REVIEW ARTICLE

Arch AHS

Archives of Allied Health Sciences 2022; 34(2): 1-15.

A systematic review of the measurement of infant posture and movement using image or video data analysis

Nisasri Sermpon[1,2], Hirotaka Gima[1*]

[1] Department of Physical Therapy, Graduate School of Human Health Sciences, Tokyo Metropolitan University, Japan.
[2] Faculty of Physical Therapy, Mahidol University, Putthamonthon, Nakhon Pathom, Thailand.

KEYWORDS
Infant movement;
Image data analysis;
Video data analysis;
Movement measurement;
Paediatric physical therapy.

ABSTRACT
Gross motor skill development (spontaneous movement and posture) is the most basic assessment domain for infant body control and movement skills. Image or video analysis in early infancy is an alternative quantitative and qualitative method for assessing movement with the advantages of being cost-effective, requiring less set-up time without attaching markers, assessing natural movement, and availability in clinical settings. This study aimed to review novel methods for measuring posture and movement of infants using image or video analysis, focusing on studies that used the markerless technique. PubMed and EBSCO were searched using three main keywords ('infants', 'posture and movement', and 'measurement'). Articles from other sources were screened and included, and a manual search was performed. Ultimately, 25 articles published since 2010 were selected. The outcomes of this review primarily focused on study purpose, subject information and position, recording tools, analysis techniques, and study features of interest. Image or video data analysis, primarily using two-dimensional and depth video cameras, was used for clinical investigation and technical evaluation, assuring assessment and treatment methods based on quantitative results. Infants aged 0–6 months were evaluated in the supine position in the studies in this review, with an analysis technique that was primarily computer-based. The parameters included variations regarding program or software; for example, the quantity of motion, the centroid of motion, area, velocity, acceleration, and coordinates. Regarding the advantages of using 2D video data analysis for natural movement assessment, further studies and novel technologies are required for clinical practice.

*__Corresponding author:__ Hirotaka Gima, PT, PhD. Department of Physical Therapy, Graduate School of Human Health Sciences, Tokyo Metropolitan University, 7-2-10 Higashi-Ogu, Arakawa-ku, Tokyo 116-8551, Japan. Email: gima@tmu.ac.jp
Received: 7 February 2022/ Revised: 10 April 2022/ Accepted: 24 May 2022

Introduction

Gross motor development is the most basic assessment domain that include infants' skills for controlling or moving their bodies. At an early age, infants learn and improve their supine, prone, sitting, and standing positions as well as the movement of their head and extremities. They also learn to transition from one position to another, such as from supine to prone position, lying down to sitting, and sitting to standing. Finally, they learn to move from one place to another (known as locomotion) by crawling, walking, or running. These motor developments are relevant to neural activity[1]. Previous studies which evaluated both typical and high-risk infants have shown the variability and complexity of postural control[2,3] and spontaneous movement[4,5] in early infancy. Poor postural control and abnormality of spontaneous movement may be caused by brain damage[3,6]. Therefore, infant posture and movement play an important role in the early detection of neurodevelopmental disorders. Early detection of atypical development allows for prompt and appropriate intervention in a clinical setting[7].

Observation is a tool used for assessment in early infancy; it provides qualitative results. For example, the General Movement Assessment (GMA) developed by Pretlch et al. (2005) can predict cerebral palsy but requires a trained assessor[4,8]. Moreover, studies have used video recordings for observation for different purposes including reassessment, result confirmation, elimination of obstacles from observation, and interpretation of information obtained from quantitative data[9]. Therefore, using video recordings and image or video data analysis may provide qualitative and more precise data.

Using images or videos for motor development measurement is a more advantageous method of assessing development as it requires less time to set up instruments, does not require attachment of markers to the body, assesses natural movement, and may be more easily available in clinical settings in addition to the laboratory[10]. In addition, most of the analysis is performed by a computer system that generates quantitative data, such as the quantity of motion, area, velocity, acceleration, and (x, y) coordination. However, the reliability and validity of this method has yet to be evaluated.

Due to the coronavirus disease 2019 (COVID-19) pandemic, there is a need to maintain a distance between individuals and adhere to safety practice guidelines, especially when dealing with vulnerable and fragile infants. Therefore, movement assessment by observation should be considered. However, as technology continues to advance and evolve, image or video data analysis may be an option for performing a quantified assessment. Considering the various techniques that generate measurable data, this study aimed to review relevant studies in the past decade that obtained measurements for infant posture and movement using image or video analysis, focusing on those that obtained quantitative data with markerless procedures. In addition, this review provides previous objectives, methodologies, and parameters used in image or video data analysis.

Materials and methods

Definition of Keywords

The first keyword, **'infant'**, included babies aged 0–12 months old[11,12], according to the Centers for Disease Control and Prevention stage of child development. The second keyword group **'posture or movement'** focused on infancy milestones, from stages in which infants use entire surfaces as the base of support for their bodies, such as the supine and prone positions, to sitting and standing without base support. Spontaneous movement and attentional activity occur in addition to postural development[13]. Finally, the third keyword group **'measurement'** entailed analysis of the image or video data, especially using novel technologies, such as artificial intelligence (AI), machine learning, and deep learning (Table 1).

Table 1 Keywords and literature search strategy in this review

Keyword	Searching formula
Infant	Infant OR Infants OR Baby OR Babies OR Newborn OR Newborns OR Neonate OR Neonates OR Neonatal
AND	
Posture or Movement	Movement OR "Movement analysis" OR Posture OR Position OR Motion OR "Motion analysis" OR "Movement estimation"
AND	
Measurement	Measurement OR Estimation OR Assessment OR Evaluation
AND	
"Image data analysis"	"Image data analysis" OR "Video data analysis" OR "Pose estimation" OR "Automated pose estimation" OR "Computer-based video" OR "Artificial Intelligence" OR "Motiongram"

Literature Search Strategy

This review focused on studies that applied novel techniques in the analysis of image or video data to assess infant posture and movement. The PubMed, Scopus, IEEE Xplore, SpringerLink, and Science Direct databases were searched Manual or Google searches were also applied to obtain as many articles as possible.

Study Selection Process

Two main steps were involved in the selection process. First, the exclusion criteria were defined as follows: 1) Non-use of image or video data analysis in infants; 2) non-use of the terms 'Posture or movement' or 'measurement' in the study; 3) reviews; 4) books or conference proceedings; and 5) research not published in English. Second, the full text of each article that fulfilled the following inclusion criteria were scanned: 1) methodology using video or image data analysis relevant to infant movement; 2) application of novel technologies such as AI, machine learning, deep learning, and computer-based video analysis; and 3) report on 'posture or movement', 'automated pose estimation', 'position', 'motion', or 'movement pattern'.

Screening Process

First, selection was conducted using keywords and strategies for all databases and then the titles and abstracts of articles retrieved were screened based on the exclusion criteria, following which full-text articles that met the inclusion criteria were selected. Finally, all included articles were classified, categorised, analysed, and reviewed.

The entire process of selecting keywords, constructing the search formula, selecting the target papers, and finally deciding which articles to include in the review was performed by S.N. and H.G.

Results

In the past decade, an increasing number of studies have focused on posture and movement assessment using image or video data analysis that provide quantitative parameters. Studies assessed infants moving in their natural habitat using the markerless procedure because attaching markers would have interfered with the performance of infant developmental skills.

Search Results

The selection process was initiated by applying all search terms to PubMed and EBSCO and was limited by year (since 2010), source type (academic journals), and language (English). The results showed 33 PubMed articles and 17,208 EBSCO articles, of which the latter was selected based on the content provider, i.e., MEDLINE, Scorpus, IEEE Xplore, SpringerLink, and Science-Direct. After eliminating duplicate articles, 414 articles were selected from EBSCO; therefore, the final search result contained 447 articles. Subsequently, after first screening titles and abstracts, 385 articles were excluded as they did not follow the inclusion criteria. Next, the researcher rechecked 62 articles and excluded duplicate articles from the two resources (PubMed and EBSCO), leaving 25 articles. The researcher then searched Google again using the keywords, and found 5 more articles; a manual search of the references of these articles yielded 11 more articles. Thus, 41 full-text articles were read, and 16 articles that did not meet the inclusion criteria were excluded. Finally, this study included 25 articles, as shown in Figure 1 and Table 2.

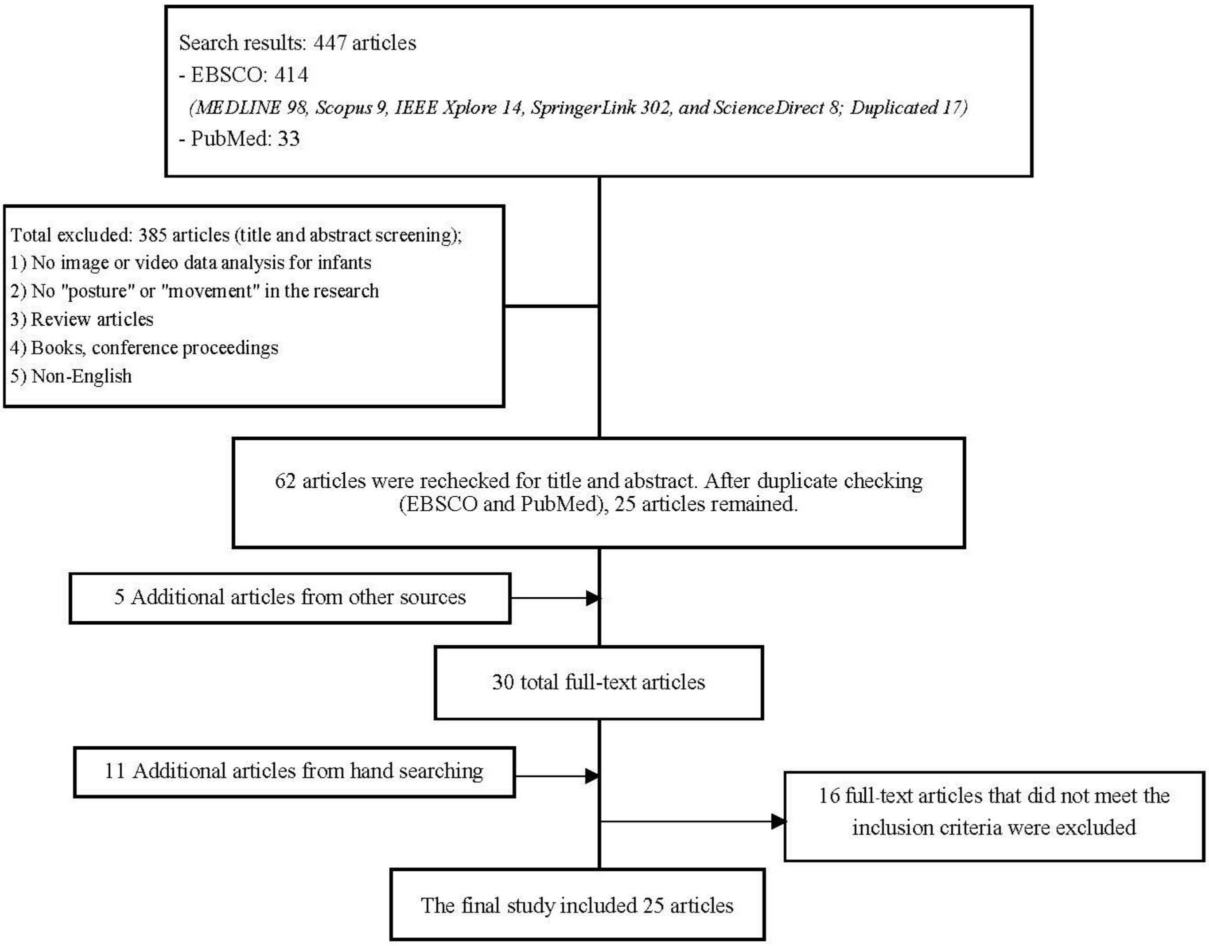

Figure 1 Flowchart of the search process

Table 2 Author, publication year, and title of final recruited articles in the study

Author (Publication Year)	Title
Adde *et al.* (2010)[14]	Early prediction of cerebral palsy by computer-based video analysis of general movements: a feasibility study
Adde *et al.* (2013)[15]	Identification of fidgety movements and prediction of CP by the use of computer-based video analysis is more accurate when based on two video recordings
Adde *et al.* (2016)[16]	Early motor repertoire in very low birth weight infants in India is associated with motor development at one year
Adde *et al.* (2018)[17]	Characteristics of general movements in preterm infants assessed by computer-based video analysis
Baccinelli *et al.* (2020)[18]	Movidea: A software package for automatic video analysis of movements in infants at risk for neurodevelopmental disorders
Caruso *et al.* (2020)[19]	Early motor development predicts clinical outcomes of siblings at high-risk for autism: Insight from an innovative motion-tracking technology
Chambers *et al.* (2020)[20]	Computer vision to automatically assess infant neuromotor risk
Dogra *et al.* (2012)[21]	Toward automating Hammersmith pulled-to-sit examination of infants using feature point based video object tracking
Doroniewicz *et al.* (2020)[7]	Writhing movement detection in newborns on the second and third day of life using pose-based feature machine learning classification
Ihlen *et al.* (2019)[22]	Machine learning of infant spontaneous movements for the early prediction of cerebral palsy: A multi-site cohort study
Kawashima *et al.* (2020)[23]	Video-based evaluation of infant crawling toward quantitative assessment of motor development
Khan *et al.* (2018) [24]	A computer vision-based system for monitoring Vojta therapy
Kinoshita *et al.* (2020) [25]	Longitudinal assessment of U-shaped and inverted U-shaped developmental changes in the spontaneous movements of infants via markerless video analysis
Li *et al.* (2021) [26]	Three-dimensional pose estimation of infants lying supine using data from a Kinect sensor with low training cost
Marchi *et al.* (2019) [27]	Automated pose estimation captures key aspects of General Movements at eight to 17 weeks from conventional videos
McCay *et al.* (2020) [28]	Abnormal infant movements classification with deep learning on pose-based features
Moccia *et al.* (2020) [29]	Preterm infants' pose estimation with spatio-temporal features
Raghuram *et al.* (2019) [30]	Automated movement analysis to predict motor impairment in preterm infants: a retrospective study
Schroeder *et al.* (2020) [31]	General Movement Assessment from videos of computed 3D infant body models is equally effective compared to conventional RGB Video rating

Table 2 Author, publication year, and title of final recruited articles in the study (cont.)

Author (Publication Year)	Title
Stahl *et al.* (2012) [32]	An optical flow-based method to predict infantile cerebral palsy
Støen *et al.* (2017) [33]	Computer-based video analysis identifies infants with absence of fidgety movements
Tacchino *et al.* (2021) [34]	Spontaneous movements in the newborns: a tool of quantitative video analysis of preterm babies
Tsuji *et al.* (2020) [35]	Markerless measurement and evaluation of general movements in infants
Valle *et al.* (2015) [36]	Test-retest reliability of computer-based video analysis of general movements in healthy term-born infants
Wu *et al.* (2021) [37]	RGB-D videos-based early prediction of infant cerebral palsy via general movements complexity

Table 3 Study categorisation based on image or video data analysis

No	Author	Study Purpose	Subjects/age	Subject position	Recording Tool	Analysis Technique	Feature of Interest
1	Adde et al. (2010)[14]	Clinical test/Predict cerebral palsy (CP)	30 high-risk infants/ 10-15 weeks post term age (PTA)	Supine	2D Video Camera	General movement toolbox (motion image, frame differencing, pixel displayed in white represent movement), using computer-based video analysis	- Mean of Quantity of Motion (Q_{mean}) - Standard deviation of Quantity of Motion (Q_{SD}) - Median of Quantity of Motion (Q_{median}) - Standard deviation of the centroid of motion (C_{SD}) - Standard deviation of the velocity (V_{SD}) - Standard deviation of the acceleration (A_{SD}) - Cerebral palsy predictor (CPP)
2	Adde et al. (2013)[15]	Clinical test/Detect fidgety movements (FMs) and Predict cerebral palsy (CP)	26 preterm, 26 term infants/ 9 and 17 weeks post term age (PTA)	Supine	2D Video Camera	General movement toolbox (motion image, frame differencing, pixel displayed in white represent movement), using computer-based video analysis	- Mean of Quantity of Motion (Q_{mean}) - Standard deviation of Quantity of Motion (Q_{SD}) - Median of Quantity of Motion (Q_{median}) - Standard deviation of the centroid of motion (C_{SD}) - Standard deviation of the velocity (V_{SD}) - Standard deviation of the acceleration (A_{SD}) - Cerebral palsy predictor (CPP)
3	Adde et al. (2016)[16]	Clinical test/Detect fidgety movements (FMs)	243 videos of very low birth weight infants/ 9-16 weeks post term age (PTA)	Supine	2D Video Camera	General movement toolbox (motion image, frame differencing, pixel displayed in white represent movement), using computer-based video analysis	- Standard deviation of the velocity (V_{SD}) - Mean of Quantity of Motion (Q_{mean}) - Standard deviation of Quantity of Motion (Q_{SD}) - Standard deviation of the centroid of motion (C_{SD})
4	Adde et al. (2018)[17]	Clinical test/Detect writhing movements (WMs) and fidgety movements (FMs)	27 preterm infants/3-5, 10-15 weeks old	Supine	2D Video Camera	Video analysis software (motion image), Motiongrams	- Mean of Quantity of Motion (Q_{mean}) - Standard deviation of Quantity of Motion (Q_{SD}) - Standard deviation of the centroid of motion (C_{SD})
5	Baccinelli et al. (2020)[18]	Technical experiment, Introduce new novel Movement detection, extract movement features	90 infants; low risk and high risk (300 videos)/10 days, 6, 12, 18, 24 weeks old	Supine	2D Video Camera	Movidea software	- Mean velocity - Mean acceleration - Area form moving average - Cross-correlation coefficient - Intersection mean distance - Total number of intersections - Periodicity
6	Caruso et al. (2020)[19]	Clinical test/Predict Autism Spectrum Disorder (ASD), Neurodevelopmental disorder (NDD)	53 low-risk infants, 50 high-risk infants/10 Days, 6, 12, 18, 24 weeks old	Supine	2D Video Camera	Movidea software	- Quantity of motion (Q_{mean}) - Centroid of motion (C_{xsd}, C_{ysd}, velocity (V_{cmean}), acceleration (A_{cmean})) - Periodicity (H-periodicity, F-perodicity)
7	Chambers *et al.* (2020)[20]	Technical experiment, Clinical test/Predict high risk	85 online videos, 19 high-risk infants/ 3-11 months	Supine	2D Video Camera	Pose estimation algorithm/OpenPose	Naïve Gaussian Bayesian Surprise metric
8	Dogra *et al.* (2012)[21]	Movement detection/using video ensuring pull-to-sit examination (part of Hammersmith Infant Neurological Examination, HINE)	30 babies/ < 12 months	Pull-to-sit	2D Video Camera*2 (top and side view)	Automatic object tracking algorithm	Degree between head and torso then, scoring follow the description of the event
9	Doroniewicz *et al.* (2020)[7]	Movement detection/ Classify general movements (GMs)	31 newborns video recording/ 2-3 days old	Supine	2D Video Camera	OpenPose/Support vector machine (SVM)-Radial basis function (RBF) kernel, Random forests (RF), Linear discriminant analysis (LDA)	16 features characterising spontaneous movement. - Factor of movement's area (FMA) - Factor of movement's shape (FMS) - Centre of movement's area (CMA)

Table 3 Study categorisation based on image or video data analysis (cont.)

No	Author	Study Purpose	Subjects/age	Subject position	Recording Tool	Analysis Technique	Feature of Interest
10	Ihlen *et al.* (2019)[22]	Movement detection Predict cerebral palsy (CP)	377 videos of high-risk infants/ 9-15 weeks post term age (PTA)	Supine	2D Video Camera	Computer-based infant movement assessment (CIMA)	Multivariate empirical mode decomposition (MEMD) - Movement frequencies - Amplitude - Covariation - (x, y) coordinates
11	Kawashima *et al.* (2020)[23]	Movement detection	16 infants/ 10 months old	Crawling	2D Video Camera*2 (top and side view)	Image segmentation, Approximated ellipse and analysis area	- Rhythm of movement - Laterality of movement - Cooperativeness of upper limbs - Number of retrogressions in image centre of gravity (CoG) - Standard deviation of image centre of gravity (CoG) in the medial and lateral directions - Vertical deviation of image centre of gravity (CoG) - Average speed of image centre of gravity (CoG) - Average acceleration of image centre of gravity (CoG)
12	Khan *et al.* (2018)[24]	Technical experiment/ Movement and position detection during Vojta therapy	10 infants/ 2 weeks - 6 months old	Supine, Prone (during treatment)	Microsoft Kinect Camera (RGBD data)	Image segmentation/video tracking	All limbs movement classification
13	Kinoshita *et al.* (2020)[25]	Technical experiment, clinical test/Spontaneous movement detection	9 infants/ -1 to 15 weeks	Supine	2D Video Camera	Image segmentation/video tracking	- Movement magnitude - Movement balance - Movement rhythm - Centre of gravity (COG) Movement
14	Li *et al.* (2021)[26]	Technical experiment, identified joints in RGB image, obtain 3D coordinates	12 sequences from MINI-RGBD dataset	Supine	Microsoft Kinect Camera (RGB image and Depth information)	RGB image (2D) - OpenPose based on PAFs Matching depth information	-Body part length - Percentage of correctly localised Parts (PCP) - Percentage of Correct Keypoint (PCK)
15	Marchi *et al.* (2019)[27]	Clinical test/Detect general movements (GMs) and fidgety movements (FMs)	21 infants/ 8-17 weeks	Supine	2D Video Camera	Pose estimation/OpenPose	Kinematic parameters: velocity, acceleration, jerk, Inter-rater reliability
16	McCay *et al.* (2020)[28]	Classify general movements (GMs)	12 videos from MINI RGBD dataset	Supine	2D Video Camera	Pose estimation/OpenPose	Feature sets: - Histograms of Joint Orientation 2D (HOJO2D) - Histogram of Joint Displacement 2D (HOJD2D) - Fused features-HOJO2D+HOJD2D
17	Moccia *et al.* (2020)[29]	Joint detection in Neonatal Intensive Care Unit, NICUs	babyPose dataset, 16 depth videos of preterm infants/ 24-38 weeks (gestation period)	Supine	RGB-D Video Camera	Pose estimation	Root mean square distance (RMSD); 2D & 3D framework
18	Raghuram *et al.* (2019)[30]	Movement detection; generating a predictive model for motor impairment (MI)	152 videos infants/ 3-5 months corrected age (CA)	Supine	2D Video Camera	Large displacement optical flow (LDOF), Logistic regression	- Minimum velocity (V_{min}) - Mean velocity (V_m) - Mean velocity of the vertical direction (V_{my}) - Receiver-operator-curve (ROC) for predictive model
19	Schroeder *et al.* (2020)[31]	Classify general movements (GMs) in infants with cerebral palsy (CP)	29 high risk infants/ 2-4 months corrected age (CA)	Supine	Kinect (RGB-D) Camera	Shape and Pose estimation Skinned Multi-Infant Linear (SMIL)	Automatic GMA classification

Table 3 Study categorisation based on image or video data analysis (cont.)

No	Author	Study Purpose	Subjects/age	Subject position	Recording Tool	Analysis Technique	Feature of Interest
20	Stahl *et al.* (2012)[32]	Detect fidgety movements (FMs), Predict cerebral palsy (CP)	82 infants (15 cerebral palsy diagnosed), 136 videos/ 10-18 weeks post term age (PTA)	Supine	2D Video Camera	Optical Flow, Computer vision-based infant movement assessment (CIMA), Support vector machine (SVM)	- Motion extraction - Feature extraction - Classification
21	Støen *et al.* (2017)[33]	Clinical test/Detect fidgety movements (FMs)	150 high-risk infants/ 10-15 weeks post term age (PTA)	Supine	2D Video Camera	Video analysis software (motion image, frame differencing, pixel changing)	Mean of Quantity of Motion (Q_{mean}) Standard deviation of the centre of motion (C_{SD})
22	Tacchino *et al.* (2021)[34]	Technical experiment, clinical test/Spontaneous movement detection abnormal vs normal	46 preterm, 21 full term infants/ Birth to 8-12 weeks post term age (PTA)	Supine	2D Video Camera	MIMAS2-Markerless Infant Movement Analysis system	39 components; - Quantitative aspects of the segmental motor activity (10 parameters) - Symmetry aspects of the segmental motor activity (13 parameters) - Rhythmic aspects of the global motor activity (12 parameters) - Geometric aspects of the global motor activity (4 parameters)
23	Tsuji *et al.* (2020)[35]	Clinical test/Detect general movements (GMs)	21 infants (47 videos)/ 25-27 weeks gestation age (GA), 8-15 weeks corrected age(CA), No report for 11 infants	Supine	2D Video Camera	Image segmentation/Approximated ellipse and analysis area	- Movement magnitude - Movement balance - Movement rhythm - Movement of the body centre
24	Valle *et al.* (2015)[36]	Clinical test, Movement detection	75 healthy infants/ 9-18 weeks post term age (PTA)	Supine	2D Video Camera	Image segmentation/Video tracking	- Mean of Quantity of Motion (Q_{mean}) - Standard deviation of Quantity of Motion (Q_{SD}) - Standard deviation of the centroid of motion (C_{SD})
25	Wu *et al.* (2021)[37]	Technique experiment, Detect general movements (GMs)	12 real record infant's movement (a public dataset, MINI-RGBD)	Supine	RGB-D Video Camera	3D Pose estimation; Openpose 2D estimation-Supine 3D estimation	Joint motion complexity, Small-world network reconstruction

Study Purpose

Among the selected studies, 11[14-17,19,27,32-36] used image or video analysis for clinical investigation or evaluation based on quantitative results, 12 studies[7,18,20,22,23,25,26,28-31,37] attempted to develop analysis techniques by applying an algorithm or finding efficiency features to represent infant movement and then planned to use it in a real-life situation, and two[21,24] developed an analysis system that was used to ensure precise assessment and treatment procedures. More than half (56%) of the selected studies[7,14-17,22,26-28,31,33,35-37] used image or video analysis to extract quantitative data relevant to comparing movement with general movement assessment.

Study Recording Tools

The recording tools used in this study can be separated into two main groups: the two-dimensional (2D) and Red Green Blue Depth (RGB-D) or Kinect video cameras. The latter can extract data and provide 3D features. In most studies on young infants, the camera setting is placed above the alert infant lying supine on the mattress and wearing a nappy or bodysuit. Video recording and the general movement assessment takes approximately 3–5 minutes per session. Some studies[21,23] used two cameras, top and side views, to record infants in different planes.

Study Analysis Techniques

The computer system performs most of the analytical process that detects body segments or joint body landmarks. The first step for the study analysis[14-16] was selecting an appropriate recording, then cropping the image or video and using it for ‘motion image’, which exhibited pixels in black (value 0: no movement), and when there were movements between the frames, the pixel is displayed in white. Other analysis processes included the use of software for motiongrams[17], large displacement optical flow[30,32], and markerless infant movements 2D analysis systems such as Movidea[18,19] and the Markerless Infant Movement Analysis System 2[34]. Some studies used a pose estimation algorithm[7,20,26-29,31,37], which programs and automatically detects joint positions and links them as skeletal images. For the RGB-D[24,26,29,31,37] video camera, the researchers used 2D and 3D pose estimation to generate images (such as skeletal images) or interpret joint or movement detection in three planes using algorithms and systems that were more complex for describing infant movements.

Study Feature of Interest

The features of interest in each study varied along with variations in image or video analysis processes, as shown in Table 3; for example, several studies[14-17,19,33,36] reported on the quantity and centroid of motion. In addition, the review studies showed other parameters; velocity, acceleration, rhythm, area, coordinate, and degree.

Discussion

Research into 2D video data analysis has increased in recent years, likely because of continuous studies using markerless movement, which demonstrates natural movement, or the ability to use the results to generate atypical infant prediction or classification models[10]. Moreover, a video can be recorded in different settings, even in remote areas, and processed using computer systems or software. This may be easily accessible for clients in clinical practice[38].

As shown in Table 3, about 80% of all articles reported that subjects were aged 0 to 5–6 months, including low-high risk, preterm, or full-term infants. Additionally, 22 studies showed that the recording was performed in a supine position. The other recording positions included crawling[23], pull-to-sit[21], and Vojta therapy[24]. These subject details and recording positions were relevant to the infant motor development and study objective. More than half of the review articles were based on general movement assessment (GMA), an observational assessment requiring experienced assessors to observe infants lying on their backs in good condition. Previous studies also recommended GMA for a part of the early assessment to predict or diagnose cerebral palsy in infants aged 3–5 months[4,39]. Therefore, researchers have attempted to use 2D video data analysis to detect movement in the supine position and obtain quantitative parameters; for example, the quantity of motion, the centroid of motion, and velocity in consideration of GMA. Thereafter, the parameters from the studies were used to analyse, predict, or classify neurodevelopmental disorders in early infancy, as shown in six studies(7,14,15,28,31,32). Many studies evaluated the supine position as an early-age assessment following infant development. However, a combination of movement directions of spontaneous movement or the ability to move upper or lower extremities toward the midline in the supine position should be included in further research.

Herein, a 2D video camera, which provided RGB data, and a depth video camera or RGB-D, were used as recording tools. The cameras were placed based on the planes of movement for the supine position, during crawling, pull-to-sit, and Vojta therapy. The motion capture and quantitative assessment precision for both RGB and RGB-D (Kinect) cameras were acceptable for biomedical research, including gait analysis, but not for surgery, which requires higher precision(40). Therefore, these tools have recently been used for infant movement assessment. Using a 2D video camera, RGB could be widely applied to low-cost cameras such as those in smartphones, tablets, and laptops, and could be used in different settings(38). The RGB-D (Kinect) is recommended for evaluation of depth information; this tool requires contrast between the subject and background, which can be calibrated easily(40), and the result may be used for 2D and 3D pose estimation(37). For example, Schroeder et al. (2020)(31) studied the correlation between computing a 3D infant full-body model using an RGB-D camera with Skinned Multi-Infant Linear (SMIL) motion video and conventional RGB video. The study concluded that the SMIL model would employ low-cost tools and RGB-D recording for automatic GMA detection and CP prediction. In addition, both RGB and RGB-D cameras do not require a large amount of space and are useful when trying to achieve non-contact with the infant, especially in health settings requiring strict infection control measures and to discourage viral transmission. Therefore, 2D video and depth cameras can be used depending on the purpose for interpreting data from a video recording.

The analyses in this review were mainly performed using computer systems. Developed packaged programs were used; for example, the General movement toolbox, Movidea software, Computer-based Infant Movement Assessment, Markerless Infant Movement Analysis system 2, and other programs for optical flow, image segmentation or video tracking, and pose estimation. In addition, a variety of techniques were used to extract video data from the supine position. Studies(7,20,26-29,37) in later years (2019-2021) included pose estimation in the methodology before extracting the features of interest, for example, movement's shape and area, body part length, kinematic parameters and joint motion complexity. Pose estimation could be used for movement detection for various purposes across the human lifespan. This has a low cost, is easy to use, and is markerless; real-time tracking can also be performed in any environment. Interestingly, pose estimation algorithms may be included in analysis techniques for infant movement assessment(38).

The features of interest in these studies were varied. Common reported parameters included quantity of motion, centroid of motion, velocity, acceleration, area, coordinate, degree of body angle, and centre of gravity. These parameters could be used to develop a prediction or classification model based on GMA. For instance, Adde et al. (2010)(14) demonstrated the variability of the centroid of motion with a sensitivity of 85% and specificity of 88% during customized computer-based analysis of the fidgety-movement period identified in those who later developed CP. The study by Stahl et al. (2012)(32), which had a similar objective but a different processing method, applied an optical flow method to extract features with a support vector machine (SVM) for classification. The study reported performance measurement with a relative frequency accuracy of 93.7±2.1%, sensitivity of 85.3±2.8%, and specificity of 95.5±2.5%. Støen et al. (2017)(33) evaluated the centre of motion standard deviation (C_{SD}) for a triage model identifying high-risk infants with a GMA sensitivity of 90% and specificity of 80% during the fidgety period. Doniewicz et al. (2020)[7] studied the automatic detection of writhing movements, focusing on general movements (GMs) presented in the first weeks of life, using three main features: factor of movement area (FMA), factor of movement shape (FMS), and centre of movement area (CMA), to analyse writhing movement or other movements. Subsequently, three classification algorithms were applied: SVM with the radial basis function kernel, random forests, and a classifier based on linear discriminant analysis, which demonstrated an accuracy rate of 80%. This study showed the potential of using human pose estimation algorithms for computer-aided diagnostics of infant movement. Ihlen et al. (2019)[22] constructed the computer-based infant movement assessment (CIMA) model for CP prediction; this model had a sensitivity pf 92.7% and specificity of 81.6%, comparable to observational GMA and neonatal cerebral imaging. This method could be an alternative machine-learning model for predicting CP. Raghuram et al. (2019)[30] conducted an automated movement analysis and built a predictive model for motor impairment; a sensitivity of 79%, specificity of 63%, and accuracy of 66% of was demonstrated for the automated GMA, suggesting the usefulness of a prediction model for screening high-risk infants when clinical GMA could not be performed. Tsuji et al. (2020)[35] performed movement classification using a system that evaluated 25 indices based on the clinical knowledge of GMs, with an accuracy rate of 90.2±0.94% for normal and abnormal GMs, and indicated this method for early infancy, such as for infant movement assessment in the neonatal intensive care unit. Evaluation of the aforementioned parameters could be confirmed through the assessment model; for example, Dogra et al. (2012)[21] applied a video-based method to examine the pull-to-sit movement, which is a part of Hammersmith Infant Neurological Examination. The study reported a sensitivity of 80% and specificity of 89% for the tracking algorithm used to evaluate pull-to-sit scores. This study showed that the tracking algorithm could more easily assess the head movement. To ensure that movements could be assessed via videos, Valle et al. (2015)[36] evaluated the test-retest reliability of computer-based video analysis of GMs, and found that C_{SD}, Q_{mean}, and Q_{SD} had intraclass correlation coefficients (ICCs) of 0.8, 0.86, and 0.9 in the ICC (3.1) model, respectively.

This review showed that movement assessment in early infants could be performed using 2D video camera recordings with computer-based processing and state-of-art technology, leading to the prediction and classification of atypical conditions. In addition to expert observation, this method may help analyse the development of infant movements at a very young age. Early atypical detection may facilitate implementation of an appropriate intervention in the young infant population. Additionally, implementation of this movement assessment methodology in a clinical setting would facilitate improvements in infant healthcare and rehabilitation, particularly in a low-source setting.

There were several limitations to applying pose estimation[38] in 2D video or image data analysis, markerless movement assessment, and quantitative precision, as this requires novel technology and further study. In addition, the prediction or classification model is still in the development process, which may limit the use of 2D video analysis in a clinical setting.

Conclusion

Herein, previous studies focusing on 2D video or image data analysis for evaluating infant posture and movements were reviewed. Most studies applied computer-based 2D video recording and data analysis to achieve quantitative results. Computer programs or algorithm may help evaluate movement detection, construct a prediction or classification model, and ensure movement during assessment or treatment in infants.

Take home messages

Image or video analysis is an alternative movement assessment technique for infants. An increasing number of image or video analysis studies involve early infants. Advantages of this analysis include facilitation of natural movement, reduced set-up time, and portability. Image or video analysis is safe and useful during the COVID-19 pandemic.

Conflicts of interest

The authors declare no conflict of interest.

Acknowledgements

The authors wish to thank Tokyo Metropolitan University, the board of professors, all reviewers for their help and advice, and the Tokyo Human Resource Fund for City Diplomacy Scholar.

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