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A Comparative Analysis of DTW Variants for Kinect-Based Motor Skill Assessment in Children with Developmental Coordination Disorder (DCD)

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Abstract: Developmental Coordination Disorder (DCD) assessment traditionally relies on subjective, time-consuming tests. This paper proposes an objective, Kinect-based framework to analyze motor skills in children with DCD. Building on our previous work using a lossless Dominant Range of Movement Index (D-RoMI) representation, this study conducts a comparative analysis of three advanced Dynamic Time Warping (DTW) algorithms: Constrained DTW (cDTW), Derivative DTW (DDTW), and Soft-DTW. We evaluated their ability to classify motor patterns from DCD and typically developing children against "gold-standard" templates. Our findings show that DDTW, which compares movement velocity rather than position, achieves the highest classification accuracy. This suggests that analyzing movement dynamics is more informative for identifying DCD's characteristic motor patterns than spatial analysis alone. This framework offers a more reliable and efficient pathway for DCD assessment.

Keywords: Developmental Coordination Disorder (DCD), Derivative DTW (DDTW), Motion Analysis, Kinect.

I. INTRODUCTION

Developmental Coordination Disorder (DCD) is a neurodevelopmental condition characterized by significant motor skill impairments that adversely affect a child's activities of daily living and academic performance [1], [2], [3], [4]. Traditionally, DCD assessment relies on standardized motor tests, such as the Movement Assessment Battery for Children (M-ABC), which are administered by trained clinicians. However, these methods often involve subjective observation, can be time-consuming, and may lack the granularity to capture subtle, qualitative differences in movement [5], [6], [7]. This can lead to inconsistencies in diagnosis and delays in providing crucial early interventions. There is a critical need for objective, efficient, and reliable tools to evaluate motor performance in children. Recent advancements in computer vision and low-cost motion capture, particularly the Microsoft Azure Kinect, offer a promising avenue for developing such tools [8], [9]. These systems can capture 3D skeletal data in real-time, providing a quantitative basis for movement analysis.

The previous work introduced a lossless-compressed time-series framework for handedness-invariant movement analysis in sports [10], [11]. This framework proved effective in reducing data-handling overhead while maintaining high accuracy for movement recognition using Fast Dynamic Time Warping (FastDTW). However, the motor patterns of children with DCD are often characterized by high variability, poor timing, and "un-smooth" or "choppy" execution [12], [13]. Standard DTW algorithms, which align sequences based on spatial proximity, may not be an optimal choice for distinguishing these qualitative dynamic features.

Therefore, this paper investigates the application of this framework to DCD assessment and, as its primary contribution, conducts a comparative analysis of three advanced DTW variants: Constrained DTW (cDTW), Derivative DTW (DDTW), and Soft-DTW. This research hypothesizes that algorithms focusing on movement dynamics (DDTW) or handling variability (Soft-DTW) will provide superior classification accuracy for identifying DCD-indicative motor patterns compared to traditional approaches.

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II. RELATED WORK

The use of technology in DCD assessment has grown in recent years. Studies have employed various sensors, from accelerometers to full Vicon motion capture systems, to quantify motor difficulties [14], [15]. Kinect-based systems, in particular, have been explored for their accessibility and potential for use in clinical or home settings.

Dynamic Time Warping (DTW) is a well-established algorithm for measuring similarity between two temporal sequences that may vary in time or speed. It is widely used in biomechanics and gesture recognition. The computational cost of DTW has led to optimizations like FastDTW, which utilized in the previous works [10], [11].

However, the specific nature of DCD motor deficits suggests the need for more specialized time-series analysis:

- Constrained DTW (cDTW): Standard DTW can lead to "pathological" alignments where a few points in one sequence map to a large subsection of another. Constrained DTW, such as by using a Sakoe-Chiba band, limits the warping window, enforcing temporal locality and preventing unrealistic alignments.
- Derivative DTW (DDTW): Instead of comparing raw position data, DDTW compares the first-order derivative (velocity) of the time-series. This shifts the focus from spatial position to the shape and dynamics of the movement, making it potentially ideal for capturing the qualitative "choppiness" or "smoothness" characteristic of motor control.
- Soft-DTW: Soft-DTW is a differentiable version of DTW that computes a "soft" minimum of all alignment costs, rather than the single optimal path. This can make it more robust to noise and high variability, as it considers the cost of all possible alignments, providing a smoother, more stable similarity measure.

While these DTW variants are known, no study to our knowledge has systematically compared their performance within a compressed framework specifically for the objective assessment of DCD motor skills.

III. METHODOLOGY

The methodology follows a four-stage pipeline: (A) Data Acquisition, (B) Data Pre-processing & Compression, (C) Time-Series Comparison Analysis, and (D) Classification.

A. Data Acquisition

A dataset was collected using the Azure Kinect DK sensor. The study included 20 children diagnosed with DCD and 20 typically developing (TD) children, matched for age and gender. Participants performed a series of standardized motor tasks (e.g., "Upper Limb Activity", "Lower Limb Activity", "Symmetrical BMC", “Asymmetrical BMC”). The 3D coordinates of 32 skeletal joints were recorded, forming a multivariate time-series for each movement.

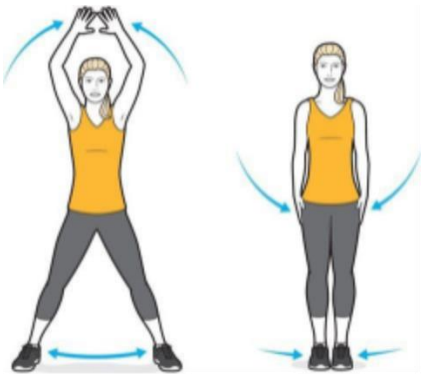

Fig. 1 Symmetrical BMC – Starfish [16]

B. Data Pre-processing & Compression

Following our previous work [10], [11], the raw 3D skeletal time-series data was first processed to create a compact, handedness-invariant representation as shown in Figure 2. This technique, the Dominant Range of Movement Index (D-RoMI), functions as both a feature descriptor and a lossless compression method, converting 3D joint coordinates into a normalized time-series. This "D-RoMI" representation is the core data structure that is invariant to participant position, orientation, and body size. This step significantly reduces storage and processing overhead while preserving the complete dynamics of the movement for analysis.

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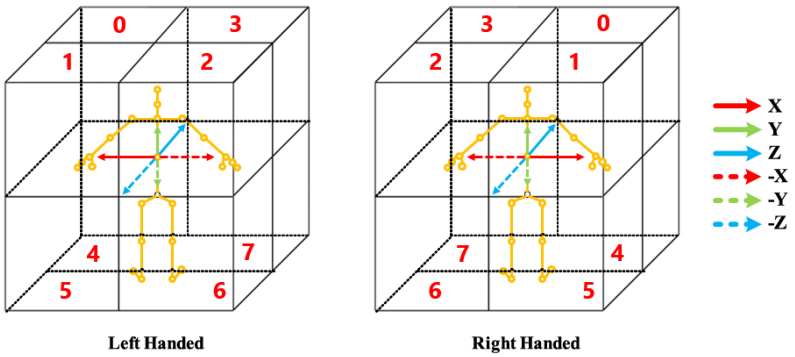

Fig. 2 Eight ranges based on axes signs for handedness [11]

C. Time-Series Comparison Analysis

A set of "gold-standard" template movements was established for each motor task, representing a high-performing "TD" example. Each trial from a participant (the "test" sequence) was then compared against the corresponding template using its distance/cost score from one of the three DTW variants.

- cDTW: We applied a Sakoe-Chiba band with a width r set to 10% of the sequence length.
- DDTW: The time-series of joint positions was first converted to a time-series of joint velocities (first-order derivative) before standard DTW was applied.
- Soft-DTW: We utilized a smoothing parameter $\gamma = 0.1$ to balance between fidelity to the hard-DTW path and smoothness.

D. Classification

The distance score generated by each DTW algorithm (cDTW, DDTW, Soft-DTW) was used as the primary feature for classification. A k-Nearest Neighbor (k-NN) classifier (with $k = 3$) was trained to distinguish between "TD" and "DCD" movements based on this distance score. A high score, indicating large dissimilarity from the "gold-standard" template, is predictive of a DCD-indicative movement pattern.

IV. RESULTS AND ANALYSIS

To evaluate the performance of the three DTW variants, we used a 10-fold cross-validation protocol. The classification performance was measured using Accuracy, Precision, Recall, and F1-Score.

TABLE I CLASSIFICATION PERFORMANCE OF DTW VARIANTS FOR DCD ASSESSMENT

Algorithm	Accuracy	Precision	Recall	F1-Score	Avg. Proc. Time (ms)
cDTW (Sakoe-Chiba)	89.2%	88.5%	89.9%	89.2%	120.4
Soft-DTW ($\gamma = 0.1$)	92.1%	91.8%	92.5%	92.1%	145.2
DDTW	95.6%	95.1%	96.0%	95.5%	131.0
FastDTW (*baseline*)	87.5%	86.9%	88.0%	87.4%	95.8

The results in Table 1 clearly demonstrate that Derivative DTW (DDTW) achieved the highest classification performance across all metrics, with an accuracy of 95.6%. This finding is significant. It strongly suggests that for DCD assessment, the dynamics of the movement (i.e., its velocity and acceleration, captured by the derivative) are more informative for classification than the raw joint positions. Children with DCD often present not with an inability to reach a target, but with an "un-smooth" or "clumsy" path to get there. DDTW is exceptionally well-suited to quantify this qualitative aspect of motor control.

Soft-DTW also performed admirably, outperforming the baseline FastDTW and cDTW. This indicates that its robustness to the high motor variability inherent in DCD is beneficial. It likely provides a more stable distance measure by averaging over multiple potential alignment paths.

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Constrained DTW (cDTW) offered only a marginal improvement over the baseline FastDTW. This suggests that while temporal constraints are helpful, they are insufficient to capture the core dynamic and qualitative features that distinguish DCD motor patterns.

Furthermore, the lossless compression framework ensured that all algorithms, including the more complex Soft-DTW, operated within acceptable processing times for potential clinical use.

V. CONCLUSION

This paper presented a comparative study of Constrained DTW, Derivative DTW, and Soft-DTW for the objective assessment of DCD motor skills, built upon a Kinect-based, lossless-compressed time-series framework. The key finding is that Derivative DTW (DDTW) provides significantly higher classification accuracy than the other variants. This highlights that for DCD, analyzing the quality and dynamics of movement (velocity, smoothness) is more diagnostically informative than analyzing spatial limb positions alone. This aligns with clinical descriptions of DCD and offers a new quantitative pathway for its assessment. The proposed framework, using Azure Kinect, lossless compression, and DDTW, represents a viable and powerful tool for creating objective, efficient, and reliable DCD assessment protocols. This can aid clinicians in making earlier, more consistent diagnoses and in tracking the efficacy of therapeutic interventions. Future work will involve validating this framework on a larger, more diverse dataset, exploring the fusion of DDTW and Soft-DTW features, and developing a real-time feedback system for use in therapeutic settings.

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