Journal of Advanced Sport Technology *6(2): 99-111.*

Received: October, 07, 2022 Accepted: December, 27, 2022

Original Research

Automated Assessment of Developmental Stage of Overhand Throwing Skill

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ABSTRACT

The trade-off between speed and accuracy in scoring process-oriented tests for fundamental movement skills (FMS) has always been challenging for a screening project. The aim of this study was the feasibility of using wearable inertial measurement units (IMU) and artificial intelligence algorithms to automatically assessment of FMS. 123 overhand throwings were performed by

children aged 4 to 10 years (age = 7±1.84) (53% = boys). Three IMU (Shokofa Tavan Vira) sent signals of angular velocity, linear acceleration of the preferred hand, non-predominant ankle, and lumbar region of the children. Each performance was scored according to the criteria of the third edition test of The Gross Motor Development (TGMD-3) by reviewing the video of the performed skills. The "k nearest neighbor" algorithm was used for automatic data classification. The minimum difference between test signals and training signals was calculated and classified. Two issues were assessed: false acceptance, in which an "incorrect" performance was classified as "correct"; and false rejection where a "correct" performance was classified as "incorrect". The classification accuracy of the K-nearest neighbor (KNN) algorithm was 85%. The automatic scoring algorithm also correctly classified 93%, 78%, 93%, and 76% in criteria 1 to 4, respectively. Low-back IMU data analysis shows the model's accuracy of 75%. Further, the total scoring time was reduced from 5 minutes to less than 30 seconds. The use of artificial intelligence in the signal processing of only three IMU was a reliable and practical method for the assessment of FMS. This approach means the monitoring and evaluation of children's movement skills can be objective. In addition, while maintaining relative accuracy, the time involved in the process-oriented analysis of FMS for research, clinical, sports, and educational purposes was reduced entirely.
Keywords: Test of Gross Motor Development, Wearable Inertial Measurement Unit, Artificial Intelligence, Motor Development, Automatic Assessment

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INTRODUCTION

In the last decade, the motor competence (MC) of children and adolescents has been recognized as the infrastructure of the most critical public health factors; such as the amount of physical activity, body composition (1-4). Therefore, to design an effective intervention, evaluation is crucial (5).

Two approaches, process or product-oriented, are standard methods of MC measurement (6). It is recommended to use the process-oriented approach to overcome the overlapping results of product-oriented tests with the level of physical fitness of the children (7). However, the reliability of scoring threatens the results of process-oriented tests, even when assessors are highly experienced (8, 9). Therefore, one of the most significant limitations of these tools is the complete dependence on human observations, which can lead to doubts about the accuracy of the results (6). Previously, to overcome this challenge, video recording of the subject's performance was on the agenda of experts (10, 11). Despite all these finesses, the accuracy of this time-consuming process is unclear (12).

Parallax error is always present in all 2D setups with a single camera, when filming a 3D motion (13). In addition, the time costs of video assessment and the limitation in physical educators' experience make this approach almost impossible (12, 14).

Recently, Wearable IMUs have achieved a unique advantage in the implementation of field research and sports situations by overcoming the limitation of the measuring space of electro-optical devices (15). The position and direction of movement of the body can be easily calculated (16). The review of previous studies shows that this technology even though still under development has sufficient validity, objectivity and reliability in the fundamental movements and sports skill processed-oriented assessment (17).

In this regard, Clark et al. (2021) studied the use of new technologies in the assessment of fine and gross motor skills systematically (18). Children aged 3 to 12 years were categorized according to the developmental level of a skill/s. The sample sizes were between 14-80 children with typical developmental characteristics. The most common assessment approach was to measure the correlation of quantitative indicators with age or developmental level. Various tasks were used to evaluate gross motor skills. Some studies were focused on specific tasks such as walking (19), running (20), hopping (21), long jumping (22) and overhand throwing (23). The Dragon Challenge (24), Locomotor subtests of TGMD-2 (14) and TGMD-3 (seven skills) (25) were also examined as a group of skills.

Most of the studies focused on locomotor and only three of them included object control skills (23-25). Just one study reported information on data processing time and the benefit of reducing the scoring time from 15 minutes to 2 minutes on the TGMD-2 per participant (14).

In the mentioned studies, two methods have been proposed for the analysis of FMS, which provided information equivalent to current process-oriented evaluations. The first method is based on the manual fitting of algorithms in temporal and kinematic thresholds that show the performance of skill criteria; it provides the possibility of quantifying the presence or absence of criteria (14). Certainly, this is more complex than could be applied by physical educators. The second approach is using artificial intelligence to automatically determine kinematic information that indicates the professional performance of FMS. The ability of Artificial intelligence to extract patterns and identify different trends of complex and ambiguous data helps humans to make a decision. With this method, the time-consuming kinematics future selection phase is omitted

It should be noted that although there is an agreement between different evaluators in the overall score of FMS, there is disagreement in some sub-scales, such as throwing (26, 27). Overhand throwing is a precursor to the effective execution of many complex sports skills such as handball shot (28), badminton toss and javelin throw (29). Therefore, this study has evaluated the feasibility of automatic assessment of overhand throwing skills using wearable IMU and artificial intelligence. Based on hypothesis, has artificial intelligence the accuracy to classify signals of angular velocity and linear acceleration of overhand throwing?

MATERIAL AND METHODS

Study method and participants

The present study, In terms of the purpose, is developmental (30), carried out in cross-sectional design (31). Based on the results of Grimpumpi et al.(2016) minimum of ten trials determined for the sample size in each age group of 4 to 10 years (23). Because of the coronavirus pandemic at the time of data gathering, by convenient sampling method, children were recruited from the city of Gorgan in the Golestan province of Iran. We tried to enroll participants from different socio-economic levels, as much as possible. Methods and aim of the study, along with the official consent form emailed to the interested parents/guardians. Furthermore, the developmental coordination disorder questionnaire(32) was completed online by the parents/guardians of the children. Participants had no developmental delay or musculoskeletal injury.

Parents/guardians provided basic demographic details (date of birth and so on) in the consent form. Unwillingness to continue the test at any time of the study was the criterion for leaving the research. The evaluation process was carried out for each child individually and preferably in his home environment according to the conditions of the coronavirus pandemic. All ethical principles were followed, including confidentiality. The Ethics Committee of the Research Institute of Physical Education and Sports Sciences of Iran (blinded) approved this study: ethical code IR.SSRI.REC.1400.1219.

Step 1: wearing inertial measurement units

Three wearable IMUs (Shkofatavan Vira-Technology Park, University of Tehran-Iran), including a three-axis accelerometer, gyroscope and magnetometer (sampling frequency, 25 Hz), were installed on the locations determined based on previous studies: No. 1 Distal region of the preferred wrist, No. 2 above the outer ankle of the opposite foot and No.3 between the fourth and fifth lumbar vertebra (low back) (33). The IMU could slip on the clothes or skin, so all of them were fixed on the child's body by a 3 cm wide elastic band and Velcro. For better adjustment, IMU was placed in a small pocket on the strap.

The for/backward linear acceleration of the body was recorded on the x-axis. As the same way, the up/down and left/right linear accelerations were recorded on the y-axis and z-axis, respectivelty. In addition, the angular velocity of yaw, pitch, and roll was evaluated around the vertical, lateral-central, and anterior-posterior axes, respectively. To comply with ethical standards during the installation of IMU (due to the presence of a sensor in the waist area), female testers for girls and male testers for boys did the job. It should be noted that the parents of the children were present in all stages of the test.

Step 2: Data Collection

Participants (n=13, girls=6) performed at least ten overhand throwings according to the third edition Test of Gross Motor Development (TGMD-3) criteria. This is a well-known international MC test that scoring 1 or 0 depending on observing the process-oriented criteria of the FMS or not, respectively (34) (https://www.proedinc.com/Products/14805/tgmd3-test-of-gross-motor-development-third-edition.aspx).
The reliability and validity of TGMD-3 approved in children aged 3–10 years in Iran (35). Before performing the test, the correct execution of the skill was shown to the children by the application program of the gross motor skill animation (https://play.google.com/store/apps/details?id=com.motorskill.gms&hl=en_US&gl=US), several times. The children were allowed to practice once or twice to ensure they understood what they had to do before starting the testing process. If a participant did not understand the skill the examiner performed one trial.

Figure 1: Execution of overhand throwing by a skillfull participant

The researchers of this study are completely familiar with TGMD-3 and have enough performing and scoring experience in previous studies (36). At the same time, the examiner's assistant filmed this process from the side view with a mobile camera (p1080 & 30 f/s). Before starting the data collection process, the assistant had received the necessary training. All the data of IMU were received and stored by MATLAB/R2016a software. An infinite impulse response (IIR) low-pass filter was used at a cutoff frequency of 25 Hz to remove the noise signals.

Step 3: Video scoring and data preprocessing

Reviewing the videos, one score was recorded for each successful criterion and stored in Excel. For a better intuitive understanding, the linear acceleration and angular velocity graphs of the IMU signals were drawn in different planes of the human body. Then, each matrix received by MATLAB was coded and entered into the database. The asynchronous signals recording of the subject's performance dropped out; nine out of 132 ones. To eliminate the effect of children's physical fitness and features, each data series was normalized by the Max Abs Scaler function. Therefore, the data range between -1 and 1. It should be noted that each data series is normalized compared to the absolute value of its maximum.

Step 4: Extracting data and scoring algorithm

First, the signals were labeled according to the obtained performance score in the TGMD-3 criteria (zero and one). However, the complete set of recorded data of each throw includes twelve time series of the 3-axis signals of the magnetometer, accelerometer, and gyroscope. Even in this study with a small sample size and relatively low sampling frequency, there are more than 20000 data. Therefore, the data were clustered using the KMedoids and DBSCAN algorithms. Cluster analysis proved that each criterion could be categorized. As a result, the dimension of movement (e.g., anterior-posterior) was selected and the correct sequence of peaks in each signal was identified.
It should be noted that the main goal of the signal analysis was to find the movement pattern for the overhand throwing skill. Therefore, the "k nearest neighbor" algorithm was used for automatic data

classification. This algorithm classifies the considered signal in its class based on the nearest neighbors. First of all, 20% of the total data were separated for testing. Then, 20% of the remaining data was allwocated for validation. The rest data were used for training. According to the validation phase, k was chosen between 3 and 7.

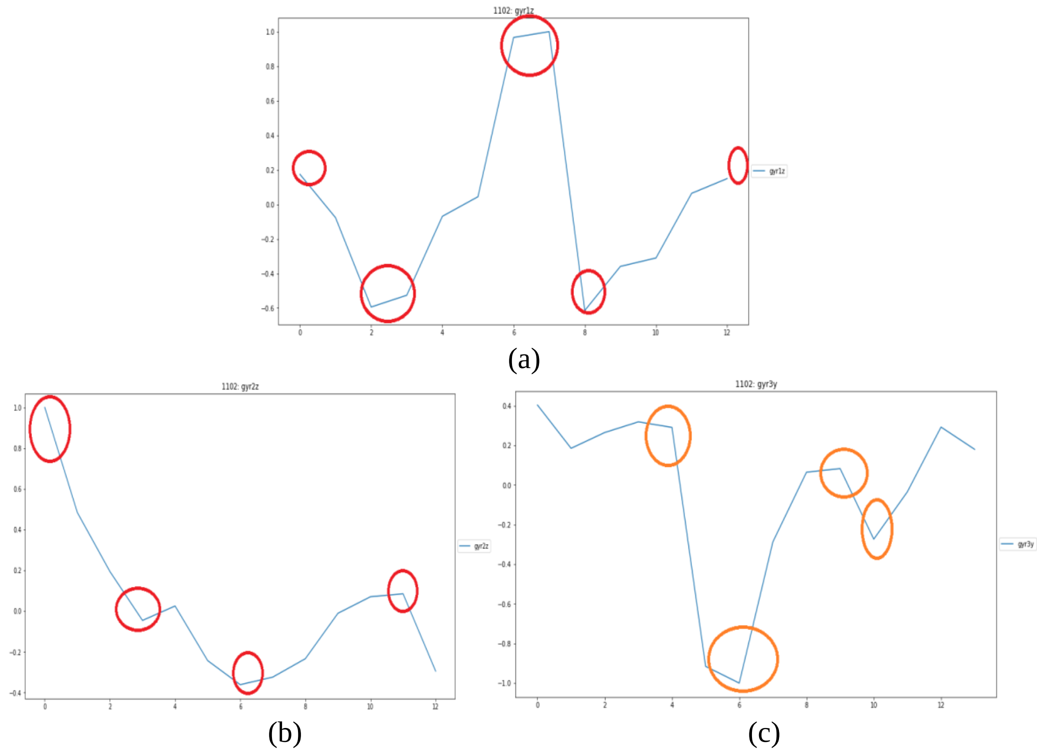

Figure 2: Identification of effective peaks in the scoring algorithm based on a: wrist angular velocity (pitch), b: ankle angular velocity (pitch), c: trunk angular velocity (yaw) in overhand throwing skill

Step 5: Data processing and algorithm evaluation

In this step, the minimum difference between test signals and training signals is calculated and classified. Two issues were assessed: false acceptance, in which an “incorrect” performance was classified as “correct”; and false rejection where a “correct” performance was classified as “incorrect”. The accuracy of the algorithm was measured by using the data that had not been used during the training of the model. At this stage, the algorithm’s output indicates the score of the TGMD-3 criteria of overhand throwing. The results of algorithm scoring represent the accuracy, precision, and recall of the model built to judge each criterion.

RESULTS

Thirteen typical children (seven boys and six girls) participated in the study. The details of participant demographics are presented in Table 1.

Table 1: Participant characteristics (n=13)

	Hight (cm)	Weight(kg)	age(Year)
Mean	129.46	28.15	7
Median	130	28	7
Standard Deviation	7.17	3.53	1.84
Maximum	144	47	10
Minimum	120	15	4

123 overhand throwings qualified for step five. Just in 7% of the performances, the end of the movement of the upper limb started with the downward movement of the arm. The thighs and shoulders rotated until the other side of the body facing the wall in 29% of the trials. Weight transfer, in 46% of the performances, was done by stepping with the foot opposite to the throwing hand. The continuous diagonal movement to the other side of the body was observed after throwing in 62% of the trials. The mentioned criteria for scoring the skill of throwing can be seen from left to right in Figure 1.
KNN algorithm was used for automatic data classification and scoring. First, 27 (20%) trials were randomly separated for testing. In the validation phase (using 22 data), the accuracy of K=3 were 90%, 68%, 82%, and 86% in criterion 1 to 4, respectively. By choosing K= 3, the algorithm was available to perform the testing phase. Classification results are categorized based on two criteria of first and second error types. In the first and third criteria, 93% of the data were classified correctly. Regarding the second and fourth criteria, this value was equal to 78 and 74 percent, respectively. To sum up, the classification accuracy in the overhand throwing skill was 85% (Table 2).

Table 2: Classification results, considering two cases: an "incorrect" performance was classified as "correct"; and false rejection where a "correct" performance was classified as "incorrect"

	No.Trials	**Correct clasification**	**Fuls acceptance**	**Fuls rejection**	**% Accuracy p/ criteria**	**% Overall Accuracy**
1-Windup is initiated with a downward movement of hand and arm	27	25	2	0	93	85
2- Rotates hip and shoulder to a point where the non-throwing side faces the wall	27	21	3	3	78	
3- Steps with the foot opposite the throwing hand toward the wall	27	25	2	0	93	
4- Throwing hand follows through after ball Release across the body toward the hip on the non-throwing side	27	20	4	3	74	

It is necessary to check the correctness and coverage ability of the model; because of the low accuracy of the criterion, in distinguishing between type 1 and 2 errors. The precision and recall parameters of criteria 1 were zero. This value was equal to 50% for criteria 2 for both of them. In criteria 3 and 4, there were 100%, 81% precision, and 83%, 76% recall, respectively.
According to the results of similar articles, lower back data is essential in distinguishing children's developmental levels of FMD. The classification accuracy of using only one IMU was compared with three simultaneous IMU in Figure 3.

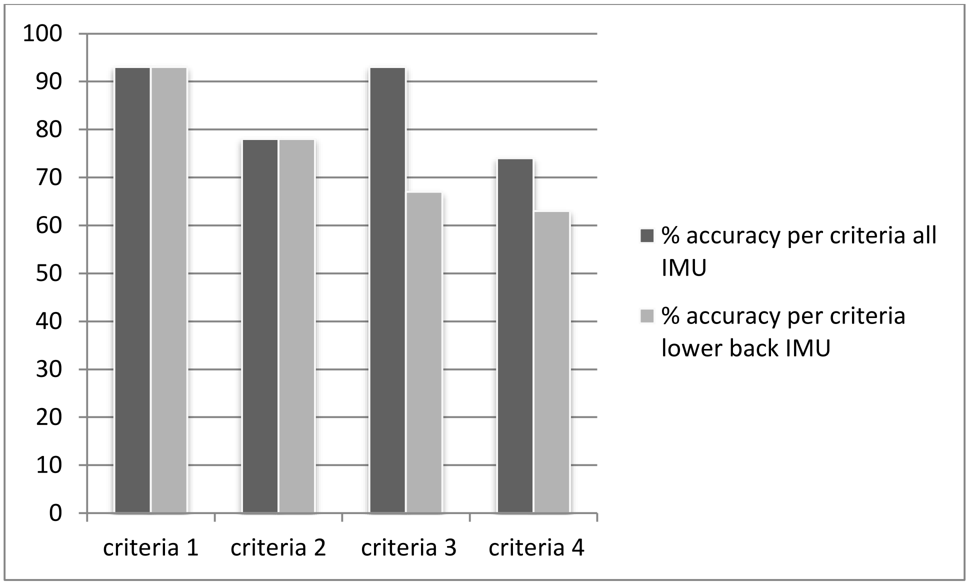

Figure 3: Comparison of the accuracy percentage of the model when using the data of all IMU versus just lumbar IMU in the overhead throwing skill.

The average assessment time of criteria per trial on recorded videos was 5 min (including time for downloading video). The approximate volume of the recorded video was 6 MB. The automatic evaluation lasts less than 30 Seconds (including time for downloading sensor data). The IMU data volume was approximately 4.00 KB per trial.

DISCUSSION

Assessment of FMS is time-consuming and often requires a minimum level of pre-training and experience for accurate scoring. Therefore, the main goal of this study was to develop an automatic method to classify the overhand throwing quality, using commercially available and affordable technologies, IMU.

This reduces the dependence of the evaluation result on the expertise of the evaluator. The results showed 85% accuracy in the classification of overhand throwing skills using just three IMU, with the minimum required accuracy for evaluation (ICC>0.6)(6). This result was obtained automatically using signal processing techniques, without the intervention of an expert evaluator. Therefore, this level of accuracy is very promising.

Performing the overhand throwing was difficult for most participants (even 10-year-olds). Less than 5% (n=6) of the trials were given one of all four criteria and labeled as "proficient". Skillfully swinging of hand in the downward and backward arc was difficult; then observed only in 6.5% of the performances. In most trials that scored one in the other three criteria, windup wasn't initiated with a downward movement of the hand and arm. Children who were thought to be in the full development of skills in terms of their chronological age were in the third stage of arm movement according to Goodway et al. (37).

As mentioned, the main focus of this study was on the automatic classification of performances based on TGMD-3 scoring criteria in the form of zero and one or correct and incorrect performances. In the first criterion, 92.6% of test trials were correctly classified, and only 7.4% of executions were wrongly accepted. Weight transfer by stepping with the opposite leg (criterion three), scored one in 56 (46%) of the trials. The automatic classification algorithm performed the same as criterion one. As a result, the dominant homogeneity of performances in criteria 1 was not a factor of high classification accuracy (93%). During

29% of the trials, the thigh and shoulder rotated until the other side of the body faced the wall. In 76 (62%) ones, the diagonal follow-through of the movement toward the other part of the body was skillfully displayed. The automatic scoring algorithm also correctly classified 78% and 76% in criteria 2 and 4, respectively. It must be acknowledged that there were a few false rejections. This means that good performance was classified as poor. There were also false acceptances, meaning poor performance was classified as skillful. As a result, more parameters may need to be considered.

Comparing other studies in this field, the classification accuracy of Lander et al. (2020) was similar to the present study. They also used the automatic scoring algorithm. Similar to the obtained results in this study, the highest evaluation accuracy in criteria one and three was 88% and 86% respectively. They reported 76% and 72% accuracy in the classification of the second and fourth criteria (25).

Grimpapi et al. (2016) investigated the kinematic and temporal parameters to distinguish between different developmental levels of overhand throwing skill. The increasing trend of trunk and hip angular velocity values were the parameters that justified the changes in children's developmental levels. Their results showed how skilled throwers could achieve higher speeds of trunk rotation compared to a beginner (23).

They suggested that mastery in overhand throwing is related to an increase in the angular velocity of the trunk and pelvis, a higher "yaw", and the maximum anterior-posterior acceleration of the trunk in the two phases before the ball release. As a result, trunk and hip angular velocity are good indexes for recognizing developmental levels. These indexes are sensitive to the categorization of children from the lowest to the highest developmental level. These are also valuable indexes in the quantitative FMS assessment process. Therefore, the absence of hip or trunk rotation was proposed as the index of the beginner's level of overhand throwing.

It is interesting that in the present study, if only the lower back data is entered into the automatic scoring algorithm (Figure 3), the classification accuracy of criteria 1 and 2 did not change; however, the accuracy of criteria 3 and 4 slightly reduced. According to the content of criteria 1 and 2, it is evident that they are most affected by the rotation of the pelvis. Therefore, the classification accuracy remained constant.

Increasing the speed of body rotation and acceptable use of the limb movement has a positive effect on the amount of energy transferred to the ball. This mechanism will increase the speed of the projectile at the moment of release. Same mechanism leads to a decrease in the final velocity of the thrown ball for beginner throwers who have a lower trunk and hip angular velocities. This deceleration is associated with the degrees of freedom under the pressure of the joints involved in the initial level of development; because the initial level is characterized by a limited number of joints involved in the movement.

In contrast, to minimize the pretest setting, recent studies have pointed out that new approaches should seek to reduce the number of IMU (38). Analyzing the kinematics of the Grimpampi's data revealed that the rotation speed of the pelvis compared to the trunk was a more accurate indicator in distinguishing the stages of motor development. Probably, the increase in throwing skills is due to the transfer of energy from the hip rotation to the trunk; therefore, the movement of the pelvis may play an essential role in the entire process of developing throwing skills. In 2016, the walking stability of toddlers to the elderly was analyzed by the multiscale entropy method in seven stages of life. By placing only one accelerometer on the L5, it was suggested that the complexity of lower back movement changes indicates the progress, perfection, and decline in walking (39).

Despite the undeniable advantages of the lower back IMU, some researchers believe that placing the sensor in that area by an adult will reduce the feasibility of implementing this protocol in the field; because this area is considered a "sensitive" part of the body. In comparison, children can place the IMUs on their wrists and ankles by their own(25). In evaluating the TGMD movement skills, the results of Bisi et al. (2017) were more accurate than Lander et al. (2020) since IMU was installed on the lower back; long jumping (87% vs. 79%), hopping (92% vs. 77%), and sliding (96% vs. 100%). Lander et al. (2020) expressed that those higher accuracies were the result of the placement of the IMU on the child's lower back. In the present study, to meet ethical standards, a female and male evaluator installed the IMU for girls and boys, respectively (25, 40).

In Grimpapi et al.'s study, no IMU was placed on the ankle. They recommended that future research seek to discover other elements of launch that were not explicitly considered in their analysis; such as the third criterion of TGMD-3. Although three IMU were also used in the present study, changing the location from the trunk to the ankle increased accuracy classification by 10%. Basically, beginner children perform the throwing action without stepping. In this study, in most trials, beginner participants tried to jump up and bend the trunk to produce maximum force. While more skillful performances were accompanied by taking a step toward the side of the throwing hand. The use of the opposite arm and leg pattern in advanced performances was seen when the participant utilized correctly the weight transfer process and benefited from foot placement for better rotation of the hip and opposite shoulder.

The nobility of this study is the use of automatic classification algorithms for evaluation. One of the advantages of this method was a more detailed analysis of the execution process without extracting temporal phases and kinematic outputs of complex signals. For example, in comparing the accuracy of criteria 2 and 3, the criteria related to leg movement was 93% accurate, but the accuracy of the distinguishing trunk and hip rotation was only 78%. After several times reviewing the videos, it was found that in some trials, the leg action was artificially "correct". In these performances, putting the opposite leg forward undergoes a separate process of hip and trunk rotation; as a result, it did not play an influential role in increasing the force of the projectile. Automatic scoring has gone one step further than TGMD evaluation. It has identified the lack of use of power transfer due to upper body rotation to the projectile. Indeed, the decrease in accuracy is not due to the weakness of the algorithm; the executions were not performed with maximum effort as they should be. These results show that the quantitative approach allows for a more detailed analysis of the overhand throwing process by highlighting differences that cannot be detected by traditional on-field assessment.

Time savings was a secondary advantage of using automated scoring algorithms. It takes at least 5 minutes in the usual way (uploading videos of the trials + several times reviewing the videoes to ensure the correctness of the score with entering the score into the computer) for any overhand throwing. In contrast, the maximum processing time was less than 30 seconds in atumatic method. As a result, it provides immediate feedback along with the advantages of portability, cost-effectiveness and ease of use, ensuring it is applicable in educational environments.

The accuracy of discrimination should be considered with caution; because of the small number of participants. Further, the low data collection rate may have resulted in missing critical points. Because of the coronavirus pandemic at the time of data collection, researchers had to rely on the available samples and use the simplest classification algorithms. Initially, the project was designed to use complex deep-learning algorithms for data analysis. In that case, it would be possible to use the raw data to form a movement schema, according to the criteria of the gross motor skill tests. It is suggested that the following researches exploit lurger sample size data and more complex algorithms.

CONCLUSION

In conclusion, using artificial intelligence in the signal processing of only three IMU was a reliable and practical method for assessment of FMS. This approach means that monitoring and evaluating children's movement skills can be objective. In addition, while maintaining relative accuracy, the time involved in the process-oriented analysis of FMS for research, clinical, sports and educational purposes was reduced entirely. As a result, it can be expected that a large population will be evaluated, and the chances of planning for targeted interventions and ultimately improving sport participation will increase.

Author Contributions: Conceptualization, methodology, SH, MSH, HV; formal analysis, SH, HV investigation, SH; resources, FM; data curation, FM, MM; writing—original draft preparation, SH, MGH; writing—review and editing, SH, HV, MGH; supervision, MSH,MGH, ; project administration, MSH,MGH, HV, FB,DH. All authors have read and agreed to the published version of the manuscript.

Funding: This study is funded by the Science and Technology Park of Tehran University and the National Sports Technology Innovation Center.

Institutional Review Board Statement: The Ethics Committee of the Research Institute of Physical Education and Sports Sciences of Iran (blinded) approved this study: ethical code IR.SSRI.REC.1400.1219.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data will be available at request.

Acknowledgments: Thanks to the parents who consented for their children to participate in this study in the acute coronavirus pandemic.

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ارزیابی خودکار رشد مهارت پرتاب از بالای شانه

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چکیده:

همواره مبادله سرعت و دقت در نمره گذاری آزمونهای فرایند محور ارزیابی رشد مهارتهای حرکتی بنیادی چالش پیش روی طرح های غربالگری رشد و تکامل حرکتی بوده است. لذا هدف این پژوهش امکان سنجی استفاده از حسگر اینرسی پوشیدنی مبتنی بر الگوریتم های هوش مصنوعی جهت ارزیابی رشد مهارت حرکتی بنیادی پرتاب از بالای شانه است. ۱۲۳ پرتاب از بالای شانه توسط کودکان ۴ تا ۱۰ ساله (سن ۱,۸۴±۷) (۵۳٪ = پسر) انجام شد. سه IMU (شکوفا توان ویرا) سیگنال‌هایی از سرعت زاویه‌ای، شتاب خطی مچ دست ترجیحی، مچ پای غیر غالب و ناحیه پایین کمر کودکان را ارسال کردند. هر اجرا بر اساس معیارهای ویرایش سوم آزمون رشد مهارت های حرکتی درشت با بازبینی فیلم مهارت های انجام شده امتیازدهی شد. برای طبقه‌بندی خودکار داده‌ها از الگوریتم k نزدیک‌ترین همسایه استفاده شد. حداقل تفاوت بین سیگنال های تست و سیگنال های آموزشی محاسبه و طبقه بندی شد. دو موضوع مورد ارزیابی قرار گرفت: پذیرش نادرست، که در آن عملکرد "نادرست" به عنوان "درست" طبقه بندی شد و رد نادرست که در آن عملکرد "صحیح" به عنوان "نادرست" طبقه بندی شده است. دقت طبقه‌بندی الگوریتم K-نزدیک‌ترین همسایه ۸۵ درصد بود. الگوریتم امتیاز دهی خودکار نیز به ترتیب ۹۳، ۷۸، ۹۳ و ۷۶ درصد را در معیارهای ۱ تا ۴ به درستی طبقه بندی کرد. تجزیه و تحلیل داده های IMU ناحیه کمر دقت ۷۵٪ مدل را نشان می دهد. همچنین زمان کل امتیازدهی از ۵ دقیقه به کمتر از ۳۰ ثانیه کاهش یافت. این نتیجه به طور خودکار با استفاده از تکنیکهای پردازش سیگنال بدون دخالت ارزیاب متبحر به دست آمده است، بنابراین این میزان دقت بسیار امیدوارکننده است. همچنین مشخص شد جنبه هایی از الگوی حرکت توسط هوش مصنوعی بررسی می شود که با چشم متخصص قابل رؤیت نیست. در نتیجه استفاده از روشهای مبتنی بر پردازش سیگنال از طریق تنها سه حسگر، روشی قابل اعتماد و عملی برای ارزیابی سه مهارت حرکتی بنیادی در کودکان بود. همچنین ضمن حفظ دقت نسبی زمان درگیر در تحلیل فرایند محور مهارتهای حرکتی برای اهداف تحقیقاتی، بالینی، ورزشی و آموزشی کامل کاهش یافت. استفاده از هوش مصنوعی در پردازش سیگنال تنها با استفاده از سه حسگر اینرسی پوشیدنی روشی قابل اعتماد و کاربردی برای ارزیابی مهارت حرکتی بنیادی بود. این رویکرد به این معنی است که نظارت و ارزیابی مهارت های حرکتی کودکان می تواند عینی باشد. علاوه بر این، با حفظ دقت نسبی، زمان درگیر در تجزیه و تحلیل فرآیندمحور مهارت های حرکتی بنیادی برای اهداف تحقیقاتی، بالینی، ورزشی و آموزشی به طور کامل کاهش یافت.

واژه های کلیدی: آزمون رشد مهارت های حرکتی درشت، واحد اندازه گیری اینرسی پوشیدنی، هوش مصنوعی، رشد حرکتی، ارزیابی خودکار