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On using human activity recognition sensors to improve the performance of collaborative mobile manipulators: Review and outlook

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ABSTRACT

The operation of mobile manipulators in a collaborative environment needs to be adapted to the characteristics and skills of human operators. Human activity recognition, utilizing wearable sensors and vision systems, could be used to fine tune the performance of the mobile manipulator so that human operators be better assisted. The goal is to develop a sense of safety and trust between the human and the manipulator in order to improve the ergonomics of the operator within the collaborative workspace. This paper reviews the technologies that can be used for activity tracking together with gait recognition as a biometric tool. These technologies could potentially allow the mobile robotic manipulator to dynamically adapt to the motion, skills, and intentions of the human operator and to the requirements of the task in action. This paper also proposes an idea of combining a gait recognition model and activity tracking towards improving the performance of mobile collaborative robots.

1. Introduction

Human-Robot Collaboration (HRC) technologies constitute one of the most promising and rapidly evolving research areas in the manufacturing domain. The main objective of HRC technologies is to develop a shared environment to facilitate humans and robots to collaborate safely. HRC may ease out the tasks which are repetitive, non-ergonomic, and hectic (Halme et al., 2018). Typically, the movement of a robot is monitored by advanced sensors for ensuring the safe operation without putting the human operator at risk (Vysocky and Novak, 2016). A bio-inspired probabilistic model utilizing an unsupervised learning approach to predict the human motion by tracking of skeletal joints using Kinect sensor in order to facilitate online human-robot interaction task is discussed in Ref. (Butepage et al., 2018). Nevertheless, it is quite complex to interpret the intention of the operator in advance using these techniques. Hence, activity tracking technologies, utilizing wearable devices combined with gait recognition techniques may be used, by taking advantage of motion capture sensors, such as Inertial Measurement Units (IMU) and vision systems (Kalkbrenner et al., 2014). This type of technologies and systems are discussed in this paper. The objective is to review the technologies and methodologies that may be used for improving the performance and safety compliance of mobile manipulators in a production environment.

Human activity tracking is in principle critical to determining the joint position and the mobility of the operator in a shared HRC environment. The measurement and analysis of human motion comprise an important technology for many fundamental applications and especially for HRC. For a start, in HRC the line of sight between the human and the robot is variable and dynamic (Joukov et al., 2017). Hence, for fully integrating robots with human operators, the motion of the operators must be captured in real-time and on a continuous basis. For this purpose, IMUs may be used. These IMUs, once attached to the user, are capable of tracking the motion in three-dimensional space as well as of sensing the exact position of the operator (Kalkbrenner et al., 2014). Then, they may feed this information back to the robot, which in turn may adapt to the intentions of the human operator to suit their motion. The use of 9 axis IMUs gives better flexibility and adaptability as they are a combination of accelerometers, gyroscopes and magnetometers (Botero Valencia et al., 2017). When attached to human operators, IMUs are capable of providing raw data pertaining to their motion (Joukov et al., 2017).

Mobile manipulators are capable of taking advantage of the dexterity of static collaborative robots, providing, at the same time,

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the ability to move around the shop-floor to work in different areas. However, these manipulators need to use special algorithms in order to deal with kinematic redundancy issues. The constraints associated with these are discussed in (Navarro et al., 2017), where a redundancy solution is proposed for improving the HRC performance.

The present paper reviews the various technologies that can be used to perform activity tracking utilizing IMU and vision sensors as well as gait recognition techniques and presents the implications of using gait analysis to improve the collaborative nature of robots. Section 2 provides a literature review of existing systems and technologies that are used in the context of HRC in the manufacturing domain. Section 3 reviews the technologies that are currently used in motion tracking to monitor human activities and tasks, such as walking or pick-and-place activities. Section 4 describes the challenges of implementing these technologies. Finally, an overview of relevant technologies and potential future work are provided in Section 5.

2. State of the art

The concept of developing collaborative environments involving mobile manipulators, utilizing activity tracking technologies complemented with human recognition techniques is relatively new. Although there has been a significant volume of research focusing on human-robot collaboration, for the most part, it is related to the safety analysis of HRC or to the use of HRC in the healthcare industry. The use of HRC in the manufacturing domain has drawn a lot of attention lately but when it comes to the concepts involving activity tracking and gait analysis for HRC, there have not been many recent relevant publications.

One of the major challenges is to have an interface between the IMU and the human operator that is accurate enough for allowing the reliable gait recognition. In Ref. (Vargas-Valencia et al., 2016), a method for the placement and calibration of the IMU on the human joints is discussed. It measures the angles of the lower-limb joints by discretizing the limbs as different technical-anatomical frames. This is then validated in three different applications. The benefit of the method is that it includes swift sensor placement without the need of using any special tools or performing any complex movements.

A method to filter the data from IMU sensors utilizing passive filtering algorithms, such as Mahony-Hamel, to reconstruct the rigid kinematic bodies is discussed in Ref. (Santaera et al., 2015). Another method to obtain the 3-dimensional skeletal points of the human operator, using multiple depth perception sensors, is discussed in Ref. (Ragaglia et al., 2018). The measured points can be combined using sensor fusion algorithms to estimate the position and velocity of the joints of the operator. Therefore, the analysis of the workspace within the proximity of the operator in real-time is enabled.

In Ref. (Tortora et al., 2019)**,** IMU sensors coupled with Electromyography (EMG), allow for the detection of the motion and the calculation of the direction of the motion of the human operator. Also, the data from IMU is used to train a Hidden Markov Model (HMM), which is responsible for motion prediction in terms of direction and intention. These two outputs from the model are then fed into a Finite State Machine (FSM) that controls the motion of the robot with respect to the movements of the human operator. An HMM-based approach presented in Ref. (Mandery et al., 2016) is used to obtain a suitable set of features for the dimensionality reduction of human motion recognition. This study showed that a small subset of features was enough to perform reasonable recognition and the center of mass of the body was always a part of the set of features.

The analysis of various algorithms for physical activity recognition using wearable sensors, such as k-Nearest Neighbor (k-NN), Support Vector Machines and HMM, for unsupervised and supervised learning models is presented in Ref. (Attal et al., 2015). The outcome of the research shows the performance of the model is better when using k-NN for supervised learning and HMM for unsupervised learning.

In Ref. (Liang et al., 2016)**,** the researchers argue the use of wearable IMU sensors, stating that wearing such devices at all times may cause inconvenience to the human operator. The use of non-contact devices and methods is preferred towards modelling the full-body motion of the human operator with 23 degrees of freedom via visual signals. The non-contact sensor used in the research was a Kinect sensor 2.0 to acquire the position of the human operator. A decision system built for recognizing graspable objects as well as for predicting the intentions of a human operator handing over a part, using IMU and EMG (Electromyography) sensors, in order to facilitate the coordination of tasks in an HRC scenario is discussed in Ref. (N. Wang et al., 2019). The sensory system is placed on the operator's forearm.

The accuracy of tracking involving a LeapMotion sensor and a Kinect V2 sensor can be improved by reducing the noise from the data obtained from them by using a Kalman filter-based algorithm, as discussed in Ref. (Li et al., 2019). Malaisé et al. made use of a wearable motion tracking suit along with a sensorized glove for the recognition of seven distinct activities in a pick-and-place scenario resembling the settings of a manufacturing environment (Malaisé et al., 2018 bib16). Using HMM for probabilistic recognition, the researchers showed that the model was able to recognize 96% of the activities precisely with the use of a wearable tracking suit and a sensorized glove.

A combination of activity recognition and task-based control model to support human operator is discussed in Ref. (Uzunovic et al., 2018). Wireless activity tracking sensors are used to recognize the intention of the operator. This information is used as an input to a task-based controller that selects one or more functions to complete the task, which results in aiding the human operator, thus reducing the physical effort. Real-time identification of six gestures and an architecture to control a mobile manipulator using a search-based algorithm is discussed in Ref. (Kulkarni et al., 2019). Furthermore, a Robotic Operating System (ROS) - based architecture facilitated the integration of different mobile manipulator platforms and allowed for the addition of new gestures to a database.

In Ref. (Weitschat et al., 2018), an experimental setup to track the motion and activity of a human arm using advanced motion capture sensors was presented. The sensors were placed on the arms of the human joint and the overall concept was validated in a manufacturing scenario. The objective of this research was to track the movement of the operator's arm to attain the robot path wherein a collision would occur. Then, the time taken for the arm to intervene in the robot's path or to reach the robot is computed, in order for the robot's velocity to be controlled towards improving the overall efficiency of an HRC process.

The next sections focus on the use of different technologies and sensors for the recognition of activities of a human operator in an HRC environment.

3. Current technologies

This section describes the concept of developing safe HRC, utilizing the identification model that can be built by using wearable sensors. This model can potentially be used in the manufacturing domain aiming at a) improving the overall process performance and b) better supporting the human operator. By extending the applicability of wearable sensors, a gait recognition model may be

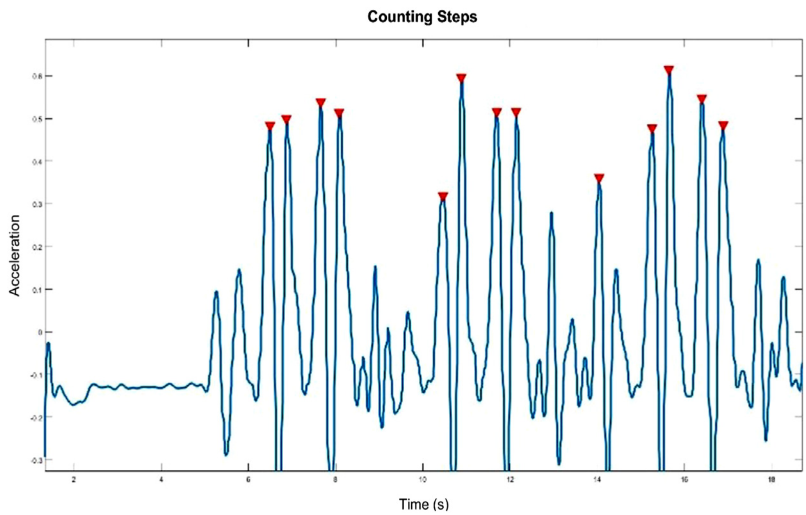

Fig. 1. Measurement of the number of steps of a human operator using IMU sensors. The peaks show the number of steps measured.

developed in order for the collaborative robot to be capable of providing more customized support in the shop floor.

3.1. Safe human-robot collaboration

Collaborative mobile manipulators are used in the manufacturing industry and serve as a platform that is capable of assisting human operators by carrying out tasks autonomously (Kousi et al., 2018). However, there are various challenges associated with the navigation and the perception of mobile manipulators within their confined environment. The Internet of Robotic Things, discussed in Ref. (Simoens et al., 2018), summarizes the added value of combining the Internet of Things (IoT) with robotic technologies to make mobile robots more adaptable to their environment.

The concept reviewed in this paper involves the use of sensors, such as IMU and Vision systems, that can potentially be used to develop safe HRC by reliably tracking the operator's activities in manufacturing shop-floor. The gait of each person is different (Birdal et al., 2018). For this reason, gait can be used as a biometric tool, integrated in a unique definitive model of individual human operators, to support their operation in the shop-floor, while carrying out different tasks. The process tracking may involve simple activity monitoring, calculating the speed of task execution or the efficiency of an operation, as well as the analysis of ergonomic factors (Malaisé et al., 2018 bib16). Later on, this information may be processed using machine learning algorithms and be fed back to the robot so that the level of assistance to the human operator be personalized. Depending on the level of assistance required, the robot can autonomously plan to carry out other production tasks.

3.2. Sensors for gait

3.2.1. IMU

IMU sensors are the widely preferred type of motion tracking sensors for analyzing the activity and gait of a human operator. With the growth of mobile phone technologies, these sensors are likely to be present on a smartphone. Typically, an IMU sensor consists of accelerometers, gyroscopes, and sometimes magnetometers. The combination of accelerometer and gyroscope is typically used in gait analysis for computing the number of steps, the step length and the distance traveled (De Marsico and Mecca, 2019; Fusca et al., 2018). The data from magnetometer is utilized to compute the direction of the magnetic field (De Marsico and Mecca, 2019). Fig. 1. illustrates how the number of steps of a human operator may be calculated by using the accelerometer data.

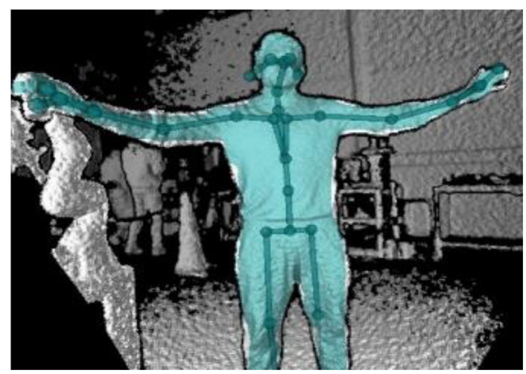

Fig. 2. Body tracking SDK from Microsoft Kinect Azure giving information about the joints of a human model.

Unlike the sensors available in mobile phones, there are various commercially developed IMU sensors that focus more on providing raw as well as processed information for analysis. They are used in gesture recognition, activity tracking, and in the assessment of ergonomic factors (Yu et al., 2017).

IMU sensors are typically placed on the body of the human operators and close to the joints. The frames of the IMU sensors need to be aligned to the frame of the joint (Narváez et al., 2018). This facilitates the collection of information that can be used in the modeling of human body in a simulation environment. Also, they can be used to monitor and track the activities of the operator.

An IMU sensor is therefore a nonintrusive contact-based sensor placed on the operator to collect the data. Whereas, a vision based system is a nonintrusive contactless method of motion capturing (Liang et al., 2016). The amalgamation of these technologies increases the overall effectiveness and the performance of the system (Glonek and Wojciechowski, 2017).

3.2.2. Vision system

A vision sensor is in principle capable of providing body tracking capabilities that enable gait recognition. Vision sensors have been used for detecting the movement of 20 joints of the human operator in a shop-floor and are also capable of tracing human activities (Gavrilova et al., 2018). The human activities that mainly occur in the shop-floor include walking, picking of parts as well as assembly of components. Fig. 2 shows the output from an application using the Azure Kinect body tracking SDK framework.

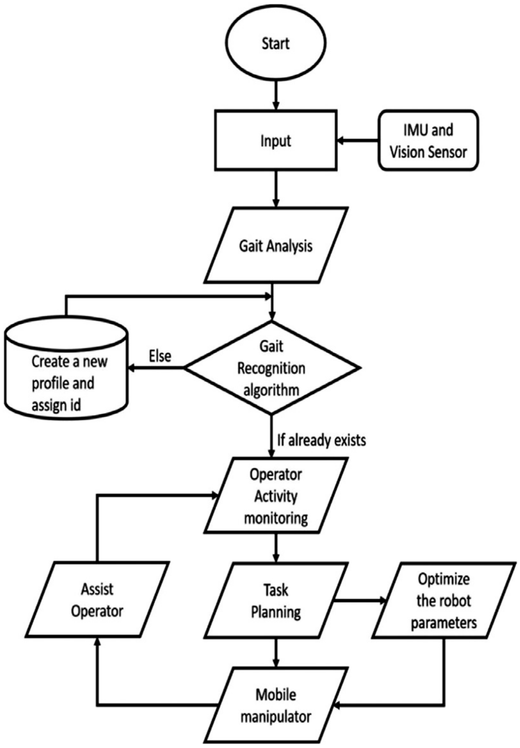

Fig. 3. Overview of the proposed framework involving activity tracking to optimize the parameters of the collaborative mobile manipulator.

Vision sensors can also be used as a tool for gesture-based control to provide instructions to the mobile manipulators through direct interaction (Kousi et al., 2019). Moreover, by taking advantage of the capabilities of sensor fusion algorithms, the information from the IMU sensors and vision sensors can be fused together.

This way, sensors complement each other and overcome the challenges faced by using each of these two devices alone (Malaisé et al., 2018 bib16; Tarabini et al., 2018).

3.2.3. A conceptual framework for the development of safe HRC using gait analysis

The combination of various sensors for monitoring and analyzing the gait of an operator towards improving the performance of collaborative mobile manipulators is a relatively new approach, which may make the execution of a task easier (Hoffman, 2019). Moreover, their successful integration in HRC cells may lead to the development of a sense of trust between humans and collaborative robots. A similar approach for capturing human data and for modeling the human operator, using motion capture and sensor data fusion in the shop-floor, may be used for creating a digital twin of the human operator carrying out tasks, and is discussed in Ref. (Nikolakis et al., 2019).

In the following paragraphs, the outline of a simple conceptual framework is presented (Fig. 3), describing how IMU sensors and vision sensors may be used to monitor the motion of an operator, who is close to a mobile manipulator.

First off, an unsupervised learning algorithm can be used to build a model to classify and assign a unique id to the human operator. A machine learning-based approach could then be implemented for identifying the human operator with an assigned id (Potluri et al., 2019). The resulting software framework would be capable of tracking various operator's activities, in order to adapt the operation of the mobile manipulator to the skills or intentions of the operator (Malaisé et al., 2018 bib16; Nikolakis et al., 2019).

An example is presented here, where an operator has to fill a box with 100 components and a mobile manipulator has to transfer the box to another area once it is filled. If there are two different operators capable of performing this task and operator 1 carries out a pick and place operation at 25 pcs / min and operator 2 does the same operation at the rate of 20 pcs / min, the idle time of the mobile manipulator waiting for operator 2 will be longer. A task planning algorithm can schedule an operation for the mobile manipulator to carry out in the meantime. This can be done, based on the feedback from the sensor fusion algorithm. Furthermore, for some cases, the velocity signal coming from an IMU sensor can potentially be used to allow the mobile manipulator to synchronize its movement in a shop floor.

3.3. Impact of these technologies

Gait analysis may serve as an identification model just like a barcode or an RFID-based identification (Prasetyo et al., 2018). But unlike the previous methods, the advantage of the proposed framework is that a model of a human operator can be built with minimum information or prior knowledge, using unsupervised learning methods for allowing gait recognition. Later on, and coupled with task and action planning algorithms, intermediate tasks may be planned for the mobile manipulator, considering the operator's speed and overall performance (Tsarouchi et al., 2016). These tasks may involve transferring parts from the warehouse to the shopfloor, robot power charging, as well as tasks that require no input from the human operator.

By taking advantage of similar models that are capable of detecting the intentions of the operator, the real-time control of the movement of mobile manipulators in complicated indoor environments could be further improved (Yang et al., 2019). This way, a smoother cooperation with the operator and a better overall production performance could be expected.

By employing big data analytics technologies, big volumes of historical data could be used for training machine learning models to improve the accuracy of activity recognition and tracking. This approach has the advantage that it will be more efficient with time as more data becomes available.

4. Challenges

A number of challenges will need to be addressed in the future, including:

- Understanding the architecture of the mobile manipulator,
- Optimizing the sensors-robot communication,
- Collecting and analyzing sensor data in real-time,
- Implementation and maintenance costs, and
- Data collection and protection issues.

Firstly, the commercially available mobile manipulators are not yet user-friendly enough in terms of allowing their easy programming. Intrinsic knowledge regarding automation and robotics as well as advanced programming skills are typically required. Mobile manipulators may be a topic of interest to many manufacturing industries, yet there are lots of areas to be further explored to make mobile manipulators fully autonomous and operational in complex environments (Madsen et al., 2015). For instance, managing a fleet of two or more mobile manipulators is significantly more complicated than just introducing one in a typical shop-floor.

Secondly, the development of operator's motion and gait models requires the effective integration of the sensors with the mobile manipulator. Some IMU sensors, for instance, require Bluetooth Low Energy (BLE) compliant modules. Hence the architecture of the mobile manipulator must support this technology (Ajerla et al.,

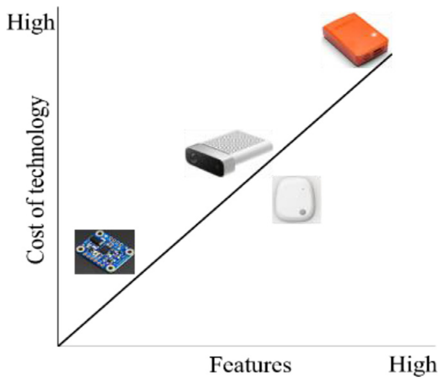

Fig. 4. Overview of the impact of cost on the feature provided by the hardware.

2019). Also, the use of IMU sensors for monitoring the indoor navigation of human operators may be affected by the presence of electromagnetic fields that may be present in typical shop-floor environments (Tarabini et al., 2018).

Thirdly, collecting and analyzing information may also prove a critical success factor. In the case of the IMU sensors, the connectivity range of the sensors is crucial. As the operational environment is complex and dynamic, there are chances that drift, connectivity and latency issues may cause significant errors. Likewise, in the case of vision systems, the operator needs to be within the field of view (Malaisé et al., 2018 bib16). Moreover, other challenges include the fact that human positions need to be constantly kept tracked, so that human operators be accurately detected and identified in a complex environment. The existence of Application Programming Interfaces (APIs), together with detailed documentation and online communities, are also factors that need to be considered when deciding to implement wearable solutions for tracking applications. Therefore, sophisticated approaches involving activity trackers and vision systems are required to deploy safe HRC (H. Wang et al., 2019).

The cost of hardware devices and associated software is also a significant factor to be considered. There are wide ranges of IMU and vision sensors available for various applications. The cost of each available technology usually depends on the range of features it provides. Fig. 4 shows the variation of cost with respect to the available features. The features may include ease of integration with simulation tools, dedicated customer support, online forums, communities, and APIs.

Finally, ethics and General Data Protection Regulation (GDPR) need to be seriously considered. The collection and storage of operators' information will have to be very transparent to the operator.

5. Discussion

This paper discusses the advantages and challenges of using wearable and vision sensors to adapt the operation of mobile collaborative manipulators to the human operators they are working with, in order to enhance the performance and safety of human-robot collaborative tasks. The integration of wearable devices in HRC configurations is expected to be an important research field over the next years. Fully automated robotic solutions may be very expensive and complex, especially in cases where a higher degree of flexibility and an increased number of product customization options are required. HRC may be the most cost-efficient option in such cases, but still, the full integration of human operators and robots would require a high degree of intelligence on the manipulators' side, so that they can match, where possible, the human operators' capabilities and skills. Towards this direction, the use of advanced wearable devices could support the continuous tracking and analysis of human activity.

IMU and vision sensors are expected to be the workhorses in operator tracking applications. The increase of computing power, the further improvement of the performance of machine learning approaches, the Industrial Internet of Things and Industry 4.0 technologies will all contribute to the faster integration of sensors in standard production environments. However, the data accuracy, the data analysis speed, implementation and maintenance costs, together with ethics and GDPR issues will be the most critical factors that will affect the when and the how wearable devices will be massively introduced and integrated in HRC applications. At the same time, it is important to note that sensor-based human operator tracking in HRC tasks will have to offer advantages that surpass the implementation costs.

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References

Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., Amirat, Y., 2015. Physical human activity recognition using wearable sensors. Sensors (Switzerland) 15, 31314–31338.
Birdal, R.G., Sertbas, A., Mihendisligi, B., 2018. Human identification based on gait analysis: a survey. In: UBMK 2018 - 3rd International Conference on Computer Science and Engineering, pp. 489–493.
Botero Valencia, J.S., Rico Garcia, M., Villegas Ceballos, J.P., 2017. A simple method to estimate the trajectory of a low cost mobile robotic platform using an IMU. Int. J. Interact. Des. Manuf. 11, 823–828.
Butepage, J., Kjellstrom, H., Kragic, D., 2018. Anticipating Many Futures: online human motion prediction and generation for human-robot interaction. In: Proceedings - IEEE International Conference on Robotics and Automation, pp. 4563–4570.
De Marsico, M., Mecca, A., 2019. A survey on gait recognition via wearable sensors. ACM Comput. Surv. 52.
Fusca, M., Negrini, F., Perego, P., Magoni, L., Molteni, F., Andreoni, G., 2018. Validation of a wearable IMU system for gait analysis: protocol and application to a new system. Appl. Sci. (Switzerland) 8, 1–16.
Gavrilova, M.L., Wang, Y., Ahmed, F., Polash Paul, P., 2018. Kinect sensor gesture and activity recognition: new applications for consumer cognitive systems. IEEE Consum. Electron. Mag. 7, 88–94.
Glonek, G., Wojciechowski, A., 2017. Hybrid orientation based human limbs motion tracking method. Sensors (Switzerland).
Halme, R.J., Lanz, M., Kämäräinen, J., Pieters, R., Latokartano, J., Hietanen, A., 2018. Review of vision-based safety systems for human-robot collaboration. Procedia CIRP 72, 111–116.
Hoffman, G., 2019. Evaluating fluency in human-robot collaboration. IEEE Trans. Hum. Mach. Syst. 49, 209–218.
Joukov, V., Cesic, J., Westermann, K., Markovic, I., Kulic, D., Petrovic, I., 2017. Human motion estimation on Lie groups using IMU measurements. In: IEEE International Conference on Intelligent Robots and Systems. IEEE, pp. 1965–1972 2017-Septe.
Kalkbrenner, C., Hacker, S., Algorri, M.E., Blechschmidt-Trapp, R., 2014. Motion capturing with inertial measurement units and Kinect: tracking of limb movement using optical and orientation information. In: BIODEVICES 2014 - 7th Int Conference on Biomedical Electronics and Devices, Proceedings; Part of 7th International Joint Conference on Biomedical Engineering Systems and Technologies. BIOSTEC, pp. 120–126 2014.
Kousi, N., Gkournelos, C., Aivaliotis, S., Giannoulis, C., Michalos, G., Makris, S., 2019. Digital twin for adaptation of robots' behavior in flexible robotic assembly lines. Procedia Manuf. 28, 121–126.
Kousi, N., Michalos, G., Aivaliotis, S., Makris, S., 2018. An outlook on future assembly systems introducing robotic mobile dual arm workers. Procedia CIRP 72, 33–38.
Kulkarni, P., Illing, B., Gaspers, B., Brüggemann, B., Schulz, D., 2019. Mobile manipulator control through gesture recognition using IMUs and online lazy neighbourhood graph search. Acta IMEKO 8, 3–8.
Li, C., Fahmy, A., Sienz, J., 2019. An augmented reality based human-robot interaction interface using Kalman filter sensor fusion. Sensors (Switzerland) 19.
Liang, P., Ge, L., Liu, Y., Zhao, L., Li, R., Wang, K., 2016. An augmented discrete-time approach for human-robot collaboration. Discrete Dyn. Nat. Soc. 2016.
Madsen, O., Bøgh, S., Schou, C., Andersen, R.S., Damgaard, J.S., Pedersen, M.R., et al., 2015. Integration of mobile manipulators in an industrial production. Ind. Robot 42, 11–18.

Malaisé A., Maurice P., Colas F., Charpillet F., Ivaldi S. Activity recognition with multiple wearable sensors for industrial applications 2018:229–34.

Mandery, C., Plappert, M., Borras, J., Asfour, T., 2016. Dimensionality reduction for whole-body human motion recognition. In: FUSION 2016 - 19th International Conference on Information Fusion, Proceedings, pp. 355–362.

Narváez, F., Árbito, F., Proaño, R., 2018. A quaternion-based method to IMU-to-body alignment for gait analysis. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 10917. LNCS, pp. 217–231.

Navarro, B., Cherubini, A., Fonte, A., Poisson, G., Fraisse, P., 2017. A framework for intuitive collaboration with a mobile manipulator. In: IEEE International Conference on Intelligent Robots and Systems, pp. 6293–6298 2017-Septe.

Nikolakis, N., Alexopoulos, K., Xanthakis, E., Chryssolouris, G., 2019. The digital twin implementation for linking the virtual representation of human-based production tasks to their physical counterpart in the factory-floor. Int. J. Comput. Integr. Manuf. 32, 1–12.

Potluri, S., Chandran, A.B., Diedrich, C., Schega, L., 2019. Machine learning based human gait segmentation with wearable sensor platform. In: 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, Germany. IEEE, pp. 588–594.

Prasetyo, H., Sugiarto, Y., Rosyidi, C.N., 2018. Design of an automatic production monitoring system on job shop manufacturing. In: AIP Conference Proceedings.

Ragaglia, M., Zanchettin, A.M., Rocco, P., 2018. Trajectory generation algorithm for safe human-robot collaboration based on multiple depth sensor measurements. Mechatronics 55, 267–281.

Santaera, G., Luberto, E., Serio, A., Gabiccini, M., Bicchi, A., 2015. Low-cost, fast and accurate reconstruction of robotic and human postures via IMU measurements. In: Proceedings - IEEE International Conference on Robotics and Automation, pp. 2728–2735 2015-June.

Simoens, P., Dragone, M., Saffiotti, A., 2018. The Internet of Robotic Things: a review of concept, added value and applications. Int. J. Adv. Rob. Syst. 15.

Tarabini, M., Marinoni, M., Mascetti, M., Marzaroli, P., Corti, F., Giberti, H., et al., 2018. Monitoring the human posture in industrial environment: a feasibility study. In: 2018 IEEE Sensors Applications Symposium, SAS 2018 - Proceedings, pp. 1–6 2018-Janua.

Tortora S., Michieletto S., Stival F., Menegatti E. Fast human motion prediction for human-robot collaboration with wearable interfaces 2019.

Tsarouchi, P., Makris, S., Chryssolouris, G., 2016. Human–robot interaction review and challenges on task planning and programming. Int. J. Comput. Integr. Manuf. 29, 916–931.

Uzunovic, T., Golubovic, E., Tucakovic, Z., Acikmese, Y., Sabanovic, A., 2018. Task-based control and human activity recognition for human-robot collaboration. In: Proceedings: IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society, pp. 5110–5115.

Vargas-Valencia, L.S., Elias, A., Rocon, E., Bastos-Filho, T., Frizera, A., 2016. An IMU–to-body alignment method applied to human gait analysis. Sensors (Switzerland) 16, 1–17.

Vysocky, A., Novak, P., 2016. Human - robot collaboration in industry. MM Sci. J. 903–906 2016-June.

Wang, L., Gao, R., Váncza, J., Krüger, J., Wang, X.V., Makris, S., et al., 2019a. Symbiotic human-robot collaborative assembly. CIRP Ann. 68, 701–726.

Wang, W., Li, R., Diekel, Z.M., Chen, Y., Zhang, Z., Jia, Y., 2019b. Controlling object hand-over in human-robot collaboration via natural wearable sensing. IEEE Trans. Hum. Mach. Syst. 49, 59–71.

Weitschat, R., Ehrensperger, J., Maier, M., Aschemann, H., 2018. Safe and efficient human-robot collaboration part I: estimation of human arm motions. In: Proceedings - IEEE International Conference on Robotics and Automation, pp. 1993–1999.

Yang, M., Yang, E., Zante, R.C., Post, M., Liu, X., 2019. Collaborative mobile industrial manipulator: a review of system architecture and applications. In: International Conference on Automation & Computing. IEEE, pp. 1–6.

Yu, H., Cang, S., Wang, Y., 2017. A review of sensor selection, sensor devices and sensor deployment for wearable sensor-based human activity recognition systems. In: SKIMA 2016 - 2016 10th International Conference on Software, Knowledge, Information Management and Applications, pp. 250–257.