Human Systems Engineering and Design (IHSED 2024), Vol. 158, 2024, 33–42
https://doi.org/10.54941/ahfe1005526

Building a Multicamera and Multimodal 3D Skeleton-Based Pose Estimation Dataset to Enhanced Human-Robot Collaboration

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ABSTRACT

Human pose estimation (HPE) is an essential computer vision task that plays a significant role in ergonomics, human-centered design of workplaces, and collaborative robotics, particularly in providing a safe, adaptive, and valuable human-robot collaboration (HRC). Nevertheless, the need for a concise and practical approach to setting up a multicamera and multimodal system for HPE dataset generation remains an open issue in the literature. The main goal of this work is to describe in concise steps a protocol that serves as a guide in the exploratory stage of the approach to construct an extensive multicamera and multimodal dataset used to enhance HRC. In this paper, the proposed protocol specifically addresses the challenge of designing a biomechanical model that can consistently reproduce complex and variable human motion analyses in an assembly task while considering ergonomic factors. Furthermore, the resulting work led to the definition of a marker set for one single-person future pipeline involving the placement of thirty-two reflective markers for 3D motion analysis, specifically emphasizing the upper segments of the human body. The future generation of this dataset will hold significant promise for advancing the study of HRC. It will introduce reliable and precise multimodal data collection, such as human kinematics and video data, including depth data, which will then be used for posture metrics analysis. Finally, the dataset will be a valuable resource for the research community, enabling the training of machine learning models. These models will empower collaborative robots (cobots) to learn from human demonstrations, enhancing their efficiency and ergonomic performance in assembly tasks.

Keywords: Human pose estimation dataset, Human-robot collaboration, Human-centered design, Ergonomics

INTRODUCTION

Industry 4.0 marked the beginning of a new era of manufacturing that utilizes digital technologies, including cobots, to create production setups that are both efficient and flexible (Colim et al., 2021a; Demir et al., 2019). However, the focus on system-centered design in Industry 4.0 sometimes reduces human workers' significance, prioritizing automation over human-centered approaches (Cunha et al., 2020; Lu et al., 2022). Hence, the paradigm of Industry 5.0 originated and developed to highlight the significance of human well-being and environmental sustainability in industrial operations (Breque et al., 2021).

In the Industry 5.0 domain, robots are perceived as ideal coworkers, capable of collaborating with human workers to accomplish shared objectives to achieve common goals (Cunha et al., 2020). However, the cobots' capacity to autonomously improve workers' physical and cognitive well-being during collaboration is restricted because current methods frequently regard ergonomic criteria as an outcome rather than an input to cobot controllers (Gualtieri et al., 2021). Human-robot collaboration (HRC) in manufacturing tasks is becoming more widely recognized as an automated solution for developing more ergonomic workstations (Colim et al., 2021b; Olivas-Padilla et al., 2022). However, the cobot's capacity to autonomously improve workers' physical and cognitive well-being during collaboration is restricted because current methods frequently treat ergonomic criteria as an outcome rather than an input to robot controllers (Gualtieri et al., 2021).

Work-related musculoskeletal disorders (WMSD) continue to be a major issue in industrial manufacturing, frequently caused by repetitive handling tasks and awkward postures at the workstations (Chen et al., 2018; Colim et al., 2023). A solid understanding of human movements and postures is necessary to address these issues, especially in tasks involving cobots and humans. Cardoso et al. (2021) emphasized the significance of including ergonomic requirements in designing cobots workstations to ensure safety and efficiency. The high occurrence of WMSD highlights the need for implementing ergonomic interventions and designing collaborative workstations that focus on human well-being. To overcome these difficulties, sophisticated human pose estimation methods, and extensive datasets are essential. These resources are vital for advancing more intelligent and adaptable HRC systems.

Recent progress in human pose estimation (HPE) has demonstrated encouraging outcomes in many fields, such as robotics and computer vision (Toshpulatov et al., 2022). However, there is a notable gap in the existence and accessibility of datasets designed to improve HRC in industrial environments, especially those that include ergonomic factors and multi-modal data. For instance, Yang et al. (2018) demonstrated the advantages of integrating multiple camera views with depth data and motion capture systems. Robinson et al. (2023) conducted an extensive survey of robotic vision for human-robot coworkers within the framework of HRC. Their research highlighted the need for precise human pose assessment in facilitating effective collaboration. Additionally, the authors indicated the necessity for more tailored datasets in industrial environments. Maurice et al. (2019) introduced a dataset designed for cobots in industry environments. The dataset primarily emphasizes human movement and ergonomics. Although their work provided useful insights, it failed to comprehensively address the intricacies of collecting multi-modal data for the difficulties associated with assembly tasks. Angleraud et al. (2024) investigated the use of sensor-based human-robot collaboration in industrial tasks, emphasizing the advantages of employing multi-modal sensing methods. Nevertheless, their research did not offer a thorough set of guidelines for creating datasets integrating both posture assessment and ergonomic factors. Cimolin et al. (2012) introduced a marker set methodology for quantitatively analyzing upper limb movements during gait. Although their research provided the groundwork for analyzing upper body motion, it did not specifically consider the need for HRC in industrial environments. Hansen et al. (2024) confirmed the accuracy of upper extremity motions by utilizing markerless motion capture, highlighting the capabilities of innovative technologies in investigating human motion. Nevertheless, their methodology failed to consider the distinct requirements of HRC or the incorporation of multiple data modalities. Fernandes et al. (2016) performed a study in the field of biomechanical modeling. They examined the three-dimensional multi-segmental trunk kinematics and kinetics during gait. The study aimed to gain insights into the reproducibility of test-retest results and the most minor detectable change. Although this work provides critical methodological considerations, it does not mainly handle the issues of HRC in industrial contexts.

Despite these advancements, there is still a notable lack of complete methods for creating multi-modal datasets explicitly intended to improve HRC in industrial environments. Current methodologies frequently fail to address the complex connection between HPE, ergonomic factors, and the specific requirements for assembly activities in collaborative settings. To fill this gap, this paper presents a procedure summarizing the necessary steps to generate a dataset that focuses on constructing a multicamera and multimodal for 3D skeleton-based pose estimation, improving HRC. The method introduced focuses in a particular way on the difficulty of creating a biomechanical model that can accurately replicate complex and diverse human motion analyses during assembly activities while considering ergonomic variables.

The proposed protocol includes the definition of a marker set for a single-person pipeline, which requires the placement of thirty-two reflective markers for 3D motion analysis. This marker set focuses on the upper segments of the human body, which are crucial for most assembly tasks in industrial settings. Subsequent sections will explain the presented protocol, including a concise description of the procedures for setting up a multicamera and multimodal acquisition vision system, data collection, processing, and organization of data recording, defining the marker set, and constructing the biomechanical model.

PROTOCOL TO GENERATE A MULTICAMERA DATASET TO APPLY IN HRC WORKSTATIONS

This section presents a strategy for generating a dataset that includes several cameras and multiple data modes for HRC while considering ergonomic factors for the upper body. This protocol contains several phases, described in a concise guide in the following sections: 1. subjects selection criteria; 2. experimental description of tasks; 3. acquisition setup; 4. data recording and organization; 5. technical validation; and 6. biomechanical protocol creation. The protocol also integrates the utilization of diverse RGB-D cameras, motion capture systems, and associated software applications.

Participants Selection Criteria

The selection criteria for participants should prioritize diversity, including various age groups, genders, and physical characteristics. This will enable the collection of a comprehensive range of ergonomic data (Maurice et al., 2019). All participants must provide informed consent, which should include a detailed explanation of the data collection procedure and the purpose of the study (as defended by Gualtieri et al., 2022), respecting the Declaration of Helsinki. It should be noted that the current study is inserted in a research project approved by the Committee of Ethics for Research in Social and Human Sciences of the University of Minho (approval number CEICSH 038/2020).

Task Selection

Tasks should replicate authentic industrial operations, such as assembly, lifting, and tool handling, that require extensive upper-body movements. More precisely, in the current study, the assigned duties involve the assembly of a window by a human and a cobot within an industrial scenario, simulating a typical assembly workstation.

Acquisition Setup

Hardware and Software Systems

For the Optical Motion Capture System (MoCap), Qualisys, Vicon, and OptiTrack are examples of high-precision optical motion capture systems. The Qualisys system employs the Qualisys Track Manager (QTM) software to record and process data (Qualisys, 2024a). Vicon systems utilize Vicon Nexus software, while OptiTrack systems employ Motive software (Fernandes et al., 2016; OptiTrack, 2024; Vicon, 2024).

In this context, the reflective markers should be strategically positioned on anatomical landmarks of the human upper body to capture precise motion data accurately (Qualisys, 2024b).

Relatively to RGB-D Cameras, multiple high-definition video cameras, such as the StereoLabs ZED, Microsoft Kinect, and Intel RealSense, should be strategically positioned around the workstation to record various perspectives of the participants' movements (Newman et al., 2022; StereoLabs, 2024a; Zhang et al., 2019).

In the current study, RGB-D cameras like the Stereolabs ZED 2i are viable options due to their high resolutions at considerable frame rates (frames per second (fps)), of up to 2208x1242 at 15 fps and 1920x1080 at 30 fps, wide-angle field of view (FOV) of 120°, and robust environmental resistance (StereoLabs, 2024b).

Calibration

In this domain, each motion capture camera must be calibrated to correct lens distortions and to establish the appropriate spatial relationship between cameras, ensuring precise 3D reconstruction (Franjcic and Wozniak, 2014). For this stage, it is essential to perform both intrinsic and extrinsic calibration for each video camera (Zhang et al., 2019).

Data Pre-Processing and Synchronization

The raw motion capture data must be collected from the MoCap system and processed using noise reduction filters to remove any additional noise (Menolotto et al., 2020).

Regarding motion capture and video cross-synchronization, various techniques can synchronize motion capture and video data in space and time. These methods include hardware synchronization, such as dedicated sync units, or software-based alignment, which indicates the beginning of recording on both systems (Qualisys, 2024c, 2024d; Yoon et al., 2021).

Data Records and Data Organization

The raw data should be structured with separate folders for motion capture and video data. Newman et al. (2022) suggest providing metadata, such as participant ID, task description, and timestamp. The objective is to convert unprocessed data into processed data by accurately recognizing and separating significant attributes, such as joint angles and ergonomic metrics. To simplify analysis, processed data should be stored in a standardized format such as CSV or JSON (Lorenzini et al., 2023).

Technical Validation

The dataset should be validated by comparing the acquired data with specified standards (data acquired from the MoCap system) or benchmarks (Colyer et al., 2018). For ergonomic assessment, established methods, such as the Rapid Upper Limb Assessment (RULA) (McAtamney and Corlett, 1993) and the Rapid Entire Body Assessment (REBA) (Hignett and Ergonomist, 2000), are recommended to assess human postures regarding the captured movements (Alberto et al., 2018).

Biomechanical Protocol Design and Marker Set Definition

This section presents the biomechanical protocol designed to standardize the data collection process for the human upper-body, considering the principal motions and actions to assemble a window.

First, considering the macro-actions to be analyzed in this specific dataset, such as pointing, hand-approach, grasping type, handover, hand-approach-me, and screwing, a description of the functional movements and joints in this particular task is presented in Table 1.

Table 2 presents the protocol for accurately and consistently repeatable placement of reflective markers on anatomical landmarks in each trial necessary for generating the dataset. The final configuration of the personalized marker set comprises thirty-two reflective markers for both the right and left parts of the human skeleton.

Table 1. Description of the functional movements (Hecht, 2020; Physiopedia, 2024; Sukari et al., 2021; Tor, 2001; Zwerus et al., 2019).

Joints	Description of the functional movements executed
Shoulder/upper arm	Flexion, extension, abduction, adduction, internal rotation, external rotation.
Elbow/lower arm	Flexion, extension, pronation, supination.
Wrist	Flexion, extension, radial deviation, ulnar deviation.
Hand	Flexion, extension, abduction.
Head/Neck - Cervical	Flexion, extension, lateral flexion, rotation.
Trunk - Lumbar	Flexion, extension, lateral flexion, rotation.

Table 2. Description of localization parameters of the custom marker set for the upper body.

Definition	Marker label	References for localization
Forehead	FH	(Vicon, 2016)
Back of the head	BH	(Vicon, 2016)
Jugular notch joint	IJ_chest	(Wikipedia, 2024)
Acromioclavicular joint	AC	(Musculoskeletal Key, 2016)
7th cervical vertebra	C7	(Athletic Training & Sports Medicine Center, n.d.)
Anterior superior iliac spine	ASIS	(Agency for Clinical Innovation, 2015)
Posterior superior iliac spine	PSIS	(Agency for Clinical Innovation, 2015)
Humerus greater tubercule	HGT	(Musculoskeletal Key, 2016)
Lateral epicondyle	LE	(Musculoskeletal Key, 2016)
Medial epicondyle	ME	(Musculoskeletal Key, 2016)
Radial styloid	RS	(Musculoskeletal Key, 2016)
Ulnar Styloid	US	(Musculoskeletal Key, 2016)
Lateral head of metacarpal	HL5_hand	Located on the most prominent bone on the little finger side of the hand, the hand closed.
Medial head of metacarpal	HL2_hand	Located on the most prominent bone on the thumb finger side of the hand, the hand closed.
Tip of the Thumb	TF_hand	Tip of the Thumb.
Tip of index finger	IF_hand	Tip of the index finger.
Tip of the little finger	LF_hand	Tip of the little finger.

The marker set created for this work was based on its ability to provide detailed and accurate motion data for the key joints in the study. The configuration of this custom marker is presented in Figure 1 and resulted from the intersection of selected standard biomechanical models known for its effectiveness in capturing upper limbs, trunk, and head/neck movements (Fernandes et al., 2016; HAS Motion, 2024; Qualisys, 2021; Vicon, 2016).

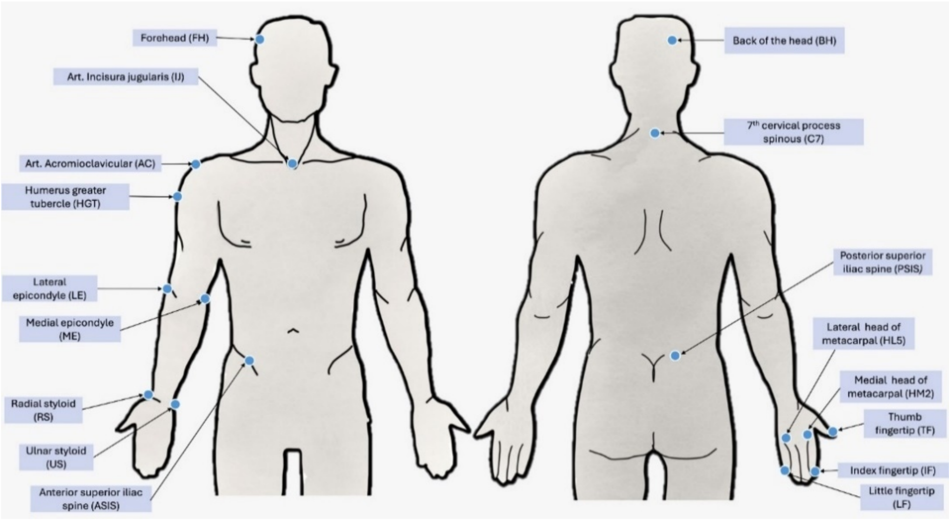

Figure 1: Configuration of the custom marker set for placement of reflective markers in anatomical landmarks of the upper body (right and left side of the human skeleton).

CONCLUDING REMARKS AND FUTURE WORK

This work is a substantial step forward in implementing Industry 5.0's vision, which focuses on ergonomic factors and human well-being in industrial settings. The proposed protocol addresses the challenge of developing a biomechanical model that can accurately replicate complex human motions during assembly tasks while considering ergonomic factors.

The research designed a comprehensive protocol for creating a multicamera and multimodal 3D skeleton-based pose estimation dataset to improve HRC. The protocol includes extensive procedures for selecting subjects, designing tasks, setting up the acquisition system, collecting data, preprocessing, calibration, synchronization, data organization, and technical validation. Additionally, the biomechanical protocol establishes a standardized approach to data collection for body movements that occur during assembly tasks. A custom marker set consisting of thirty-two reflective markers was developed to facilitate the precise 3D motion analysis of the upper-body.

Future research will concentrate on creating a comprehensive dataset to record human motions in collaboration with a cobot, utilizing the protocol that has been developed. This dataset will be used to train and verify machine learning models to enhance HRC's efficiency and ergonomic performance for a particular assembly task: assembling a window. The resultant dataset will include human kinematics and video data with depth information, providing precise and consistent multimodal data for posture metrics analysis.

In summary, this investigation establishes the groundwork for advancing HRC research by offering an advancement of collaborative robotic systems that are more adaptive and intelligent in industrial environments.

ACKNOWLEDGMENT

This work has been supported by FCT within the Project I – CATER: Intelligent Robotic Coworker Assistant for Industrial Tasks with an Ergonomics Rationale, reference PTDC/EEI-ROB/3488/2021. Additionally, this work has been supported by FCT – Fundação para a Ciência e Tecnologia under doctoral Grant 2022.13737.BDANA.

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