robotics

Review

A Narrative Review on Wearable Inertial Sensors for Human Motion Tracking in Industrial Scenarios

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Abstract: Industry 4.0 has promoted the concept of automation, supporting workers with robots while maintaining their central role in the factory. To guarantee the safety of operators and improve the effectiveness of the human-robot interaction, it is important to detect the movements of the workers. Wearable inertial sensors represent a suitable technology to pursue this goal because of their portability, low cost, and minimal invasiveness. The aim of this narrative review was to analyze the state-of-the-art literature exploiting inertial sensors to track the human motion in different industrial scenarios. The Scopus database was queried, and 54 articles were selected. Some important aspects were identified: (i) number of publications per year; (ii) aim of the studies; (iii) body district involved in the motion tracking; (iv) number of adopted inertial sensors; (v) presence/absence of a technology combined to the inertial sensors; (vi) a real-time analysis; (vii) the inclusion/exclusion of the magnetometer in the sensor fusion process. Moreover, an analysis and a discussion of these aspects was also developed.

Keywords: IMUs; industry 4.0; human-robot collaboration; upper limb

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1. Introduction

The focus of the industrialization stage called Industry 4.0 is to guarantee an optimal communication among human beings, machines, and resources, and hence to create smart products, procedures, and processes [1]. The appeal of Industry 4.0 is based on two reasons: (i) it represents an industrial revolution predicted a priori and not observed ex post, providing the opportunity to actively shape the future; (ii) it has a huge economic impact, developing new business models and services [2]. Even though automation is one of the core principles of Industry 4.0, the worker's ability to supervise the environment remains an important resource within the factory [3]. In this context, the World Health Organization has identified physical work, organizational, and psycho-social risk factors that cause the so-called work-related musculoskeletal disorders (WMSDs). These multifactorial diseases (Figure 1) occur when there is a mismatch between the physical capacity of the human body and the physical requirements of the task [4]. The WMSDs reduce work productivity, affect the working capacity, decrease worker satisfaction, and increase medical and compensation costs [5]. For all of these reasons, human safety has to be preserved by assessing the biomechanical risk associated with the industrial tasks performed [6].

Considering all of the technological innovations introduced by Industry 4.0, the central role assumed by the concept of automation has led to include robotic systems in the working environment. According to the last estimates of the International Federation of Robotics (IFR) report, the demand for industrial robots has been affected by a continuous increase since 2010. Moreover, regardless of the global pandemic situation, the year 2020 also featured a growth rate of robot installations of nearly 0.5% [7].

Despite the high levels of repeatability, accuracy, and speed guaranteed by traditional industrial robots, their lack of versatility makes them unsuitable for an effective adaptation to the changes in production or dynamic working environments [8]. To overcome the limitations of the traditional industrial robots while maintaining the central role of humans, collaborative robots, or cobots, have been introduced. Indeed, they enable a direct interaction with human operators supporting task execution, reducing fatigue, and shortening times of production. Accordingly, robot precision and repeatability are combined with human perception, intelligence, and flexibility [9]. Based on the level of the interaction between the human and the robot, IFR [10] identifies five distinct scenarios (Figure 2):

- Cell. It is not a real cooperating scenario, because the robot is located in a traditional cage far away from the human.
- Coexistence. The human and the robot work alongside each other but they do not share a workspace.
- Synchronized. The human and the robot share a workspace, but only one of the interaction partners is present in the workspace at a time.
- Cooperation. Both the human and the robot perform tasks at the same time in the shared workspace, but they do not work simultaneously on the same product or component.
- Collaboration. The human and the robot work simultaneously on the same product or component.

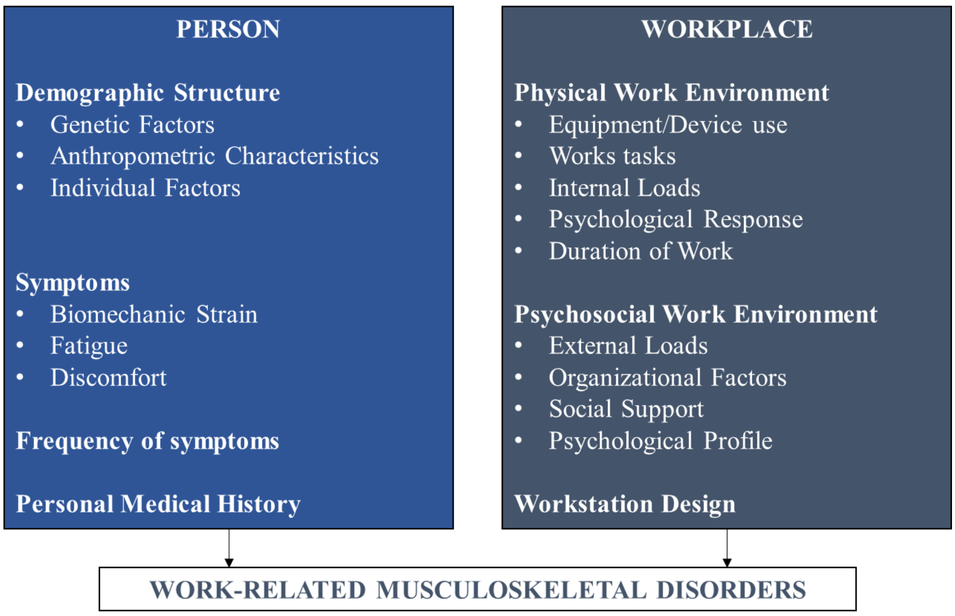

Figure 1. Factors contributing to the WMSDs [4].

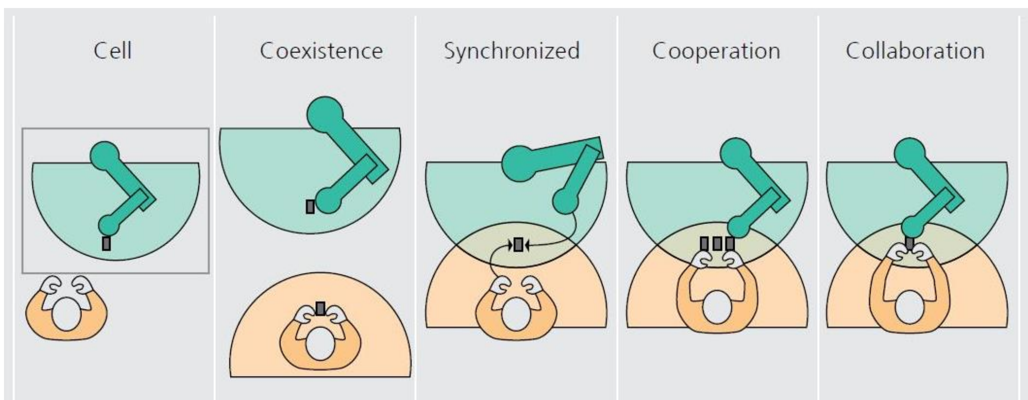

Figure 2. Scenarios of interaction between the human and the robot [10].

As shown in the last three scenarios, the presence of a shared workspace implies a higher level of interaction between the human and the robot and hence the necessity to guarantee the safety of the operator. The guidelines presented in the technical specification ISO/TS 15066:2016 contain the safety requirements for collaborative robots, in terms of power and force limitations, and aim at avoiding damages in case of collisions with the human [11]. In addition to safety, another important requirement for collaborative robotics is to improve the effectiveness and performance of the interaction between the human and the robot [12].

To achieve the appropriate responsive behavior within the shared workspace, sensors enabling the tracking of the human motion can be exploited to plan the robot's control logic and thus optimize its path, timing, and velocity. This operation of motion capture can be performed with a variety of technologies. Vision instruments, such as stereophotogrammetric systems and RGB-D cameras are considered the gold standard for the human motion analysis because of their precision and accuracy. However, they have many disadvantages, such as high costs, occlusion problems, encumbrance, long subject preparation and data post-processing times, and constraints related to the laboratory environment. To overcome these limitations, wearable technologies, such as magnetic-inertial measurement units (MIMUs) have been promoted, thanks to the recent diffusion of micro-electro-mechanical systems. Once MIMUs are fixed on body segments, the human movement can be quantitatively characterized by collecting data from the triaxial accelerometer, gyroscope, and magnetometer embedded in each sensor [13]. Moreover, the complementary information of acceleration, angular velocity, and magnetic field can be exploited by means of a sensor fusion algorithm to estimate the absolute orientation and displacement of the MIMU [14].

Considering an industrial scenario, MIMUs represent a suitable solution because they are low-cost, portable, easy to wear, minimally invasive, and free from laboratory constraints. However, the estimation of the MIMUs orientation through the sensor fusion process involves drift problems. These can be mitigated by implementing additional biomechanical constraints and specific calibration procedures. In addition, ferromagnetic disturbances, typical of the manufacturing environment, can affect the MIMU magnetometer reading and thus deteriorate the quality of the analysis. To solve this problem, it is advisable to exclude the magnetometer from the sensor fusion process, de facto using IMUs (inertial measurement units) instead of MIMUs.

In light of all of these considerations, the present survey was conducted with the final aim of providing a general overview about the use of wearable MIMUs/IMUs, to track the movement of the human upper body in the industrial field.

2. Materials and Methods

Three main concepts were combined to plan and implement the analysis: motion tracking, wearable IMUs, and industrial context. Accordingly, the following search string was searched for in the Scopus electronic database on 23 November 2022:

TITLE-ABS (motion* OR trajectory* OR kinemat* OR track*) AND (imu OR mimu OR inertial OR wearable) AND (industry* OR manufactur* OR ergonom* OR (robot* AND collab*) OR worki*))

Additional filters were introduced: (i) the publication year was restricted from 2011 to 2022; (ii) the document type was limited to articles, conference papers, and reviews; (iii) the only included language was English. The search gave 2645 results, which were manually screened, based on specific exclusion criteria (Figure 3).

At the end of the screening phase, 54 full-text papers were selected and read (Table 1). Once the articles were collected, some important aspects were identified and analyzed:

- Number of publications per year;
- Aim of the work;
- Body district involved in the motion tracking;
- Number of adopted MIMUs/IMUs;
- Presence/absence of a technology combined to MIMUs/IMUs;

- Presence/absence of a real-time analysis;
- Inclusion/exclusion of the magnetometer in the sensor fusion process.

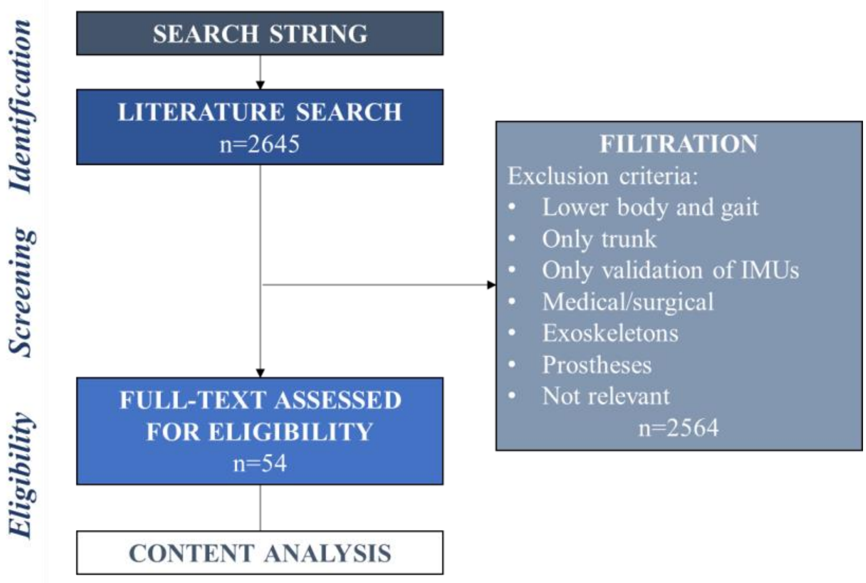

Figure 3. Flow chart of the literature analysis.

Table 1. Results of the literature analysis focused on human motion tracking with MIMUs/IMUs in the industrial context.

Study	Year	Aim	Body District	MIMUs/IMUs Number	Technology	Real-Time	Magnetometer
Huang C. [15]	2020	Risk assessment	Total body	17	MIMUs	Yes	Yes
Peppoloni L. [16]	2016	Risk assessment	Upper limb	3	MIMUs + EMGs	Yes	Yes
Giannini P. [17]	2020	Risk assessment	Total body	11	MIMUs + EMGs	Yes	Yes
Monaco M.G.L. [18]	2019	Risk assessment	Upper body	8	MIMUs + EMGs	No	Yes
Santos S. [19]	2020	Risk assessment	Upper body	4	MIMUs	Yes	Yes
Humadi A. [20]	2021	Risk assessment	Upper body	17	MIMUs	No	Yes
Peppoloni L. [21]	2014	Risk assessment	Upper limb	4	MIMUs	Yes	Yes
Yan X. [22]	2017	Risk assessment	Upper body	2	MIMUs	Yes	Yes
Merino G. [23]	2019	Risk assessment	Total body	17	IMUs	No	No
Chan Y. [24]	2022	Risk assessment	Upper body	6	MIMUs	No	Yes
Fletcher S.R. [25]	2018	Risk assessment	Total body	17	MIMUs	Yes	Yes
Li J. [26]	2018	Risk assessment	Total body	7	MIMUs	Yes	Yes
Caputo F. [27]	2019	Risk assessment	Upper body	6	MIMUs	No	Yes
Nunes M.L. [28]	2022	Risk assessment	Upper body	7	MIMUs	No	Yes
Martinez K. [29]	2022	Risk assessment	Total body	9	MIMUs	Yes	Yes
Hubaut R. [30]	2022	Risk assessment	Upper body	4	IMUs + EMGs	No	No
Colim A. [31]	2021	Risk assessment	Upper body	11	MIMUs	No	Yes
Schall M.C. [32]	2021	Risk assessment	Upper body	4	IMUs	No	No
Olivas-Padilla B. [33]	2021	Risk assessment	Total body	52	MIMUs	No	Yes
Winiarski S. [34]	2021	Risk assessment	Total body	16	MIMUs	No	Yes
Zhang J. [35]	2020	Collaborative robotics	Upper body	5	MIMUs + vision	Yes	Yes
Ates G. [36]	2021	Collaborative robotics	Upper body	5	MIMUs	No	Yes
Skulj G. [37]	2021	Collaborative robotics	Upper body	5	IMUs	Yes	No
Wang W. [38]	2019	Collaborative robotics	Upper limb	1	IMUs + EMGs	Yes	No
Sekhar R. [39]	2012	Collaborative robotics	Upper limb	1	IMUs	Yes	No
Chico A. [40]	2021	Collaborative robotics	Upper limb	1	MIMUs + EMGs	Yes	Yes
Tao Y. [41]	2018	Collaborative robotics	Upper limb	6	MIMUs	No	Yes
Al-Yacoub A. [42]	2020	Collaborative robotics	Upper body	1	IMUs + EMGs + vision	Yes	No

Table 1. *Cont.*

Study	Year	Aim	Body District	MIMUs/IMUs Number	Technology	Real-Time	Magnetometer
Tortora S. [43]	2019	Collaborative robotics	Upper limb	2	IMUs + EMGs	Yes	No
Resende A. [44]	2021	Collaborative robotics	Upper body	9	MIMUs	Yes	Yes
Amorim A. [45]	2021	Collaborative robotics	Upper limb	1	MIMUs + vision	Yes	Yes
Pellois R. [46]	2018	Collaborative robotics	Upper limb	2	IMUs	No	No
Grapentin A. [47]	2020	Collaborative robotics	Hand	6	IMUs	Yes	No
Bright T. [48]	2021	Collaborative robotics	Hand	15	IMUs	No	No
Digo E. [49]	2022	Collaborative robotics	Upper limb	2	IMUs	Yes	No
Lin C.J. [50]	2022	Collaborative robotics	Upper limb	3	MIMUs + EMGs	Yes	Yes
Rosso V. [51]	2022	Collaborative robotics	Upper limb	1	IMUs	No	No
Tuli T.B. [52]	2022	Collaborative robotics	Upper limb	3	MIMUs + vision	Yes	Yes
Tarabini M. [53]	2018	Tracking in industry	Upper body	6	MIMUs + vision	Yes	Yes
Tarabini M. [54]	2018	Tracking in industry	Upper body	6	MIMUs + vision	No	Yes
Caputo F. [55]	2018	Tracking in industry	Total body	10	MIMUs	No	Yes
Digo E. [56]	2022	Tracking in industry	Upper body	3	IMUs	Yes	No
Borghetti M. [57]	2020	Tracking in industry	Hand	2	MIMUs	No	Yes
Bellitti P. [58]	2019	Tracking in industry	Hand	2	MIMUs	No	Yes
Fang W. [59]	2017	Tracking in industry	Head	1	IMUs + vision	Yes	No
Manns M. [60]	2021	Action recognition	Total body	8	MIMUs	Yes	Yes
Al-Amin M. [61]	2019	Action recognition	Upper body	2	MIMUs + EMGs + vision	Yes	Yes
Al-Amin M. [62]	2022	Action recognition	Upper limb	2	MIMUs	No	Yes
Kubota A. [63]	2019	Action recognition	Upper limb	1	IMUs + EMGs + vision	No	No
Calvo A.F. [64]	2018	Action recognition	Total body	4	MIMUs + EMGs + vision	Yes	Yes
Antonelli M. [65]	2021	Action recognition	Upper body	4	IMUs	No	No
Digo E. [66]	2020	Other	Upper body	7	MIMUs + vision	No	Yes
Maurice P. [67]	2019	Other	Total body	17	MIMUs + vision	No	Yes
Li J. [68]	2017	Other	Hand	10	MIMUs	Yes	Yes

3. Results and Discussion

In this section, the selected 54 full-text papers of the review are presented through bar diagrams identifying some important aspects. Moreover, the results are discussed canalizing these aspects in a typical industrial scenario. Even if extreme attention was paid to include any possible synonymous terms, when the search string was built, some terms may be missing. In addition, the limitation of the publication year from 2011 to 2022 may have restricted the number of results. However, this choice is in line with both the development of Industry 4.0 and the spread of wearable inertial sensors for the human motion tracking.

3.1. Number of Publications per Year

Considering the publication year of the selected papers, the interest towards the use of MIMUs/IMUs for the human motion tracking in industry has proportionally grown from 2016 (Figure 4). The only exceptions are represented by 2020, which might be explained by the global pandemic situation, and 2022, because it has not ended yet. This growing trend is in line with the emergence and development of Industry 4.0, the increase of automation processes, and the spread of collaborative robotics.

3.2. Aim of the Work

Scientific research exploiting MIMUs/IMUs in industrial scenarios is focused on several aspects (Figure 5). A first part of the studies has been devoted to the biomechanical risk assessment of manufacturing workers. Due to the high impact of WMSDs on the safety and quality of work, many studies have focused on the prevention of these upper body disorders, recognizing the improper task settings, identifying uncomfortable postures, and assessing the exposure to risk factors, with a biomechanical analysis. Some studies have concentrated on the development, validation, and accuracy evaluation of a wearable system for the estimation of the WMSD risks in manufacturing [15–22]. Other studies have adopted MIMUs/IMUs to collect human activity data and perform an ergonomic analysis in specific industrial and working tasks, such as harvesting [23,24], installing [25], assembling [26–28], or handling [29,30]. In addition, MIMUs/IMUs have been exploited to quantify the WMSD risk exposure in the upper body, by assessing the influence of a robotic implementation [31], comparing different tasks [32], identifying the main joints contributing to the motion [33], or complementing the ergonomic procedures into workstation design [34].

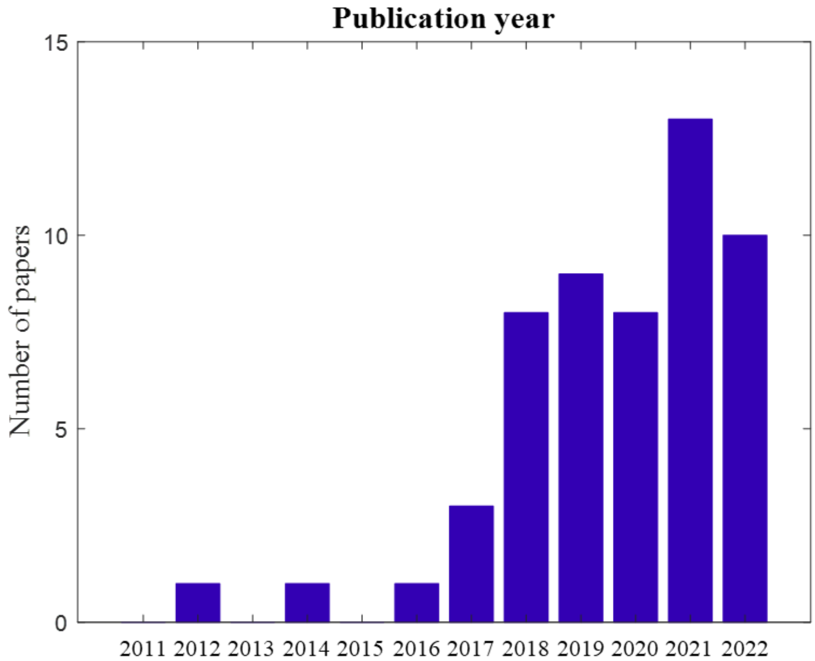

Figure 4. Publication year of the literature studies focused on human motion tracking with MIMUs/IMUs, in the industrial context.

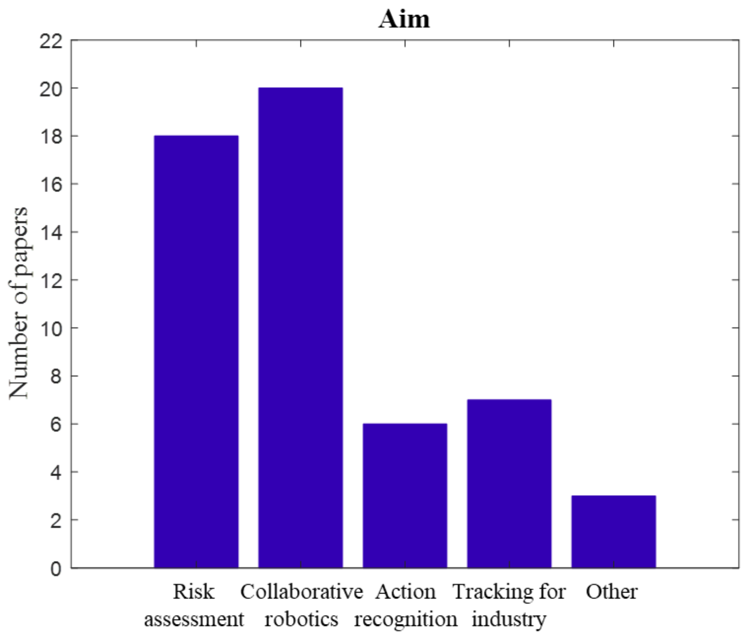

Figure 5. Aim of the literature studies focused on the human motion tracking with MIMUs/IMUs, in the industrial context.

In addition to a risk assessment, collaborative robotics also represents a frequent aim of the literature studies using MIMUs/IMUs, for industrial applications (Figure 5). In this case, the main intent is to improve the human-robot interaction, in terms of safety, effectiveness, and timing [35,36]. Some studies have adopted MIMUs/IMUs to estimate the position and orientation of the worker and consequently to teleoperate [37], control [38–40], or teach [41] the robot. Some studies have focused on predicting human motion and the reached target to make the robot aware of the operator's intentions within the shared workspace [42–44]. In other cases, more attention has been paid to safety and, in particular, to collision avoidance within the shared dynamic and unstructured workspace [45]. Moreover, the possibility of adapting human motion tracking to industrial scenarios by excluding the magnetometer from the sensor orientation estimation, has been investigated [46,47].

Finally, some studies have generally focused on the industrial context proposing methods for human motion tracking [53–59] and human action recognition [60–65], with the aim of improving productivity while ensuring safety.

3.3. Involved Body District and Number of Adopted MIMUs/IMUs

The body district involved in the human motion analysis (Figure 6) and the resulting number of adopted MIMU/IMUs (Figure 7) are other important aspects to consider in the literature. When studies were conducted with the aim of assessing biomechanical risk in the manufacturing or creating databases for ergonomics purposes, a total body analysis involving a high number of sensors (≥17) has been performed [15,23,25,33,67].

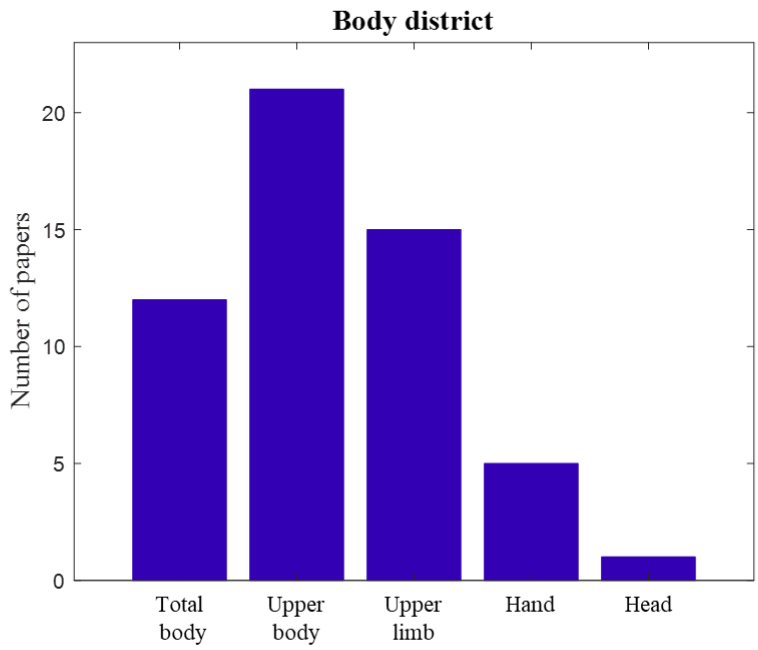

Figure 6. Human body district involved in the motion tracking process, according to the literature studies on MIMUs/IMUs, in the industrial context.

In other studies that generally focused on human motion tracking in different industrial scenarios, the motion analysis involved only the upper body (number of sensors between six and 11) positioned on the trunk and upper limbs [18,27,31,44,53–55]. Considering the context of the collaborative robotics, the main interaction between the human and cobot generally involves the upper limbs with a limited number of adopted MIMUs/IMUs (from one to three) positioned on the upper arm and forearm [38–40,43,45,46,49–52]. Moreover, given the importance of the manual operations in industrial environments, other studies have adopted a variable number of MIMUs/IMUs (between two and 16) to focus on hand and finger tracking [47,48,57,58,68].

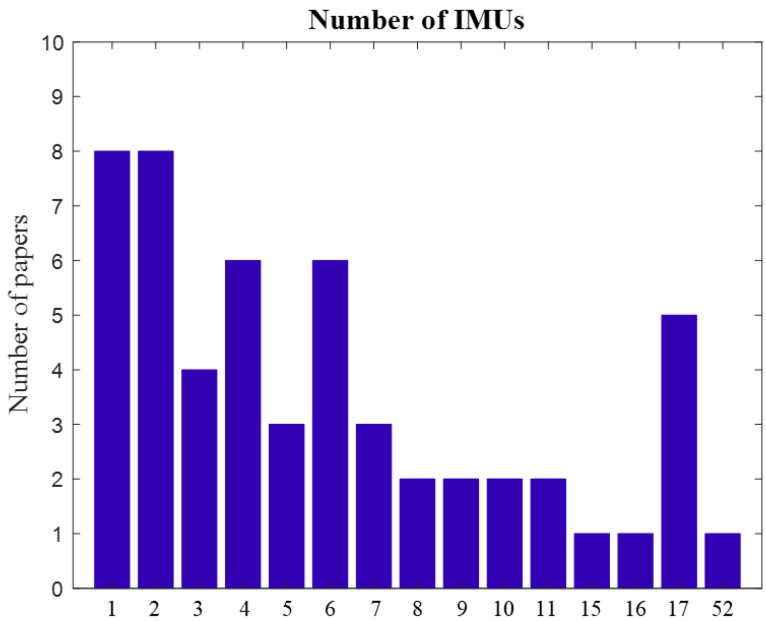

Figure 7. Number of MIMUs/IMUs involved in the motion tracking process, according to the literature studies, and focused on the industrial context.

3.4. Presence/Absence of a Technology Combined to MIMUs/IMUs

Another important aspect to be analyzed is the presence of another mocap technology, associated with MIMUs/IMUs, for the human motion tracking in the industrial context (Figure 8). All articles identified in the analysis chose MIMUs/IMUs because of their many advantages for human motion tracking in the manufacturing field. However, two streams of thought can be identified in the literature. On the one hand, the MIMUs/IMUs performance is considered to be sufficient for the industrial context and for this reason they have replaced other systems. Based on their portability and minimal invasiveness, MIMUs/IMUs have been selected as the only technology for improving human-robot collaboration [36,37,39,41,44,46,47,65]. On the other hand, although the advantages of MIMUs/IMUs are recognized and stated, the magnetometer sensitivity to the ferromagnetic disturbances and the orientation drift due to the sensor fusion make their performance insufficient for the industrial context. Some studies on human motion tracking in industrial and collaborative robotic scenarios, have compensated for the limits of the MIMUs/IMUs, by combining them with vision systems [35,45,54,59,60,66]. In other cases, the biomechanical risk assessment of workers has been performed by integrating MIMUs/IMUs with electromyographic sensors (EMGs) to complete the analysis with information of the muscular activation [17,18,21,23,26]. Finally, some literature studies have exploited the data collected by MIMUs/IMUs, EMG sensors, and vision systems, to recognize human actions [61,63,64].

3.5. Presence/Absence of a Real-Time Analysis

Independently from the aim, real-time human motion tracking is a fundamental requirement for the industrial context. First, an online risk assessment is suitable to evaluate the biomechanical load in the manual material handling [17] or repetitive efforts [21], to improve the assembly workstations [26,31], and to build an alert system for the prevention of musculoskeletal disorders [15,22]. Furthermore, collaborative robotics can also advantageously exploit the real-time tracking of human motion in terms of safety and efficiency [69]. Indeed, an online information exchange between the operator and the robot improves both the interaction [35,42,44,56] and the robot control [37,40]. As Figure 9 shows, studies dealing with the real-time capture of human motion are more than those that do not consider this concept.

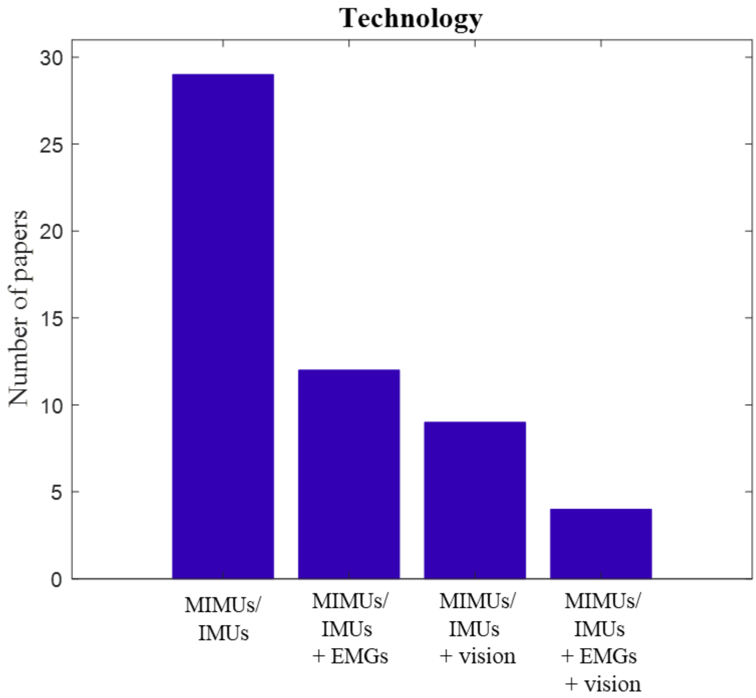

Figure 8. Technology adopted for the motion tracking process, according to the literature studies, and focused on the industrial context.

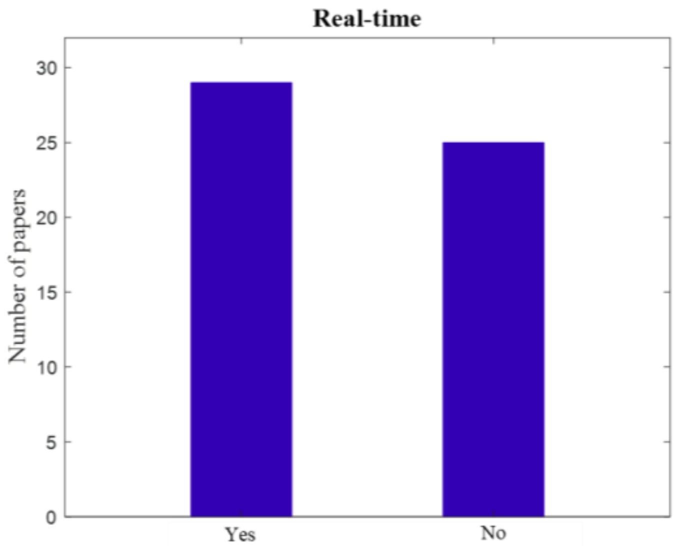

Figure 9. Presence/absence of a real-time motion tracking process, according to the literature studies that focused on the industrial context.

3.6. Inclusion/Exclusion of the Magnetometer in the Sensor Fusion Process

When the human motion analysis is performed in the manufacturing environment, the presence of ferromagnetic disturbances makes the magnetometer readings an unreliable source of information [56,70]. Consequently, it is necessary to exclude the magnetometer from the estimate of the MIMUs orientation and hence to adopt IMUs. In this case, the drift occurring around the vertical axis can no longer be compensated for. Moreover, the relative orientation on the horizontal plane (i.e., perpendicular to the gravity vector) among two or more units, which is fundamental to estimate the segment pose and consequently the joint kinematics, is unknown.

To overcome these limitations, additional biomechanical constraints and specific calibration procedures have to be introduced. The exclusion of the magnetometer from the sensor fusion process is gaining attention (Figure 10). Indeed, some literature studies have estimated the orientation of IMUs only exploiting the accelerometer and the gyroscope. Focusing on the context of collaborative robotics, since the robot itself represents a ferromagnetic disturbance, one of the main goals is the magnetometer-free human motion tracking [37–39,42,43,46,47].

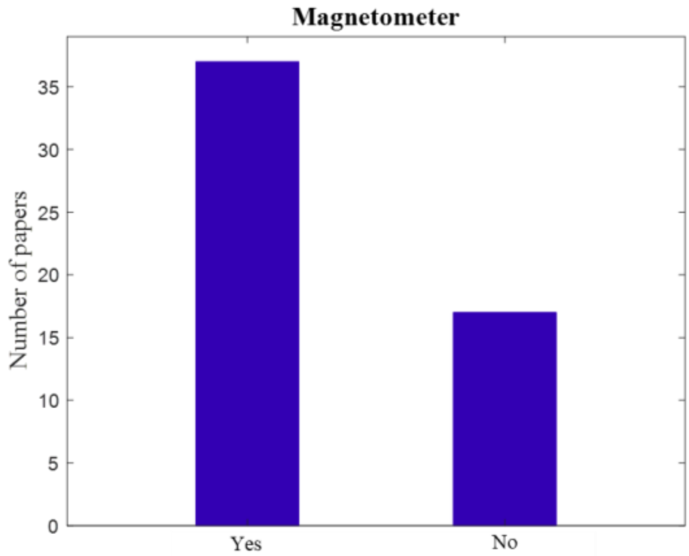

Figure 10. Inclusion/exclusion of the magnetometer for the human motion tracking, according to the literature studies that focused on the industrial context.

4. Conclusions

This review summarizes the state-of-the-art knowledge on wearable sensors used to track human motion in different industrial scenarios, particularly focusing on the year of publication, the purpose, the number and placement of sensors, the presence of other additional technologies, the concept of real-time, and the exclusion of the magnetometer. The results suggest that MIMUs/IMUs are a suitable solution for capturing human motion in the manufacturing field. Accordingly, the efforts in the exploitation of these systems, instead of, or in addition to traditional technologies should focus on implementing a real-time analysis and excluding the magnetometer from the sensor fusion process.

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