




# Human Motion Capture for Physical Human-Robot Interaction: A Systematic Review

Jayan Greenwood , Vincent Crocher , Denny Oetomo , Ying Tan 

**Abstract**—This paper systematically reviews state-of-the-art motion capture systems in the context of physical Human-Robot Interaction (PHRI), where humans and robots are in direct physical contact and motion sensing directly affects control stability, interaction safety, and task performance. As robots are increasingly deployed in industrial and healthcare settings that require close and continuous human contact, reliable real-time estimation of human motion has become a critical bottleneck for safe and effective PHRI. However, existing motion capture solutions for PHRI are reported across disparate research communities—including robotics, biomechanics, computer vision, and wearable sensing—using inconsistent assumptions, evaluation metrics, and experimental contexts, making it difficult to compare methods or identify general design principles. This fragmentation motivates the need for a systematic review. Accordingly, 54 studies were analysed, as selected from an initial pool of 4,406 manuscripts, that focus on implementations and evaluations of human motion capture for kinematic analysis in PHRI scenarios. The findings show that current approaches predominantly rely on wearable or vision-based systems, despite persistent limitations related to occlusion, environmental sensitivity, calibration burden, and cost. While some studies exploit the robot itself as a high-fidelity sensing platform, the integration of robotic sensing into multi-modal sensor fusion frameworks remains underdeveloped, despite being well established in other areas of robotics. In addition, the lack of standardised evaluation protocols limits meaningful cross-study comparison. Overall, this review highlights the need for motion capture solutions that integrate robotic and complementary sensing modalities through robust sensor fusion, alongside standardised evaluation methodologies, to enable reliable and scalable motion estimation in real-world PHRI applications.

**Index Terms**—human kinematics, motion capture, physical Human-Robot Interaction (pHRI), systematic review

## I. INTRODUCTION

PAST the stage of full task automation, robots are increasingly implemented in close physical contact to humans, sharing the execution of a task while occupying a shared space. This physical contact typically manifests through wearable robotic attachments on the user’s limb(s), namely exoskeleton-type robots, and with co-manipulator systems in direct physical contact or indirect sharing of a tool/load with a human cooperater. Such physical Human-Robot Interaction (PHRI) has applications in industry contexts, performing an assistive role in increasingly close proximity

with a human user [1], and in healthcare, through surgical co-manipulation [2]–[5] and physical rehabilitation [6]–[8] in particular. Industrial and surgical applications share an objective of dividing a task between the operator and robot, taking advantage of both agents’ best abilities. Rehabilitation, however, sees the robot as a tireless clinician, providing consistent feedback to patient and clinician alike. Irrespective of domain, PHRI scenarios necessitate safe and efficient control of the robot, which requires knowledge and understanding of the human behaviour and possibly their intention.

One fundamental element of human behaviour is the human body kinematics, both posture and movement. Capturing this information, termed “human motion capture”, is particularly useful for the evaluation of human actions; for example, the ergonomics of a task can be evaluated to limit the possible strain induced. In the specific case of rehabilitation, the actual kinematic behaviour of the patient is of primary concern. It is relevant for online and offline evaluation to both adapt the robotic assistance and monitor the patient’s progress [9]. The consideration of human kinematic information can allow the robot to react to human movement patterns that are not directly controlled or measured by the robot kinematics. The human kinematic can also complement the estimation of interaction forces, helping to decipher how they are or can be produced by the human (*e.g.* via the expression of manipulability ellipsoid or anticipation of foot-ground contact). In other PHRI applications, analysing the past, current and estimated future human postures can suggest the user’s intention; all of which can be employed to inform the robot’s actions or how it adapts to human behaviour. This, in particular, is often essential to avoid any harmful contact with the user [10] or improve the appropriateness of robot behaviour.

Indeed, while kinematic information for the robotic device is generally readily available with high accuracy, precision, and temporal resolution, the human pose is by default unknown or uncertain in most PHRI: unlike robotic devices with internal sensors, there is no direct method of obtaining measurements for human motion [11], [12]. In the case of PHRI, the robot and human are physically connected, but any mapping between the robot information and human kinematics is a mere estimate of the true joint motion: external sensors cannot align perfectly with human joints, and models based on interaction contact are incomplete with respect to the kinematic redundancy of the human body [13], [14]. This uncertainty is particularly concerning when motion capture is applied to control a robot device in close proximity to humans: here, there is an increased criticality for robots to be able to respond reliably, accurately and fast in order to avoid restrictive, uncomfortable or even

Manuscript received...

This research was supported by the Commonwealth through an Australian Government Research Training Program Scholarship [DOI: <https://doi.org/10.82133/C42F-K220>]

All authors are with the Department of Mechanical Engineering, The University of Melbourne, Melbourne, Australia. The Corresponding author, Jayan Greenwood, can be contact via e-mail at [jayan.greenwood@unimelb.edu.au](mailto:jayan.greenwood@unimelb.edu.au).

dangerous interactions [10], [15], [16].

Motion capture techniques are well-researched for the estimation of human motion through the use of wearable or vision sensors [9], [17]–[27]. However, the application of human motion capture in PHRI contexts is scarce [16], [28]–[30], with suggestions that PHRI constrains the practicability and efficacy of traditional motion capture techniques.

The de facto industry standard is optoelectronic Marker-Based Motion Capture (MBMC), such as Vicon [31] and OptiTrack [32], where small retroreflective markers are placed on the skin and tracked using infrared sensors. While highly precise, these systems are often inaccessible [33]–[35] for PHRI settings. Markerless Motion Capture (MMC) is a practical alternative that purely considers the visual information from cameras to produce estimations of the human pose [36]. However, the physical presence of the robotic device, the operator or therapist and other equipment could pose a challenge for these vision-based systems, marker-based or markerless alike.

Inertial sensors such as Inertial Measurement Units (IMUs) can be attached to body segments to measure acceleration and angular velocity [37], yet suffer from degrading performance over time [38] and susceptibility to disturbances [39]. Electromyography (EMG) sensors measure muscle activity, which can be translated to kinematics; however, the nature of robotic assistance can affect human muscle activity and, subsequently, the accuracy of EMG systems [40]. Additionally, both these systems require wearable attachments to the body, which is more intrusive and requires involved calibration and setup [38].

Despite these complications, PHRI scenarios also present an interesting opportunity for motion tracking: robotic devices provide accurate and reliable measurements of internal configurations which are partially shared with the human at the interaction point(s). Such accurate measurement could thus potentially be leveraged to improve the performance or robustness of current motion capture systems. Specifically, the physical contact and interaction between human and robot may provide useful information for supplementing or constraining the human kinematics estimated by motion capture. Finally, it's important to note that PHRI applications may benefit from a fast, online (*i.e.* real-time) human kinematics estimate such that it can be used as an input to the robot control loop. Still, existing motion capture systems, not leveraging internal robot sensor information, are generally limited to a few hertz or require post-processing to improve their accuracy, making them insufficiently responsive for such use.

As such, PHRI is a specific motion capture context with unique challenges and opportunities. This literature review thus looks to answer the following three research questions to explore this specificity.

- To what extent is human motion capture negatively affected by PHRI involvement, and what subsequent specific challenges currently exist?
- What techniques currently exist for human motion tracking in PHRI contexts?

- Can the additional external kinematic information provided by robotic devices be leveraged to improve the robustness or accuracy of human motion capture systems?

## II. METHOD

### A. Search strategy

A total of two databases (IEEE Xplore and PubMed) and the meta-database Engineering Village (including Compendex and Inspec) were used for this review. IEEE Xplore and Eng. Village were used to capture all engineering literature as the review is primarily concerned with motion capture in robotics applications; while PubMed was used to capture all possible clinical and biomechanical applications.

The key search parameters were the phrases “human motion capture”, “human kinematics” and “physical human robot interaction”. In this review, “human motion capture” is defined as a system for capturing (or sensing) the movement of a human subject. Other technologically synonymous techniques include the localisation or tracking of a human's motion or skeleton. Search was defined such that motion capture is not limited to specific body segments or joints; however, recognition, detection and identification of people or gestures were excluded as classification of movement does not provide quantitative and explicit characterisation of motion. Similarly, the phrase “human kinematics” and any functionally synonymous terms were included to capture studies involving a specific analysis of human movement (*i.e.* which aim to measure joint positions and/or orientations). There is no standardised or widely adopted set of terminology for the nature of human-robot interaction. As such, to capture “physical human robot interaction” as defined previously, the search was semantically broadened to include implementations of robots that could be applied to physically interact with (or contact) humans, as well as domains that inherently involve PHRI, such as cobotics, exoskeletons, wearable robotics and assistive robotics.

The key search parameters and their respective synonymous terminologies were combined into a single boolean search query (translated for specific search databases), reflecting the requirements for human motion capture, human kinematics and physical human-robot interaction. Where possible, proximity search operators were included within two words for synonymous phrases.

The full search tree and the specific search queries used for each database can be seen in Appendix A.

### B. Manuscripts selection

Following source identification using the search strategy above, the obtained manuscripts were subsequently screened according to the following inclusion and exclusion criteria:

- human motion capture:
  - + sources must involve the capture of human motion via sensing devices
  - omit sources with a focus on identification, recognition or detection of people, faces or gestures
- kinematic analysis:

- + sources must perform kinematic analysis on retrieved human motion
- omit sources that solely perform other analyses, such as human kinetics
- physical human-robot interaction:
  - + sources must involve the direct physical interaction between a robotic device and a human subject
  - + physical interaction should be continuous at one or more points on the body
  - exclude handover tasks and non-contact interaction modes (e.g. audio, gaze)
- contribution:
  - + sources make a contribution to human motion tracking for PHRI: develops, validates, or evaluates an implementation of motion capture in a PHRI context

Screening was performed by a single reviewer (JG) according to the inclusion/exclusion criteria, with uncertain cases discussed with two additional authors (VC and DO). To mitigate the risk of false negatives, a second reviewer (VC) independently screened a random 10% sample of sources.

### C. Data extraction

Data was manually extracted and coded by one of the authors (JG) and discussed among the authors in cases of doubt. The extraction targeted five categories that covered both the motion tracking technique and methodology, as well as the related experimental evaluation where included.

- The nature of the physical human-robot interaction: the classification of the robot involved, the proximity of the contact, and the application of the technology;
- The human motion capture system: the specific sensing system used to capture the movement of a human subject, including the type of sensors and their spatial arrangement around or on the subject;
- The kinematics modelling techniques: the techniques used to determine human kinematics from the sensor data, including constraints and assumptions (detailed in Table I), and methods of fusing different measurements;
- The focus of analysis: the outcomes of the kinematic modelling, namely how the outputs are represented and for which part of the human subject’s body;
- The validation and evaluation: the methodology or system used for validating or evaluating the motion capture technique, and specific experimental results.

## III. RESULTS

### A. Search and selection overview

The search was conducted on 27 August 2025 and yielded 4,406 records. After removing 1,266 duplicates, 3,140 records were screened, of which 2,989 were excluded as irrelevant and 4 were not retrievable. The eligibility of the remaining 153 full-text reports was assessed by the first reviewer (JG), with uncertain cases discussed among all authors. Studies were excluded for not implementing human motion tracking with appropriate validation, not involving a robotic device in

continuous physical contact with a human, or not explicitly estimating joint kinematics. No disagreements were identified in the random sample independently screened by a second reviewer (VC). In total, 54 studies met the inclusion criteria and were included in the review (Fig. 1). Although the retention rate was low (1.2%), the search strategy intentionally used broad queries to account for inconsistent use of PHRI terminology (see Section IV-E).

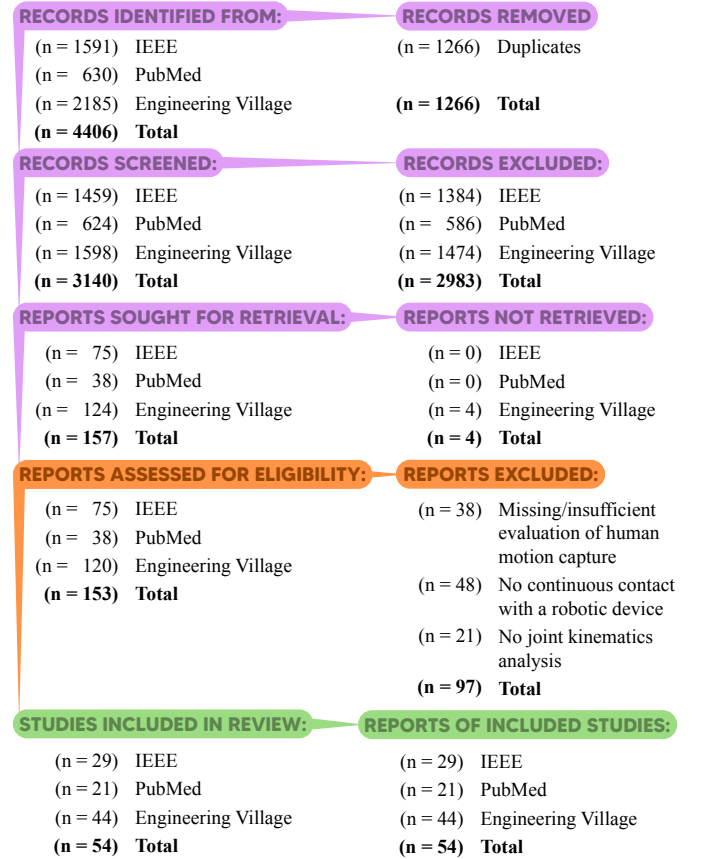


Fig. 1: PRISMA diagram for the search results. Duplicate records are counted in each database subtotal; totals refer to the number of distinct records.

TABLE I: Description of assumptions extraction

Assumption	Description
$\frac{H}{S}T$	Assumption that the sensor-human transformation(s) is rigid and known.
$\frac{H}{R}T$	Assumption that the robot-human transformation(s) is rigid and known.
$MP$ (motion priors)	Requirement for subject-specific movements or poses for model training, initialisation or calibration.
$PM$ (prior measurement)	Requirement for subject-specific morphological measurements <i>e.g.</i> segment lengths or height.
$CK$ (constrained kinematics)	Assumption of fixed or known human kinematic information, <i>e.g.</i> fixed or stationary joints.

TABLE II: Motion capture implementation details

Source	Motion capture approach	Assumptions					Kinematics focus
		$\frac{H}{S}T$	$\frac{H}{R}T$	$MP$	$PM$	$CK$	
SINGLE MODALITY (EXCLUDING ROBOT)							
[43]	RGB-D → MMC (YOLOv8) → IK → $\theta$						$F(b)$
[44]	RGB-D → MMC (Theia3D) → IK → $\theta$						$H(far)K(far)A(f)$
[45]	IR → MBMC (BTS) → $x$		✓				$A(x)$
[46]	RGB-D → Kinect → IK → $\theta$						$S(far)E(f)$
[47]	RGB-D → Kinect → IK → $\theta/l$						$E(f)$
[48]	RGB-D → Kinect → IK → $\theta$ IR → MBMC (OptiTrack) → IK → $\theta$	✓					$S(f)T(b)K(f)$
[49]	RGB → Optical flow → $\theta$					✓	$S(far)$
[50]	IMU → $\int$ → IK → $\theta$			✓			$E(f)$
[51]	IMU → $\int$ → IK → $\theta$	✓				✓	$T(fbr)$
[52]	IMU → $\int$ → IK → $\theta$	✓					$H(f)K(f)$
[53]	IMU → $\int$ → IK → $\theta$	✓					$L(f)H(f)K(f)A(f)$
[54]	IMU → $\int$ → IK → $\theta$	✓		✓			$S(far)E(f)$
[55]	IMU → $\int$ → IK → $\theta$ → $x$	✓					$W(x)$
[56]	IMU → Estimator → $p$	✓					$W(p)$
[57]	IMU → ML (TCN, LTSM, WMSA) → $\theta$	✓					$A(f)$
[58]	IMU → $\int$ → DMP → $\theta$	✓				✓	$H(f)K(f)$
[59]	EMG → ML (transformer) → $\theta$	✓		✓			$H(f)K(f)$
[60]	EMG → ML (CNN-LTSM) → $\theta$	✓		✓			$H(f)K(f)$
[61]	EMG → ML (CNN-LTSM) → $\theta$	✓		✓			$A(f)$
[62]	EMG → ML (PSO-LTSM) → $\theta$	✓		✓			$K(f)$
[63]	EMG → ML (CWT-BPNN) → $\theta$	✓		✓			$E(f)$
[12]	GONIO <sup>†</sup> → $\theta$	✓					$S(\$)$
[41]	GONIO <sup>†</sup> → $\theta$	✓					$W(f)$
[42]	GONIO <sup>†</sup> → $\theta$	✓	✓				$E(f)$
MULTIPLE MODALITIES (EXCLUDING ROBOT)							
[13]	IMU → $\int$ → $x$ MARG → EKF → IK → $\theta$	✓	✓		✓		$S(farx)E(f)W(s)$
[64]	IMU → $\int$ → IK → ML (transformer) → $\theta$ Force → ML (transformer) → $\theta$	✓					$H(f)K(f)$
[65]	IMU → $\int$ → IK → $\theta$ EMG → KF → IK → $\theta$	✓		✓			$E(f)$
[66]	IMU → $\int$ → IK → $\theta$ EMG → EKF → IK → $\theta$	✓		✓	✓		$K(f)$
[67]	VR* → VR (HTC Vive) → $x$	✓					$W(x)$

(continued on next page)

ROBOT ALONE							
[68]	EXO	Encoder	$\theta$	✓			$W(fds)$
[69]	EXO	Encoder	$\theta$	✓			$K(f)A(f)$
[70]	EXO	Encoder	$\theta$	✓			$S(far)E(f)W(fds)$
[71]	EXO	Encoder	$\theta$	✓			$S(fa)E(f)W(s)$
[72]	EXO	Encoder	$\theta$	✓			$W(fd)$
[73]	EXO	Encoder	$\theta$	✓			$S(\S)E(f)W(s)$
[74]	EXO	Encoder	$\theta$	✓	✓		$E(f)W(fs)$
[75]	EXO	Encoder	$\theta$	✓	✓		$F(\S)$
[76]	EXO	Encoder	$\theta$	✓		✓	$S(far)E(f)W(fds)$
[77]	EXO	Encoder	$\theta$	✓			$A(fer)$
[78]	EXO	Lookup table	$\theta$	✓			$F(b)$
[79]	EXO	Pressure	ML (clustering)	$\theta$	✓	✓	$H(f)$
[80]	END EFFECT	$p$ $v$	Particle filter	IK	$\theta$	✓	$S(far)E(f)W(fds)$
[81]	END EFFECT	$p$	IK	$\theta$	✓	✓	$S(far)E(f)W(s)$
[82]	END EFFECT OTHER DATA	$p$	IK	$\theta$	✓	✓	$T(p)$
ROBOT + OTHER MODALITY							
[83]	IMU	$\int$	IK	$\theta$	✓	✓	$S(far)EW(fd)$
	END EFFECT	$x$					
[84]	IMU	$\int$	IK	$\theta$	✓	✓	$S(far)E(f)W(fds)$
	END EFFECT	$p$ $v$					
[85]	IMU	$\int$	IK	$\theta$	✓	✓	$S(far)E(fx)W(fdsx)$
	END EFFECT	$p$		$x$			
[11]	IMU	$\int$	IK	$\theta$	✓	✓	$S(far)E(f)W(fdsx)$
	END EFFECT	$p$ $v$		$x$			
[86]	IMU	$\int$	IK	$\theta$	✓	✓	$S(farx)E(f)W(s)$
	END EFFECT	$p$		$x$			
[87]	IMU	$\int$	IK	$\theta$	✓	✓	$S(x)E(fx)$
	END EFFECT	$p$		$x$			
[88]	IMU	$\int$	IK	$\theta$	✓	✓	$H(f)K(f)A(f)$
	ROBOT						
[89]	IMU	$\int$	IK	$\theta$	✓	✓	$K(f)$
	EXO						
[14]	RGB-D	Kinect	IK	$\theta$	✓	✓	$S(fa)E(f)$
	END EFFECT	$p$					
[90]	RGB-D	Coloured markers	IK	$\theta$	✓	✓	$S(far)$
	EXO	$p$					

**System coding:**  $x$  - joint position,  $\theta$  - joint angles,  $p$  - pose,  $v$  - velocity,  $\int$  - numerical integration, IK - inverse kinematics

**Assumptions:** detailed in Table I, where ✓ indicates an assumption made/required by the respective study

**Joints coding:**  $S$  - shoulder,  $E$  - elbow,  $W$  - wrist,  $F$  - hand/fingers,  $T$  - torso,  $L$  - lumbar,  $H$  - hip,  $K$  - knee,  $A$  - ankle

**Joint kinematics coding:**  $f$  - flexion/extension,  $a$  - adduction/abduction,  $r$  - rotation (*i.e.* internal/external),  $d$  - radial/ulnar deviation,  $s$  - supination/pronation,  $e$  eversion/inversion,  $b$  - bending,  $x$  - position,  $p$  - pose

**Notes:** \* VR systems include inertial, lighthouse, and vision techniques. § Non-standard/other anatomical descriptions of joint angles. † Goniometer refers to electronic goniometer through resistive [12], [41] or capacitive [42] sensing.

## B. PHRI applications of motion capture

Fig. 2 provides details of the type of interaction and intended application of each paper, where a large proportion focused on rehabilitation [11]–[14], [41]–[47], [52], [54], [55], [57]–[66], [68], [70]–[74], [76]–[79], [81], [84]–[88], [90], followed by assistive (*i.e.* augmenting motion for non-rehabilitation scenarios) [51], [53], [56]–[58], [65], [69], [77], [79], [81], [89] and industrial applications [42], [48], [56], [67], [79], [80], [82], [83].

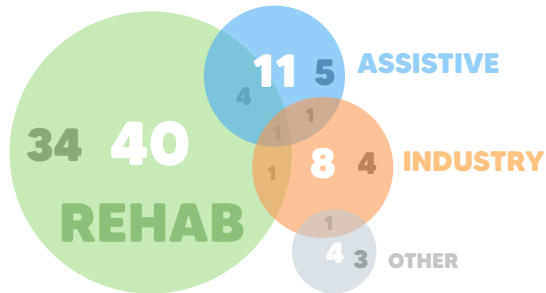


Fig. 2: Application of pHRI with domain totals in white (full circle) and the subsets totals in their respective colours.

Of the 54 studies, 33 involved robotic exoskeletons [12], [42], [44], [45], [47], [48], [50], [52]–[55], [57]–[62], [64], [65], [68]–[79], [89], [90] and 17 involved end-effector robots [11], [13], [14], [46], [49], [56], [63], [66], [67], [80]–[87]. Other studies featured a robotic verticalisation bed with additional function to mobilise the legs [88], a robotic wheelchair [51], and soft-robotic actuators [41], [43]. Almost all included works focused on the direct interaction between a human and a robotic device, with only one studies involving indirect contact, *i.e.* through a rigid object (co-lifting application) [56].

## C. Challenges for current motion capture in PHRI

The development of human motion capture techniques for kinematics analysis is largely motivated by the shortcomings of current technologies and techniques.

Some motion capture systems are deemed not sufficiently accurate for PHRI contexts [44], [57], [76], [80], [85], [87], [91]. In particular, vision-based systems are subject to occlusions and environment variables [14], [48], [52], [53], [56], [69], [70], [76], [80], [82], [83], [87], [92] such as inconsistent lighting, clothing and the capture space; inertial devices suffer from drift and magnetic disturbances, and require calibration [76], [83], [85]; and the modelling required for EMGs can introduce noticeable decrease in temporal resolution [59]. The high cost of such systems [11], [44], [47], [51], [69], [73], [85], [87], combined with an involved setup/calibration [11], [14], [44], [45], [52], [73], [76], [80], [82], [87] or post-processing [44], [45], [69] requirement, are a major dissuasion for the adoption of motion capture systems.

Additionally, with respect to a pHRI context, the presence of the robot itself impacts the effectiveness of motion capture [45], [48], [53], [67]. With exoskeletons, the misalignment between sensors and the human joints, contributes to inaccurate joint pose estimation and damage

to the human arm [11], [14], [44], [68], [72], [76], [78], [81], [85], [87]–[90]. Exoskeleton, inertial and EMG sensing systems alike can be obtrusive or influence natural movement [11], [43], [46], [51], [53], [61], [72], [73], [75], [76], [80]–[82], [87]. To calibrate such systems, patients are often required to perform specific motions or postures, which is not suitable for those with motor impairments [90], while EMGs systems also suffer from high inter-subject variability [60].

Methods for attending to such shortcomings have employed simplified models or assumptions that do not necessary hold in real-world scenarios [11], [73]: in particular, assumptions on the body pose (particularly the shoulder and upper arm for upper body) [13], [14], [72], [87] and the requirement of information that is not available in clinical contexts, such as known anatomical joint centre positions or initial poses [76].

## D. Motion capture implementation

Table II provides the implementation details of the human motion capture systems employed.

1) *Body focus*: The majority of studies focused on tracking the kinematics of the upper body, looking at various combinations of shoulder, elbow and wrist joint angles and positions. Sixteen studies focused on the lower body, for analysis of the hip, knee and/or ankle. Few studies looked at other kinematics such as for the torso, lumbar or fingers.

2) *Sensing modalities and use of robot measurement*: Twenty-four studies used a single motion capture modality, with the most popular choice being inertial sensors. Overall, 22 studies used IMUs in a single-sensor configuration attached to the arm [11], [13], [84]–[87], chest [51] or wrist [56], or with multiple sensors placed on the upper body [50], [54], [55], [65], lower body [52], [57], [58], [64], [66], [89], whole body [53], [67], [83], or robot [88]. Eleven studies used vision-based tracking sensors to capture motion requiring physical attachments to be fixed to the user: three sources used marker-based methods for identifying landmarks attached to the human body, with an optoelectronic [45], [48] or a virtual reality tracking system [67]. In contrast, the remaining eight vision-based studies chose MMC that detects human joint positions from 2D images using computer vision and machine learning techniques with Red-Green-Blue (RGB) [44], [49] or Red-Green-Blue-Depth (RGB-D) cameras [14], [43], [46]–[48], [90], most of which using the Microsoft Kinect V2 sensor and Kinect MVN. Six studies attached EMG sensors to the upper body [60], [63] or lower limbs [59], [61], [62], [66]. The remaining systems featured a vertical ground reaction force sensor [64], soft position sensor to map bending to joint angle [42], and flexible resistive sensors attached to the shoulder to provide an estimate of shoulder angles [12] or attached within a glove to measure wrist flexion [41].

Twenty-five studies leveraged the robot interaction, to obtain additional information from the robots' internal sensors. End-effector robots provided information for the subject's point of contact (typically the forearm or wrist) with position [11], [14], [80]–[87] or velocity [11], [80], [84]. Exoskeletons are commonly used to provide estimates of human joint angles through encoders at the robot joints [68]–[78], [89], [90].

In addressing the technical shortcomings of particular sensing systems, some studies combined the information from multiple different sensors. [67] used both IMUs (Xsens) attached to the whole body in conjunction with HTC Virtual Reality (VR) trackers, fusing visual and inertial information. More interestingly for PHRI applications, nine studies combined robot localisation information with external sensors. Here, inertial data [11], [83]–[87] and vision data [14] were employed to augment or supplement the localisation provided by end-effector robots. Given the more extensive human localisation provided by exoskeletons (despite misalignment issues), only three studies augmented this information with either vision or inertial data [88]–[90].

3) *Modelling assumptions*: Most studies relied upon modelling simplifications and assumptions in order to overcome incomplete observability of the human kinematic chain (see Table II). Thirty-two studies assumed a known, or prior measured, position of the sensor system with respect to the human anatomical joints or segments, in particular with wearable sensors. Twenty-nine studies made assumptions on the physical human-robot interaction, assuming a known robot pose relative to human joints or segments and a rigid connection. Fourteen studies involved systems that required specific movements or poses to be performed prior for training, calibration or initialisation of the motion capture system. Thirteen studies assumed known segment lengths, requiring prior measurement of each human subject. Only one study proposed methods for determining segment lengths online for use in modelling the human kinematics [80]. Thirteen studies made assumptions on the pose of the human subject, constraining the kinematics by assuming a known or fixed joint.

### E. Experimental evaluation

Table IV summarises the experimental evaluation of the motion capture of the different studies. Most studies included human trials to experimentally evaluate the performance of a human motion capture system; however, trials were largely conducted in ideal conditions with a limited number of human subjects. Additionally, several failed to report sufficient protocol details such as number of subjects [41], [43], [46], [50], [52], [55], [56], [66], [67], [83]. Two studies provided simulation results only [84], [90].

The majority employed MBMC systems for ground truth measurements of joint positions and angles. Others employed more rudimentary measurement systems such as goniometers, auxiliary sensors (*i.e.* additional IMUs) or the robotic device as the ground truth. Most studies reported results as standard metrics, primarily as a Root-Mean-Squared Error (RMSE) (29 studies), a Pearson’s correlation (CORR) between measures (10 studies), difference in Range Of Motion ( $\Delta$ ROM) (6 studies) or occasionally as Mean Absolute Error (MAE) (5 studies). Still, several studies failed to report any meaningful numerical analysis relevant to human kinematics.

Some studies devised protocol for comparing different motion capture methods against a shared ground truth, whereby a proposed system and setup is operated

TABLE IV: Experimental evaluation details

Source	Subjects	Ground truth	Methods comparison	Metrics
[90]	N/A	N/A	-	RMSE
[84]	N/A	N/A	-	RMSE
[43]	nd	-	-	None
[83]	nd	-	-	None*
[56]	nd	-	-	MAE*
[66]	nd	-	Fusion models	RMSE
[41]	nd	MBMC (Vicon)	-	RMSE
[55]	nd	MBMC (Vicon)	-	MAE
[46]	nd	MBMC (Vicon)	-	None
[52]	nd	MBMC (Vicon)	ML models	RMSE CORR
[67]	nd	Robot	-	RMSE None
[49]	nd	Robot	RGB sensors	CORR
[50]	nd	Other sensors (IMU)	-	Other
[48]	1	Goniometer	-	None
[79]	1	Goniometer	-	RMSE*
[62]	1	Goniometer	-	RMSE
[45]	1	MBMC (BTS)	-	RMSE
[81]	1	MBMC (Qualysis)	-	MAE
[71]	1	MBMC (Vicon)	-	RMSE
[86]	2	MBMC (OptiTrack)	-	RMSE
[77]	2	MBMC (Vicon)	-	RMSE
[47]	2	Exoskeleton	-	Other
[44]	2†§	MBMC (Vicon)	-	MAE
[89]	3	MBMC (MAC3D)	Exoskeleton, IMU	None*
[69]	3	MBMC (Vicon)	-	CORR
[42]	3	MBMC (OptiTrack)	-	RMSE
[82]	3	MBMC (OptiTrack)	-	None*
[61]	4	MBMC (Vicon)	-	RMSE
[13]	4	MBMC (OptiTrack)	-	RMSE $\Delta$ ROM
[76]	4	MBMC (Codamotion)	Exoskeleton	RMSE $\Delta$ ROM CORR
[74]	4	MBMC (Polaris)	-	RMSE $\Delta$ ROM
[87]	5	MBMC (colour)	-	Median
[75]	5	MBMC (Vicon)	-	MAE
[57]	5	MBMC (PST Pico)	ML models	RMSE CORR MAE
[59]	5	Other sensors (IMU)	ML models	RMSE CORR
[65]	5	Exoskeleton	-	RMSE
[58]	5	-	Filter methods	MAE
[11]	4, 2†	MBMC (Smart-D)	-	RMSE*
[64]	7	Other sensors (IMU)	-	RMSE
[14]	8	MBMC (Vicon)	Kinect	RMSE
[70]	8	MBMC (Vicon)	-	$\Delta$ ROM
[51]	8	MBMC (Qualysis)	-	RMSE
[54]	8	MBMC (Qualysis)	-	RMSE
[80]	8	MBMC (OptiTrack)	IK methods	Other*
[78]	8	MBMC (colour)	-	Other
[72]	9	MBMC (OptiTrack)	-	RMSE
[73]	9	MBMC (OptiTrack)	-	RMSE CORR
[12]	10	MBMC (OptiTrack)	IMU	Other
[60]	10	Other sensors (IMU)	ML models	RMSE CORR
[63]	10	Goniometer	-	RMSE
[85]	7, 3†	MBMC (OptiTrack)	-	RMSE CORR
[88]	12	MBMC (Vicon)	-	RMSE $\Delta$ ROM CORR
[53]	12	MBMC (Vicon)	-	RMSE CORR
[68]	12	MBMC (Vicon)	-	$\Delta$ ROM

**Subjects**: “N/A” refers to simulation only without physical validation. “nd” refers to internal testing only where participants are not described. Multiple values indicates separate experiments. † Patient with neuromotor disorder, § Child participant (<12 years old)

**Methods comparison** details the other approaches tested and validated against the proposed method.

**Metrics**: “None” refers to missing relevant metrics for kinematics analysis. “Other” refers to non-standard metrics of kinematics evaluation. \* Relevant numerical results are missing or poorly displayed.

simultaneously with a baseline system such as IMU [12] or exoskeleton joint encoders [76], [89]. One studies reported comparisons of the individual constituent sub-systems or sub-algorithms in addition to the full proposed motion capture systems, specifically focusing on permutative configurations of MMC and robot pose information [14]. Similarly, some studies compared different modelling techniques, such as with EMG-based kinematics estimation [52], [59], [60] and inverse kinematic algorithms [80]. It should be noted, however, that as there is no consistent or standardised experimental protocol and analysis techniques between the included studies, no meaningful cross-study comparisons can be made.

See Supplementary Materials for full data extraction table.

#### IV. DISCUSSION

The studies included in this review encompass a broad range of robotic systems and experimental configurations. Robotic devices differ substantially in morphology, scale, actuation, and degrees of freedom, with representative examples shown in Fig. 3. This heterogeneity introduces system-specific constraints on human motion capture, as robot geometry and dynamics shape occlusion patterns, limit the feasibility of particular sensing modalities, and introduce interaction-induced disturbances that propagate into kinematic reconstruction.

Beyond robot design, PHRI inherently couples motion capture performance to the operational context in which interaction occurs. Motion capture may be deployed in environments such as physiotherapy clinics, industrial workspaces, or domestic settings, each imposing distinct constraints on sensing infrastructure, capture volume, and environmental robustness. These contextual factors directly influence which sensing architectures can be reliably integrated into the human-robot control loop. Moreover, the PHRI application defines the structure of human behaviour and task execution: controlled, repetitive movements performed from quasi-static base positions—typical of rehabilitation scenarios—permit simplified kinematic assumptions, whereas unstructured actions in dynamic or unsupervised environments require motion capture systems that are resilient to variability, occlusion, and non-stationarity.

Considering these observations, human motion tracking in PHRI cannot be treated as a context-independent problem. Effective motion capture must account for the interaction between sensing modality, robot morphology, task structure, and environmental constraints. This context-dependence is reflected in practice: most studies included in this review (74%) focus on rehabilitation applications, where controlled task settings and predictable human movements both facilitate kinematic reconstruction and demonstrate how application constraints directly shape sensing strategies, which are critical for closed-loop robotic control and objective assessment of motor performance and recovery.

To organise the discussion of the reviewed literature, four key themes are identified that capture the major challenges and opportunities in human motion capture for PHRI: (A) the limitations of current motion capture techniques in

PHRI contexts, (B) the potential of robotic systems to provide complementary information for human kinematic reconstruction, (C) the need for developing multi-modal sensor fusion strategies in PHRI, and (D) the lack of standardised or context-relevant evaluation approaches.

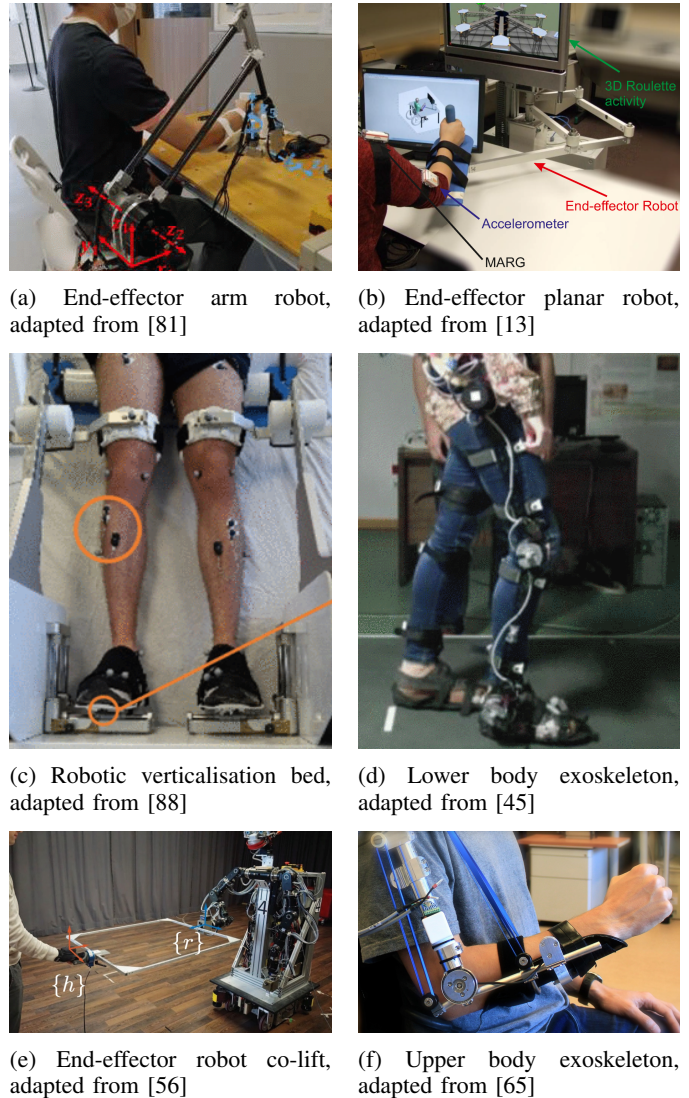


Fig. 3: Sample of included sources' robotic systems

##### A. Current motion capture techniques are not suitable in PHRI contexts

Human motion capture in PHRI contexts presents unique challenges, as sensors must operate reliably despite occlusions, environmental variability, and interference from robotic devices. Consequently, many standard motion capture techniques are often unsuitable without adaptation, and these limitations manifest differently across sensing modalities.

Vision-based approaches, such as MBMC and MMC, are particularly susceptible to errors caused by occlusions or constrained environments. For instance, Rubin et al. [44] evaluated a MMC for estimating lower limb joint angles with and without a lower limb exoskeleton; mean absolute

errors for knee and ankle angles increased by up to  $8.7^\circ$  when the exoskeleton was present. These findings illustrate how environmental constraints and robot morphology can substantially degrade vision-based tracking.

IMUs, while not affected by occlusion, provide reliable tracking only for short durations due to sensor drift. Their accuracy can also be compromised by nearby robotic devices that affect magnetometer readings [93]. Calibration procedures using motion or posture priors can improve performance [50], [54], but such methods are often impractical in PHRI, especially for users with motor impairments.

EMGs offer an alternative sensing modality but require prolonged subject-specific calibration to train predictive models. This requirement limits their applicability for real-world, unsupervised interactions, as extensive pre-session movement protocols are often infeasible.

Although single IMU or EMG sensors are minimally intrusive, full-body motion capture typically requires multiple wearable attachments, which can be bulky and restrict natural movement [94]. To achieve comprehensive kinematic tracking with a limited number of sensors, additional assumptions or complementary information (e.g., from robotic contacts or motion priors) are often needed, but such assumptions may not hold across diverse PHRI scenarios.

Across modalities, standard human motion capture techniques are frequently inadequate for PHRI applications. Effective tracking in these contexts would require either adaptations to the sensing method or enhancements to kinematic modelling, often involving multi-modal integration and careful consideration of the specific robotic and environmental context.

### *B. The robot can provide valuable information for human kinematic reconstruction*

In PHRI, robotic devices serve not only as actuators that assist or constrain human motion, but also as sensing tools that provide valuable information for reconstructing human kinematics. By measuring their own internal states at points of contact with the human, robots can offer precise data about the motion of constrained joints, complementing or even replacing conventional sensors that may be affected by occlusions, drift, or environmental factors. This dual role allows robotic devices to enhance the accuracy and reliability of human motion capture, particularly in scenarios where standard techniques struggle. The manner in which robot measurements inform human kinematics depends on the type of device and interaction. Exoskeletons, which directly constrain or actuate specific joints, can provide measurements closely aligned with the corresponding anatomical motions. In contrast, end-effector devices, splints, or hand grips only capture the position and orientation at the point of contact; full-body or joint-level reconstruction must then rely on additional modelling, assumptions, or sensor fusion techniques.

Despite their potential, robot-derived measurements are not inherently accurate representations of human motion. Exoskeletons, for example, are prone to joint misalignment [95], [96], as the device is externally attached and cannot

perfectly match anatomical joint axes. The human-robot interface—whether via cuffs, handles, or straps—is rarely rigid, and soft tissue deformation, uncertain attachment placement, and limited interface stiffness can all reduce measurement fidelity [97], [98].

Nevertheless, robot measurements can serve as ‘known’ positions within the human kinematic chain, reducing reliance on additional sensors and enabling calibration of other estimates. To fully leverage this information, it is essential to account for or model the rigidity and reliability of the human-robot connection [99], ensuring that the robot’s precise kinematic data effectively contributes to reconstructing human motion.

### *C. Sensor fusion techniques should be developed in PHRI*

While robotic devices can provide precise measurements at points of human-robot contact, these measurements alone are often insufficient to reconstruct the full kinematics of the human body. Conventional sensors, such as IMUs, EMGs, or vision-based systems, each have strengths and limitations—ranging from occlusion and drift to limited spatial coverage. Combining robot-derived data with complementary modalities through sensor fusion can therefore leverage the advantages of each system, improving overall accuracy and robustness of human motion capture in PHRI.

Currently, however, most studies employ multiple sensors in a rudimentary manner. In many cases, each sensor is treated independently: for example, a conventional motion capture system measures shoulder pose, robot contact measures wrist pose, and elbow pose is inferred subsequently [14], [87]. While analytically sound, this approach does not exploit the anatomical interdependence of human joints, limiting the potential benefit of combining multiple data sources. Only one study fused IMU and EMG using an extended Kalman filter [66], demonstrating that more sophisticated fusion approaches remain rare for PHRI.

An illustrative example comes from Yazdani et al. [100], who fused a markerless vision-based system with human-robot contact data using a particle filter. Here, a complete but low-robustness model (vision-based capture) was complemented by precise measurements at a single joint (robot contact) to estimate the full human arm posture. The fusion also mitigated artificially introduced occlusions in the vision system, significantly improving reliability. This highlights how complementary robotic measurements—drift-free, robust, and precise—can compensate for the shortcomings of conventional sensing modalities.

Complementary sensor fusion is widely employed in other robotics domains, often using Kalman filters, optimisation methods, support vector machines, neural networks, or probabilistic approaches such as Gaussian mixture models or particle filters [101]. Mobile robots, for instance, routinely fuse odometry, IMUs, GPS, and vision (via SLAM) to exploit the strengths of each modality [102]. The relative scarcity of similarly advanced fusion strategies in PHRI is therefore surprising, particularly given the complementary nature of robotic and conventional motion capture sensors.

In light of these observations, future work should focus on developing sensor fusion techniques that combine high-precision robot measurements with conventional sensors. Such approaches can substantially improve robustness and accuracy in human motion capture, enabling more reliable kinematic reconstruction for PHRI applications.

#### D. Approaches lack standardised or relevant evaluation

While sensor fusion and complementary use of robotic devices can improve human motion capture in PHRI, the quality and consistency of experimental evaluation remain critical limitations. Current research often suffers from poor reporting and limited experimental validation, making it difficult to assess the effectiveness and generalisability of proposed methods. Many studies include minimal sample testing and lack standardised protocols that are robust to variations in robotic devices, joints measured, or task constraints (see Table IV).

Where experimentation was conducted, some studies exhibited inconsistent metrics, incomplete numerical or visual results, and insufficient methodological detail. This variability complicates meaningful comparison across studies, and hinders replication and cumulative knowledge building. Even though direct comparison may sometimes be challenging due to differences in robots, joints, or tasks, approaches should still be evaluated systematically.

To improve rigour and reproducibility, future research should provide: (1) comparison to accurate ground-truth measurements; (2) clear validation against existing methods or baselines; (3) detailed descriptions of the evaluation protocol, including performed movements and task duration; and (4) precise documentation of experimental conditions, such as robotic device, human-robot attachment points, and marker placement (if applicable). Additionally, given the variability in human participants (e.g., body composition, movement patterns), evaluations should include sufficient sample sizes to assess robustness and repeatability, ensuring that sensor systems perform reliably across diverse users.

#### E. Limitations of this review

This review has several important limitations that should be considered when interpreting the results.

1) *Terminology inconsistencies*: The lack of standardised terminology in PHRI research made systematic searching challenging. Definitions of physical Human-Robot Interaction vary across fields (e.g., medical, computer science, engineering) and even between studies, particularly regarding the proximity, directness, and continuity of interaction. Similarly, what constitutes a “robot” is inconsistently defined, leading to potential exclusion of studies using passive devices with only measurement functionality. As a result, some relevant studies may not have been identified.

2) *Scope constraints*: To focus the review, only studies exploring human motion capture with potential to ‘close the loop’—i.e., using motion capture to inform robot actions—were included. Studies with intermittent contact (e.g., hand-off tasks) or purely observational robots were excluded,

even if they provided insights relevant to human motion capture. These criteria may have omitted work relevant to industrial or assistive robotics contexts.

3) *Variability in motion capture terminology*: Terms such as “human motion capture” and “human kinematics” were inconsistently applied in the literature. For this review, we defined “human motion capture” as capturing large-scale body movements at sufficient resolution [36], excluding fine-scale gestures or facial expressions. “Human kinematics” refers to gross limb segment movements quantified through anatomical joint centre positions and joint angles [103]. Studies using alternative terminology may have been missed.

4) *Limited methodological reporting*: As highlighted in Section IV-D, many studies provided insufficient details on experimental setup, sensor calibration, modelling assumptions, and constraints. Consequently, data extraction was restricted to explicitly reported or clearly inferred information, which may limit the completeness and reproducibility of the review’s findings.

Taken together, these limitations highlight that while this review provides a structured overview of motion capture in PHRI, it is constrained by terminology inconsistencies, scope decisions, and incomplete reporting in the literature. Future work should aim for standardised terminology, broader inclusion criteria, and rigorous methodological reporting to improve the completeness and generalisability of systematic reviews in this field.

## V. CONCLUSION

Physical Human-Robot Interaction (PHRI) is becoming increasingly prevalent in assistive and rehabilitation applications, where humans share physical space with robots and maintain continuous contact. Accurate human motion capture in these contexts is essential for understanding how humans move and for enabling robots to respond safely and effectively, thereby ‘closing the loop’ in human-robot collaboration. However, many conventional motion capture techniques face limitations in PHRI: vision-based systems are prone to occlusions and environmental variability, while inertial systems can be disturbed by robot-induced forces or surrounding conditions, and both approaches often require calibration and multiple wearable sensors, increasing complexity and setup time. Although some methods exist to mitigate these challenges, robustness and practicality remain limited. Very few techniques are specifically designed for PHRI, yet robotic devices themselves can provide valuable measurements that complement conventional motion capture. Future work should therefore focus on sensor fusion approaches that integrate traditional motion capture with robot-derived information to achieve more complete and reliable human kinematic reconstruction. In parallel, the field would benefit from standardised terminology and more systematic evaluation protocols to allow meaningful comparison across studies and facilitate the implementation of the most effective motion capture techniques in real-world PHRI scenarios.

## REFERENCES

- [1] K. Horan and G. Paggetti, "White paper: Collaborative robotics," Irish Manufacturing Research, Rathcoole, Co. Dublin, Ireland., Tech. Rep., January 2020. [Online]. Available: <https://imr.ie/wp-content/uploads/2020/05/Cobotics-White-Paper.pdf>
- [2] L. Dong and G. Morel, "Robust trocar detection and localization during robot-assisted endoscopic surgery," in *2016 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2016, pp. 4109–4114.
- [3] M.-A. Vitrani, M. Baumann, D. Reversat, G. Morel, A. Moreau-Gaudry, and P. Mozer, "Prostate biopsies assisted by comanipulated probe-holder: first in man," *International Journal of Computer Assisted Radiology and Surgery*, vol. 11, pp. 1153–1161, 2016.
- [4] M. Roizenblatt, A. T. Grupenmacher, R. B. Junior, M. Maia, and P. L. Gehlbach, "Robot-assisted tremor control for performance enhancement of retinal microsurgions," *British Journal of Ophthalmology*, vol. 103, no. 8, pp. 1195–1200, 2019.
- [5] A. Nassar, F. Vérité, F. Pechereau, G. Morel, and M.-A. Vitrani, "Adaptive damping assistance in bimanual laparoscopic surgery," *International Journal of Computer Assisted Radiology and Surgery*, vol. 18, no. 4, pp. 741–751, 2023.
- [6] P. Maciejasz, J. Eschweiler, K. Gerlach-Hahn, A. Jansen-Troy, and S. Leonhardt, "A survey on robotic devices for upper limb rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, vol. 11, pp. 1–29, 2014.
- [7] D. R. Louie and J. J. Eng, "Powered robotic exoskeletons in post-stroke rehabilitation of gait: a scoping review," *Journal of NeuroEngineering and Rehabilitation*, vol. 13, pp. 1–10, 2016.
- [8] S. Khalid, F. Alnajjar, M. Gochoo, A. Renawi, and S. Shimoda, "Robotic assistive and rehabilitation devices leading to motor recovery in upper limb: a systematic review," *Disability and Rehabilitation: Assistive Technology*, vol. 18, no. 5, pp. 658–672, 2023.
- [9] L. Mündermann, S. Corazza, and T. P. Andriacchi, "The evolution of methods for the capture of human movement leading to markerless motion capture for biomechanical applications," *Journal of NeuroEngineering and Rehabilitation*, vol. 3, pp. 1–11, 2006.
- [10] S. Haddadin and E. Croft, "Physical human-robot interaction," *Springer handbook of robotics*, pp. 1835–1874, 2016.
- [11] E. Papaleo, L. Zollo, N. Garcia-Aracil, F. J. Badesa, R. Morales, S. Mazzoleni, S. Sterzi, and E. Guglielmelli, "Upper-limb kinematic reconstruction during stroke robot-aided therapy," *Medical & Biological Engineering & Computing*, vol. 53, no. 9, p. 815–828, apr 2015. [Online]. Available: <http://dx.doi.org/10.1007/s11517-015-1276-9>
- [12] J. L. Samper-Escudero, A. F. Contreras-González, M. Ferre, M. A. Sánchez-Urán, and D. Pont-Esteban, "Efficient multi-axial shoulder-motion tracking based on flexible resistive sensors applied to exosuits," *Soft Robotics*, vol. 7, no. 3, p. 370–385, jun 2020. [Online]. Available: <http://dx.doi.org/10.1089/soro.2019.0040>
- [13] A. Bertomeu-Motos, L. Lledó, J. Díez, J. Catalan, S. Ezquerro, F. Badesa, and N. Garcia-Aracil, "Estimation of human arm joints using two wireless sensors in robotic rehabilitation tasks," *Sensors*, vol. 15, no. 12, p. 30571–30583, dec 2015. [Online]. Available: <http://dx.doi.org/10.3390/s151229818>
- [14] Y. Hwang, S. Lee, J. Hong, and J. Kim, "A novel end-effector robot system enabling to monitor upper-extremity posture during robot-aided planar reaching movements," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, p. 3035–3041, apr 2020. [Online]. Available: <http://dx.doi.org/10.1109/LRA.2020.2974453>
- [15] R. Alami, A. Albu-Schäffer, A. Bicchi, R. Bischoff, R. Chatila, A. De Luca, A. De Santis, G. Giralt, J. Guiochet, G. Hirzinger *et al.*, "Safe and dependable physical human-robot interaction in anthropic domains: State of the art and challenges," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2006, pp. 1–16.
- [16] A. De Santis, B. Siciliano, A. De Luca, and A. Bicchi, "An atlas of physical human-robot interaction," *Mechanism and Machine Theory*, vol. 43, no. 3, pp. 253–270, 2008.
- [17] J. Bray, "Markerless based human motion capture: a survey," *Department Systems Engineering Brunel University*, 2001.
- [18] Y. Desmarais, D. Mottet, P. Slangen, and P. Montesinos, "A review of 3d human pose estimation algorithms for markerless motion capture," *Computer Vision and Image Understanding*, vol. 212, p. 103275, 2021.
- [19] B. R. Hindle, J. W. Keogh, and A. V. Lorimer, "Inertial-based human motion capture: A technical summary of current processing methodologies for spatiotemporal and kinematic measures," *Applied Bionics and Biomechanics*, vol. 2021, no. 1, p. 6628320, 2021.
- [20] M. Menolotto, D.-S. Komaris, S. Tedesco, B. O'Flynn, and M. Walsh, "Motion capture technology in industrial applications: A systematic review," *Sensors*, vol. 20, no. 19, p. 5687, 2020.
- [21] T. B. Moeslund, A. Hilton, and V. Krüger, "A survey of advances in vision-based human motion capture and analysis," *Computer Vision and Image Understanding*, vol. 104, no. 2-3, pp. 90–126, 2006.
- [22] Z. Niu, K. Lu, J. Xue, X. Qin, J. Wang, and L. Shao, "From method to application: A review of deep 3d human motion capture," *IEEE Transactions on Circuits and Systems for Video Technology*, 2024.
- [23] E. Van der Kruk and M. M. Reijne, "Accuracy of human motion capture systems for sport applications; state-of-the-art review," *European journal of sport science*, vol. 18, no. 6, pp. 806–819, 2018.
- [24] M. Yahya, J. A. Shah, K. A. Kadir, Z. M. Yusof, S. Khan, and A. Warsi, "Motion capture sensing techniques used in human upper limb motion: A review," *Sensor Review*, vol. 39, no. 4, pp. 504–511, 2019.
- [25] J. K. Aggarwal and Q. Cai, "Human motion analysis: A review," *Computer Vision and Image Understanding*, vol. 73, no. 3, pp. 428–440, 1999.
- [26] A. Filippeschi, N. Schmitz, M. Miezal, G. Bleser, E. Ruffaldi, and D. Stricker, "Survey of motion tracking methods based on inertial sensors: A focus on upper limb human motion," *Sensors*, vol. 17, no. 6, p. 1257, 2017.
- [27] L. Wang, W. Hu, and T. Tan, "Recent developments in human motion analysis," *Pattern recognition*, vol. 36, no. 3, pp. 585–601, 2003.
- [28] C. Fang, L. Peternel, A. Seth, M. Sartori, K. Mombaur, and E. Yoshida, "Human modeling in physical human-robot interaction: A brief survey," *IEEE Robotics and Automation Letters*, 2023.
- [29] T. Xue, W. Wang, J. Ma, W. Liu, Z. Pan, and M. Han, "Progress and prospects of multimodal fusion methods in physical human-robot interaction: A review," *IEEE Sensors Journal*, vol. 20, no. 18, pp. 10 355–10 370, 2020.
- [30] H. Zhou and H. Hu, "Human motion tracking for rehabilitation—a survey," *Biomedical signal processing and control*, vol. 3, no. 1, pp. 1–18, 2008.
- [31] Vicon Motion Systems Ltd., "Vicon Motion Capture System," <https://www.vicon.com>, 2025, accessed: YYYY-MM-DD.
- [32] OptiTrack, NaturalPoint Inc., "OptiTrack Motion Capture System," <https://www.optitrack.com>, 2025, accessed: 2025-08-09.
- [33] S. R. Simon, "Quantification of human motion: gait analysis—benefits and limitations to its application to clinical problems," *Journal of biomechanics*, vol. 37, no. 12, pp. 1869–1880, 2004.
- [34] S. Chen, J. Lach, B. Lo, and G.-Z. Yang, "Toward pervasive gait analysis with wearable sensors: A systematic review," *IEEE journal of biomedical and health informatics*, vol. 20, no. 6, pp. 1521–1537, 2016.
- [35] C. Buckley, L. Alcock, R. McArdle, R. Z. U. Rehman, S. Del Din, C. Mazzà, A. J. Yarnall, and L. Rochester, "The role of movement analysis in diagnosing and monitoring neurodegenerative conditions: Insights from gait and postural control," *Brain sciences*, vol. 9, no. 2, p. 34, 2019.
- [36] T. B. Moeslund and E. Granum, "A survey of computer vision-based human motion capture," *Computer Vision and Image Understanding*, vol. 81, no. 3, pp. 231–268, 2001.
- [37] I. Weygers, M. Kok, M. Konings, H. Hallez, H. De Vroey, and K. Claeys, "Inertial sensor-based lower limb joint kinematics: A methodological systematic review," *Sensors*, vol. 20, no. 3, p. 673, 2020.
- [38] A. Muro-De-La-Herran, B. Garcia-Zapirain, and A. Mendez-Zorrilla, "Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications," *Sensors*, vol. 14, no. 2, pp. 3362–3394, 2014.
- [39] W. Tao, T. Liu, R. Zheng, and H. Feng, "Gait analysis using wearable sensors," *Sensors*, vol. 12, no. 2, pp. 2255–2283, 2012.
- [40] F. Sylos-Labini, V. La Scaleia, A. d'Avella, I. Pisotta, F. Tamburella, G. Scivoletto, M. Molinari, S. Wang, L. Wang, E. van Asseldonk *et al.*, "Emg patterns during assisted walking in the exoskeleton," *Frontiers in human neuroscience*, vol. 8, p. 423, 2014.
- [41] A. Sepehri, M. T. Tolley, and T. K. Morimoto, "Retrofitting soft assistive robots with sew-free sensing garments for joint motion tracking and kinematic feedback," in *2025 International Conference On Rehabilitation Robotics (ICORR)*. IEEE, may 2025, p. 1–7. [Online]. Available: <http://dx.doi.org/10.1109/ICORR66766.2025.11062992>
- [42] D. Pont-Esteban, A. F. Contreras-González, J. L. Samper-Escudero, F. J. Sáez-Sáez, M. Ferre, and M. a. Sánchez-Urán, "Validation of an elbow position super-twisting sliding-mode controller for upper-limb

- exosuit using a soft position sensor,” *Journal of Physics: Conference Series*, vol. 1828, no. 1, p. 012074, feb 2021. [Online]. Available: <http://dx.doi.org/10.1088/1742-6596/1828/1/012074>
- [43] N. Ghobadi, W. Kinsner, T. Szturm, and N. Sepehri, “Design and evaluation of a soft robotic actuator with non-intrusive vision-based bending measurement,” *Sensors*, vol. 25, no. 13, p. 3858, jun 2025. [Online]. Available: <http://dx.doi.org/10.3390/s25133858>
- [44] N. Rubin, J. Dembsky, D. L. Damiano, and T. C. Bulea, “Effects of exoskeletons on error between marker and markerless motion capture in children with crouch gait: A pilot study,” in *2025 International Conference On Rehabilitation Robotics (ICORR)*. IEEE, may 2025, p. 1–6. [Online]. Available: <http://dx.doi.org/10.1109/ICORR66766.2025.11062947>
- [45] M. T. Alvarez, D. Torricelli, A. J. del Ama, D. Pinto, J. Gonzalez-Vargas, J. C. Moreno, A. Gil-Agudo, and J. L. Pons, “Simultaneous estimation of human and exoskeleton motion: A simplified protocol,” in *2017 International Conference on Rehabilitation Robotics (ICORR)*. IEEE, jul 2017, p. 1431–1436. [Online]. Available: <http://dx.doi.org/10.1109/ICORR.2017.8009449>
- [46] A. Lioulemes, M. Theofanidis, and F. Makedon, “Quantitative analysis of the human upper-limb kinematic model for robot-based rehabilitation applications,” in *2016 IEEE International Conference on Automation Science and Engineering (CASE)*. IEEE, aug 2016, p. 1061–1066. [Online]. Available: <http://dx.doi.org/10.1109/COASE.2016.7743521>
- [47] S. K. Manna and V. N. Dubey, “Assessment of joint parameters in a kinect sensor based rehabilitation game,” in *Volume 1: 39th Computers and Information in Engineering Conference*, ser. IDETC-CIE2019. American Society of Mechanical Engineers, aug 2019. [Online]. Available: <http://dx.doi.org/10.1115/DETC2019-97519>
- [48] S. Yoon, Y.-S. Li-Baboud, A. Virts, R. Bostelman, and M. Shah, “Feasibility of using depth cameras for evaluating human - exoskeleton interaction,” *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 66, no. 1, p. 1892–1896, sep 2022. [Online]. Available: <http://dx.doi.org/10.1177/10711813222661190>
- [49] B. Gandhi, L. Mihaylova, and S. Dogramadzi, “Head tracking using an optical soft tactile sensing surface,” *Frontiers in Robotics and AI*, vol. 11, jul 2024. [Online]. Available: <http://dx.doi.org/10.3389/frobt.2024.1410858>
- [50] D. Nowka, M. Kok, and T. Seel, “On motions that allow for identification of hinge joint axes from kinematic constraints and 6d imu data,” in *2019 18th European Control Conference (ECC)*. IEEE, jun 2019, p. 4325–4331. [Online]. Available: <http://dx.doi.org/10.23919/ECC.2019.8795846>
- [51] S. Y. Song, Y. Guo, C. Yuan, N. Marin, C. Xiao, A. Bleakney, J. Elliott, J. Ramos, and E. T. Hsiao-Wecksler, “Design and validation of a torso-dynamics estimation system (tes) for hands-free physical human-robot interaction\*,” in *2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. IEEE, aug 2023, p. 171–178. [Online]. Available: <http://dx.doi.org/10.1109/RO-MAN57019.2023.10309422>
- [52] X. YUE, A. ZHU, J. SONG, G. CAO, D. AN, and Z. GUO, “The design and implementation of human motion capture system based on can bus,” in *2020 17th International Conference on Ubiquitous Robots (UR)*. IEEE, jun 2020, p. 415–420. [Online]. Available: <http://dx.doi.org/10.1109/UR49135.2020.9144858>
- [53] W. Yin, Y. Chen, C. Reddy, L. Zheng, R. K. Mehta, and X. Zhang, “Flexible sensor-based biomechanical evaluation of low-back exoskeleton use in lifting,” *Ergonomics*, vol. 67, no. 2, p. 182–193, may 2023. [Online]. Available: <http://dx.doi.org/10.1080/00140139.2023.2216408>
- [54] T. Proietti, C. O’Neill, C. J. Hohimer, K. Nuckols, M. E. Clarke, Y. M. Zhou, D. J. Lin, and C. J. Walsh, “Sensing and control of a multi-joint soft wearable robot for upper-limb assistance and rehabilitation,” *IEEE Robotics and Automation Letters*, vol. 6, no. 2, p. 2381–2388, apr 2021. [Online]. Available: <http://dx.doi.org/10.1109/LRA.2021.3061061>
- [55] L. Chen, J. Qiu, X. Zou, and H. Cheng, “A dual-arm participated human-robot collaboration method for upper limb rehabilitation of hemiplegic patients,” in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, may 2023, p. 12617–12623. [Online]. Available: <http://dx.doi.org/10.1109/ICRA48891.2023.10160949>
- [56] D. Cehajic, S. Erhart, and S. Hirsche, “Grasp pose estimation in human-robot manipulation tasks using wearable motion sensors,” in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, sep 2015. [Online]. Available: <http://dx.doi.org/10.1109/IROS.2015.7353497>
- [57] D. Wei, J. Gong, Z. Tang, Z. Liu, T. Gao, and F. Ficuciello, “Amip-n: Ankle motion intention prediction network combined tcn, lstm, and wavelet multi-head self-attention based on imus,” *Biomedical Signal Processing and Control*, vol. 111, p. 108282, jan 2026. [Online]. Available: <http://dx.doi.org/10.1016/j.bspc.2025.108282>
- [58] S. Qiu, W. Guo, D. Caldwell, and F. Chen, “Exoskeleton online learning and estimation of human walking intention based on dynamical movement primitives,” *IEEE Transactions on Cognitive and Developmental Systems*, vol. 13, no. 1, p. 67–79, mar 2021. [Online]. Available: <http://dx.doi.org/10.1109/TCDS.2020.2968845>
- [59] M. Zeng, J. Gu, and Y. Feng, “Motion prediction based on semg-transformer for lower limb exoskeleton robot control,” in *2023 International Conference on Advanced Robotics and Mechatronics (ICARM)*. IEEE, jul 2023, p. 864–869. [Online]. Available: <http://dx.doi.org/10.1109/ICARM58088.2023.10218920>
- [60] H. Li, S. Guo, D. Bu, H. Wang, and M. Kawanishi, “Subject-independent estimation of continuous movements using cnn-lstm for a home-based upper limb rehabilitation system,” *IEEE Robotics and Automation Letters*, vol. 8, no. 10, p. 6403–6410, oct 2023. [Online]. Available: <http://dx.doi.org/10.1109/LRA.2023.3303701>
- [61] B. Wei, Z. Ding, C. Yi, H. Guo, Z. Wang, J. Zhu, and F. Jiang, “A novel semg-based gait phase-kinematics-coupled predictor and its interaction with exoskeletons,” *Frontiers in Neurobotics*, vol. 15, aug 2021. [Online]. Available: <http://dx.doi.org/10.3389/fnbot.2021.704226>
- [62] J. Chen, Y. Tao, Y. Huang, Z. Zhao, and S. Zhou, *Joint Angle Prediction of Lower Extremity Exoskeleton Based on sEMG Signal*. Springer Singapore, oct 2021, p. 677–688. [Online]. Available: [http://dx.doi.org/10.1007/978-981-16-6324-6\\_68](http://dx.doi.org/10.1007/978-981-16-6324-6_68)
- [63] Y. Huang, K. Chen, X. Zhang, K. Wang, and J. Ota, “Motion estimation of elbow joint from semg using continuous wavelet transform and back propagation neural networks,” *Biomedical Signal Processing and Control*, vol. 68, p. 102657, jul 2021. [Online]. Available: <http://dx.doi.org/10.1016/j.bspc.2021.102657>
- [64] C. Li, L. Luo, Z. Liu, T. Chen, S. Liu, Y. He, X. Chen, L. Li, and W. T. Ang, “Adaptive control of lower-limb exoskeletons for walking assistance based on inter-joint coordination,” *Journal of Bionic Engineering*, vol. 21, no. 4, p. 1775–1787, may 2024. [Online]. Available: <http://dx.doi.org/10.1007/s42235-024-00537-z>
- [65] T. Desplenter, J. Lobo-Prat, A. H. A. Stienen, and A. L. Trejos, “Extension of the wearme framework for emg-driven control of a wearable assistive exoskeleton,” in *2016 IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*. IEEE, jul 2016, p. 288–293. [Online]. Available: <http://dx.doi.org/10.1109/AIM.2016.7576781>
- [66] X. Wang, X. Li, J. Wang, and T. Luo, “A kinect-based trajectory capturing and tracking scheme for upper-limb robot-aided rehabilitation,” in *2017 IEEE 7th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER)*. IEEE, jul 2017, p. 249–254. [Online]. Available: <http://dx.doi.org/10.1109/CYBER.2017.8446204>
- [67] T. B. Tuli, M. Manns, and S. Zeller, “Human motion quality and accuracy measuring method for human–robot physical interactions,” *Intelligent Service Robotics*, vol. 15, no. 4, p. 503–512, jul 2022. [Online]. Available: <http://dx.doi.org/10.1007/s11370-022-00432-8>
- [68] J. G. Perez Blanco, M. Josué Valenzuela Cruz, L. V. Carrasco, N. Andrés Castellanos Velandia, L. C. Félix-Herrán, and J. Carlos Huegel West, “Kinematic validation of a wrist training robotic device,” in *2024 IEEE 37th International Symposium on Computer-Based Medical Systems (CBMS)*. IEEE, jun 2024, p. 37–42. [Online]. Available: <http://dx.doi.org/10.1109/CBMS61543.2024.00015>
- [69] M. R. Haque, M. H. Imtiaz, S. T. Kwak, E. Sazonov, Y.-H. Chang, and X. Shen, “A lightweight exoskeleton-based portable gait data collection system,” *Sensors*, vol. 21, no. 3, p. 781, jan 2021. [Online]. Available: <http://dx.doi.org/10.3390/s21030781>
- [70] L. Liu, L. Xie, Y.-Y. Shi, and B.-C. An, “Generation of a movement scheme for positive training,” *Frontiers in Neuroscience*, vol. 11, mar 2017. [Online]. Available: <http://dx.doi.org/10.3389/fnins.2017.00096>
- [71] A. C. de Oliveira, K. Warburton, Y. Yun, E. M. Ogden, J. Sulzer, and A. D. Deshpande, “Arm kinematics estimation with the harmony exoskeleton,” in *2017 International Symposium on Wearable Robotics and Rehabilitation (WeRob)*. IEEE, nov 2017, p. 1–2. [Online]. Available: <http://dx.doi.org/10.1109/WEROB.2017.8383839>
- [72] C. G. Rose, C. K. Kann, A. D. Deshpande, and M. K. O’Malley, “Estimating anatomical wrist joint motion with a robotic exoskeleton,” in *2017 International Conference on Rehabilitation*

- Robotics (ICORR)*. IEEE, jul 2017, p. 1437–1442. [Online]. Available: <http://dx.doi.org/10.1109/ICORR.2017.8009450>
- [73] A. C. De Oliveira, J. S. Sulzer, and A. D. Deshpande, “Assessment of upper-extremity joint angles using harmony exoskeleton,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, p. 916–925, 2021. [Online]. Available: <http://dx.doi.org/10.1109/TNSRE.2021.3074101>
- [74] C. Cortés, A. Ardanza, F. Molina-Rueda, A. Cuesta-Gómez, L. Unzueta, G. Epelde, O. E. Ruiz, A. De Mauro, and J. Florez, “Upper limb posture estimation in robotic and virtual reality-based rehabilitation,” *BioMed Research International*, vol. 2014, p. 1–18, 2014. [Online]. Available: <http://dx.doi.org/10.1155/2014/821908>
- [75] A. Pereira, G. Stillfried, T. Baker, A. Schmidt, A. Maier, B. Pleintinger, Z. Chen, T. Hulin, and N. Y. Lii, “Reconstructing human hand pose and configuration using a fixed-base exoskeleton,” in *2019 International Conference on Robotics and Automation (ICRA)*. IEEE, may 2019, p. 3514–3520. [Online]. Available: <http://dx.doi.org/10.1109/ICRA.2019.8794059>
- [76] C. Cortés, A. de los Reyes-Guzmán, D. Scorza, a. Bertelsen, E. Carrasco, a. Gil-Agudo, O. Ruiz-Salguero, and J. Flórez, “Inverse kinematics for upper limb compound movement estimation in exoskeleton-assisted rehabilitation,” *BioMed Research International*, vol. 2016, p. 1–14, 2016. [Online]. Available: <http://dx.doi.org/10.1155/2016/2581924>
- [77] M. Dežman, C. Marquardt, and T. Asfour, “Mapping encoder values to ankle angles in a 3 dof parallel ankle exoskeleton,” in *2025 International Conference On Rehabilitation Robotics (ICORR)*. IEEE, may 2025, p. 326–332. [Online]. Available: <http://dx.doi.org/10.1109/ICORR66766.2025.11063214>
- [78] E. Peperoni, S. L. Capitani, T. Fiumalbi, E. Capotorti, A. Baldoni, F. Dell’Agnello, I. Creatini, E. Taglione, N. Vitiello, E. Trigili, and S. Crea, “Self-aligning finger exoskeleton for the mobilization of the metacarpophalangeal joint,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, p. 884–894, 2023. [Online]. Available: <http://dx.doi.org/10.1109/TNSRE.2023.3236070>
- [79] T. Kadokura, T. Miyazaki, T. Kawase, M. Sogabe, and K. Kawashima, “Posture estimation by clustering pressure information and control implementation for pneumatically driven gait-assistive robot,” *IEEE Access*, vol. 11, p. 35874–35887, 2023. [Online]. Available: <http://dx.doi.org/10.1109/ACCESS.2023.3265580>
- [80] A. Yazdani, R. S. Novin, A. Merryweather, and T. Hermans, “Is the leader robot an adequate sensor for posture estimation and ergonomic assessment of a human teleoperator?” in *2021 IEEE 17th International Conference on Automation Science and Engineering (CASE)*. IEEE, aug 2021, p. 1946–1952. [Online]. Available: <http://dx.doi.org/10.1109/CASE49439.2021.9551471>
- [81] S. Yang, L. Luo, M. Liu, J. Chen, W. C. Law, M. Yuan, L. Li, and W. T. Ang, “Adaptive gravity compensation framework based on human upper limb model for assistive robotic arm extender,” in *2023 International Conference on Rehabilitation Robotics (ICORR)*. IEEE, sep 2023, p. 1–6. [Online]. Available: <http://dx.doi.org/10.1109/ICORR58425.2023.10304690>
- [82] R. Khonasty, M. G. Carmichael, D. Liu, and K. J. Waldron, “Upper body pose estimation utilizing kinematic constraints from physical human-robot interaction,” in *Australasian Conference on Robotics and Automation, ACRA*, 2017.
- [83] G. Avallone, E. Monari, Y. Chen, L. Agostini, N. Sancisi, and R. Verthey, *A COBOT-IMU Hand-Guiding System with Online Collision Avoidance in Null Space*. Springer International Publishing, 2022, p. 151–159. [Online]. Available: [http://dx.doi.org/10.1007/978-3-031-06409-8\\_16](http://dx.doi.org/10.1007/978-3-031-06409-8_16)
- [84] A. Bertomeu-Motos, R. Morales, L. D. Lledo, J. A. Diez, J. M. Catalan, and N. Garcia-Aracil, “Kinematic reconstruction of the human arm joints in robot-aided therapies with hermes robot,” in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, aug 2015, p. 1190–1193. [Online]. Available: <http://dx.doi.org/10.1109/EMBC.2015.7318579>
- [85] A. Bertomeu-Motos, A. Blanco, F. J. Badesa, J. A. Barrios, L. Zollo, and N. Garcia-Aracil, “Human arm joints reconstruction algorithm in rehabilitation therapies assisted by end-effector robotic devices,” *Journal of NeuroEngineering and Rehabilitation*, vol. 15, no. 1, feb 2018. [Online]. Available: <http://dx.doi.org/10.1186/s12984-018-0348-0>
- [86] A. Bertomeu-Motos, R. Morales, J. A. Diez, L. D. Lledo, F. J. Badesa, and N. Garcia-Aracil, “Kinematic reconstruction of the upper limb joints in planar robot-aided therapies,” in *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)*. IEEE, aug 2015, p. 888–893. [Online]. Available: <http://dx.doi.org/10.1109/ICORR.2015.7281315>
- [87] A. Passon, T. Schauer, and T. Seel, “Inertial-robotic motion tracking in end-effector-based rehabilitation robots,” *Frontiers in Robotics and AI*, vol. 7, nov 2020. [Online]. Available: <http://dx.doi.org/10.3389/frobt.2020.554639>
- [88] K. K. Peper, E. R. Jensen, and S. Haddadin, “Estimating joint kinematics and muscles forces during robotic rehabilitation to detect and counteract reduced ankle mobility,” in *2023 International Conference on Rehabilitation Robotics (ICORR)*. IEEE, sep 2023, p. 1–6. [Online]. Available: <http://dx.doi.org/10.1109/ICORR58425.2023.10304782>
- [89] T. Sugino, Y. Shimoda, M. Okui, and T. Nakamura, “Knee joint assist method focusing on joint viscosity properties using imu - based exoskeleton assist device,” in *2024 16th International Conference on Human System Interaction (HSI)*. IEEE, jul 2024, p. 1–7. [Online]. Available: <http://dx.doi.org/10.1109/HSI61632.2024.10613543>
- [90] C. Cortés, L. Unzueta, A. de los Reyes-Guzmán, O. E. Ruiz, and J. Flórez, “Optical enhancement of exoskeleton-based estimation of glenohumeral angles,” *Applied Bionics and Biomechanics*, vol. 2016, p. 1–20, 2016. [Online]. Available: <http://dx.doi.org/10.1155/2016/5058171>
- [91] G. Ates, M. F. Stolen, and E. Kyrkjæbo, “A framework for human motion estimation using imus in human-robot interaction,” in *2022 IEEE International Conference on Industrial Technology (ICIT)*. IEEE, aug 2022, p. 1–8. [Online]. Available: <http://dx.doi.org/10.1109/ICIT48603.2022.10002746>
- [92] —, “Force and gesture-based motion control of human-robot cooperative lifting using imus,” in *2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, mar 2022, p. 688–692. [Online]. Available: <http://dx.doi.org/10.1109/HRI53351.2022.9889450>
- [93] S. A. Salinas, M. Berjjs, K. Grolinger, and A. L. Trejos, “Estimating thorax and shoulder motion using magnetic-free quaternion-based functional sensor-to-segment calibration,” in *2025 International Conference On Rehabilitation Robotics (ICORR)*, 2025, pp. 1–8.
- [94] X. Liu, J. Li, H. Zeng, X. Zhang, and T. Liu, “A dual-module-driven method for foot posture indirect measurement with potential application in rehabilitation robots,” *IEEE Transactions on Instrumentation and Measurement*, vol. 74, pp. 1–9, 2025.
- [95] N. Jarrassé and G. Morel, “Connecting a human limb to an exoskeleton,” *IEEE Transactions on Robotics*, vol. 28, no. 3, pp. 697–709, 2011.
- [96] R. Mallat, M. Khalil, G. Venture, V. Bonnet, and S. Mohammed, “Human-exoskeleton joint misalignment: A systematic review,” in *2019 Fifth International Conference on Advances in Biomedical Engineering (ICABME)*, 2019, pp. 1–4.
- [97] M. B. Näf, K. Junius, M. Rossini, C. Rodriguez-Guerrero, B. Vanderborght, and D. Lefeber, “Misalignment compensation for full human-exoskeleton kinematic compatibility: State of the art and evaluation,” *Applied Mechanics Reviews*, vol. 70, no. 5, p. 050802, 2018.
- [98] Y. Akiyama, S. Okamoto, Y. Yamada, and K. Ishiguro, “Measurement of contact behavior including slippage of cuff when using wearable physical assistant robot,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 7, pp. 784–793, 2015.
- [99] M. Sun, T. Baček, D. Kulić, J. McGinley, D. Oetomo, and Y. Tan, “Modelling physical human-robot interface with different users, cuffs, and strapping pressures: A case study,” in *2023 International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2023, pp. 1–6.
- [100] A. Yazdani, R. S. Novin, A. Merryweather, and T. Hermans, “Occlusion-robust multi-sensory posture estimation in physical human-robot interaction,” *arXiv preprint arXiv:2208.06494*, 2022.
- [101] M. L. Fung, M. Z. Q. Chen, and Y. H. Chen, “Sensor fusion: A review of methods and applications,” in *2017 29th Chinese Control And Decision Conference (CCDC)*, 2017, pp. 3853–3860.
- [102] M. B. Alatisé and G. P. Hancke, “A review on challenges of autonomous mobile robot and sensor fusion methods,” *IEEE Access*, vol. 8, pp. 39 830–39 846, 2020.
- [103] K.-N. An, “Kinematic analysis of human movement,” *Annals of biomedical engineering*, vol. 12, pp. 585–597, 1984.

## APPENDIX

## A. Search strategy

1) Search queries: The following lines can be used to replicate search results for the databases IEEE, Pubmed and Engineering Village.

## IEEE and Engineering Village (Compendex, Inspec):

```
( "human motion capture" OR ("reconstruction" NEAR/2 "posture") OR ("reconstruction" NEAR/2 "kinematic") OR
("reconstruction" NEAR/2 "motion") OR ("estimation" NEAR/2 "posture") OR ("estimation" NEAR/2 "kinematic") OR
("estimation" NEAR/2 "motion") OR ("capture" NEAR/2 "joint") OR ("capture" NEAR/2 "motion") OR ("capture" NEAR/2
"skeleton") OR ("capture" NEAR/2 "human") OR ("capture" NEAR/2 "body") OR ("capture" NEAR/2 "upper limb") OR ("capture"
NEAR/2 "lower limb") OR ("capture" NEAR/2 "arm") OR ("capture" NEAR/2 "shoulder") OR ("capture" NEAR/2 "elbow") OR
("capture" NEAR/2 "wrist") OR ("capture" NEAR/2 "leg") OR ("capture" NEAR/2 "knee") OR ("capture" NEAR/2 "ankle") OR
("tracking" NEAR/2 "joint") OR ("tracking" NEAR/2 "motion") OR ("tracking" NEAR/2 "skeleton") OR ("tracking" NEAR/2
"human") OR ("tracking" NEAR/2 "body") OR ("tracking" NEAR/2 "upper limb") OR ("tracking" NEAR/2 "lower limb") OR
("tracking" NEAR/2 "arm") OR ("tracking" NEAR/2 "shoulder") OR ("tracking" NEAR/2 "elbow") OR ("tracking" NEAR/2 "wrist")
OR ("tracking" NEAR/2 "leg") OR ("tracking" NEAR/2 "knee") OR ("tracking" NEAR/2 "ankle") OR ("localisation" NEAR/2
"joint") OR ("localisation" NEAR/2 "motion") OR ("localisation" NEAR/2 "skeleton") OR ("localisation" NEAR/2 "human")
OR ("localisation" NEAR/2 "body") OR ("localisation" NEAR/2 "upper limb") OR ("localisation" NEAR/2 "lower limb") OR
("localisation" NEAR/2 "arm") OR ("localisation" NEAR/2 "shoulder") OR ("localisation" NEAR/2 "elbow") OR ("localisation"
NEAR/2 "wrist") OR ("localisation" NEAR/2 "leg") OR ("localisation" NEAR/2 "knee") OR ("localisation" NEAR/2 "ankle") )
AND ( "human kinematic" OR ("pose" NEAR/2 "estimation") OR ("pose" NEAR/2 "joint") OR ("pose" NEAR/2 "body") OR ("pose"
NEAR/2 "upper limb") OR ("pose" NEAR/2 "lower limb") OR ("pose" NEAR/2 "arm") OR ("pose" NEAR/2 "shoulder") OR ("pose"
NEAR/2 "elbow") OR ("pose" NEAR/2 "wrist") OR ("pose" NEAR/2 "leg") OR ("pose" NEAR/2 "knee") OR ("pose" NEAR/2 "ankle")
OR ("angle" NEAR/2 "estimation") OR ("angle" NEAR/2 "joint") OR ("angle" NEAR/2 "body") OR ("angle" NEAR/2 "upper limb")
OR ("angle" NEAR/2 "lower limb") OR ("angle" NEAR/2 "arm") OR ("angle" NEAR/2 "shoulder") OR ("angle" NEAR/2 "elbow") OR
("angle" NEAR/2 "wrist") OR ("angle" NEAR/2 "leg") OR ("angle" NEAR/2 "knee") OR ("angle" NEAR/2 "ankle") OR ("position"
NEAR/2 "estimation") OR ("position" NEAR/2 "joint") OR ("position" NEAR/2 "body") OR ("position" NEAR/2 "upper limb") OR
("position" NEAR/2 "lower limb") OR ("position" NEAR/2 "arm") OR ("position" NEAR/2 "shoulder") OR ("position" NEAR/2
"elbow") OR ("position" NEAR/2 "wrist") OR ("position" NEAR/2 "leg") OR ("position" NEAR/2 "knee") OR ("position"
NEAR/2 "ankle") OR ("orientation" NEAR/2 "estimation") OR ("orientation" NEAR/2 "joint") OR ("orientation" NEAR/2
"body") OR ("orientation" NEAR/2 "upper limb") OR ("orientation" NEAR/2 "lower limb") OR ("orientation" NEAR/2 "arm")
OR ("orientation" NEAR/2 "shoulder") OR ("orientation" NEAR/2 "elbow") OR ("orientation" NEAR/2 "wrist") OR ("orientation"
NEAR/2 "leg") OR ("orientation" NEAR/2 "knee") OR ("orientation" NEAR/2 "ankle") OR ( "kinematic" ) OR ("motion" NEAR/2
"estimation") OR ("motion" NEAR/2 "human") OR ("motion" NEAR/2 "joint") OR ("motion" NEAR/2 "limb") OR ("motion" NEAR/2
"simulation") OR ("motion" NEAR/2 "reconstruction") OR ( "joint" ) ) AND ( "physical human robot interaction" OR (
"cobotics" ) OR ( "phri" ) OR ( "hri" ) OR ( "human robot interaction" ) OR ("robot" NEAR/2 "collaborative") OR ("robot"
NEAR/2 "collaboration") OR ("robot" NEAR/2 "compliant") OR ("robot" NEAR/2 "rehabilitation") OR ("robot" NEAR/2 "rehab")
OR ("robot" NEAR/2 "assistive") OR ("robot" NEAR/2 "end effector") OR ("robot" NEAR/2 "end-effector") OR ("robot" NEAR/2
"wearable") OR ( "exoskeleton" ) OR ( "manipulandum" ) ) NOT ( "identification" NEAR/2 "gesture" ) NOT ( "identification"
NEAR/2 "sign" ) NOT ( "identification" NEAR/2 "signal" ) NOT ( "identification" NEAR/2 "people" ) NOT ( "identification" NEAR/2
"person" ) NOT ( "identification" NEAR/2 "face" ) NOT ( "detection" NEAR/2 "gesture" ) NOT ( "detection" NEAR/2 "sign" ) NOT
( "detection" NEAR/2 "signal" ) NOT ( "detection" NEAR/2 "people" ) NOT ( "detection" NEAR/2 "person" ) NOT ( "detection" NEAR/2
"face" ) NOT ( "recognition" NEAR/2 "gesture" ) NOT ( "recognition" NEAR/2 "sign" ) NOT ( "recognition" NEAR/2 "signal" ) NOT
( "recognition" NEAR/2 "people" ) NOT ( "recognition" NEAR/2 "person" ) NOT ( "recognition" NEAR/2 "face" )
```

## PubMed

```
( human motion capture OR ( "joint capture" ) OR ( "motion capture" ) OR ( "skeleton capture" ) OR ( "human capture"
) OR ( "body capture" ) OR ( "upper limb capture" ) OR ( "lower limb capture" ) OR ( "arm capture" ) OR ( "shoulder
capture" ) OR ( "elbow capture" ) OR ( "wrist capture" ) OR ( "leg capture" ) OR ( "knee capture" ) OR ( "ankle capture"
) OR ( "kinematic capture" ) OR ( "joint tracking" ) OR ( "motion tracking" ) OR ( "skeleton tracking" ) OR ( "human
tracking" ) OR ( "body tracking" ) OR ( "upper limb tracking" ) OR ( "lower limb tracking" ) OR ( "arm tracking" )
OR ( "shoulder tracking" ) OR ( "elbow tracking" ) OR ( "wrist tracking" ) OR ( "leg tracking" ) OR ( "knee tracking"
) OR ( "ankle tracking" ) OR ( "kinematic tracking" ) OR ( "joint localisation" ) OR ( "motion localisation" ) OR (
"skeleton localisation" ) OR ( "human localisation" ) OR ( "body localisation" ) OR ( "upper limb localisation" ) OR (
"lower limb localisation" ) OR ( "arm localisation" ) OR ( "shoulder localisation" ) OR ( "elbow localisation" ) OR (
"wrist localisation" ) OR ( "leg localisation" ) OR ( "knee localisation" ) OR ( "ankle localisation" ) OR ( "kinematic
localisation" ) OR ( "motion reconstruction" ) OR ( "posture reconstruction" ) OR ( "kinematic reconstruction" ) OR (
"motion estimation" ) OR ( "posture estimation" ) OR ( "kinematic estimation" ) ) AND ( human kinematic OR ( kinematic
) OR ( "pose joint" ) OR ( "pose estimation" ) OR ( "pose body" ) OR ( "pose upper limb" ) OR ( "pose lower limb" ) OR
( "pose arm" ) OR ( "pose shoulder" ) OR ( "pose elbow" ) OR ( "pose wrist" ) OR ( "pose leg" ) OR ( "pose knee" ) OR (
"pose ankle" ) OR ( "angle joint" ) OR ( "angle estimation" ) OR ( "angle body" ) OR ( "angle upper limb" ) OR ( "angle
lower limb" ) OR ( "angle arm" ) OR ( "angle shoulder" ) OR ( "angle elbow" ) OR ( "angle wrist" ) OR ( "angle leg" )
OR ( "angle knee" ) OR ( "angle ankle" ) OR ( "position joint" ) OR ( "position estimation" ) OR ( "position body" ) OR
( "position upper limb" ) OR ( "position lower limb" ) OR ( "position arm" ) OR ( "position shoulder" ) OR ( "position
elbow" ) OR ( "position wrist" ) OR ( "position leg" ) OR ( "position knee" ) OR ( "position ankle" ) OR ( "orientation
joint" ) OR ( "orientation estimation" ) OR ( "orientation body" ) OR ( "orientation upper limb" ) OR ( "orientation lower
limb" ) OR ( "orientation arm" ) OR ( "orientation shoulder" ) OR ( "orientation elbow" ) OR ( "orientation wrist" ) OR
( "orientation leg" ) OR ( "orientation knee" ) OR ( "orientation ankle" ) OR ( "human motion" ) OR ( "limb motion" ) OR
( "joint motion" ) OR ( "motion simulation" ) OR ( "motion reconstruction" ) OR ( "motion estimation" ) ) AND ( physical
human robot interaction OR ( cobotics ) OR ( phri ) OR ( hri ) OR ( human robot interaction ) OR ( exoskeleton ) OR (
manipulandum ) OR ( "collaborative robot" ) OR ( "collaboration robot" ) OR ( "compliant robot" ) OR ( "rehabilitation
robot" ) OR ( "rehab robot" ) OR ( "assistive robot" ) OR ( "end effector robot" ) OR ( "end-effector robot" ) OR (
"wearable robot" ) ) NOT ( "gesture identification" ) NOT ( "sign identification" ) NOT ( "signal identification" ) NOT (
"people identification" ) NOT ( "person identification" ) NOT ( "face identification" ) NOT ( "gesture detection" ) NOT (
"sign detection" ) NOT ( "signal detection" ) NOT ( "people detection" ) NOT ( "person detection" ) NOT ( "face detection"
) NOT ( "gesture recognition" ) NOT ( "sign recognition" ) NOT ( "signal recognition" ) NOT ( "people recognition" ) NOT (
"person recognition" ) NOT ( "face recognition" )
```

2) Search tree visualisation:

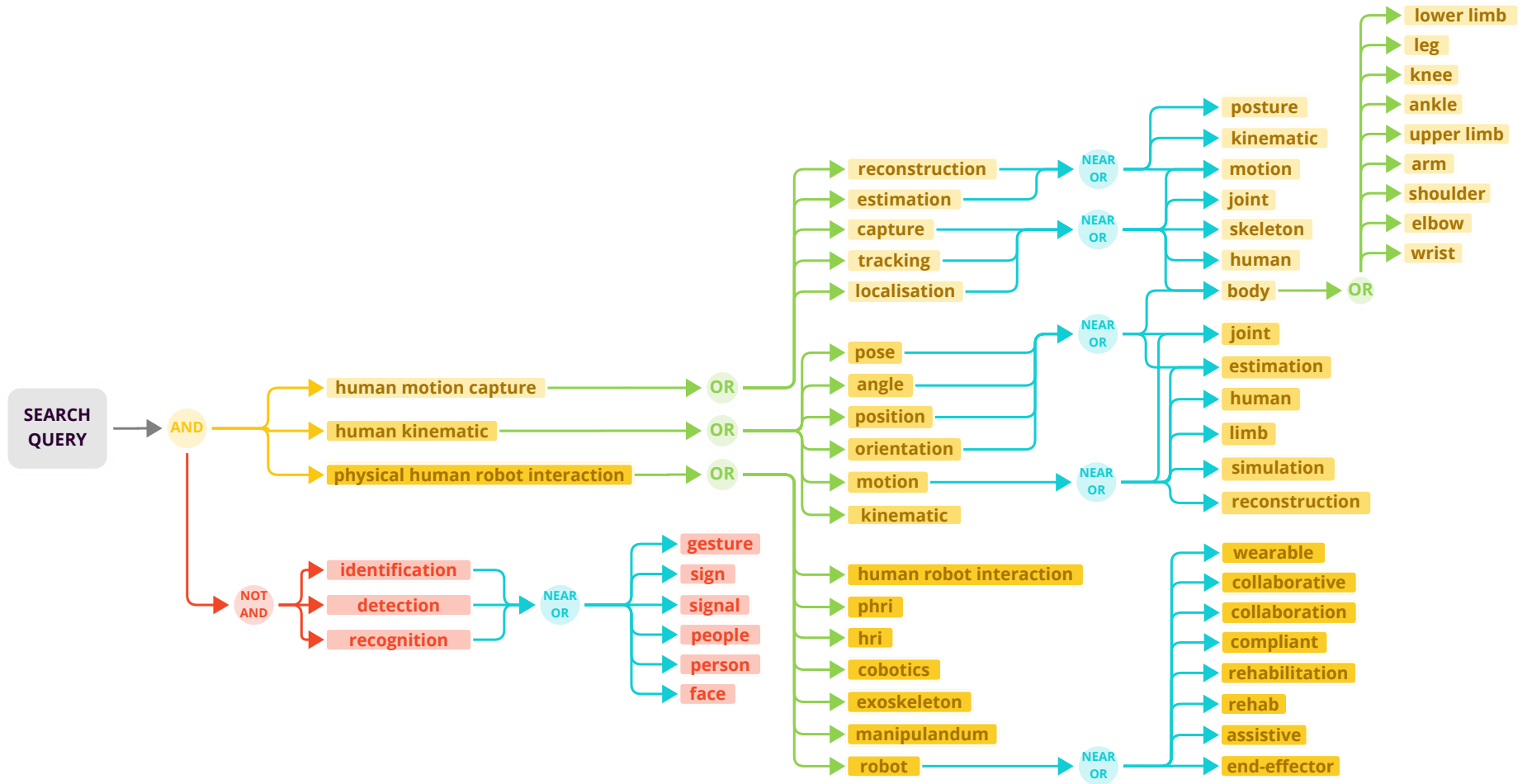


Fig. 4: Search tree with key terms and boolean relationships