented human body. In other words, the displacement values were obtained by extracting the centroid position of the subject in each frame, computing the vector differences with respect to the subsequent frame, and accumulating these changes as an indicator of motion over time. As can be

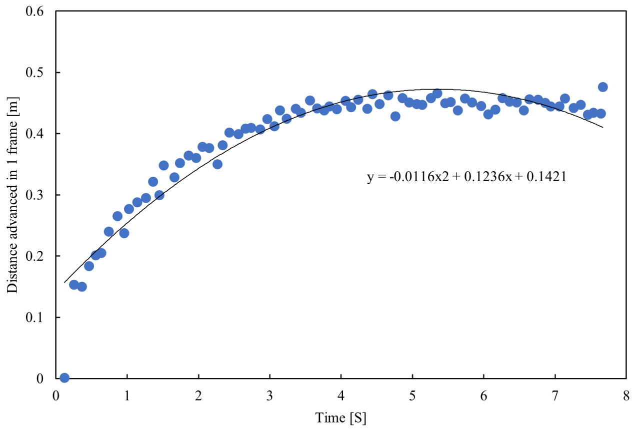

Fig. 2. Time-Distance Advanced in 1 Frame Function

observed in Fig. 2, the movement distance gradually increases as the sprint progresses. This trend reflects the natural acceleration of the runner, and at the same time, highlights the fact that rapid body motion leads to an expansion of inter-frame displacements. The vertical axis in Fig. 2 indicates the inter-frame displacement, reflecting the magnitude of the x-component at which motion blur may potentially arise. Therefore, the noise processing was performed by fitting the radius r_t to the approximation curve presented in Fig. 2. The algorithm was designed to suppress the influence of motion-induced noise by adapting r_t according to the magnitude of the observed displacement. This improves the robustness of human recognition under high-speed sprinting conditions.

2) How to Determine the Threshold Values for y and z: We derived the position coordinates for each frame of the vertex plot of the head of the running person in the y and z axes. The extraction of the head region was conducted by first estimating the approximate head location based on the centroid of the entire body point cloud. Within this designated region, the point possessing the maximum value along the vertical (z) axis was identified in each frame. This point was considered to represent the head vertex, and its corresponding y- and z-coordinates were subsequently extracted for analysis. Fig. 3 shows the y-axis and z-axis components of the head of the person running at full speed in each frame. In this figure, the left axis represents the y-coordinate, while the right axis represents the z-coordinate.

From the plotted results, two important trends can be observed. First, the sprinter exhibits slight lateral meandering, reflected in fluctuations of the y-axis component, which can be attributed to natural body sway during high-speed locomotion. Second, the vertical (z) component reveals that the sprinter begins the sprint with a forward-leaning posture and gradually transitions to a more upright position as the sprint progresses. These observations show that the

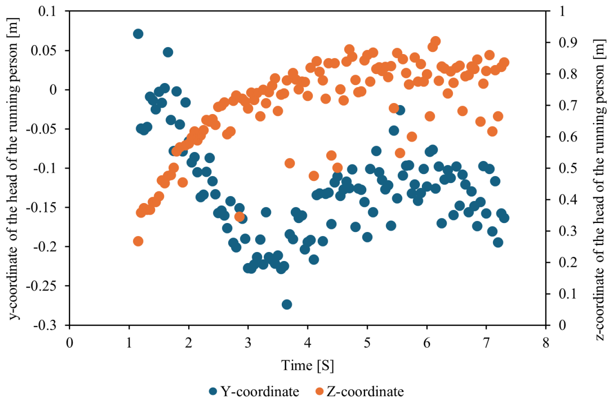

Fig. 3. Lateral (Y) and Vertical (Z) Position of the Runner's Head (The left axis is the y-coordinate, and the right axis is the z-coordinate.)

head trajectory provides key information on body stability and posture, essential for analyzing motion blur in non-forward directions. To quantify these variations, the inter-frame differences of the y- and z-coordinates were computed, providing a measure of displacement between consecutive frames. This calculation enables the detection of motion blur specifically in the lateral and vertical directions. Since raw displacement values often include noise, a moving average filter was applied to smooth the data. The smoothed values were then adopted as dynamic thresholds (y_t, z_t) that adapt to the subject's motion across frames. Accordingly, the thresholds for the y- and z-components in a given frame, denoted as y_t and z_t, respectively, determine the correction range for these components. This range becomes more limited as y_t and z_t decrease, as indicated by the black frame in Fig. 1. These thresholds are formally expressed in (2).

$$|y - y_i| \leq y_t, \quad |z - z_i| \leq z_t \tag{2}$$

Finally, for each point cloud, noise correction was applied by selecting n neighboring points that satisfied both the spherical region defined by radius r_t and the dynamic threshold conditions expressed in (2). For these neighboring points, the correction was performed according to the formulation in (1). By integrating the adaptive thresholds derived from the head trajectory, the proposed method ensures that noise suppression remains sensitive to motion variations in both the lateral and vertical axes. At the same time, it preserves the natural geometry of the sprinting motion.

B. Algorithm of this Proposal

Fig. 4 shows an overview of the filter. First, the raw point

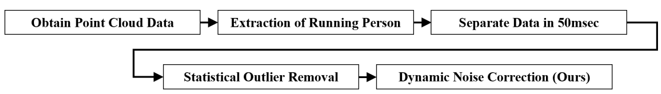

Fig. 4. Flowchart of the Algorithm of this Proposal

cloud data acquired from the LiDAR sensor was preprocessed by extracting the target sprinter from the surrounding environment. Since point cloud data are continuous over time, it was necessary to introduce a temporal segmentation scheme in order to enable frame-wise analysis. In this study, the data were divided into frames of 50ms each. After conducting preliminary experiments examining different temporal resolutions, it was determined that a frame duration of 50 ms provided an optimal balance between temporal resolution and computational efficiency. By setting one frame to 50ms, sufficient temporal detail could be preserved for analyzing rapid sprinting motion, while avoiding excessive computational overhead. Following segmentation, statistical outlier removal was applied to eliminate points that significantly deviated from their neighbors. This step is crucial because raw LiDAR data often contains erroneous points caused by reflection errors, sensor limitations, or interference. In the statistical outlier removal procedure, the average distance between a point of interest x_i and its k nearest neighbors is calculated. Using these distances, an average μ_i is computed for each point. Subsequently, the global average μ and standard deviation σ_μ are derived from the collection of μ_i across all points. A threshold is then defined by scaling the standard deviation using a constant parameter l. Points whose mean distances exceed the threshold are classified as outliers and removed from the dataset. The mathematical formulation of this process is expressed in (3).

$$\mu_i = \frac{1}{k}\sum_{j=1}^{k} d(x_i, x_j), \quad \mu_i \geq \overline{\mu} + l \times \sigma_\mu \tag{3}$$

The effectiveness of this outlier removal depends on appropriate selection of the parameters k (the number of neighboring points considered) and l (a scaling constant used for thresholding). In this study, several parameter combinations were tested experimentally in order to evaluate their effect on noise reduction and shape preservation. Based on these experiments, values of $k = 10$ and $l = 2.0$ were adopted, as they provided the most stable balance between removal of spurious noise and preservation of genuine point cloud structure. Finally, after statistical outlier removal, the proposed correction approach, as previously explained, was applied to further refine the point cloud data. Through this sequential processing pipeline, the algorithm ensures that the input point cloud data are sufficiently clean and stable to enable accurate recognition and analysis.

IV. VALIDATION OF EFFECTIVENESS

A. Experimental Method

This experiment was conducted at the Sagamihara Gion Stadium in Asamizodai, Sagamihara City, Kanagawa Prefecture. A healthy semi-professional athlete was asked to perform a short-distance sprint, and the running conditions were captured as point cloud data using LiDAR. The LiDAR LIVOX Tele-15 used to collect the point cloud data had an instrumental error of 2cm at a distance of 20m from the object and a reflectivity of 80%. Therefore, it is possible to compensate for relative dynamic noise even in an environment with a person in sprinting motion. In addition, the system uses a nonrepetitive scanning pattern and multiple laser emissions, enabling high-density field of view coverage with a maximum of 240,000 points within a 15deg field of view angle. When conducting measurements in an outdoor stadium environment, attention must be paid to potential obstacles that may occlude the line of sight between the LiDAR sensor and the subject. In particular, if a third party or object enters the measurement space, occlusion can cause missing or corrupted point cloud data, thereby reducing accuracy. For this reason, the experimental setup was carefully managed to ensure that no obstacles were present within the measurement path during the sprint trials. In terms of placement, the LiDAR was set up 10m behind the starting position and fixed with a tripod at a height of about 80cm. This placement was chosen through experimentation to minimize body occlusion, ensure continuous point cloud capture along the running trajectory, and balance the recording of both lower-limb motion and overall body posture. Fig. 5 shows the actual driving environment and Fig. 6 shows the subject's driving scene.

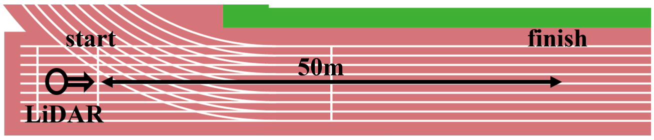

Fig. 5. Experimental Environment

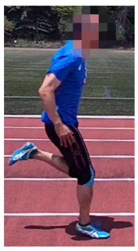

Fig. 6. Sprinting Scene of the Runner

To evaluate the effectiveness of the proposed method, we conducted a classification task using PointNet++ [13]. The evaluation compared recognition performance between the original point cloud data and the noise-corrected data produced by the proposed filter, as illustrated in Fig. 4. Specifically, the assessment focused on the model's ability to correctly classify the target point clouds into the "person" category. In total, 106 frames of LiDAR-acquired point cloud data from sprinting individuals were used as evaluation samples. PointNet++ is an extension of the original PointNet architecture [14], designed to capture not only global but also local geometric structures of point cloud data. By employing hierarchical grouping and shared multilayer perceptrons (MLPs), PointNet++ achieves robustness to variations in sampling density while maintaining permutation invariance. Owing to these properties, PointNet++ has been widely applied across diverse 3D vision tasks [15]–[17], and thus provides a reliable framework for assessing recognition accuracy in this study. For the training stage, we employed a subset of the ModelNet40 dataset [18], a widely used benchmark for 3D object classification. To simplify the classification problem and emphasize person recognition, five categories were selected: person, car, airplane, bottle, and table. Each sample in the dataset was represented solely by its spatial coordinates (X,Y,Z), without additional features such as reflectance or color. The model was implemented using a PyTorch version of PointNet++ [19] and trained with the Adam optimizer for 155 epochs. The training configuration included a batch size of 24, a learning rate of 0.001, and a weight decay of 0.0001. Importantly, the model was trained exclusively on ModelNet40 and had no prior exposure to the LiDAR-acquired data, thereby ensuring unbiased evaluation. In the testing phase, only point cloud data of sprinting individuals obtained from the LiDAR system were used. Both the original and the noise-corrected data were used as test inputs. To reduce the impact of randomness, the classification experiment was repeated five times, and the average recognition accuracy across these trials was reported as the final metric.

This work involved human subjects in its research. The authors confirm that all human subject research procedures and protocols are exempt from review board approval.

B. Results

The original data is shown in Fig. 7, the data from previous research [12] is shown in Fig. 8, and the point cloud data after applying the proposed filter is shown in Fig. 9. Comparing Fig. 7 to Fig. 9 above, it was confirmed that motion blur can be removed while preserving the original "person" shape, such as the knee joints becoming clearly visible. Table I shows the evaluation results based on PointNet++ classification.

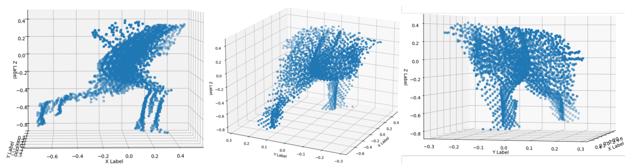

Fig. 7. Original Data (Left figure: side view, Middle figure: rear view, Right figure: front view)

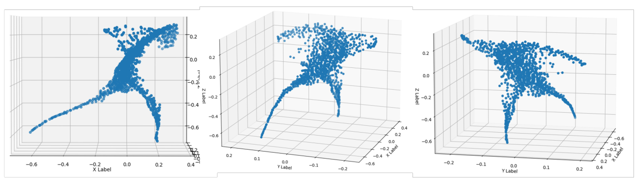

Fig. 8. Previous Data from [12] (Left figure: side view, Middle figure: rear view, Right figure: front view)

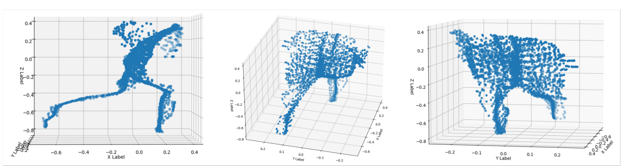

Fig. 9. Filtered Data (Left figure: side view, Middle figure: rear view, Right figure: front view)

TABLE I

EVALUATION RESULTS BY POINTNET++

Item	Accuracy [%]
Original Data	37.0
Previous Data from [12]	53.2
Filtered Data (Ours)	**69.6**

Table I shows that the proposed filter provides higher recognition accuracy than the results reported in [12]. This confirms that the proposed method can remove motion blur caused by sprinting more effectively. Additionally, the computation time was approximately 3.11 seconds per frame (s/frame) for the previous method and 3.73 seconds per frame (s/frame) for the proposed method. This increase was due to the additional processing required for dynamic noise reduction. Table II presents the evaluation results for the first half of the sprinting phase, including the average number of points and recognition accuracy. Similarly, Table III summarizes the results for the second half of the sprinting phase. The first half corresponds to the acceleration phase, where the running speed is relatively low, whereas the second half represents the period in which speed fluctuations are small but the sprinting speed itself is high.

TABLE II

EVALUATION RESULTS OF THE FIRST HALF PART

Item	Average Number of Points	Accuracy [%]
Original Data	1859.0	27.8
Filtered Data	1782.4	**61.2**

TABLE III

EVALUATION RESULTS OF THE SECOND HALF PART

Item	Average Number of Points	Accuracy [%]
Original Data	614.5	45.9
Filtered Data	590.6	**80.6**

Table II, III show that the recognition accuracy tends to be higher in the second half of the sprint period than in the first half of the sprint period. Furthermore, the average number of points tended to be higher in the first half of the sprinting phase, where the subject was closer to the LiDAR. A reduction in the number of point clouds was also observed due to the removal of statistical outliers.

V. DISCUSSION

Table I demonstrates that the proposed method achieved higher recognition accuracy than the results reported in [12]. This improvement is primarily due to the introduction of directional constraints derived from displacement in all three spatial dimensions. These constraints guided the correction process to reflect the actual movement of the subject. As a result, corrections were selectively applied only to regions where motion blur was likely to occur rather than indiscriminately to all components. This selective application effectively suppressed the excessive corrections previously observed in the lateral and vertical directions, enabling more faithful preservation of the original motion characteristics. Consequently, the overall recognition accuracy improved significantly. Furthermore, Table II, III indicate a tendency for recognition accuracy to be higher in the latter half of the sprinting phase, when the athlete's velocity is relatively stable and high. This is compared with the first half, when the subject is accelerating. This suggests that fluctuations in velocity, particularly those associated with acceleration and deceleration, influence recognition accuracy more than absolute speed. In other words, recognition appears to benefit from periods of steady velocity, whereas transitional phases of speed change introduce variability that reduces accuracy.

In addition, the results also imply that the number of acquired point clouds does not exert a substantial effect on recognition performance. This finding suggests that the quality of the acquired data, determined by stability of movement and effective correction of noise, plays a more crucial role than the sheer quantity of data points. Taken together, these results highlight the importance of accounting for dynamic changes in velocity and focusing on effective correction strategies, rather than merely increasing data density, when aiming to improve recognition accuracy in sprinting motion analysis.

VI. CONCLUSIONS

This study focused on addressing the problem of motion blur generated during sprinting by presenting a refined correction method that estimates inter-frame displacement in three dimensions. By applying the proposed technique, the point cloud data could be corrected more effectively, leading to improved recognition accuracy when compared with our previous work [12]. These results clearly demonstrate the potential of the method for enhancing the reliability of LiDAR-based motion analysis. Although the experimental validation was limited to a single subject, it was conducted using a substantial number of frames, thereby ensuring a certain degree of robustness in the evaluation. Nevertheless, the reliance on one participant remains a limitation, and further investigations are required to confirm the generalizability of the method. Future research will therefore include a more diverse range of subjects, covering different ages, genders, and body types, in order to examine how individual variations in sprinting form and dynamics influence the effectiveness of the noise correction process. By extending the evaluation in this manner, the proposed method is expected to be applicable not only to recognition tasks but also to broader applications such as human pose estimation. Ultimately, this line of research aims to contribute to the development of advanced analytical systems that can be used to support training optimization and athletic performance enhancement in real-world sports environments.

ACKNWLEDGMENT

This work was supported by MEDIA ROBOTECH INC.

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