Behavior Analysis With Integrated Visual-Motor Tracking for Developmental Coordination Disorder

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***Abstract*— Developmental coordination disorder (DCD) is a motor learning disability with a prevalence of 5%-6% in school-aged children, which may seriously affect the physical and mental health of affected children. Behavior analysis of children helps explore the mechanism of DCD and develop better diagnosis protocols. In this study, we investigate the behavioral pattern of children with DCD in the gross movement using a visual-motor tracking system. First, visual components of interest are detected and extracted using a series of intelligent algorithms. Then, the kinematic features are defined and calculated to describe the children behavior, including eye movement, body movement, and interacting object trajectory. Finally, statistical analysis is conducted both between groups with different motor coordination abilities and between groups with different task outcomes. The experimental results show that groups of children with different coordination abilities differ significantly both in the duration of eye gaze focusing on the target and in the degree of concentration during aiming, which can serve as behavioral markers to distinguish children with DCD. This finding also provides precise guidance for the interventions for children with DCD. In addition to increasing the amount of time spent on concentrating, we should focus on improving children's attention levels.**

***Index Terms*— Developmental coordination disorder (DCD), behavior analysis, visual-motor tracking, behavioral marker, gross movement.**

Manuscript received 15 September 2022; revised 27 February 2023 and 10 April 2023; accepted 16 April 2023. Date of publication 25 April 2023; date of current version 3 May 2023. This work was supported in part by the National Natural Science Foundation of China under Grant 62102296 and Grant 62101416; in part by the Fundamental Research Funds for the Central Universities under Grant XJS222221; in part by the Dean's Research Fund under Grant 2021/22DRF/SRAS-1/9th, FLASS, The Education University of Hong Kong; and in part by the Wuxi Taihu Lake Talent Plan Supporting for Leading Talents in Medical and Health Profession, China. *(Corresponding authors: Hong Fu; Shuiping Gou.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Research Ethics Safety Committee of Chu Hai, College of Higher Education, Hong Kong.

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This article has supplementary downloadable material available at https://doi.org/10.1109/TNSRE.2023.3270287, provided by the authors.

Digital Object Identifier 10.1109/TNSRE.2023.3270287

I. Introduction

DEVELOPMENTAL Coordination Disorder (DCD) [1], also referred to as developmental dyspraxia, is a type of neuromotor disorder that affects approximately 5%-6% of school-age children [2], [3]. Children with DCD typically exhibit 'clumsy' movements and have limited flexibility in their limbs when participating in some daily activities, such as, playing sports, catching objects, and using scissors [4]. The motor coordination abilities of children with DCD lag far behind that of their peers at typical developmental stages [5]. What's more, some children with DCD have problems with perceptual, sensory, tactile, and visual perception [6]. Without timely diagnosis and interventions, the symptoms of most children with DCD will continue into adolescence or adulthood [7], which seriously affects the social, academic, and emotional development of patients [8], [9], [10], and brings some secondary health problems, such as obesity [11], depression [12], and poor social adaptability [13]. Timely assessment is of great importance to the physical and mental health for children with DCD.

At present, the etiology and pathogenesis of DCD are unclear [14], [15]. How specific cognitive and neurological deficits affect developmental coordination disorders remains a mystery [16]. The current clinical diagnosis of DCD is made by observing the child's performance in completing specific assessment tasks specified in a standard diagnostic assessment tool [17]. This diagnosis based on naked-eye observation has the following drawbacks: 1) Human visual observation is highly subjective, and it is easy to ignore some important details due to occasional fatigue; 2) Longitudinal or horizontal comparative analysis is difficult to conduct in the one-time observation and diagnosis; 3) The assessment tools are too specialized for non-professional users (such as teachers and parents), and the charge of professional diagnosis is expensive, leading to many inconveniences in early screening. With the rapid development of computer vision and data mining technologies, intelligent behavior analysis and in-depth exploration of diagnostic behavioral markers of DCD may provide novel solutions to the above problems.

Poor motor coordination is one of the main features of children with DCD [1], [7]. Motor coordination is the ability to combine the nervous and musculoskeletal systems to product fast, precise, and well-balanced motor responses [18]. The most visual manifestation of motor coordination is the body movements, while visual perception plays a key role in the development of motor coordination [19], [20]. Body movement and visual perception are coupled: the information from the perceptual system is associated with changes in body dynamic, which in turn is used to adaptively regulate body behavior, ultimately leading to the development of stable motor coordination pattern. When interacting with the object, the state or the trajectory of the objects interacting with human also reflects body movement to some extent. Thus, a comprehensive behavior analysis of DCD includes analysis of body movement, visual movement and interacting object trajectory.

Many studies [21], [22], [23], [24], [25], [26], [27], [28] have been conducted on DCD from the perspective of body motion analysis, and most of the works has been devoted to excavating the walking and running gait of children with DCD. Among them, the most representative is the works from the Perception and Motion Analysis Research Group (PuMA) at Oxford Brookes University. They used the Vicon Nexus 3D motion capture system with 12 cameras to study the motor mechanism and motor coordination of DCD patients [21], [22], [23]. As shown in Fig. 1, the movement variability of adults with and without DCD [21], and the gait patterns of children with DCD [22] are studied by tracking the movement of spherical markers attached to the skin surface of participants. They also studied the movement differences when avoiding obstacles in order to explore the motor control mechanism of DCD patients [23]. PuMA's research works show that the digital motion analysis system has great potential in exploring the motion mechanism of DCD. Some works [29], [30], [31], [32], [33] have investigated the disorder mechanism of DCD from the perspective of visual pattern analysis with the help of non-intrusive eye-tracker. Wilson et al. [29] used an Applied Science Laboratories (ASL) Mobile Eye gaze registration system and applied the quiet eye (QE) as an object measure to distinguish children with different motor coordination abilities. Licari et al. [32] studied the visual tracking behaviors of boys in the task of two-handed catching using the Mobile Eye (ME) tracking system. These works indicate that the visual movement analysis is meaningful to explore the pathogenesis of DCD.

There are a few works [34], [35] that consider body movement and visual movement jointly to make a comprehensive behavioral analysis of DCD. Parr et al. [34] used a 26-camera motion capture system (Vicon MX) and a Pupil labs eye-tracker to analysis the kinematic variables and gaze variables and investigate the visuomotor control strategies of children with and without DCD. Similarly, in [35], Arthur et al.

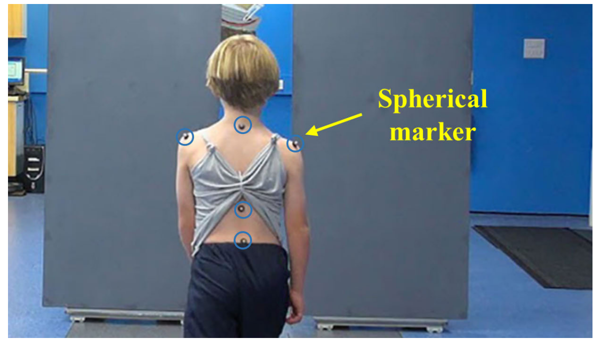

Fig. 1. Vicon Nexus 3D motion capture system used by the Perception and Motion Analysis Research Group [21], [22], [23].

applied the same equipment to examine the hand and eye movements of children with DCD during object interaction. However, the motion capture system used in [34] and [35] requires many reflective markers to be attached on the participants, which limits the application range of this type of motion capture system, especially in the motion ability assessment of children, because the pasted markers may distract children and bring physical discomfort. Besides, this motion capture system is expensive, which is not convenient for system popularization. In addition to above DCD related works, there are also some other works [36], [37], [38] dedicated to the study of jointly visual-motor analysis. Eye-tracker is used to capture eye motion information in these works. In the work [36], sensors are used to capture the position of the hand or fingertips, while the other two works [37], [38] use the movement of the mouse cursor to reflect the movement of the hand. There are strict limitations on the experimental scenes and tasks, whether using the positioning sensors or the mouse cursor to capture hand movement. Attaching the sensors to the hand is not suitable for the experimental scenes that require large-scale swings of upper limb, and the sensors may cause a certain degree of interference to the participants. The limitation of using the mouse cursor to reflect the hand movement is even more obvious, because most of the motion tasks in the actual scene cannot be simulated by moving the mouse, which lacks authenticity and operability.

In our previous works [39], a marker-less visual-motor tracking system was developed, which captures both eye movement and body motion of children as well as scene information during DCD fine and gross motor assessment. With the help of the designed system, we conducted several studies [40], [41] on fine movements of DCD in the early stage. In [40], the eye-hand coordination ability in the fine motor task was analyzed based on the visual-motor data, and the experimental results showed that the eyes of children without DCD have an obvious leading role, that is, their eyes focus on the target before their hands move. In [41], automated fine motor evaluation of DCD was achieved by the designed task localization algorithm and task evaluation algorithm. Gross motor analysis is qualitatively different from fine motor analysis, because the fine motor refers to movements that focus mainly on the upper limbs, especially the hands, while gross movements usually require the participation of the whole body.

In this paper, we focus on developing a framework for behavior analysis in gross movements and mining quantified behavioral markers of children with DCD in the gross tasks. Taking the task of throwing beanbag specified in the DCD assessment tool [42] as an example, we investigate the behavior pattern of children with DCD through the analysis of eye movement, body movement, and interacting object trajectory. First, a series of artificial intelligence-based algorithms are adopted to detect and extract interested visual components in the beanbag throwing task, including single throw clip extraction, human body tracking, and objects of interest detection. Subsequently, the kinematic features in single throwing are defined and extracted to describe the beanbag trajectory, gaze movement, and body movement. Finally, statistical analysis is applied between groups with different motor coordination abilities to explore the quantified behavioral markers of DCD.

The rest of the paper is organized as follows. Section II presents the data collection system and the experimental design. In Section III, visual components detection and kinetics feature extraction are introduced in detail. Section IV presents the statistical analysis and the experimental results. The mined behavioral markers of DCD are discussed in Section V. Finally, the paper is concluded in Section VI.

II. Data Collection

The experimental setup in this study is carefully designed following the standard assessment tool Movement ABC-2 [42] and in consultation and collaboration with experts on sports rehabilitation experienced with DCD.

A. Task and Participant

Movement ABC-2 is a standardized assessment tool to identify a child with motor difficulties by comparing his/her score to their peer normative performance. This tool has been widely used for clinical diagnosis and scientific research. Therefore, Movement ABC-2 was used in this study to evaluate participants' motor competence and give a quantified motor coordination score. Eight tasks (three fine motor tasks and five gross motor tasks) are designed for each age band in Movement ABC-2. The performance of the participant in each task is scored and adjusted to an item standard score by age. A total test score and an age-adjusted standard score are calculated and converted to the percentile rank for clinical diagnosis. 63 children aged 7∼10 years old were recruited from primary schools in Hong Kong to participate in the research. Before commencing this study, full parental and participant's informed written consents were provided, and the ethical approval was acquired from Research Ethics Safety Committee of Chu Hai College of Higher Education, Hong Kong.

B. System Design

A marker-less visual-motor tracking system for gross movements proposed in our previous work [39] is used to record the body movement and the eye gaze of the participants, as well as the scene information, as shown in Fig. 2. The system consists of a binocular head-mounted eye-tracker (Pupil Labs) and three Kinects (Microsoft Kinect V2) surrounding the participant. To ensure the continuity of the assessment process, three Kinects are designed to meet the recording requirements of all the gross motor tasks, of which one Kinect is used for the task of throwing beanbag. The eye-tracker has a front world camera and two eye cameras. In addition to providing eye gaze data, the eye-tracker also provides the first-person images by the world camera. The resolution of the world camera is 1280×720 at 60 fps, and the field of view (FOV) of its lenses is 100 degrees. Kinect captures the third-person videos, and the resolution is 1920×1080 at 30fps. In summary, the designed visual-motor tracking system provides us with the eye gaze, the first-person images, and the third-person images of the participants and the scenes.

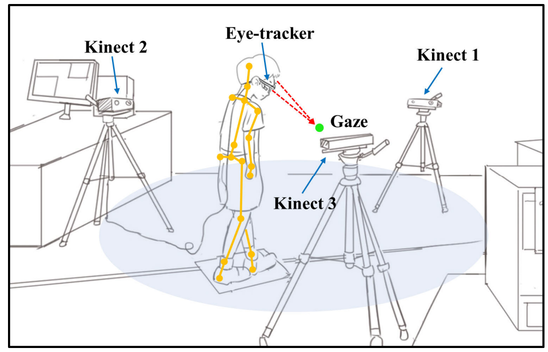

Fig. 2. The proposed gross movement system.

C. Experimental Protocol

Each participant is required to conduct a dominant hand test, namely one-handed catching, to determine the dominant hand, and then to complete eight tasks specified in Movement ABC-2 under the instructions of a well-trained assessor to obtain his/her motor coordination score. The performance of the participants in five gross motor tasks is recorded by the proposed gross movement system, and these five gross tasks are catching with two hands, throwing beanbag onto mat, one-board balance, walking heel-to-toe forwards, and hopping on mats. In this study, we conduct behavior analysis in the task of throwing beanbag onto mat, because the specific throwing skill is highly related to children's sport or games, and the throwing prediction ability is also the basis of other targeting tasks.

In the task of throwing beanbag onto mat, the participant is required to stand on the solid-blue mat wearing the eye-tracker, and then throw the beanbag onto the red circle on the target mat, as shown in Fig. 3. The participants are encouraged to perform underarm throwing with one hand, but an overarm or two-hand throw is not penalized. Participants are allowed to change hands during formal trials. The task is explained and demonstrated to the participant firstly, then each participant is given five practice attempts and ten formal trials. In the formal test phase, a hit is counted if any part of the beanbag overlaps with the designated red area on the target mat upon landing. The throwing performance is recorded by both an absolute score out of ten and a standard score (accounting for

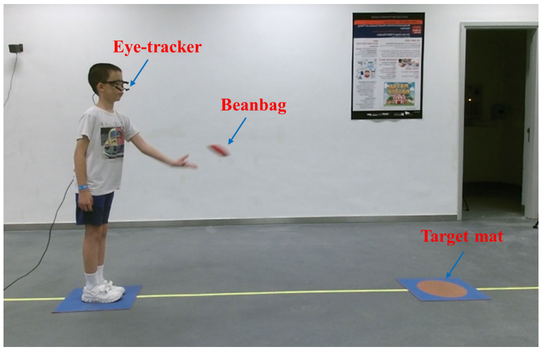

Fig. 3. ∗. The task of throwing beanbag onto mat specified in Movement ABC-2. (∗The parents of the child in the image gave permission to use this image.)

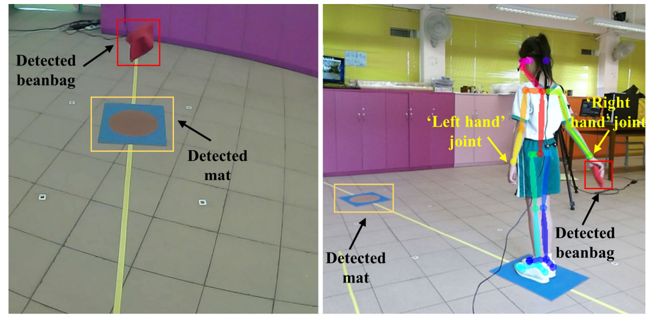

Fig. 4. Human pose estimation and beanbag & mat detection results. (a) First-person view image; (b) Third-person view image.

age differences) taken from tables in the Movement ABC-2 Examiner's Manual.

III. Methodology

A. Visual Components Detection and Extraction

Prior to behavior analysis, intelligent detection and extraction of the visual components of interest are required. The data captured by the Kinect and eye-tracker are long videos containing multiple beanbag throwing trials, so it is necessary to extract the video clips that contain only one beanbag throwing trial to facilitate subsequent analysis with a single throwing as the unit. During each beanbag throwing process, the posture of the participant (especially the hand pose primarily involved in the task), the position of the beanbag and the target mat need to be detected to analyze the human body movement, and beanbag trajectory. In this section, how to detect and extract these visual components of interest is presented.

1) Single Throw Clip Extraction: The performance of each participant is recorded as two long videos, one is the first-person view video from eye-tracker's world camera and the other is the third-person view video from Kinect. These two videos were processed using the action progression network (APN) proposed in our previous work [43] for single throw clip extraction. The APN network estimates the start and the end of a throwing trial based on the learning of action temporal structure, thus extracting the video clips of each beanbag throwing trial. Then the automated results obtained by APN are manually adjusted by a research specialist in motor coordination disorder. The eye gaze sequence belonging to each throwing trial is located and extracted according to the synchronization relationship between the first-person view video and the eye gaze data. In this way, the clips extracted by single throw extraction are triplets $\{(F_k, T_k, E_k)\}_{k=1}^{K}$, where $k \in \{1, 2, \cdots K$ is the index of the single throw clips, and K is the total number of the single throw clips.Each triple (F_k, T_k, E_k) consists of three elements, *i.e.*, the first-person view video clip F_k, the third-person view video clip T_k, and the eye gaze sequence E_k in one single beanbag throwing.

2) Human Pose Estimation: To analyze the body movement, the exact position of the key skeletal points of human body, especially the hand throwing the beanbag, at each moment are required to be known. This claim can be achieved by image-based human pose estimation. Plenty of researchers are currently working on human pose estimation, and there are many mature pose estimation methods [44], [45], [46]. The OpenPose [44] human pose estimation framework is an open-source library developed based on convolutional neural networks and partial affinity fields, which enables real-time single and multi-person pose estimation with good robustness. Therefore, OpenPose is adopted here to estimate the 2D coordinates of human skeleton points from the third-person view RGB images. The positions of hands are obtained by the estimated position of the corresponding key points ("left hand" joint and "right hand" joint), as shown in Fig. 4 (b). The colored lines in the figure are the pose estimation results obtained by the OpenPose.

Once the positions of two hands are known, the hand which is used to throw the beanbag is determined by jointly considering the position of the beanbag. Finally, the 2D coordinates of the hand throwing the beanbag is obtained, and denoted as $p_h^{(i)}$ at the *i-th* frame.

3) Beanbag and Mat Detection: Beanbag and target mat are two notable objects in the throwing process. The trajectory of beanbag and the position of the target mat together with the eye movement data reflect the targeting ability and the concentration level of the participant. Therefore, the beanbag and the mat in both the first- and third-person view videos should be accurately detected. The classic object detection algorithm Faster R-CNN [47] is adopted to detect the beanbag and the target mat. The positions of beanbag and mat are partially annotated, and the Faster R-CNN pre-trained on the COCO dataset [48] is fine-tuned on the annotated data. The detected results are shown in Fig. 4. The center coordinates of the detected box are taken as the 2D coordinates of the detected beanbag and target mat, which is denoted as $p_b^{(i)}$ and $p_m^{(i)}$ at the *i-th* frame.

B. Kinematic Features in Single Throwing

After extracting and detecting the visual components, the kinematic features in a single throwing are analyzed in this section. The beanbag is the object of interaction with the participants. The beanbag trajectory reflects the direction and strength when throwing the beanbag, and is decisive for the throwing result. The human eye gaze movement and hand

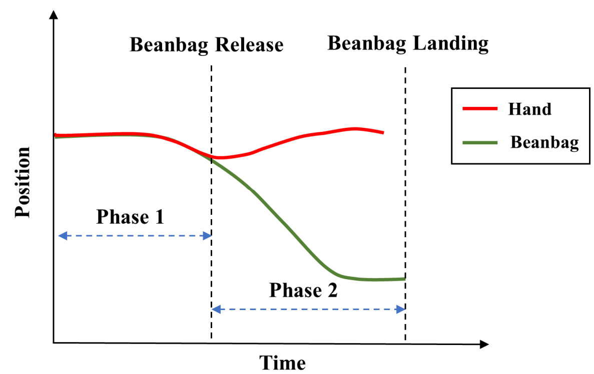

Fig. 5. The definition of the beanbag release time.

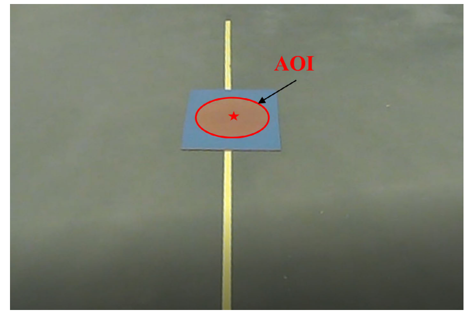

Fig. 6. An area of interest (AOI) in the visual scene is defined as the red circle in the blue mat.

movement are indispensable components of motor coordination studies, which are analyzed to explore the behavioral markers between children with and without DCD.

1) Beanbag Trajectory: A complete beanbag throw refers to the process from aiming, raising the hand to the end of beanbag landing. It contains two distinct phases: 1) Phase 1 (beanbag throwing) is defined as the time from preparation to the beanbag releasing. Aiming the target and waving the arm take place during this phase, which determine the outcome of the throwing (hitting on or not). 2) Phase 2 (beanbag flight) is defined as the time from beanbag releasing to beanbag landing on the mat or ground. Any actions of the participants at this stage do not have an impact on the result of beanbag throwing.

Phase 1 and Phase 2 are separated by a critical moment, namely beanbag release time, which is defined as the moment at which the beanbag begins to leave the hand, as shown in Fig.5. The red curve represents the trajectory of the hand, and the green curve represents beanbag's trajectory. The beanbag release time is the frame where the red and green curves no longer overlap. The determination of beanbag release time is important for temporally fine-grained behavior analysis.

The beanbag release time is calculated according to the relative position of the hand and the beanbag. During the beanbag throwing process, the movement trajectories of the hand and the beanbag are completely recorded in the third-person view video clip. The hand and the beanbag are detected frame by frame. The beanbag is considered to be thrown out when the distance between the hand and the beanbag exceeds a preset threshold. Therefore, the beanbag release time is calculated as $t_r = \frac{n_r}{f_K}$, where f_K is the sampling rate of the Kinect RGB camera, n_r is the frame index which satisfies formula (1).

$$\left\| p_b^{(n_r-1)}) - p_h^{(n_r-1)}) \right\|_1 \leq \varepsilon \& \left\| p_b^{(n_r)} - p_h^{(n_r)} \right\|_1 > \varepsilon \quad (1)$$

where, $p_b^{(n_r)}$ and $p_h^{(n_r)}$ are the coordinates of the beanbag and hand in the n_r-*th* frame. ε is a preset threshold, which is set to $\varepsilon = 20$ (pixel-level distance) in our experiment.

In addition to the beanbag release time, the tangent angle at the beanbag release time, the highest height that the beanbag reaches, and the time from the beanbag releasing to that the beanbag reaches the highest height are calculated to analyse the beanbag trajectory.

2) Gaze Movement: The eye-tracker outputs a series of gaze data, *i.e.,* the position of the subject's gaze point within the coordinate system of the world camera. Eye gaze points provide profound and precise information about the mechanism in cognitive processes, and eye gaze is the most commonly used features by researchers to reveal attention model in cognitive processes of interest. In this part, only the gaze movement during Phase 1 is analyzed, since aiming occurs during this phase.

To focus on the specific area of stimulus, an area of interest (AOI) in the visual scene (first-person view image) is defined as the red circle in the blue mat as shown in Fig. 6, which is consistent with the fact that the red circle is the focusing target in the task of throwing beanbag. With the definition of AOI, the eye gaze points are divided into two groups. One group is inside the AOI, and the other is outside of the AOI.

a) Effective Aiming Time (EAT): Aiming is important in the throwing games. Effective aiming refers to focusing eyes within the defined AOI, and the effective aiming time is calculated to measures the proportion of cumulative time duration that the eye gaze point falls within the defined AOI over a period of time. The effective aiming time is calculated according to the first-person view video clip, in which the eye gaze point is obtained as $p_g^{(i)}$ and the center of mat is detected as $p_m^{(i)}$ in the *i-th* frame. The effective aiming time during Phase 1 is calculated as follows.

$$EAT = \frac{1}{f_E \times t_r} \sum_{i=n_e^n} \delta(\left\| p_g^{(i)} - p_m^{(i)} \right\|_1 - \epsilon) \quad (2)$$

where, f_E is the frame rate of the world camera of the eye-tracker. t_r is the beanbag release time. n_s and n_e are the start frame index and the ending frame index of Phase 1, respectively. ϵ is a preset threshold. The function $\delta(\left\| p_g^{(i)} - p_m^{(i)} \right\|_1 - \epsilon)$ is used to determine whether the eye gaze point falls within the defined AOI frame by frame. The value of this function is equal to 1 if the distance between the eye gaze point and the center of the mat is less than or equal to the preset threshold, if not, the value of this function is equal to 0.

b) Relative Gaze Stability (RGS): The stability of the eye gaze points reflects person's concentration of attention [49], [50]. Generally, the variance of the eye gaze over a period of time is calculated to reflect the eye gaze stability assuming that the camera's field of view (FOV) remains unchanged.

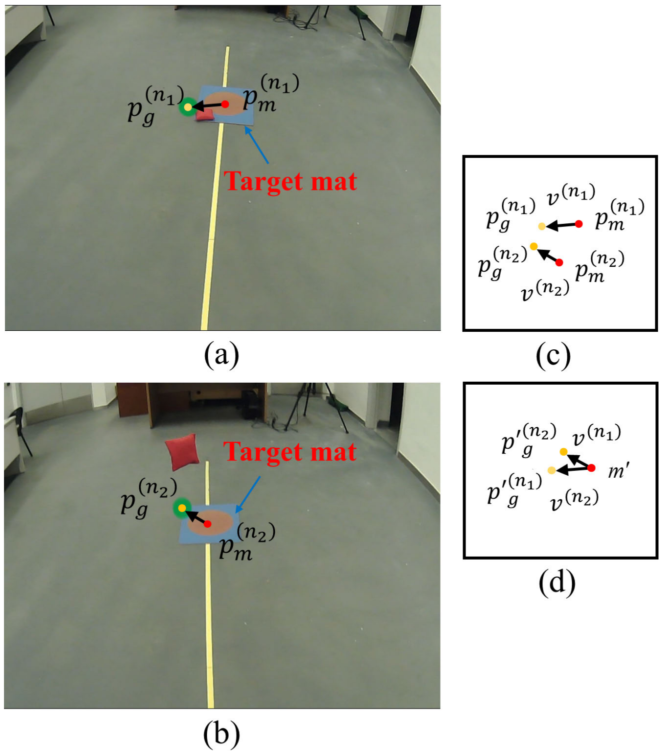

Fig. 7. The first-person view images captured under the constantly changing FOV. (a) Captured n_1-*th* frame image; (b) Captured n_2-*th* frame image; (c) Unaligned gaze points; (d) Aligned gaze points.

However, this assumption is invalid here, because the FOV of the world camera is constantly changing during the process of throwing beanbag. There is an example as shown in Fig.7 (a) and Fig.7(b). $p_g^{(n_1)}$ is the position of eye gaze at the n_1-*th* frame, and $p_g^{(n_2)}$ is the position of eye gaze at the n_2-*th* frame. The FOV of the world camera changed slightly from n_1 to n_2 due to the movement of the subject's head. Obviously, $p_g^{(n_1)}$ and $p_g^{(n_2)}$ are not in the same coordinate system, and there is no physical meaning to calculate the variance of $p_g^{(n_1)}, p_g^{(n_2)}, \cdots p_g^{(n_k)}$.

Considering that the focus of attention in the process of throwing beanbags is the target mat, and the position of the target mat is calculated and denoted as $p_m^{(i)}$ at the *i-th* frame. Therefore, we take the center of the mat as the reference point and use the vector from the center of the mat to the gaze point in place of the original gaze point to calculate the relative gaze stability. As shown in Fig. 7 (c), $v^{(n_1)}$ and $v^{(n_2)}$ are the vectors from the center of the mat to the gaze point at the n_1-*th* frame and the n_2-*th* frame, and these two vectors have different start points $p_m^{(n_1)}$ and $p_m^{(n_2)}$. Then the start points of these two vectors are moved to a fixed point, denoted as m', thus the ends of these two vectors are the aligned gaze points $p'^{(n_1)}_g$ and $p'^{(n_2)}_g$, as shown in Fig. 7(d). The aligned gaze points denote the direction and distance of the original gaze point to the focusing target mat. Therefore, the relative gaze stability during Phase 1 can be calculated using the aligned gaze points as shown in formula (3).

$$RGS = \Psi(p'^{(n_s)}_g, p'^{(n_{s+1})}_g, \cdots, p'^{(n_e)}_g) \tag{3}$$

where, $\Psi(\cdot)$ is the function to calculate the standard deviation.

3) Body Movement: In the task of throwing beanbag, the body movement mainly focuses on the hands, *i.e.*, the arm swings to throw out the beanbag. The amplitude of the arm swing determines the initial parameters of the released beanbag. Therefore, the amplitude of arm swing is calculated to analyze the effect of the hand movement on the beanbag throwing result.

IV. Results

During the data collection process, a small amount of data was lost due to equipment problems. There are a total of 572 single throw clips from 62 participants in the dataset. The one-handed catching test shows that 5 participants are left-handed and 57 participants are right-handed. In the 572 single throw clips, 498 (87.06%) throws are completed with the right hand, 11 (1.92%) with the left hand, and 63 (11.01%) with both hands. Only right-handed or two-handed throws (561 clips from 61 participants) are used for the statistical analysis, while left-handed throws are excluded in this study to avoid statistical results being influenced by the factor of using different hands. Statistical analysis with the parametric test of ANOVA and non-parametric test of Kruskal-Wallis test (KW test) are adopted here to identify whether there are significant differences among children with various motor coordination on the proposed kinematic features.

A. Grouping Principle

According to the Movement ABC-2 test results, the motor coordination abilities vary greatly among the 61 children involved in the study (Movement ABC-2 standard score=9.07±2.57, percentile rank=39.80±26.23). Four participants have significant movement difficulty, whose Movement ABC-2 percentile rank are at or below 5th percentile. They are highly likely to suffer from the clinical movement disorder, *i.e.,* DCD. Five children are found to be at risk of having DCD, as their Movement ABC-2 percentile rank are between 5th and 15th percentile. The remaining 52 participants have no detectable signs of DCD, among which 6 children' scores equal to or higher than 84th percentile, demonstrating superior motor coordination abilities.

The samples of 61 children are naturally divided into three groups based on the Movement ABC-2 percentile rank, *i.e.*, Low Motor Coordination group (LMC, percentile rank<25), Middle Motor Coordination group (MMC, 25=<percentile rank<63), and High Motor Coordination group (HMC, percentile rank>=63). The basic information of these three groups is shown in TABLE I. The Movement ABC-2 percentile ranks of the LMC, MMC, and HMC groups are 10.33±5.33, 32.82±8.37, and 75.22±10.90, respectively. The Pearson correlation analysis indicates that Movement ABC-2 percentile rank is significantly correlated with age (r= -0.40, p= 0.0015), height (r=-0.32, p= 0.0119), and weight (r=-0.34, p= 0.0081), but these correlations are weak (-0.5<r<-0.25).

B. Single Clip Extraction

The APN network is adopted for single throw clip extraction. The parameters of the APN network are set as:

TABLE I
THE BASIC INFORMATION OF THE LMC, MMC, AND HMC GROUPS

	LMC		MMC		HMC	
Group number	Boy	Girl	Boy	Girl	Boy	Girl
	9	6	12	16	8	10
Age (year)	9.40±0.51		8.54±0.74		8.33±1.19	
Hight (cm)	139.93±7.41		136.71±7.29		133.19±9.44	
Weight (kg)	31.91±10.45		30.81±8.70		24.60±7.34	
Standard score	6.00±1.07		8.64±0.68		12.28±1.49	
Percentile rank	10.33±5.33		32.82±8.37		75.22±10.90	

TABLE II
RESULTS OF SINGLE THROW CLIP EXTRACTION

Method	Backbone	AP@0.5
APN method	ResNet3d	0.901
	X3D	0.929

$T_{len} = 15, T_{start} = 40, T_{end} = 60$. The metric of average precision (AP) is used to evaluate the performance of the APN for the task of single clip extraction, and the higher AP indicates better performance. The results are reported in TABLE II.

The AP of single throw clip extraction reaches 0.901 when the feature extraction backbone of APN is ResNet3d. The performance is further improved when the backbone is set as X3D, achieving the AP of 0.929. The experimental statistical results illustrate that APN well achieves accurate single throw extraction, which means the research specialist only needs to adjust slightly the APN results.

C. Group Comparison

The kinematic features for each participant in all beanbag throwing trials are calculated and the average values are taken as the final result. The results are reported and analyzed as follows.

1) Throwing Performance (TP): This refers to participant's standard score in the beanbag throwing task. The boxplot of the throwing performance of these three groups is shown in Fig. 8. The HMC group has the largest median, followed by the MMC group, and the LMC group has the smallest median. ANOVA test reveals a significant group difference in the throwing performance (p=0.0399), which provides evidence for the plausibility of setting the beanbag throwing task in Movement ABC-2. Further comparation tests between each pair groups reveal that the significant differences among these three groups mainly stem from the difference between the LMC and HMC groups (p= 0.0227).

2) Effective Aiming Time (EAT): The advanced observation and planning of eyes are crucial in the throwing task. EAT reflects the percentage of time that the participants' eyes effectively focusing on the target mat before the beanbag releasing from the hand. The EAT in the Phase 1 for each participant is calculated and the statistical results of different groups are shown in TABLE III. ANOVA test reveals there is a significant group difference on the EAT in Phase 1 ($p<0.05$, effect size= 0.40, power=0.7833). It is obvious that the group of children with higher motor coordination score spends more time effectively aiming at the target.

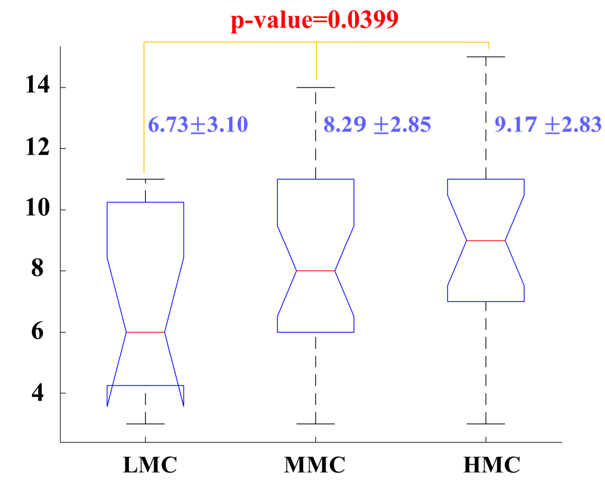

Fig. 8. Throwing performance boxplot of the LMC, MMC, and HMC groups. The mean and standard deviation of each group are presented as mean ± SD. ANOVA test reveals a significant group difference on the throwing performance.

TABLE III
STATISTICAL ANALYSIS RESULTS OF GAZE MOVEMENT

	LMC	MMC	HMC	p-value
EAT	26%±41%	64%±59%	74%±50%	0.0128*
RGS	99.34±70.83	63.71±60.87	32.51±35.44	0.0022**

Data are presented as mean ± SD. *p<0.05, **p<0.005.

3) Relative Gaze Stability (RGS): RGS reflects the stability of the eye gaze points and the degree of concentration during aiming. ANOVA test reveals a significant group difference on the RGS in Phase 1($p<0.005$, effect size=0.48, power=0.9153), as reported in TABLE III. The RGS value of the LMC group and the MMC group is about three times and twice that of the HMC group respectively, which indicates the fact that the participants in the HMC group have highly concentrated attention. This kind of high-attention observation in Phase 1 is very like to plan and prepare for the action of throwing the beanbag, which may benefit to an accurate hit.

In addition to the quantitative analysis, we also make some visual analysis below in order to show the group difference intuitively. Heatmaps are often used as representative results of eye tracking, which provide a visualization means to show the distribution of gaze points. Considering the constantly changed FOV of the world camera, we take the aligned gaze point in place of the original gaze point to generate the relative gaze heatmap. The generated relative gaze heatmap reveals the distribution of subject's gaze points during the process of throwing beanbag, as shown in Fig. 9. The first to third rows are the heatmaps of three samples randomly selected in the LMC, MMC, and HMC groups respectively. In each heatmap, the Movement ABC-2 percentile rank of the sample is given. The red star represents the position of target mat. The information around the target mat is so aboundent that the area near the target mat in the yellow boxes are enlarged and displayed in the red boxes for better observation.

It is easy to observe that the heatmaps of the samples in the LMC group are the most scattered, and their spread is widest, almost covering the entire red magnified box. The

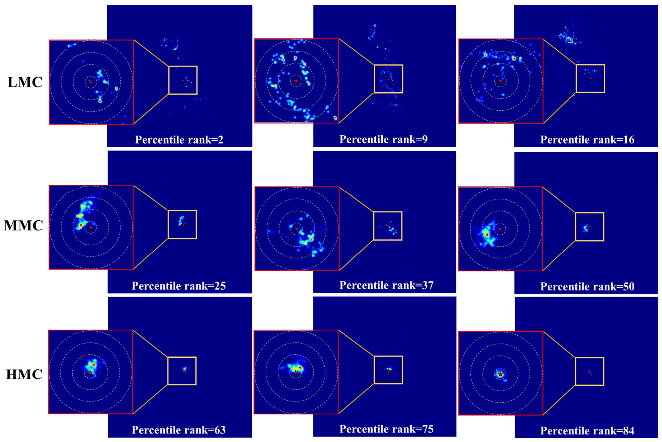

Fig. 9. Relative gaze heatmaps of nine samples from the LMC, MMC, and HMC groups.

TABLE IV
GAZE MOVEMENT ANALYSIS OF THE LMC, MMC, AND HMC GROUPS ONLY WITH THE HITTING-ON TRIALS

	LMC	MMC	HMC	p-value
EAT	23%±41%	67%±64%	83%±57%	0.0045**
RGS	114.86±89.95	70.66±72.46	35.92±42.21	0.0139*

Data are presented as mean ± SD. *p<0.05, **p<0.005.

heatmaps of the samples in the MMC group is slightly more concentrated than that of the LMC group, and their spread area only occupies a certain part of the red magnified box. The heatmaps of the samples in the HMC group are the most compact, and they are all concentrated around the target mat. The heatmap comparison intuitively illustrates that the eye gaze points of the HMC group are the most stable, and they are all concentrated around the target. This means that the attention of the participants in the HMC group is most concentrated and focus on the target. The samples in the MMC group are the second, and the attention of the samples in the LMC group are the most distracted during beanbag throwing.

4) Body Movement & Beanbag Trajectory: There is no significant group difference on the body movement and beanbag trajectory in terms of the proposed variables, and the detailed results are reported in the supplementary material.

D. Hitting-on Trials Only

To avoid the impact on the data analysis caused by functional variation between the hitting-on and missing attempts, we also perform statistics analysis of gaze movement only with the hitting-on trials of these three groups, and the results are reported in TABLE IV.

ANOVA test reveals that there are significant group differences on the EAT ($p<0.005$, effect size=0.46, power=0.8842) and RGS ($p<0.05$, effect size=0.4, power=0.7757), which is consistent with the group comparison containing both the hitting-on trials and the missing trials in Part C. These are some minor changes in the significant effect of these two variables, this is, the significant effect of the EAT is increased, and the significant effect of the RGS is decreased. It can be concluded that the results indicate that the significant differences among these three groups on EAT and RGS do not change depending on whether the missing trials are considered or not.

TABLE V
QUANTITATIVE COMPARISON BETWEEN HITTING-ON AND MISSING GROUPS

	Hitting-on	Missing	p-value
EAT	75%±74%	54%±72%	0.0048**
RGS	54.34±89.95	59.86±96.38	0.4448

Data are presented as mean ± SD. **p<0.05.

E. Hitting-on Vs Missing

In this section, we investigate the relationship between the beanbag throwing results (hitting-on or missing) and behavioral kinematic features (especially EAT and RGS) in order to provide recommendations for improving children's motor coordination ability and beanbag throwing accuracy. A natural split is performed on the 561 beanbag throwing trials, creating a Hitting-on group (336 throws) and a Missing group (225 throws). A significant comparison experiment is performed on these two groups, and the results are reported in TABLE V.

KW test reveals a significant group difference on the EAT in Phase 1($p<0.005$). The average percentage of time focusing on the target of the hitting-on group is significantly higher than that of the missing group. Although the mean value of RGS of the hitting-on group is smaller than that of the missing group, there are no significant group differences on the RGS according to the KW test. In conclusion, whether the beanbag hitting on is related to the effective aiming time that focusing on the target, and the longer the time spent on focusing on the target, the more likely it is to accurately hit the target.

V. DISCUSSION

In this study, we focus on exploring behavioral markers of DCD by examining differences among groups with high, middle and low motor coordination scores. Specifically, the main work is to detect visual components, extract kinetic features, and conduct group significance tests in a typical aiming and throwing task (throwing beanbag onto mat) based on the simultaneous recordings of participants' eye gaze, body movement, and interacting object. Moreover, we explore the critical factors for the success of this task (the beanbag is hitting on) by analyzing the difference between the hitting-on trials and the missing trials, which provides theoretical support for how to improve children's scores in the aiming and throwing task.

The process of beanbag throwing is divided into two phases according to the moment of beanbag releasing. Advanced observation and planning of eyes in the Phase 1 are essential for effectively performing the target action tasks, such as beanbag throwing and ball catching. Therefore, two metrics (EAT and RGS) are proposed to measure eye movement in Phase 1. EAT reflects the duration of time that a participant focuses on the target, and RGS indicates the degree of the concentration during aiming. The experimental results demonstrate significant discrepancies on both EAT and RGS among children with different coordination abilities. These differences suggest that the short effective aiming time and the poor gaze stability may serve as behavioral markers of children with low coordination abilities.

This finding is consistent with the previous studies [29], [30]. In [29] and [30], researchers have found that quiet eyes can distinguish between children with high and low motor coordination and quiet eye training can improve children's throwing and catching performance. Quiet eye is defined as the final fixation or tracking gaze to a target before the motor response [29], and quiet eye training [30] emphasizes focusing the eyes on the target for a few seconds before throwing. Our study provides more precise and specific guidance for the intervention of children with DCD: focusing on improving the quality of children's concentration in addition to increasing the total amount of time children spending on concentrating. Furthermore, the statistical analysis between hitting-on and missing also suggests increasing EAT may be helpful to improve children's performance on the task of beanbag throwing on the mat.

As for body movement and beanbag trajectory, no significant differences among the LMC, MMC, and HMC groups have been found in our data for the time being. We speculate that the body movements contained in this task are too simple to show differences between children with different motor coordination abilities. This study provides a practical standard framework and methodology to explore behavioral markers of DCD in specific tasks. Our future work will extend to other more complex gross motor tasks in the Movement ABC-2 to do more in-depth analysis of body movement and further explore behavioral markers of children with DCD.

VI. Conclusion

In this paper, a unified portable framework was proposed to conduct behavioral analysis in gross movements and investigate the behavioral markers of DCD. The performance of children with different coordination abilities were analyzed in the task of throwing beanbag. We proposed kinematic features such as EAT and RGS, and conducted comprehensive analysis on children's gaze data, body movement, and the beanbag trajectory to investigate the difference between children with different motor coordination abilities. The experiment results reveal significant group differences in the EAT and RGS of participants with different motor coordination scores, and there is no significant group difference on the measurement of body movement and beanbag trajectory. This finding suggests that the duration of eye gaze focus on the target and the degree of concentration during gazing are distinguishable characteristics of children with different coordination ability scores, which can be served as behavioral markers to distinguish children with DCD. In the future, we will use the setup of three Kinects to help optimize the detection of body key points and extend this research to other gross tasks in Movement ABC-2 for further explorations in behavioral markers of children with DCD.

References

[1] R. C. Barnhart et al., "Developmental coordination disorder," *Phys. Therapy*, vol. 83, no. 8, pp. 722–731, 2003.

[2] I. Heus, D. Weezenberg, S. Severijnen, T. V. Vlieland, and M. van der Holst, "Measuring treatment outcome in children with developmental coordination disorder; responsiveness of six outcome measures," *Disability Rehabil.*, vol. 44, no. 7, pp. 1023–1034, Mar. 2022.

[3] L. Delgado-Lobete, R. Montes-Montes, S. Pértega-Díaz, S. Santos-Del-Riego, E. Hartman, and M. M. Schoemaker, "Motor performance and daily participation in children with and without probable developmental coordination disorder," *Develop. Med. Child Neurol.*, vol. 64, no. 2, pp. 220–227, Feb. 2022.

[4] A. Ip, E. C. R. Mickelson, and J. G. Zwicker, "Assessment, diagnosis, and management of developmental coordination disorder," *Paediatrics Child Health*, vol. 26, no. 6, pp. 375–378, Sep. 2021.

[5] E. Wang, "A review of the neural mechanisms of developmental coordination disorder," *Acta Meteorolog. Sinica*, vol. 31, no. 4, pp. 503–509, 2015.

[6] M. M. Schoemaker, M. van der Wees, B. Flapper, N. Verheij-Jansen, S. Scholten-Jaegers, and R. H. Geuze, "Perceptual skills of children with developmental coordination disorder," *Hum. Movement Sci.*, vol. 20, nos. 1–2, pp. 111–133, Mar. 2001.

[7] J. G. Zwicker, C. Missiuna, S. R. Harris, and L. A. Boyd, "Developmental coordination disorder: A review and update," *Eur. J. Paediatric Neurol.*, vol. 16, no. 6, pp. 573–581, Nov. 2012.

[8] I. Harrowell, L. Hollén, R. Lingam, and A. Emond, "Mental health outcomes of developmental coordination disorder in late adolescence," *Develop. Med. Child Neurol.*, vol. 59, no. 9, pp. 973–979, Sep. 2017.

[9] I. Harrowell, L. Hollén, R. Lingam, and A. Emond, "The impact of developmental coordination disorder on educational achievement in secondary school," *Res. Develop. Disabilities*, vol. 72, pp. 13–22, Jan. 2018.

[10] J. G. Zwicker, M. Suto, S. R. Harris, N. Vlasakova, and C. Missiuna, "Developmental coordination disorder is more than a motor problem: Children describe the impact of daily struggles on their quality of life," *Brit. J. Occupational Therapy*, vol. 81, no. 2, pp. 65–73, Feb. 2018.

[11] C. G. Hendrix, M. R. Prins, and H. Dekkers, "Developmental coordination disorder and overweight and obesity in children: A systematic review," *Obesity Rev.*, vol. 15, no. 5, pp. 408–423, May 2014.

[12] J. P. Piek et al., "Depressive symptomatology in child and adolescent twins with attention-deficit hyperactivity disorder and/or developmental coordination disorder," *Twin Res. Hum. Genet.*, vol. 10, no. 4, pp. 587–596, Aug. 2007.

[13] B. W. Van der Linde, J. J. van Netten, B. Otten, K. Postema, R. H. Geuze, and M. M. Schoemaker, "Activities of daily living in children with developmental coordination disorder: Performance, learning, and participation," *Phys. Therapy*, vol. 95, no. 11, pp. 1496–1506, Nov. 2015.

[14] J. F. van Hoorn et al., "Risk factors in early life for developmental coordination disorder: A scoping review," *Develop. Med. Child Neurol.*, vol. 63, no. 5, pp. 511–519, May 2021.

[15] S. Deng et al., "Understanding the mechanisms of cognitive impairments in developmental coordination disorder," *Pediatric Res.*, vol. 75, nos. 1–2, pp. 210–216, Jan. 2014.

[16] T. P. Alloway and L. Archibald, "Working memory and learning in children with developmental coordination disorder and specific language impairment," *J. Learn. Disabilities*, vol. 41, no. 3, pp. 251–262, May 2008.

[17] R. Blank et al., "International clinical practice recommendations on the definition, diagnosis, assessment, intervention, and psychosocial aspects of developmental coordination disorder," *Develop. Med. Child Neurol.*, vol. 61, no. 3, pp. 242–285, Mar. 2019.

[18] D. A. Szabo, N. Neagu, S. Teodorescu, and I. S. Sopa, "Eye-hand relationship of proprioceptive motor control and coordination in children 10–11 years old," *Health, Sports Rehabil. Med.*, vol. 21, no. 3, pp. 185–191, Sep. 2020.

[19] F. J. A. Deconinck et al., "Visual contribution to walking in children with developmental coordination disorder," *Child, Care, Health Develop.*, vol. 32, no. 6, pp. 711–722, Nov. 2006.

[20] D. Coetzee and A. Pienaar, "The role of visual functions in persisting developmental coordination disorder (DCD) among 7-year-old children: A follow-up study," *Afr. J. Phys., Health Educ., Recreation Dance*, vol. 16, no. 2, pp. 251–264, Jun. 2010.

[21] W. Du, K. Wilmut, and A. L. Barnett, "Level walking in adults with and without developmental coordination disorder: An analysis of movement variability," *Hum. Movement Sci.*, vol. 43, pp. 9–14, Oct. 2015.

[22] K. Wilmut, W. Du, and A. L. Barnett, "Gait patterns in children with developmental coordination disorder," *Exp. Brain Res.*, vol. 234, no. 6, pp. 1747–1755, Jun. 2016.

[23] K. Wilmut and A. L. Barnett, "When an object appears unexpectedly: Anticipatory movement and object circumvention in individuals with and without developmental coordination disorder," *Exp. Brain Res.*, vol. 235, no. 5, pp. 1531–1540, May 2017.

[24] T. T. T. Yam and S. S. M. Fong, "Leg muscle activation patterns during walking and leg lean mass are different in children with and without developmental coordination disorder," *Res. Develop. Disabilities*, vol. 73, pp. 87–95, Feb. 2018.

[25] M. Smith, E. Ward, C. M. Williams, and H. A. Banwell, "Differences in walking and running gait in children with and without developmental coordination disorder: A systematic review and meta-analysis," *Gait Posture*, vol. 83, pp. 177–184, Jan. 2021.

[26] S. A. Cermak et al., "Participation in physical activity, fitness, and risk for obesity in children with developmental coordination disorder: A cross-cultural study," *Occupational Therapy Int.*, vol. 22, no. 4, pp. 163–173, 2015.

[27] L. C. Chia, M. K. Licari, K. J. Guelfi, and S. L. Reid, "A comparison of running kinematics and kinetics in children with and without developmental coordination disorder," *Gait Posture*, vol. 38, no. 2, pp. 264–269, Jun. 2013.

[28] F. J. A. Deconinck et al., "Differences in gait between children with and without developmental coordination disorder," *Motor Control*, vol. 10, no. 2, pp. 125–142, Apr. 2006.

[29] M. R. Wilson, C. A. L. Miles, S. J. Vine, and J. N. Vickers, "Quiet eye distinguishes children of high and low motor coordination abilities," *Med. Sci. Sports Exercise*, vol. 45, no. 6, pp. 1144–1151, 2013.

[30] C. A. L. Miles, S. J. Vine, G. Wood, J. N. Vickers, and M. R. Wilson, "Quiet eye training improves throw and catch performance in children," *Psychol. Sport Exercise*, vol. 15, no. 5, pp. 511–515, Sep. 2014.

[31] C. A. L. Miles, G. Wood, S. J. Vine, J. N. Vickers, and M. R. Wilson, "Quiet eye training facilitates visuomotor coordination in children with developmental coordination disorder," *Res. Develop. Disabilities*, vol. 40, pp. 31–41, May 2015.

[32] M. K. Licari et al., "Visual tracking behaviour of two-handed catching in boys with developmental coordination disorder," *Res. Develop. Disabilities*, vol. 83, pp. 280–286, Dec. 2018.

[33] E. Sumner, S. B. Hutton, G. Kuhn, and E. L. Hill, "Oculomotor atypicalities in developmental coordination disorder," *Develop. Sci.*, vol. 21, no. 1, Jan. 2018, Art. no. e12501.

[34] J. V. V. Parr, R. J. Foster, G. Wood, N. M. Thomas, and M. A. Hollands, "Children with developmental coordination disorder show altered visuomotor control during stair negotiation associated with heightened state anxiety," *Frontiers Hum. Neurosci.*, vol. 14, p. 512, Nov. 2020.

[35] T. Arthur et al., "Visuo-motor attention during object interaction in children with developmental coordination disorder," *Cortex*, vol. 138, pp. 318–328, May 2021.

[36] R. S. Johansson, G. Westling, A. Bäckström, and J. R. Flanagan, "Eye-hand coordination in object manipulation," *J. Neurosci.*, vol. 21, no. 17, pp. 6917–6932, 2018.

[37] M. D. Samad, N. Diawara, J. L. Bobzien, J. W. Harrington, M. A. Witherow, and K. M. Iftekharuddin, "A feasibility study of autism behavioral markers in spontaneous facial, visual, and hand movement response data," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 2, pp. 353–361, Feb. 2018.

[38] A. Kovari, J. Katona, and C. Costescu, "Quantitative analysis of relationship between visual attention and eye-hand coordination," *Acta Polytechnica Hungarica*, vol. 17, no. 2, pp. 77–95, 2020.

[39] S. Li et al., "A markerless visual-motor tracking system for behavior monitoring in DCD assessment," in *Proc. Asia–Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA ASC)*, Dec. 2017, pp. 774–777.

[40] R. Li et al., "Evaluation of the fine motor skills of children with DCD using the digitalised visual-motor tracking system," *J. Eng.*, vol. 2018, no. 2, pp. 123–129, Feb. 2018.

[41] R. Li et al., "Automated fine motor evaluation for developmental coordination disorder," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 5, pp. 963–973, May 2019.

[42] T. T. Brown and A. Lalor, "The movement assessment battery for children-second edition (MABC-2): A review and critique," *Phys. Occupational Therapy Pediatrics*, vol. 29, no. 1, pp. 86–103, 2009.

[43] C. Lu et al., "Precise temporal localization for complete actions with quantified temporal structure," in *Proc. 25th Int. Conf. Pattern Recognit. (ICPR)*, Jan. 2021, pp. 4781–4788.

[44] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh, "Realtime multi-person 2D pose estimation using part affinity fields," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 291–7299.

[45] C. Lugaresi et al., "MediaPipe: A framework for perceiving and processing reality," in *Proc. 3rd Workshop Comput. Vis. AR/VR IEEE Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 1–4.

[46] K. Sun, B. Xiao, D. Liu, and J. Wang, "Deep high-resolution representation learning for human pose estimation," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 5693–5703.

[47] S. Ren et al., "Faster R-CNN: Towards real-time object detection with region proposal networks," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 28, 2015, pp. 1–14.

[48] T. Lin et al., "Microsoft COCO: Common objects in context," in *Proc. Eur. Conf. Comput. Vis.*, Sep. 2014, pp. 740–755.

[49] M. Frutos-Pascual and B. Garcia-Zapirain, "Assessing visual attention using eye tracking sensors in intelligent cognitive therapies based on serious games," *Sensors*, vol. 15, no. 5, pp. 11092–11117, May 2015.

[50] C.-W. Liang, J.-L. Tsai, and W.-Y. Hsu, "Sustained visual attention for competing emotional stimuli in social anxiety: An eye tracking study," *J. Behav. Therapy Experim. Psychiatry*, vol. 54, pp. 178–185, Mar. 2017.