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A review of the evolution of scientific literature on technology-assisted approaches using RGB-D sensors for musculoskeletal health monitoring

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ABSTRACT

The human musculoskeletal (MSK) system (also known as the locomotor system) provides strength and assistance to perform functional tasks and daily life activities. The MSK health monitoring plays a vital role in maintaining the body mobility and quality of life. Manual approaches for musculoskeletal health monitoring are subjective and require a clinician's intervention. The evolution in motion tracking technology enables us to capture the fine details of body movements. The research community has proposed various approaches to help clinicians in diagnosis and monitor treatment sessions. This paper succinctly reviews the evolution of technology-assisted approaches for musculoskeletal health monitoring, using motion capture sensors. To streamline the search through the literature database, the PICOS framework and PRISMA method have been incorporated. The present study reviews methods to transform motion capture data into kinematics variables and factors that affect the tracking performance of RGB-D sensors. Furthermore, widely utilized time-series filters for skeletal data denoising and smoothing for kinematics analysis, stochastic models for movement modeling, rule-based and template-based approaches for rehabilitation exercises assessment, and telerehabilitation sessions for remote health monitoring are explored. This article analyzes skeletal tracking methods by providing advantages and drawbacks of the state of the art rehabilitation sessions assessment, skeletal joint kinematics analysis, and MSK Telerehabilitation approaches. It also discusses the possible future research avenues to improve musculoskeletal disorder diagnosis and treatment monitoring. Our review signifies that RGB-D sensor-based approaches are inexpensive and portable for disorder diagnosis and treatment monitoring. It can also be a viable option for clinicians to provide contactless healthcare access to patients in the current scenario of the COVID-19 pandemic.

1. Introduction

The Musculoskeletal (MSK) system builds a framework for the human body to perform functional tasks and daily activities. The joints of the human body connect two different bone segments and provide mobility, strength, and assistance to the human locomotor system. However, with aging, degradation of cartilage (connective tissue) causes pain, stiffness, and inflammation in the body joints. These factors reduce mobility in joints, which leads to musculoskeletal disorders (MSD). It is the second leading cause of years lived with disability (YLDs), loss of mobility, and significant deprivation in productivity and efficiency among the working population [1]. According to the study [2], due to prolonged sitting for hours in work-places, there is a 75% increase in patients with MSD. The body joint movement monitoring and kinematics analysis are essential for MSK health assessment. Such assessments aid in diagnosing MSD, thus enabling the clinician to initiate timely medications and therapy sessions for the patient. The Range of Motion (RoM) is an essential parameter for the kinematics analysis among several other parameters [3]. A body joint has two types of RoM, namely active (movement with internal force) and passive (movement with external force). The goniometry is used to measure active and passive RoM in clinical settings [4]. It uses a goniometer instrument consisting of a fixed arm, a moveable arm, and a fulcrum, as shown in Fig. 1.

Although it is considered a gold standard method, there are few limitations of using goniometry, such as the requirement of manual intervention to place the instrument on a joint location. Its inaccurate positioning, and manual intervention are the primary causes of measurement errors. The goniometry-based method has a human error component with an average value 7°–9° [5]. Also, this method can obtain measurements only for the static postures. These limitations motivated the research community towards the development of devices

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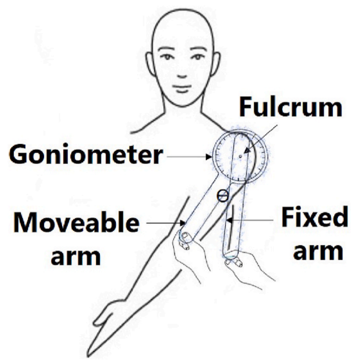


Fig. 1. Goniometry.

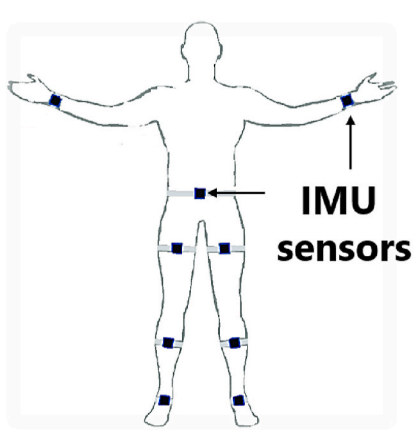
to capture and analyze dynamic human movements.

In the past few years, technology has revolutionized the field of motion capture by introducing wearable and optical sensors to enable an automatic acquisition of reliably accurate movement data for biomechanics analysis. The wearable motion capture technology commonly utilizes the Inertial Measurement Unit (IMU), which combines an accelerometer and gyroscope to measure the linear acceleration and angular motion in three axes, respectively [6]. The IMUs are fixed to different body parts to acquire linear acceleration and angular position data. A setup of wearable IMU sensors on the human subject is shown in Fig. 2a. The joint position and orientation data obtained with IMU are used for movement analysis. The studies in Refs. [7,8] have evaluated the validity and reliability of IMU sensors to capture body movements in activity classification and recognition. Although the IMUs can track postures in an occluded environment, they are expensive, bulky, and uncomfortable to wear.

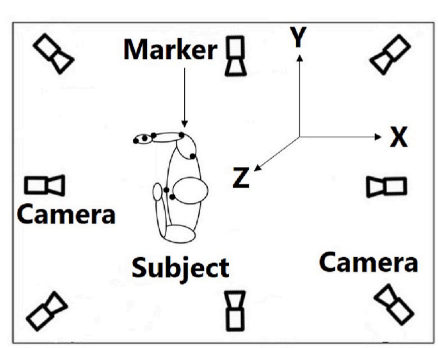
Optical motion capture (MoCap) advancements devised two types of motion sensing technologies *viz.* marker-based and markerless motion capture system. The marker-based system can be categorized into active marker-based [9] and passive marker-based [10] systems. The active marker-based system uses Light Emitting Diode (LED) markers for motion capture. These systems yield a large field of view and capture movement at a high frame rate with reliable accuracy and less latency. The passive marker-based system uses retroreflective markers, which adhere to the body's bony landmarks for motion capture. Both active and passive marker-based systems use multiple camera set ups to track the marker's position in order to extract the joint's spatial location as shown in Fig. 2b. The popular active and passive marker-based motion capture systems are PTI-PHOENIX [11] and VICON [12], respectively. Such sophisticated MoCap systems capture movements with reliable accuracy. However, factors such as high installation costs, expertise to set-up and operate the system, laborious tasks associated with marker placement and calibration restricting their utility in the home and clinical environments [13]. The limitations of marker-based systems have led to the development of camera sensing technology to capture and perceive real-world 3D data.

In the year 2010, Microsoft introduced an inexpensive motion tracking 3D camera for Xbox game consoles, known as Kinect. Two generations of this camera were launched *viz.* Kinect v1 and Kinect v2. The core of the Kinect v1 camera is the structured light (SL) sensor (PrimeSense, 2010) with 320 x 240 spatial resolution. It projects phase-shifted infrared × d (IR) pattern, and its distortion computation provides depth information [14]. SL-based systems are advantageous to overcome the issue of correspondence in computer-vision. However, few limitations exist with SL-based systems; for example, the two viewpoints to capture the depth information, and matching ambiguity develop holes in depth images due to occlusions. The depth discontinuities in the scene and sensitivity to ambient light are other limitations, which limit its application to controlled environments. Kinect v2 utilizes 0.13 μm system-on-chip Time-of-Flight (ToF) sensor with 512 × 424 spatial resolution that is maximum for ToF-based 3D cameras [15]. It floods the whole scene with the IR pattern, and a phase difference between emitted and received signal estimates depth data. ToF cameras utilize a single viewpoint, which makes them robust to occlusion and ambient lights, and preserve the sharp edges in depth images. The ToF technology has upgraded the quality of data acquisition of Kinect v2 by providing maximum spatial resolution for the depth images and improved skeletal tracking performance. Thus, it became a suitable and inexpensive sensor for indoor and outdoor environments [15]. Several authors [14,16–19], and [20] evaluated and compared the accuracy and validity of depth and skeletal data obtained using Kinect sensors. Also, KiReS (Kinect Rehabilitation System) [21] and VERA (Virtual Exercise Rehabilitation Assessment) [22] are popular healthcare systems to support rehabilitation sessions. These incorporate a Kinect sensor for movement tracking, an interactive user interface to display reference exercise movements, and provide real-time feedback for movement correction. The second generation of Kinect sensor had improved depth sensing accuracy, color resolutions, and a large field of view, making it a preferred device for motion capture and analysis in biomedical applications. Although Microsoft had stopped the production of Kinect sensors in the fall of 2017, it is used in motion analysis for research purposes due to its reliable performance in motion tracking. For instance, several studies in Refs. [13,23–26], and [27] used Kinect sensor for motion capture and analysis in the biomedical application.

The other popular next-generation 3D cameras, alternative to Kinect, such as Astra (Orbbec) [28,29], RealSense (Intel) [30], Xtion Pro Live



(a) IMU



(b) Marker-based motion capture

Fig. 2. Wearable (Left) and Optical motion capture system (Right).

(Asus) [31], *etc.* are commercially available for motion capture and analysis. The Azure Kinect (Microsoft) [32] is ToF and AI-based state of the art 3D depth sensor, which was launched in February 2019. In literature, few studies are available on the accuracy and reliability assessment of sensors mentioned above and their application to capture and analyze therapeutic movements. For instance, studies in Refs. [33–35], and [36] have evaluated the accuracy and precision of Azure Kinect for application in human-computer interaction (HCI). More studies could be conducted on the performance evaluation of this sensor for motion tracking in biomedical applications. The acquired depth image sequences with RGB-D sensors are fed to the skeleton pose estimation algorithms for motion capture and analysis. The depth data is preferred, as it is invariant to the subject's color and texture, and suitable for work in low-light conditions. Our review focuses on technology-assisted approaches in musculoskeletal health monitoring, using depth data for disorder diagnosis, treatment monitoring, and telerehabilitation sessions.

In view of RGB-D sensors' application, we formed a clinical question regarding their efficacy in kinematics analysis, rehabilitation session assessment, and telerehabilitation. To answer this, we built a literature search strategy and screened articles from various literature databases related to MSD diagnosis and treatment monitoring using RGB-D sensors. The following taxonomy is adopted to categorize the articles: skeletal joint kinematics analysis, rehabilitation session assessment, and MSK telerehabilitation. The comprehensive details of the analyzed articles have been tabulated. Furthermore, we discussed the advantages and drawbacks of various approaches and the possible future research avenues to improve MSK health monitoring.

The rest of the paper is organized as follows. Section 2 explains the extraction and taxonomy of literature. Section 3 elucidates the research contributions reported in literature. Various technology-assisted approaches and future research avenues are discussed in Section 4. Section 5 concludes and summarizes the review article.

2. Methods of literature extraction

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist was included to develop the literature search strategy and maintain an adequate standard of the proposed review [37]. Furthermore, we determined relevant keywords and Medical Subject Headings (MeSH) terms and incorporated the PICOS framework – Population, Intervention, Comparison, Outcome, and Study Design to define appropriate literature search phrases. Various terms of the PICOS framework are explained as follows; the Population refers to the patients, the Intervention refers to technology-assisted approaches for healthcare, the Comparison refers to comparing the results of manual and technology-assisted clinical interventions, the Outcome term refers to the health-related benefits of the technology-based clinical interventions, and the Study Design term refers to the selection of the type of study for literature review [38].

2.1. Literature databases and search strategy

This review includes related findings reported in the articles published in PubMed, IEEE Xplore, and Scopus databases. To streamline the search, a clinical question using the PICOS framework has been framed as follows: "In patients with MSD, how much are the depth sensor-based approaches effective for MSK health monitoring against manual approaches?" To answer this question in detail, some keywords and MeSH terms were adopted as follows: "Musculoskeletal Disorders", "RGB–D Sensors", "Depth images", "Kinematics Analysis", "Physical Rehabilitation", "Telerehabilitation", "Accuracy", "Feasibility", and "Validity". As mentioned in the previous sub-section, various terms of the PICOS in context of our clinical question were defined as follows: The Patients term refers to patients suffering from MSD related to both upper and lower extremities. The Intervention mentions technology–based approach for kinematics analysis and rehabilitation sessions assessment. The Comparison refers to the similarity in results between the technology-assisted approach with gold standard methods. The Outcome describes the advantages of using the proposed healthcare approach, and the Study Type refers to quantitative studies for literature review.

2.2. Literature extraction

A total of 899 peer-reviewed conferences and reputed journal articles published during the last decade (from 2010 to 2020) were screened. Finally, 65 of them in the English language were selected for analysis. Fig. 3 shows the flow chart of literature extraction from databases, using PRISMA method [37]. The tables from 1 to 4 provide comprehensive details of proposed approaches. These were focused on skeletal joint kinematics analysis, rehabilitation session assessment, and MSK Telerehabilitation, with distributions of the research articles, as shown in Fig. 4.

3. Technology-assisted approaches for MSK health monitoring

The conventional approaches of MSK health monitoring incorporate visual observation of body movement for disorder diagnosis and therapeutic sessions assessment. These approaches are subjective, and require manual intervention. The advancements in wearable and optical sensor–based motion capture technologies allow researchers to develop motion analysis systems that physiotherapists can use for biomechanics analysis. The vision–based sensor technology attracted researchers because it uses the contactless approach for motion capture. The motion capture and analysis system should have the following characteristics: reliable movement tracking without influencing its naturalness, extraction of kinetic and kinematic parameters with reliable accuracy, and movement tracking in controlled and outdoor environments. Markerless motion capture sensor acquires a sequence of raw depth images in which each pixel has 3D structural information (distance from the sensor). The pose estimation algorithms convert the raw depth image sequences into time–series frames for movement analysis of localized body joint. Several authors had proposed classical algorithms [39], and [40] using handcrafted features, together with a decoder for detecting human subjects. The handcrafted features, such as Scale-Invariant Feature Transform (SIFT), Histogram of Gradients (HoG), Speeded Up Robust Features (SURF), are designed such that these are invariant to scale, illumination, and orientation. Several studies on machine learning-based approach *viz.*, Support Vector Machine (SVM) [41], Random Decision Forest [42], and AdaBoost [43] algorithms were reported in the literature for pose estimation. Recent approaches using Deep Neural Networks (DNN) incorporate encoder and decoder subnetworks to optimize the human detection from the sequences of the depth images. The encoder (backbone) of estimation algorithms extract features, and the decoder (output header) localizes the body joints in each frame. DNN–based estimation approaches outperformed the classical algorithms to a great extent due to optimal strategies for feature representation and extraction. Convolution Neural Network (CNN) based encoders down-sample the input image, and regression model estimates the feature vectors. The decoder incorporates deconvolution layers (same network as encoder but in opposite orientation) to cast the output to the pixel grid and up–sample the image to the desired resolution. The CNNs have been trained on large–scale datasets, which have labeled input (depth image)–output (pose) pairs. The DNNs, such as DenseNets [44], MobileNetV2s [45], EfficientNets [46], *etc.* are widely used for human detection and pose estimation. The technological progression has introduced open-source pose estimation toolbox, such as PoseNet [47] and OpenPose [48] for faster and improved performance. The position and orientation of a localized joint are estimated over successive frames that are useful to compute kinetic (force, torque, moments, *etc.*) and kinematic (angle, orientation, velocity, *etc.*)

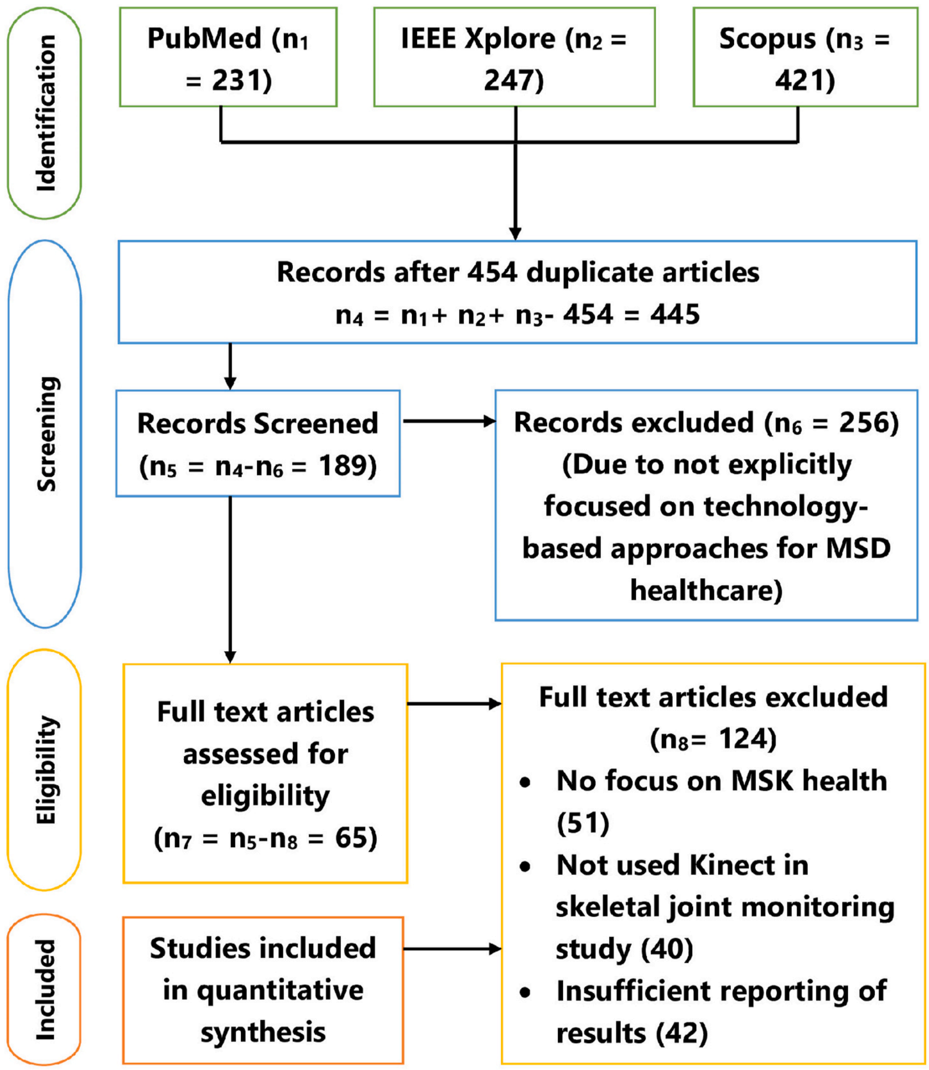


Fig. 3. Flow chart of literature selection using PRISMA.

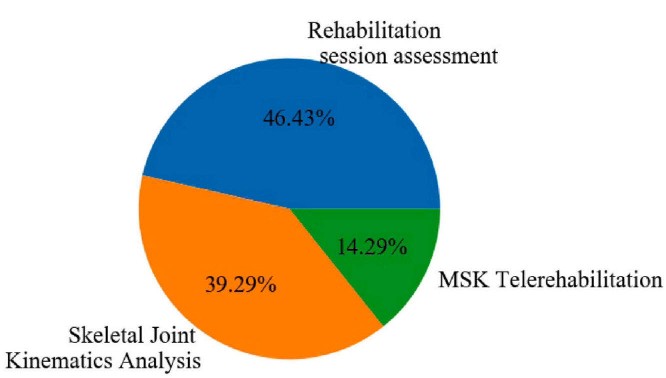


Fig. 4. Pie chart of literature distribution.

parameters, and performance assessment in rehabilitation sessions.

3.1. Skeletal joint kinematics analysis

The kinematics analysis computes the quantities used to describe the motion of body limbs and joints. Mathematical modeling-based approaches are widely used for human movement biomechanics (kinetic and kinematic) analysis. These approaches can be categorized into *latent states–based* and *local features–based* approaches. The *latent states* characterize the temporal sequences of movement. Commonly used methods under the latent states–based approaches are Kalman Filter (KF) [49], Hidden Markov Model (HMM) [50], and Gaussian mixture models (GMM) [51]. The *local feature-based* approaches use motion specific local features to hypothesize body joints, posture recognition, and compute movement–related statistical parameters (such as mean, standard deviation, *etc.*).

In motion tracking using an RGB–D sensor, captured depth images are fed to the skeletonization algorithm [52] to compute the 3D position and orientation data of joints for kinematics analysis. Although skeletonization algorithms provide a reasonably accurate position of the tracked joint, two types of noise are usually found in the joint positions. One is white noise, which occurs due to imprecise joint position, and the other is temporary spike noise, which occurs due to the inferred state of joint tracking [14]. Several other factors affect the skeletal tracking performance of RGB–D sensors: ambient light, the body size of the subject, distance of the subject from a sensor, quantization noise, occlusion of joint with other joint or object, and joint data loss due to the sensor's restricted field of view. Consequently, an undeniable amount of jitter gets incorporated in joint position during data acquisition.

Therefore, algorithms have been developed to improve the tracking accuracy of such sensors. To minimize jitters, several filters are widely used, namely Arithmetic Average Filter [53], Holt Double Exponential

Filter [54] (non-stochastic filters), and Kalman Filter [49] (stochastic filter), as given in (1), (2) & (3), and (4) to (9), respectively. The filtering algorithm is applied to all 3D coordinates of each frame by considering each coordinate x, y, and z separately. A brief description of these filters is given below.

Consider X_n to be a 3D coordinate of a joint at the n^{th} frame and $\widehat{X_n}$ to be a filtered coordinate. A moving arithmetic average filter of length L can be applied to minimize the noise effects as given in (1).

$$\widehat{X}_n = \frac{1}{L}\sum_{k=0}^{L-1} X_{n-k} \tag{1}$$

This filter provides satisfactory results when its input data (joint coordinates) is stationary (has no trend and statistical parameters are constant over time) in successive frames. Its application on joints with a constant speed can introduce bias in the output [55].

The next filter under discussion is Holt Double Exponential Filter [54]. At the n^{th} frame, the trend (tendency) denoted by b_n can be obtained using (2). In (2) and (3), γ ($0 \le \gamma \le 1$) and α ($0 \le \alpha \le 1$) are trend and data smoothing parameters, respectively.

$$b_n = \gamma\left(\widehat{X}_n - \widehat{X}_{n-1}\right) + (1-\gamma)b_{n-1} \tag{2}$$

$$\widehat{X}_n = \alpha X_n + (1-\alpha)\left(\widehat{X}_{n-1} + b_{n-1}\right) \tag{3}$$

A higher value of γ increases the sensitivity of the filter and provides output with less latency [54]. It is a suitable filter for the joints having constant speed and sudden movements.

Kalman filter (KF) is popular among various stochastic filters. In skeletal tracking, this filter is appropriate when the joint movements are highly uncertain. To estimate the joint position's improved value, when the tracked joint position contains jitters, it uses consecutive joint position data as input. An iterative process is adopted, which uses two courses of action, namely prediction and update. For prediction step at n^{th} frame, X_{n-1} and P_{n-1} from previous update stage is utilized to estimate current values for this frame as given in (4) and (5), respectively. However, the state matrix X and the process covariance matrix P must be initialized before filtering.

$$X_n^p = FX_{n-1} + Bu_{n-1} \tag{4}$$

$$P_n^p = FP_{n-1}F^T + Q \tag{5}$$

Here, X^p and P^p are the estimated values of state and process covariance matrix, respectively. F is the state transition matrix, u is the control vector, B is the control input matrix, and Q is process noise, as given in Ref. [49].

In the update step, we use actual values of X to calculate the difference between X and X^p, and the selection of either X or X^p is made by calculating Kalman Gain, K ($0 < K \le 1$), as given in (6). The low value of Kalman Gain shows that the predicted value is near the actual value and vice-versa.

$$K_n = P_n^p H^T\left(HP_n^p H^T + R\right)^{-1} \tag{6}$$

Here, R is the covariance of the measurement noise vector. With given actual data, Z, and measurement matrix H, measurement residual Y can be calculated as given in (7).

$$Y_n = Z_n - HX_n^p \tag{7}$$

The updated state and process covariance matrix can be calculated as given in (8) and (9), respectively.

$$X_n = X_n^p + K_n Y_n \tag{8}$$

$$P_n = (I - K_n H)P_n^p \tag{9}$$

It is important to note that F, B, H, Q, and R are time invariant, so no time index was used with these terms in equations of KF. The output of update stage is given back to the prediction state, i.e., $X_n \to X_{n-1}$ and $P_n \to P_{n-1}$, and the computation cycle continues until the difference between the predicted and actual values tend to small value.

Several contributions have been made towards accuracy improvement of skeletal tracking using RGB–D sensor. Authors in Refs. [6,56], and [57] fused the joint coordinates obtained with Kinect and IMU to reduce errors in position and orientation estimation. Furthermore, these methods have reduced time and difficulties associated with IMU. To enhance the quality of motion tracking, various methods in Refs. [23,29,49], and [58] had incorporated KF and its variants to smooth the erroneous motion captured data. Another cluster of contributions in Refs. [12,13,59,60], and [61] were focused on the recovery of the lost skeletal joint tracking coordinates. In Ref. [28], depth images obtained with Orbbec sensor were used for biometric calculation of gait. Results obtained with depth sensor were compared with values acquired using VICON MoCap system, and showed increased spatial errors on high gait velocity. The comprehensive details of the literature on kinematics analysis are given in Table 1.

3.2. Rehabilitation session assessment

According to the World Health Organization (WHO), rehabilitation is a set of measures for patients with a disability, and it helps to achieve optimal functionality and quality of life. It consists of four steps: assessment, assignment, intervention, and evaluation [68]. Timely recovery from MSD and restoration of mobility require correct execution of repetitive exercises. In rehabilitation sessions, physiotherapists guide the exercise movements to patients. Performance evaluation of these exercises is an essential step to monitor the treatment progress. The feedback from physiotherapists helps patients to correct erroneous movements, and encourages them to repeat the exercises. Although few clinical tests such as Functional Movement Screen (FMS), Wolf Motor Function Test (WMFT), *etc.* are objective and quantitative, visual methods for movement monitoring and evaluation often suffer from subjectivity involved in rating. Since in–clinic rehabilitation sessions require many physiotherapists, these sessions are often shifted to home–based regimens for treatment continuity. The home–based sessions are challenging due to lack of motivation, poor adherence, and unavailability of feedback which result in increased drop-out rate from the rehabilitation sessions [51]. Challenges in the home–based sessions have led to the development of technology–assisted approaches for rehabilitation movement assessment. Such approaches incorporate an inexpensive motion capture sensor(s) and framework for rehabilitation movement assessment. Furthermore, it quantifies the exercise movements, and provides real–time feedback for exercise correction to strengthen the home-based rehabilitation sessions.

According to scientific literature, human motion assessment approaches can be categorized into two classes, namely *rule–based* approaches [69,70] and *template–based* approaches [71,72]. The *rule–based* approach incorporates the clinician's defined set of rules (such as joint angle and distance values for movement representation) and their tolerance values for assessing exercise movements. For instance, in Ref. [69], the authors had proposed a fuzzy rule–based kinematic model to assess static postures and dynamic movements. However, such approaches are exercise specific and suitable for simple movements, but it becomes difficult to extract features and define rules for different complex exercise movements.

The *template–based* approaches are data-driven and compute the difference between reference template and patient's movement for performance evaluation. Such movement templates are created using correct exercises performed by clinicians or healthy subjects. Several studies have proposed Machine Learning (ML) and Deep Learning (DL) methods to quantify exercise movements by classifying them into incorrect and correct repetitions. For instance, Adaboost classifier [43],

Table 1
Summary of skeletal joint kinematics analysis.

Study (Year)	Salient Features	Advantages	Drawback(s)
[9,14, 17–19]	Accuracy and reliability assessment of full body skeleton tracking using Kinect.	Kinect v2 has improved depth and skeleton tracking accuracy compared to its predecessor.	Less accuracy reported in tracking of lower limb joints.
[56] (2011)	Kinect-IMU data integration for online calibration for skeletal joint monitoring using KF.	Improved performance in therapeutic movement tracking.	Tested only on healthy participant and lack of filtering technique to reduce errors in joint position.
[59] (2012)	Exemplar–based method for skeleton pose correction in depth images and tag (coordinate) prediction	Regression cascade provided robust estimation of skeletal pose compared to Kinect SDK approach.	Considered static body size.
[12] (2013)	Natural posture space construction using local PCA and correction of erroneous postures using reliability measurement.	Improved reconstruction of incompletely tracked posture, including occluded environment.	Results reported for single class of motion.
[20] (2014)	Kinect–based application for upper limb joint RoM measurement	Objective method for clinicians with good test–retest reliability	Poor agreement with goniometer values and inability to measure internal and external rotations.
[58] (2014)	Sound enhanced skeleton tracking of upper limb joint position using Extended KF	Jitter reduction and good skeletal joint extrapolation when subject is out from sensor's Field of View.	Lack of generalization of results in therapeutic movements.
[62] (2014)	Framework to model tracked body skeleton with 3D position values	Quantification of full body kinematics analysis.	Unavailability of comparison of results with gold standard methods.
[63] (2014)	KF–based multi depth sensor skeletal data fusion for rehabilitation monitoring.	Reliable accuracy in tracking fused skeletal joint trajectory.	Lack of consideration of skeletal joint tracking noise.
[64] (2015)	Voxel–based skeletal joint RoM measurement using two depth sensors	Joint RoM values are in acceptable range compared to VICON.	Lack of accuracy in complex movements of upper limb.
[6] (2016)	Extended KF–based fusion of quaternions obtained with IMU and depth sensor	Improved accuracy in lower limb kinematics analysis and RoM values validated through goniometry.	RoM measurement error during fast movements.
[57] (2016)	Unscented KF–based fusion of quaternions obtained with IMU and depth sensor	Proposed measurement model showed 50% less error compared to the measurements obtained with either IMU or depth sensor.	Tracking results showed for upper limb joints.
[49] (2016)	Denoising of skeletal tracking using Tobit KF and kinematics constraints	Improved skeletal tracking and smooth trajectories of joint movements.	Joint coordinates smoothing results for a single movement only.
[65] (2016)	Optimization method to estimate true joint location utilizing RGB and depth image.	Improved accuracy in body segment length and orientation estimation.	Considered healthy participants and non clinical movements.
[60] (2017)	3D Parametric model for body segment construction using depth and skeleton data, and kinematic constraints.	Recovery of joint coordinates from erroneous data and smooth tracking of upper limb joints.	Unavailability of results in occluded joint tracking and complex movements.
[61] (2017)	Joint trajectory denoising using gaussian regression model.	Reduced error in upper limb joint reconstruction and improved skeletal tracking.	Results showed only for tracking of upper limb joints.
[66] (2017)	Kinematics measurement and exergames for shoulder rehabilitation.	RoM valuse depicted high correlation with the goniometry.	Lack of clinical validation of exergames.
[31] (2018)	Human locomotion mode recognition using depth images.	Improved recognition method with 82.4% accuracy.	Lack of real–time recognition.
[67] (2018)	Skeletal joint data denoising and posture recognition for physical fitness evaluation.	Smoothing of noisy skeletal joint data with reduced time–delay between frames.	Absence of clinically validated annotation of joint angle threshold values in posture dataset.
[23] (2020)	Modified KF-based model for joint data correction	Smoothing and correction of erroneous joint data in both static and dynamic postures.	Unavailability of joint correction and smoothing results for complex therapeutic movements.

Bayesian classifier [73], an ensemble of multi-layer perceptron neural networks [74], and k-nearest neighbours [75] are popular ML-based methods for movement quantification. The recent development in neural networks have motivated researchers to exploit them in movement classification and recognition tasks. For instance, Deep Neural Networks (DNN) [76], Convolution Neural Network (CNN) [77] (capable of learning spatial deep features and prefers to recognize repetitive movements), Recurrent Neural Network (RNN) [51] (utilize the temporal sequences between data frames and prefers to recognize short movements) and their variants Long Short Term Memory (LSTM) [78] and Gate Recurring Units (GRU) [79] are popular DL-based methods for movement classification. Also, few studies have proposed a hybrid model, which incorporates the combination and modification in the network's computational units for movement classification. Additionally, unsupervised DL models, such as Stacked Autoencoder (SAE) networks [80] and Restricted Boltzmann Machine (RBM) [81], are also preferred for movement classification. However, the trained ML and DL models classify the exercise movements in two discrete classes; such approaches are unable to monitor and quantify the continuous exercise movements during complete rehabilitation sessions.

The regression–based performance metrics for continuous evaluation of rehabilitation exercises can be divided into two categories *viz.* Direct matching approach and Model–based matching approach. The direct matching approach incorporates distance function to measure the dissimilarity between the template sequences of the patient and reference movements at each time step. Since the distance functions are not movement specific, they can be applied to assess new exercise movements. Dynamic Time Warping (DTW) [82] is a widely adopted approach for performance evaluation. The model–based approach uses probabilistic density functions for rehabilitation movement evaluation, as these are capable of modeling stochastic variations of human movements. For instance, Hidden Markov Model (HMM) [50] and Gaussian mixture models (GMM) [51] are used for movement segmentation and evaluation. Such models are advantageous, as they can be generalized to evaluate new exercise movements with reliable accuracy. The disadvantage of template–based approaches is that they only provide an overall evaluation score of movement, and difficulty involved in model application at a different level of abstraction. A detailed description of template–based approaches deployed in exercise movement evaluation is given below.

DTW is the popular algorithm to compare and evaluate exercise postures in real-time. For a given reference posture sequences $x = (x_1, x_2, \dots x_n)$ of length n and subject's posture sequences $y = (y_1, y_2, \dots y_m)$ of length m, it is required that both time-series signals should have equal sampling rate. This algorithm first calculates the distance between each element of above two sequences, known as Manhattan distance, as given in (10).

$$d_{i,j} = |x_i - y_i| \tag{10}$$

Here, $i = (1, 2, 3...n)$ and $j = (1, 2, 3, ...m)$.

The values obtained from (10) create Distance Matrix (DM) and Cost Matrix (CM) of size n × m. The elements of DM and CM are $d_{i,j}$ and $c_{i,j}$, respectively, where $c_{i,j}$ can be computed as given in (11).

$$c_{i,j} = d_{i,j} + min\left(c_{i-1,j-1}, c_{i-1,j}, c_{i,j-1}\right) \tag{11}$$

The values obtained from (11) were utilized to find warping path positions $wp_{i,j}$ as in (12).

$$wp_{i,j} = min\left(c_{i-1,j-1}, c_{i-1,j}, c_{i,j-1}\right) \tag{12}$$

Where warping path elements w can be calculated using (13).

$$w = \left[d_{(n,m)}, \ldots d_{(i,j)}, ..d_{(1,1)}\right] \tag{13}$$

Hence, DTW distance can be calculated by plugging values in (14), where p is the number of warping path elements.

$$DTW_d = \frac{1}{p}\sum_{i=1}^{p} w_i \tag{14}$$

RNN is a deep learning–based model, which recognizes complex human postures. The repetitive connections between network's neurons enable to capture temporal dependencies in input data. For a given input sequence $I = (I_1, I_2, \ldots I_k)$ of length k, it incorporates k hidden states (H) *i.e.* $H = (H_1, H_2, \ldots H_k)$. Fig. 5 shows unfolded architecture of RNN. Although it is required to normalize the data before fed to the neural network, it is not essential for movement data because information regarding variation in each dimension need to be preserved.

In this figure, the hidden states H are gray-colored boxes, the hidden nodes d are green circles, and the number of nodes is determined by hyper-parameter d. Matrices W_X, W_H, and W_Y are weights, and O is the predicted output. The repetitive nature of states helps to share data from the past to the current node and works as a memory for RNN. The hidden node a_n, output of hidden state hn, and prediction at n^{th} frame is given by (15), (16), and (17), respectively.

$$a_n = W_H H_{n-1} + W_X I_k \tag{15}$$

$$h_n = tanh(a_n) \tag{16}$$

$$O_n = softmax(W_Y h_n) \tag{17}$$

where, tanh and *softmax* are activation functions.

HMM is a Markov chain (state transition graph with transition probabilities) process. It finds application in posture recognition and characterization of skeletal tracking spatio-temporal data as a parametric stochastic model [50]. In HMM, observations and states (related to observation) are visible and hidden, respectively. Since physical exercises are a series of posture sequences, they consider postures as observation data, and different exercise steps as states. The observation symbol x is the normalized feature (such as the angle between two postures) of each frame (state). For N states, complete parameter set λ for HMM is given in (18).

$$\lambda = (N, A, B, \pi) \tag{18}$$

Here, A is state transition probability matrix and each of its each element a_{ij} represents state transition (*i.e.* $i \rightarrow j$), B is emission probability matrix (likelihood), and π is probability distribution for initial state of HMM. When the likelihood of observed posture is close to the state, such posture is recognized. The flow diagram of the HMM for posture recognition is shown in Fig. 6.

The Generative Adversarial Network (GAN) is a deep learning-based advanced model to reconstruct postures from acquired noisy data, and to evaluate the rehabilitation movements. It consists of two subnetworks *i.e.* generative network (G) and discriminator network (D) [83], as shown in Fig. 7. Both subnetworks are trained in an adversarial manner such that the generative network produces synthetic data that resembles the original data. Furthermore, the discriminator network detects synthetic data. Once the matching error between the probability distribution of synthetic and real data is calculated, it is backpropagated to train the discriminator network. Hence, at each iteration, G is trained to maximize, and D is trained in adversarial to minimize the classification error, respectively. Let x be the input (skeletal joint displacements or angles) to the discriminator network D with probability distribution P_x, and a random noise sample z with uniform probability distribution P_z is input to the generative network G. The reconstructed data from G is $G(z)$ with probability distribution P_g such that it follows P_x. A value function V (inspired from binary cross-entropy network loss function) is introduced, as given in (19).

$$min_G max_D V\left(G, D\right) = E_{\mathbf{x}\sim P_x}[lnD(x)] + E_{\mathbf{z}\sim P_z}[ln(1 - D(G(z))] \tag{19}$$

Where D and G are trained to maximize and minimize the V, respectively.

In literature, various authors have proposed Artificial Intelligence (AI)-based automated exercise evaluation systems for rehabilitation session assessment. These are data-driven approaches that use a large dataset of reference movements to train the model. The exercise evaluation framework involves the comparison of patient's movement and reference movements, and based on the similarity, the quantitative scores are provided. For ease of understanding, we can categorize AI-based algorithms, according to motion capture technology used for recognizing and evaluating rehabilitation exercises, as follows:

• **Recognition and evaluation using IMU sensor:** In literature, several authors have proposed rehabilitation session assessment approaches using motion capture data obtained with inertial sensors. In Ref. [98], authors developed RecoFit system for strength-training exercise movements segmentation, recognition, and counting. Movement

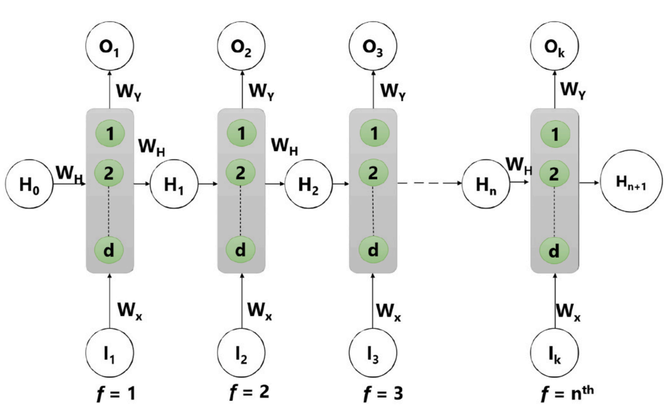


Fig. 5. Architecture of unfolded Recurrent Neural Network.

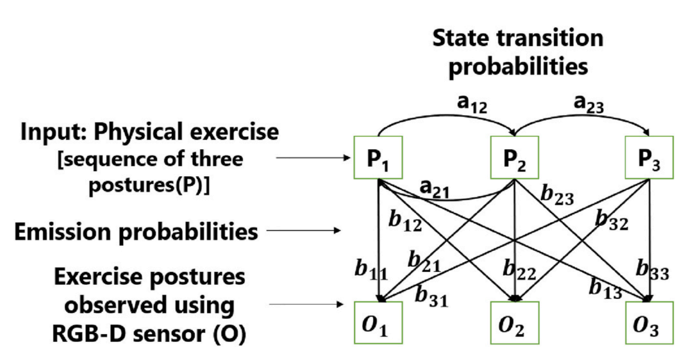


Fig. 6. HMM for posture recognition.

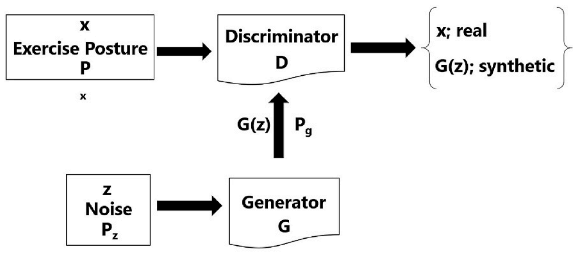


Fig. 7. Block representation of GAN.

data related to 26 different exercises were recorded as training data. An L2-SVM model was trained with features matrix obtained in segmentation, and achieved 96% classification accuracy on the circuit (exercise subset) of 13 exercises. In Ref. [99], the IMU-based rehab session evaluation method had been proposed. The placement positions of the sensor for motion capture were thighs and foot. Authors employed the PCA method to reduce the numbers of features and leave–one–subject–out–cross–validation regression classifier for performance assessment. For different sensor placements combinations, the trained model achieved accuracy between 93% and 95%. Similarly, other ML algorithms, such as Decision Tree classifier [100], Random Forest classifier [101], Support Vector Machine (SVM) [102], and Convolutional Neural Networks (CNN) [77] were used to develop the movement evaluation model.

• **Recognition and evaluation using RGB-D sensor:** RGB–D sensor–based motion capture systems are contactless, require minimum interventions, and are easy to set–up in controlled and outdoor environments [14]. Artificial Neural Networks (ANN) [103], mixed density neural networks [51], recurring self-organization [73], and generative bayesian networks [74] have been used in the performance assessment of rehabilitation exercise movements. For instance, in Ref. [51], authors employed autoencoder subnetwork for dimensionality reduction, and ANN for probabilistic modeling of therapeutic movements. Jun et al. [75] employed PCA for dimensionality reduction, and k-nearest neighbours classifier for movement classification. The proposed model achieved 95.6% classification accuracy. Additionally, the study by L. Yao et al. [89] proposes a rehabilitation session assessment system according to the therapist's point of view. They propose that customized rehabilitation sessions may be helpful to recover patients with different levels of disorders. Authors in Refs. [24,50] had proposed HMM–based framework, and [96,104] had proposed DTW–based framework for rehabilitation exercise assessment. The comprehensive details on rule–based approaches and template–based approaches for rehabilitation session assessment are given in Tables 2 and 3, respectively.

3.2.1. *Dataset annotation*

The rehabilitation exercise dataset is a huge collection of various movements performed by healthy subjects in various ways and orders. These movement data are collected with heterogeneous sensors (either wearable or optical) deployed in the laboratory environment. The major requirement of the dataset is to benchmark the AI algorithm of human activity recognition (HAR) because these are data-driven and require huge annotated movement data for training and testing. The major application area of HAR is fall detection, gait abnormality detection, stress detection, behavior monitoring, and rehabilitation exercise evaluation. Dataset annotation is a process, which incorporates data organization (training, testing, and validation), and labeling of each timestamp with the type of movement data. The annotated dataset is considered as ground truth in evaluating rehabilitation exercises because it incorporates labels that provide a true representation of exercise movements [105]. Manual annotation approaches are labor intensive and time-consuming. Many approaches, such as those based on speech recognition–based [106], video log–based [107], time slot–based [108], notes–based [109], semi-automated [110], and automated [111], have been reported in the literature to facilitate the annotation process. For instance, in Ref. [112], the authors had proposed an online annotation tool for a video dataset of human activities in home environments. They also had proposed a dataset schema and mechanism to add labels. Also, a case study was included to evaluate the feasibility of the proposed solution. Authors in Ref. [113] had proposed an annotation approach for human-object interaction, and detect object movement in video frames. The objects were tracked using stereo cameras. The annotated frame includes object ID, label, and associated global coordinates with the label. In an alternative approach [114], a graph–based label propagation algorithm was trained to annotate the dataset, and to minimize the user invention in the training of HAR models. However, human intervention was still required in the approaches mentioned above. Cruciani et al. [115] had proposed an automatic dataset annotation tool to facilitate the collection and labeling of human activities using a smartphone. Their study incorporates a heuristic function to estimate the reliability of weak labels in the activities of daily living. In the context of rehabilitation exercise monitoring, popular datasets, which incorporate manual annotation procedure, are *Staircase Dataset -University of Bristol* [116], *University of Idaho-Physical Rehabilitation Movement Dataset* (UI-PRMD) [117,118], and *Kinect-based Movement Rehabilitation* (KIMORE) dataset [119]. The *Home-based Physical Therapy Exercise (HPTE) dataset* [74] utilized generative Bayesian networks to label each exercise video. No information were provided regarding the clinical validation of *Kinect-3D Active* [120,120] dataset annotation.

3.2.2. *Serious games in musculoskeletal rehabilitation*

Physical rehabilitation incorporates therapeutic exercises to regain locomotor functionality. Such exercises are often repetitive and boring for patients, which leads to poor adherence to therapy schedule [121]. Also, regular visits to clinics for rehabilitation sessions are time-consuming, and increase the healthcare cost to patients. Here, home–based rehabilitation sessions can be useful and time-saving.

Table 2
Summary of rule-based approaches for rehabilitation Session Assessment.

Study (Year)	Salient Features	Advantages	Drawback(s)
[68, 84–88]	Accuracy and robustness assessment of RGB–D sensor in postures estimation from therapeutic movements.	Reliable accuracy in the joint position tracking.	Pose estimation fails due to occluded environment and non anthropometric kinematic model.
[89] (2014)	Framework for programmable rehabilitation system.	Clinician's approach for rehab session evaluation.	Less trails for results generalization.
[90] (2015)	Rule–based rehabilitation tool using RGB–D sensor	Affordable and easy to operate framework for performance assessment.	Evaluation results on simple movements only.
[30] (2017)	Exergame for upper body rehabilitation using RealSense depth sensor.	Configurable gameplay with real–time feedback for movement correction.	Less participants, and results on healthy participants only.
[91] (2018)	Fuzzy logic and scoring functions for movement evaluation using depth sensor.	Easy to use method, and evaluation scores were highly correlated with clinician's scores.	Requires domain knowledge to design rules for new exercises.
[92] (2019)	Framework for therapeutic exercise description and recognition incorporating ISB standards.	Effective posture recognition and rehab motion evaluation.	Inability of skeleton detection under no visual pose change.

Table 3
Summary of template-based approaches for rehabilitation Session Assessment.

Study (Year)	Salient Features	Advantages	Drawback(s)
[50] (2012)	Movement segmentation and identification using velocity features and HMM.	Objective method with improved accuracy in exercise movement segmentation.	Segmentation results on single user only.
[93] (2013)	Hand grip type classification and kinematics measurement for rehabilitation monitoring.	Improved accuracy in finger landmark detection and joint angle computation.	Unavailability of results in occluded environment.
[74] (2014)	Generative bayesian network-based exercise recognition system using RGB and Depth videos.	Generation of physical exercise dataset. Good accuracy in exercise posture recognition and repetition count.	Recognition in offline mode and non availability of feedback for correction.
[94] (2015)	Template–based approach for query video retrieval and therapeutic movement assessment using depth sensor.	Real–time feedback for pose correction and performance analysis at the end of session.	Need to integrate domain knowledge to make robust method for retrieval and evaluation.
[95] (2015)	Self organizing feature map–based trajectory recognition in motion templates using body skeleton data.	Robust method and improved recognition results for varying body types.	Recognition results deficit for complex therapeutic movements.
[82] (2016)	DTW–based multi level exergame for incorrect posture detection.	Corporal posture correction and evaluation scores at the end of session.	Lack of long-term evaluation results to assess the feasibility.
[51] (2016)	Probabilistic model–based exercise exercise evaluation using mixed density subnetwork.	Daily activities recognition in out-clinic environments.	Unavailability of recognition results for suboptimal movements.
[65] (2016)	Optimization method to estimate true joint location using RGB and depth image.	Improved accuracy in body segment length and orientation estimation.	Considered healthy participants and non clinical movements.
[24] (2018)	HSMM based rehabilitation exercise assessment.	Assessment results showed high correlation with clinical scores.	Small sample size.
[92] (2019)	Framework for therapeutic exercise description and recognition incorporating ISB standards.	Effective posture recognition and rehab motion evaluation.	Inability to detect skeleton under no change in visual pose.
[80] (2019)	Formulation of evaluation metrics and deep learning model to encode movement to scores.	Effective performance quantification and quality scores for intermediate movements.	Evaluation results for healthy subjects only and lack of clinical validation of quality scores.
[96] (2019)	DTW–based virtual coach for performance evaluation.	Linearity in scores obtained with proposed method and clinician's method.	Lack of results in complex therapeutic movements.
[97] (2019)	Real–time subsequence DTW based exercise movements segmentation and performance analysis in patients with impaired mobility.	Robust method to segment noisy, unstable, and reduced mobility movements.	Need of clinical validation of performance analysis.
[25] (2020)	Comparison of DTW and HMM algorithms to quantify therapeutic exercises performance.	HMM provides general assessment and DTW focuses on finer comparison.	Unavailability of assessment results on complex movements.

Serious games are popular in various fields such as education, healthcare, marketing, *etc.* Serious games, often known as "Digital Games", are the application of gaming principles into non-gaming context [122]. The exercise-based games that use motion capture sensors to track movements, and AI algorithms for performance assessment, are known as "exergames" [66,123]. Several authors studied the impact of exergames in rehabilitation scenarios [124,125]. These digital tools can motivate the patient to complete rehabilitation sessions, and offer therapeutic benefits. Its development phase consists of several stages, which are described as follows:

- **3D Computer Graphics-based Game Engines:** The game engines are game development software that provides functionality for graphics rendering, file access (save and load), gameplay sound, networking, multiplayer scenarios, *etc.* The selection of a suitable computer graphics tool plays a vital role in the development of serious games for rehabilitation. Several authors [66,82], and [96] utilized Unity 3D, cryENGINE, Unreal Engine, and Microsoft XNA game engine to develop both movement-oriented and action-oriented serious games.
- **Game Physics:** The effective serious game should follow the concepts of fundamental physics for its realistic simulation. It incorporates dynamics, forces and gravity, and rules to detect multi-object interactions. One popular rule of interaction is to create a circle around a body and object. Once the distance between the circles becomes smaller than the threshold value, the interaction is detected, and the game executes the programmed task. The integration of augmented reality/virtual reality makes exergames amusing, adhering, and motivating patients to complete the rehabilitation session for their speedy recovery [66,126].
- **Natural User Interfaces:** The Natural User Interface (NUI) is a type of human-computer interaction, and the user interacts with computers by devices other than keyboard, mouse, *etc.* [127]. Augmentation of the NUI devices enables participants to interact with the game environments using real-time body movements. Motion capture sensors play a crucial role in tracking body movements. Skeletonization algorithms of RGB–D sensors extract the 3D coordinates of the tracked joint, and the tracked skeletal joints' movement is mapped to the virtual human object. The execution of therapeutic movements trigger action in exergame, and measure the movement kinematics (such as angles between two body segments, angles between body segment and anatomical plane, *etc.*) [128,129], and [130]. Also, it provides feedback to correct the therapeutic movements and generate a quality score at the end of the session.
- **Performance Assessment:** In exergames, the subject's exercise movements lead to the completion of game tasks. The automated assessment of movement quality is essential to recognize correct therapeutic movements. The exercise evaluation algorithms of exergames are trained using a clinically annotated dataset of reference motion templates. Such algorithms evaluate the movement and classify them in incorrect or correct repetition. During gameplay, captured movements of subjects are compared, evaluated, and the overall score was provided at the end of the exergame session. Bayesian classifier [74,131], ANN [132,133], SVM [134,135], and k-nearest neighbours [136] are popular ML algorithms used for therapeutic movement assessment. For instance, Morando et al. [135] used SVM-based learning approach for evaluation of motion quality. The method incorporates radial basis function kernel and grid search optimization process for hyperparameter tuning. The proposed approach achieved 80% classification accuracy to recognize correct movements.

3.3. MSK telerehabilitation

Major cases of acute MSD undergo surgical interventions for effective treatment [137]. Postoperative rehabilitation sessions are essential to regain mobility in the affected joint. However, such sessions require frequent visits to the clinic and extend up to a long duration. These factors often result in diminishing the patient's enthusiasm. The telerehabilitation allows patients to receive remote healthcare services effectively and efficiently. It incorporates information and communication technology (ICT) to deliver healthcare services over the Internet. Such advancements assist the therapist in providing treatment and monitoring its progress remotely. It facilitates in-home treatment sessions reducing the patient's efforts and the time required for frequent visits to clinics. Consequently, healthcare related costs lessen, thereby improving the patient's quality of life. In the context of MSK healthcare, video–based systems are gaining importance in telerehabilitation because it utilizes RGB–D sensors for motion data acquisition. Telerehabilitation enables clinicians to interact with patients, provide therapy sessions, and monitor progress remotely. Hence, this technology can be a viable substitution for the in-person consultation, and can create the therapy sessions adhering and interactive for the patients [138]. A brief discussion of the main components of ICT to facilitate remote healthcare in telerehabilitation is given in the following subsections.

3.3.1. Internet of things (IoT)

IoT is a collection of devices, such as sensors, phones, cameras, *etc.*, which have unique addresses, are connected through the internet to each other [139]. Sensor networks play an essential role in IoT, which incorporates multiple sensing nodes that communicate wirelessly.

3.3.2. Cloud computing

Cloud computing provides shared resources for data storage and computation over the Internet [140]. The data centers for cloud computing are distributed at different locations. There are various cloud computing service providers, namely Google Cloud, Microsoft Azure, and Amazon Web Services, *etc.* for data storage and analytics.

3.3.3. Fog computing

Fog computing is a distributed architecture that spans between cloud and edge computing. The fog layer consists of various fog nodes that allow data storage, preprocessing, control, and networking between different edge devices and edge to cloud [141].

3.3.4. Edge computing

Edge computing is an emerging concept that brings the data processing to the sensor itself [142]. The generated big data is processed at the sensor instead of sending it to the cloud for processing. It removes processing latency and improves computing performance and data transfer speed. Both edge and fog computing services can reduce the dependency on cloud services for data preprocessing, and bring computation and storage resources close to the edge for monitoring and analysis.

The hierarchical architecture of the cloud, fog, and edge computing is shown in Fig. 8.

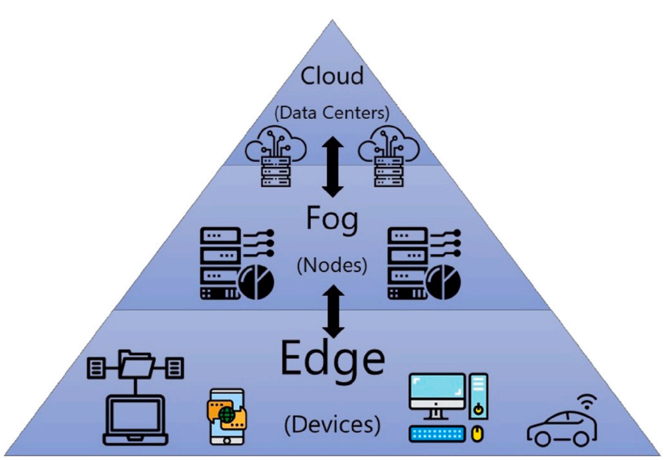


Fig. 8. Hierarchy of cloud, edge, and fog computing.

3.3.5. Blockchain

The blockchain is a shared ledger technology to record and track the transactions in a network. Its architectural components are Transaction, Block, Peer to Peer (P2P) Network, and Consensus Algorithm, which can be modified according to the specific application. Each component incorporates hash, data, and the hash of the previous block, and the chain of connected blocks provides a secured P2P network [143]. In the MSK telerehabilitation scenario, it stores a large number of medical records, recorded therapy sessions for home-based rehabilitation, and provides secure sharing of data, which helps clinicians in continuous remote monitoring of the patients. A few studies have been conducted in MSK telerehabilitation, and comprehensive details are given in Table 4.

The telerehabilitation consists of a patient module (data acquisition), cloud computing module (data storage and analysis), and clinicians module (data visualization), collectively known as Medical Cyber Physical System (MCPS) [144]. The patient connects with the clinician using the web application to transfer health records and clinical data for analysis. The necessity to provide uninterrupted healthcare services emphasizes on the cybersecurity protocols to prevent clinical data breaching. For this objective, an encrypted connection should be established for secure data transfer. Various authors [144–146], and [147] had proposed architectures to secure MCPS network. For instance, in Ref. [145], authors have developed CPeSC3 architecture for communication, computation, and management core for secured healthcare sessions. Similarly, in Ref. [147], a secured patient telerehabilitation system was developed for assistance in exercise sessions.

4. Discussion and future research avenues

Our review focus on the evolution of technology-assisted approaches for MSK health monitoring using RGB–D sensors. The timely assessment of body joint(s) movement is crucial to maintain mobility and functionality in the locomotor system. Over the year, revolution in the technology has introduced wearable and marker–based optical sensors for motion capture in biomedical applications. Although such sensors provide reliably accurate data of human kinematics, the requirement of expertise to set-up, calibrate, and operate the motion capture system for data acquisition and analysis restricts its application in clinical and home environment. Computer Vision–based markerless depth sensors are inexpensive, portable, and easy to use for motion capture in biomedical applications. The conventional approaches in MSK health monitoring involve visual observation of body movements, which are subjective and require manual intervention. Various technology-assisted approaches, using motion capture sensors, have been reported in the literature for kinematics analysis and performance assessment of rehabilitation exercises. Several factors, such as long–term clinical trials for validation, patient engagement, time and physical intensity involved, feedback, and motivation decide the effectiveness of MSK healthcare approaches. The frameworks for motion capture using depth sensors have a huge impact on human kinematics analysis, posture estimation, and exercise movement assessment in physical rehabilitation and telerehabilitation sessions. Several authors in Refs. [14,17,19], and [12] have evaluated the accuracy and validity of Kinect RGB–D sensor for its use in clinical and sports environments for motion capture and analysis. Apart from Kinect, other popular RGB–D sensors, such as Asus Xtion Pro, Intel RealSense, Orbbec, *etc.* are commercially available for motion capture in clinical applications. Very few studies have been reported in the literature regarding the accuracy and validity assessment of such sensors in motion tracking and analysis. More studies could be conducted on the performance evaluation of such sensors for motion capture in biomedical applications. The 3D skeletal joint coordinates obtained with skeletonization algorithms often have acceptable accuracy. However, several factors such as ambient light, incomplete tracking, different body size, distance from the sensor, loss of body

Table 4
Summary of MSK telerehabilitation.

Study (year)	Salient features.	Movement Tracking	Outcome
[148] (2015)	Feasibility of telerehabilitation system for veterans.	Rehabilitation exercises.	Improvement in physical and cognitive functioning.
[149] (2015)	Exercise assessment during telerehabilitation sessions using depth sensor.	Therapeutic movements of neck, shoulder, and knee.	Improved posture classification and recognition accuracy.
[138] (2016)	Neural network–based telerehabilitation for elderly people using RGB–D sensor.	Sitting, standing, and arm raise.	Good accuracy in exercise posture recognition and assessment.
[150] (2016)	Kinect rehabilitation system (KiReS) for patients with hip replacement.	Abduction, flexion, extension, and balance movements.	Improved adherence of patients to exercise sessions.
[26] (2018)	HMM–based exercise assessment for telerehabilitation sessions.	Knee, hip, ankle, and spine joint movements.	Robust method to assess exercise in telerehab sessions.
[151] (2018)	Telerehabilitation framework for patients with shoulder MSD	Upper & Controlled movements of shoulder joint	Application software to display and guide exercise movements.
[152] (2019)	Depth camera–based movement recognition and performance assessment in telerehabilitation sessions.	Upper limb therapeutic movements.	Real–time feedback showed 90% improvement in incorrect repetitions.
[27] (2020)	Feasibility of “AGT-Reha” Kinect based telerehabilitation system for MSD patients.	Abduction, flexion, extension, and rotation movements.	Patients reported improvement in SPADI scores.

frames in fast movements, and occlusion of joint with another joint or object cause jitters in the joint positions affect the depth sensor's performance.

The limited availability of clinically annotated exercise movements datasets of is a barrier to benchmark the algorithms for rehabilitation session assessment. Development and clinical validation of huge datasets of various exercise movements can help researchers to benchmark the AI-based algorithms for exercise movement classification and assessment. The GAN–based models have emerged as a popular technique to generate high-quality synthetic datasets of various exercise movements. The majority of ML-based approaches make use of handcrafted features for performance evaluation. It requires domain knowledge of kinematics to create different features manually for various types of exercise movements. DL–based feature engineering is a popular approach over traditional methods (such as PCA, Manifold learning, *etc.*) for automatic extraction of essential features without any domain knowledge. Authors in Refs. [153,154] had proposed modifications in neural network architectures for feature selection in spatial and temporal domains.

The manual approaches consist of functional measurement and patient reported questionnaires, such as Fugal Mayer Assessment (FMA), Postural Assessment Scale (PASS), Assessment for Motor Ability (AMA), Wolf motor function test (WMFT), and Functional Independence Measure (FIM) [155] to evaluate the rehabilitation sessions. Such approaches are quantitative and rely on the clinician's visual observation. The unavailability of exercise movement assessment metrics and lack of frameworks for automated performance evaluation create difficulty for patients to complete home–based rehabilitation sessions. Since human movements are stochastic and non-linear [18], direct matching and probabilistic models can be utilized for devising recognition and evaluation algorithms. The development of an end to end framework for automated rehabilitation session assessment comprises the following stages: development a labeled dataset, motion detection, movement modeling, exercise performance assessment, and assessment score or report generation at the end of the session. The recent advancements, such as hybrid and lightweight deep neural networks, in deep learning should be exploited for the development of a framework for exercise performance evaluation and smart assistant in home-based rehabilitation sessions. Additionally, the development of exercise movement-oriented exergames for patient engagement and cybersecurity architectures for MCPS is crucial to make telerehabilitation sessions interactive and effective for patients with MSD.

The process of medical device development consists of three phases: identification, innovation, and implementation [156]. In the identification phase, a thorough study of the disease state and the existing solution is conducted. It helps to define the need and motivation behind the development of the medical device. The invention phase consists development of a novel solution to address the problem identified in the identification stage. Once the prototype is ready, an approval from ethical committee is obtained to protect the patient's rights and confidentiality of the patient's identity, and for patient safety and data collection. Clinical trials on various human participants need to be executed to evaluate the performance of the prototype. At a later stage, the implementation phase plays a crucial role in transforming the prototype into a medical solution. Few challenges exist in the medical device development, such as the market size (prevalence of disease and how much size of the market can be captured), product competition (how the various established companies solve the problem and their future perspective towards the product), intellectual property (patents filing for freedom of use), and customer evaluation (does the customer actually like the product, and the scope of improvement to increase its usability) [157].

The contagious nature of COVID–19 has affected healthcare services to a great extent. The safety guidelines have restricted the direct contact between the patient and the clinician for disorder diagnosis and treatment monitoring. In this scenario, contactless techniques are precious to facilitate healthcare services in the continuity of care. The telerehabilitation session is a suitable option for monitoring, assessment, supervision, and consultation. Since the markerless RGB-D sensors are based on contactless motion capture technology, telerehabilitation sessions using such sensors may assist clinicians to provide contactless healthcare access to the patients [26,27,151], and [152]. For instance, Oudah et al. [158] had proposed a hand gesture recognition approach using Kinect sensor for bedridden deaf and mute elderly care. The segmentation of hand movements was executed using sequences of depth images. Furthermore, CNN was used for gesture classification. In another study, a single Kinect sensor was used to acquire depth image sequences of different breathing patterns. AI–based Bi–direction–Attention–Gated Recurring Unit model was trained to classify the pattern of tachypnea, which is a symptom of COVID–19. The trained model achieved 94.5% classification accuracy [159]. Additionally, Kimhy et al. [160] conducted a randomized controlled trial to assess the effectiveness of aerobic fitness in schizophrenia patients. The exercise intervention consists of Kinect-based exergames to capture full body movement. Results showed that participants spent most of the time using exergames and showed significant improvement in social functioning.

5. Conclusion

This review paper encapsulates the essential theories, concepts, evolution of motion capture technologies, state of the art technology-assisted approaches with their advantages and drawbacks. Furthermore, it discusses possible future research avenues that could be explored to develop technology-based solutions to improve MSK health monitoring. We categorized the research contributions into three major groups: kinematics analysis, rehabilitation session assessment, and telerehabilitation. The progression in computer vision-based motion capture sensors motivated the research community to steer the development of the ML and DL–based frameworks in the direction of movement kinematics analysis and rehabilitation movement assessment. This scientific overview discusses depth image denoising and smoothing algorithms for kinematics analysis, probabilistic models for human movement modeling, rule–based and template–based approaches for rehabilitation exercise evaluation in rehabilitation sessions and exergames, datasets annotation to benchmark template–based algorithms of movement assessment, and frameworks to design telerehabilitation sessions for MSK healthcare.

We included several possible future research avenues in motion capture and analysis for diagnosis and treatment monitoring. For instance, the Azure Kinect is a next–generation ToF technology and AI–based depth sensor announced in February 2019 and a successor to the Microsoft Kinect sensor line. While its previous generations were primarily focused on entertainment and gaming industries, Azure Kinect is aimed towards object tracking and recognition in several other areas such as industries, retail, healthcare, *etc.* It has improved color and depth camera resolution, and works on four different depth modes. It can also be exploited for modeling human movements for MSD diagnosis and evaluation of rehabilitation exercises in biomedical applications. We expect this scientific overview to encourage innovative research and implementations in the discussed areas.

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