

Short communication

Markerless motion analysis to assess reaching-sideways in individuals with dyskinetic cerebral palsy: a validity study

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Abstract

This study aimed to evaluate clinical utility of 2D-markerless motion analysis (2DMMA) from a single camera during a reaching-sideways-task in individuals with dyskinetic cerebral palsy (DCP) by determining (1) concurrent validity by correlating 2DMMA against marker-based 3D-motion analysis (3DMA) and (2) construct validity by assessing differences in 2DMMA features between DCP and typically developing (TD) peers.

2DMMA key points were tracked from frontal videos of a single camera by DeepLabCut and accuracy was assessed against human labelling. Shoulder, elbow and wrist angles were calculated from 2DMMA and 3DMA (as gold standard) and correlated to assess concurrent validity. Additionally, execution time and variability features such as mean point-wise standard deviation of the angular trajectories (i.e. shoulder elevation, elbow and wrist flexion/extension) and wrist trajectory deviation by mean overshoot and convex hull were calculated from key points. 2DMMA features were compared between the DCP group and TD peers to assess construct validity.

Fifty-one individuals (30 DCP;21 TD; age:5-24 years) participated. An accuracy of approximately 1.5 cm was reached for key point tracking. While significant correlations were found for wrist ($\rho=0.810$; $p<0.001$) and elbow angles ($\rho=0.483$; $p<0.001$), 2DMMA shoulder angles were not correlated ($\rho=0.247$; $p=0.102$) to 3DMA. Wrist and elbow angles, execution time and variability features all differed between groups (Effect sizes 0.35-0.81; $p<0.05$).

Videos of a reaching-sideways-task processed by 2DMMA to assess upper extremity movements in DCP showed promising validity. The method is especially valuable to assess movement variability.

Introduction

Upper extremity assessment in cerebral palsy (CP) has gained increasing interest in the past decade, with marker-based three-dimensional motion analysis (3DMA) establishing as gold standard within clinical movement assessment (Cacioppo et al., 2023; Habermehlner et al., 2020; Jaspers et al., 2009). In 3DMA, markers are attached to the skin, providing reliable calculations of joint angles and spatio-temporal parameters based on biomechanical models (Jaspers et al., 2011). However, drawbacks of 3DMA are that measurements are time-consuming, they imply discomfort for children (such as attachment and removal of skin markers), and they require expensive equipment. A cost-effective and convenient alternative could be 2D-markerless motion analysis (2DMMA) from single camera recordings (Scott et al., 2022).

2DMMA is a rapidly evolving technology based on computer vision. DeepLabCut (Mathis et al., 2018) is one of the recently developed open-source codes that allows users to automatically track pre-defined and user-defined (body)key points. These key points can be subsequently extracted as time-series of 2D pixel-coordinates from the video and used to calculate 2D movement features. Although 2DMMA does not allow calculation of 3D parameters, extracted 2D key points and movement features have already been shown to be of added value for applications in movement assessment in CP (Groos et al., 2022; Habermehlner et al., 2023a; Kidzinski et al., 2019; Passmore et al., 2023). The use of 2DMMA and which features could be useful have not yet been reported for assessment of upper extremity movements in children with CP (Scott et al., 2022).

Current research on upper extremity assessment in children with CP mainly focuses on the spastic or general CP population, with underrepresentation of the dyskinetic CP (DCP) group. For this group, assessing an upper extremity task is especially challenging due to the high variability in movement execution caused by involuntary movements and abnormal postures (i.e. dystonia and choreoathetosis) (Butler and Rose, 2012; Sanger, 2006; Vanmechelen et al., 2022). Apart from a high movement variability, children and adults with DCP are known to perform upper extremity tasks slower, with a longer trajectory and reduced joint range of motion compared to typically developing (TD) peers (Artalheiro et al., 2014; Sanger, 2006; Vanmechelen et al., 2022). For individuals with DCP, an easily applicable tool is especially needed to objectively assess their movement characteristics for potential use in an out-of-lab environment such as a therapist's office due to an increase of dystonia and choreoathetosis within unfamiliar

environments. A video-based assessment - using DeepLabCut to extract 2D-key point coordinates and subsequently calculate movement features from these coordinates – could therefore be very useful in this context.

The current study is a first step towards a video-based assessment method of upper extremity movement within DCP. Validity of 2DMMA is assessed for a reaching-sideways task. Following movement features that can be evaluated by 2DMMA were assumed to be clinically relevant for DCP: (1) 2D joint angles (i.e. shoulder elevation, elbow flexion/extension and wrist flexion/extension) at point of task achievement (PTA), (2) execution time and (3) variability features (measured as mean point-wise standard deviation of angular trajectories of the shoulder, elbow and wrist angles trajectories during the movement cycle and by means of overshoot and convex hull). Two aims were established to assess validity: (1) to validate 2DMMA joint angles at PTA and as variability feature the 2DMMA angular trajectories against 3DMA as gold standard (i.e., concurrent validity) and (2) assess if differences in movement features between a DCP and TD group can be evaluated using 2DMMA (i.e., construct validity). We hypothesized to find differences between individuals with DCP compared to TD peers in upper extremity joint angles (i.e. less shoulder elevation, less elbow extension and less wrist extension at PTA), a longer execution time, and higher variability.

Materials and methods

This study is a secondary analysis of videos and 3DMA data from a multicentre study on Instrumented Dystonia and Choreoathetosis Assessment (IDCA) (Vanmechelen et al., 2022, Vanmechelen et al., 2023a; Vanmechelen et al., 2023b).

The primary study as well as the secondary use of the data was approved by the Medical Ethics Committees of the University Hospitals Leuven/KU Leuven and Vrije Universiteit Medical Center, Amsterdam. Written informed consent was obtained from participants and/or their parents.

Participants

Participants were recruited at movement laboratories in Belgium and the Netherlands. The dataset consisted of 30 participants with DCP and 21 typically developing participants. Inclusion criteria for the IDCA study were: a diagnosis of DCP, aged between 5-25 years and the ability to execute the requested tasks. Participants were

excluded if they had neurological disorders other than DCP. Additionally, TD participants within the same age range were recruited.

Task execution

All participants were asked to perform a reaching-sideways-task towards a target. Start position of the hand was indicated with an elastic band on the ipsilateral knee. The reaching height was set at shoulder height (acromion). The reaching distance was determined according to arm length (from acromion to metacarpophalangeal III joint (MCP3) using a custom-made frame to keep reaching distance constant (see for figure of set-up supplementary material S1). All repetitions were performed at self-selected speed with the non-preferred or more impaired arm. A few repetitions were allowed to practice. For all participants, eight repetitions from the data were extracted.

Markerless motion analysis (2DMMA)

The videos were recorded frontally with a single Sony video camera (HDR-CX450, Sony Europe B.V., Dublin, Ireland) fixated to a tripod at a distance of two meters. Videos had a resolution of 1280x720 pixels and were recorded with a frequency of 25 Hz. From the target size as a known distance in the videos one pixel is estimated as 2 mm.

DeepLabCut version 2.3 (Mathis et al., 2018) was used for 2DMMA. Twenty frames for labelling were automatically selected from the videos using k-means. A ResNet-101-based neural network pretrained on the MPII Human pose dataset (Andriluka et al., 2014) provided by DeepLabCut was used as backbone to train a model for additional 400,000 iterations. The MPII pretrained model includes the following anatomical landmarks: ankle, knee, hip, shoulders, elbow, wrist, forehead and chin. MCP3 and the target were added to these pre-defined points. (see for examples for 2D-key points S1, S5, S6).

To avoid privacy issues federated learning was applied (Khalid et al., 2023), meaning that original video data of different labs were not pooled together during 2DMMA. Thus, model training, evaluation and extraction of 2D-key points were performed locally and only extracted 2D-key points were aggregated for further analysis.

An accuracy of approximately 1.5 cm was reached for tracking all key points. Tracking accuracy was assessed in the datasets of each location by comparing machine labels with human's labels (for more information of this analysis see Supplement S3, note

for interpretation of results in S3 that tracking was performed with attached clusters from 3DMA).

2DMMA feature calculation

Automated selection of movement cycles (i.e. start position on the tight and end position at PTA) was performed by detecting minima and maxima within the distance between the target and knee and wrist, respectively. The selection of start and end position was inspected visually on the original videos and corrected if necessary. Calculation of the movement features of 2DMMA was performed with customized code in Python (Version 3.8.15, <https://www.python.org/>). The code is online available together with the extracted key point data (Haberfehlner et al., 2023b). 2D frontal plane joint angles were calculated from the 2D key points of hip, shoulder, elbow, wrist and MCP3 (for example, see Supplement S4). Shoulder elevation, elbow and wrist flexion extension at PTA were used for further analysis.

Gap-filling and filtering was performed for the whole trajectories of the joint angles (i.e. shoulder, elbow, wrist) as described recently (Haberfehlner et al. 2024). Additionally, trajectories were normalized to 1-100 datapoints. From these trajectories of 2DMMA joint angles, the mean and standard deviation of eight trials from each individual were calculated for each time node (1-100), yielding a time-dependent standard deviation (Vanmechelen et al. 2024). This point-wise standard deviation reflects intra-individual variability along each point of the movement cycle. For comparison with 3DMA data and between groups, the mean of the point-wise standard deviation was used.

Additionally, trajectory deviation was calculated from the wrist trajectories. For these calculations x and y coordinates were normalized to the distance between start position and PTA of the wrist. First, the overshoot above the object (as y-distance) for each repetition was calculated. Secondly, an analysis of the convex hull was applied as a measure of trajectory deviation. The boundary of the convex hull is a closed curve surrounding all wrist points traced over time for all eight repetitions, within the 2D space. From the convex hull, the area and perimeter were used for further analysis (Nica et al., 2017) (Fig 1.). For a consistent trajectory, the overshoot of the wrist was expected to be minimal, with a very small area of the convex hull and a perimeter close to two (i.e. two is the minimal distance of the trajectory from start to PTA and back).

Three-dimensional motion analysis (3DMA)

During the reaching-sideways-task, seventeen reflective markers placed over the upper body in five clusters. 3DMA was performed using 12 infra-red Vicon optical motion capture cameras sampling at 100 Hz and analysed following Upper Limb Evaluation in Motion Analysis (U.L.E.M.A) as previously described in detail (Jaspers et al., 2011; Vanmechelen et al., 2022). A brief description is provided in the supplementary material (S2).

3DMA feature calculation

From the 3DMA protocol, shoulder elevation and elbow and wrist flexion/extension angles throughout task performance were extracted. From these angular trajectories, joint angles at PTA as well as the point-wise standard deviations were obtained for comparison with the 2DMA data.

Statistical analysis

To establish concurrent validity, the 2DMMA movement features and 3DMA movement features were individually correlated. Additionally Bland–Altman plots are provided. For construct validity of 2DMMA, hypothesis testing was used assessing known-group differences (Mokkink et al., 2010).

For all variables, normality was tested using the Shapiro–Wilk test. As normality was not confirmed, correlations were calculated with Spearman correlation coefficients (ρ) on the pooled data of the DCP and TD group. Correlations ranging from 0.00-0.25 were interpreted as low or no relationship, 0.25-0.50 as fair, 0.50-0.75 as moderate to good and above 0.75 as excellent (Portney, 2020). Between-group comparisons was performed using Mann Whitney U-Tests. Effect size (ES) was calculated by $(r=|z|)/\sqrt{n}$. Statistics were calculated with SPSS 22.0 (IBM Corp., Armonk, NY, USA). A p-value of <0.05 was considered statistically significant.

Results

Participants

Characteristics of the 30 participants with DCP were: age 17.3 ± 5.3 (mean $\pm$ standard deviation) years; 10 females/20 males; Manual Ability Classification System (MACS): I (n = 3), II (n = 13), III (n = 12), IV (n = 2); and of the 21 TDs: age 17.3 ± 4.2 years; 16 females/5 males. Within the DCP group, 18 participants performed the task with the left arm, 12 with the right arm. Within the TD group, 18 participants performed the task with the left arm and three with the right arm.

Concurrent validity

For five of the participants with DCP, no 3DMA data was available (technical reasons in three cases and problems with marker visibility due to impairment in two cases). These participants were not included in the calculation for concurrent validity. 3DMA shoulder elevation showed a low, non-significant correlation to 2DMMA shoulder angle at PTA ($\rho=0.247$ [CI: -0.059-0.511]; $p=0.102$), while elbow flexion/extension and wrist flexion/extension at PTA from 3DMA were significantly correlated to elbow and wrist angle at PTA from 2DMMA, respectively ($\rho=0.483$ [CI: 0.215-0.683]; $p<0.001$) and $\rho=0.810$ [CI: 0.672-0.893]; $p<0.001$) (Fig 2.). Mean point-wise standard deviation of the 2DMMA joint angle trajectories showed good to excellent correlations with the angular trajectories of 3DMA: shoulder elevation ($\rho=0.712$ [CI: 0.510-0.839]; $p<0.001$), elbow flexion/extension ($\rho=0.659$ [CI: 0.436-0.805]; $p<0.001$) and wrist flexion/extension ($\rho=0.887$ [CI: 0.794-0.939]; $p<0.001$).

Bland and Altman plots of the two methods for wrist flexion/extension at PTA, elbow flexion/extension at PTA, shoulder elevation at PTA and the mean point-wise standard deviation are provided within supplementary material S7.

Construct validity

Median and inter-quartile ranges of 2DMMA-measured features are presented in Fig 3. Significant differences between TD and DCP groups were found for the wrist flexion/extension angles at PTA (ES=0.35; $p=0.016$) and elbow flexion/extension angles at PTA (ES=0.50; $p<0.001$), with more flexion in the wrist and elbow in the DCP group at PTA (Fig 3.C,E). Shoulder angles at PTA did not differ between groups (ES=0.04;

p=0.797) (Fig.3.A). Participants with DCP performed the task on average slower in comparison with TD peers (ES=0.56; $p<0.001$) (Fig.3.G). All features of movement variability significantly differed between groups, with higher values (i.e., more variability) in the DCP group compared to the TD participants: Mean point-wise standard deviation of the 2DMMA angular trajectory of shoulder elevation (ES=0.59), elbow flexion/extension (ES=0.61) and wrist flexion/extension (ES=0.74). (Fig 3.B,D,F), overshoot (ES=0.75), convex hull area (ES=0.81) and the convex hull perimeter (ES=0.76) (all $p<0.001$) (Fig. 3.H,I,J).

Discussion

Within the current research the clinical utility of a video-based assessment of upper extremity movements using 2DMMA during a reaching-sideways-task in individuals with DCP was tested.. A selected set of movement features was calculated from 2D-key points extracted from videos. The calculated features represent clinically relevant movement features in DCP, such as joint angles at PTA, execution time and movement variability. Validity of the proposed method was promising, opening possibilities to facilitate remote movement analysis in DCP.

Concurrent validity was sufficient for wrist angles at PTA measured by 2DMMA and for all angular trajectories calculated by mean point-wise standard deviation, whereas correlations between 3DMA and 2DMMA were fair for the elbow angles and low for the shoulder angles. Most likely the lack of 3D representation within the 2DMMA angle features have affected correlations at PTA due to out-of-plane movements, such as combined shoulder rotation and elevation.

Nevertheless, the expected between-group differences concerning joint angles necessary to establish construct validity of 2DMMA angles at PTA were found. As hypothesized, less elbow and less wrist extension were found in the DCP group compared to the TD group. The hypothesis of less shoulder elevation within the DCP group was not confirmed, which corroborates previous research failing to find deviant shoulder elevation angles during a reaching-sideways-task (Vanmechelen et al., 2022). These differences were, however found within tasks in the vertical plane such as simulating drinking and reach-and-grasp vertically (Artilheiro et al., 2014; Vanmechelen et al., 2022). Also, the hypothesized longer task execution time and higher movement variability was confirmed. The newly introduced features - convex hull perimeter, convex

hull area and overshoot indicating trajectory deviation - all revealed an ES above 0.75 for the group difference between DCP and TD group. Additionally, for all measured joint angles a group difference for 2DMMA angular trajectory through the movement cycle could be confirmed. Future research could augment the currently presented methodology of 2DMMA with additional features on the movement trajectory (e.g. smoothness or trajectory length).

Within the current work, DeepLabCut was used as toolbox for 2DMMA, however also other open-source solutions within 2D tracking are available (e.g. OpenPose (Cao et al. 2021)) and recently also 3D-solutions with two cameras (e.g. OpenCap (Uhlrich et al., 2023)) are emerging and can possibly further improve upper extremity analysis within DCP in the future.

In conclusion, this study is a first step towards a video-based method to assess upper extremity movements in children and adolescents with dyskinetic CP. Here, the degree of validity of such an approach is presented. Markerless motion analysis offers possibilities for an easily applicable evaluation of upper extremity function in a group of patients showing high movement variability. Tracking of the 2D-key points was performed using federated learning, which requires no pooling of video data at one location. Such a workflow can facilitate multi-center collaborations especially necessary for rare disorders and small patient populations.

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Declaration of Interest

The authors report there are no competing interests to declare.

Data availability statement

The data and code used in the current study is available online at the RDR KU Leuven <https://doi.org/10.48804/BZM9SJD>.

Supplemental online material.

S1 Task execution of reaching-sideways at point of task achievement (PTA) including 2D-key points used within 2D markerless motion analysis (2DMMA)

S2 Brief description of three-dimensional motion analysis (3DMA)

S3 Accuracy analysis of key point extraction

S4 Examples of calculated 2D joint angles from markerless motion analysis of eight repetitions of a reaching-side ways task

S5 Video: Example of extracted stick figure of typically developing (TD) child during a reaching-sideways task

S6 Video: Example of extracted stick figure of a child with dyskinetic cerebral palsy (DCP) during a reaching-sideways task

S7 Bland and Altman plots of the two methods for shoulder elevation at point of task achievement (PTA), elbow flexion/extension at PTA, wrist flexion/extension at PTA, mean point-wise standard deviation (PSD) of the angular trajectory of shoulder elevation, elbow and wrist flexion/extension.

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