Performance Evaluation of Leap Motion Controller for Hand Motion Assessment

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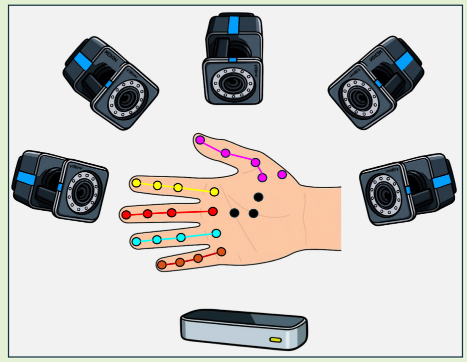

***Abstract*—The use of markerless depth cameras for hand kinematic reconstruction is gaining interest due to their ability to enable more natural and unconstrained motion analysis. The leap motion controller (LMC) is a compact and widely adopted example, equipped with an integrated skeleton-tracking algorithm that estimates 3-D joint positions without the need for reflective markers. Several studies in the literature have assessed the accuracy of the LMC in reconstructing hand kinematics; however, they have generally overlooked the following critical aspects: 1) the use of kinematic protocols capable of capturing metacarpophalangeal (MCP) joint abduction–adduction (A/A); 2) the presence of static and dynamic offsets that can degrade angle estimation accuracy; and 3) the evaluation of additional kinematic features such as intrafinger couplings. In this article, an offset correction strategy is proposed to improve the accuracy of LMC in reconstructing hand joint angles during flexion–extension (F/E) and A/A movements. The proposed approach was evaluated through a comparative analysis of the joint angles extracted using the LMC and a marker-based optoelectronic system (MOS). Ten healthy subjects were recruited to collect joint angle data during F/E and A/A movements. The results demonstrated significant improvements in angle estimation accuracy: in 95% of cases, the angular error was below 0.17 rad, and in 85% of cases, the Spearman correlation coefficients exceeded 0.7. Nevertheless, the Bland–Altman analysis indicated that the LMC and MOS measurements are not yet interchangeable in applications where high accuracy is required, such as clinical evaluation and hand prosthesis design.**

***Index Terms*—Hand joint reconstruction, intrafinger couplings, leap motion controller (LMC), offsets' estimation.**

I. Introduction

THE human hand is the most versatile and dexterous part of the body, consisting of 27 bones actuated by both intrinsic and extrinsic muscles. Aristotle defined this anatomical structure as the "tool of tools" [1], [2] due to its remarkable ability to perform complex movements that range from precise manipulation to powerful grasping. The kinematic chain of the hand involves multiple degrees of freedom: flexion–extension (F/E) and abduction–adduction (A/A) at the metacarpophalangeal (MCP) joints and F/E at the proximal (PIP) and distal (DIP) interphalangeal (IP) joints. Of particular importance is the oppositional movement of the thumb, which allows for a variety of grip patterns that are essential for daily activities. Thus, understanding hand kinematics is crucial for analyzing human motor control [3], developing rehabilitation [4], [5] and human robot interaction strategies [6], [7], and designing robotic systems that can replicate human hand functionality [8], [9].

The kinematic analysis of the hand is traditionally performed using marker-based optoelectronic systems (MOSs). These systems consist of multiple infrared cameras strategically positioned around the acquisition volume to track reflective markers placed on specific anatomical landmarks of the hand. Through stereophotogrammetry and triangulation, these systems obtain the 3-D coordinates of each marker in space over time. Thanks to these characteristics, MOSs are considered the noninvasive gold standard for 3-D hand and upper-limb kinematic reconstruction, due to their superior spatial and temporal accuracy, submillimeter precision in tracking reflective markers, and well-established

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protocols that ensure high reliability in laboratory settings [10], [11], [12].

However, these systems require structured environments and lengthy setup times. Furthermore, the position of the markers may hinder the proper execution of movements. As a result, there has been a steady increase in the development of markerless hand tracking methods, particularly those that use RGB and RGB-D cameras. Approaches based on RGB-D cameras tend to be more accurate because they can directly estimate depth information, whereas RGB cameras are limited to capturing only 2-D information [13].

The leap motion controller (LMC) is a popular compact depth camera that incorporates a hand skeleton tracking algorithm to retrieve the 3-D positions of each joint without the need for reflective markers. This represents a significant advancement in hand tracking technology, allowing for a more natural and unconstrained analysis of hand kinematics, as users can move their hands freely in 3-D space. In addition, the LMC's portability and short setup time make it an appealing tool for various applications such as entertainment [14] and video-game-based therapy [15]. In the literature, several studies have focused on assessing the accuracy of the LMC in reconstructing hand joint angles. Ganguly et al. [16] compared the hand joint angle values reconstructed with the LMC to those obtained with an MOS. They reconstructed the F/E angles of all the long fingers and thumb abduction using the kinematic protocol introduced in [17]. The results obtained from static tasks showed an error in the estimation of finger length of up to 1 cm, while the results from dynamic trials showed range of motion (ROM) differences ranging from 0.25° (PIP index F/E) and 61.51° (PIP middle finger F/E). The correlation analysis between the results obtained with the two systems indicated acceptable values only for PIP F/E of the little and ring fingers ($r = 0.9062$ and $r = 0.8978$).

To improve the accuracy of the LMC, in [18], three LMC devices were simultaneously used by merging their data using a Kalman filter sensor fusion algorithm. To validate the proposed approach, the data obtained through the LMCs were compared with those obtained with only one LMC and with those acquired from an MOS. The MCP and PIP joint angles of a prosthetic hand (BeBionic, Ottobock, Duderstadt, Germany) were reconstructed using the three approaches during the fist and index finger pointing motions. The results demonstrated that using three LMCs instead of one improved system accuracy, increasing the correlation coefficient between LMC and MOS data. For instance, the correlation coefficient for the little finger increased from 0.67 to 0.79 when comparing the use of one LMC to three MOSs. However, despite this improvement, significant peak-to-peak differences in joint angle estimation between the MOS system and the 3-LMC setup remained. These differences exceeded 15° for all joints except the PIP of the ring finger, which showed an error of 5°.

The performance of the LMC in measuring wrist F/E, radial/ulnar deviation, and forearm pronation/supination angles was also evaluated. In [19], these angles were retrieved with an LMC and MOS system. The authors found that the LMC was able to provide clinically meaningful data for wrist F/E and wrist deviation with root mean square errors (RMSEs) of 11.6° and 12.4°, respectively. However, the study showed an RMSE of 38.4° for forearm pronation/supination.

As evident from the literature, the performance of the LMC has so far demonstrated poor accuracy in reconstructing wrist and hand joint angles. This makes it suitable as an interface for virtual reality applications, but not reliable for precise hand motion assessment. The literature analysis also revealed several limitations in existing studies, which, if addressed, could improve the accuracy of the LMC and allow a more comprehensive evaluation of its performance. The limitations can be summarized as follows.

1) The LMC accuracy in estimating A/A angles of the MCP joints of the long fingers has not been evaluated.
2) Possible angular offsets between reference data and LMC ones, defined as systematic differences in joint angle measurements under static or dynamic conditions, which could affect joint angle estimation, have not been taken into account.
3) From a clinical and prosthetic design perspective, existing leap motion studies have been limited to joint angle analysis. The device's ability to accurately extract more sophisticated parameters, such as intrafinger couplings, remains unexplored. However, these metrics play a crucial role in the design of prostheses capable of faithfully reproducing the behavior of the human hand. Estimating these metrics typically requires the use of MOS, which need structured environments that are not always available in clinical settings, such as hospitals. In this study, the extraction of intrafinger couplings using the LMC was conducted as a proof of concept, to illustrate the potential of quickly and easily estimating these parameters without the need for structured environments.

The aim of this article is to address the aforementioned limitations by: 1) introducing a validated hand kinematic protocol [20] in the elaboration of the LMC data to estimate the absolute A/A angle of the long fingers MCP joints; 2) evaluating both static and dynamic angular offsets to enhance the LMC performance in joint angle estimation; and 3) assessing the validity of using the LMC to extract additional parameters with respect to joint angles, such as intrafinger couplings. It aimed at demonstrating the validity of using the LMC not only as a tool for assessing hand motion capabilities but also as a resource whose outputs can inform the design of hand prostheses [21]. Table I summarizes the advancements of the proposed work compared with previous studies.

II. Materials and Methods

The workflow of the proposed study is shown in Fig. 1. The trajectories of the hand finger joints during F/E and A/A movements were recorded in a synchronized manner using both an LMC and an MOS. Hand joint angles were extracted by applying literature kinematic protocols to the joint trajectories obtained from both the systems. The resulting joint angles and intrafinger joint couplings were then compared.

A. Experimental Setup

The experimental setup used to conduct the study consisted of: an MOS composed of 8 Vicon Vero 2.2 cameras (100 Hz),

TABLE I
NOVELTY OF THE PROPOSED WORK WITH RESPECT TO PREVIOUS LITERATURE STUDIES

	Our Study	Previous Studies [16], [18], [19]
Kinematic Protocol used	Estimation of all hand joint angles	Do not consider A/A angles
Offset Correction	Estimation and application of dynamic offset to improve LMC accuracy	N.A
Performance outcomes	RMSE, Spearman Correlation, Bland-Altman plot, Intra-Finger couplings	RMSE, Pearson Correlation, Bland-Altman plot

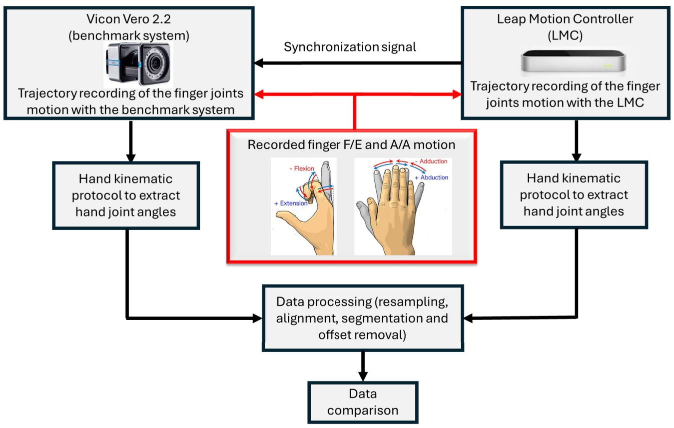

Fig. 1. Workflow of the study showing the steps taken to go from the data recorded by the LMC to the results about the comparison of the performance obtained with the LMC and with the MOS.

an LMC, and a Windows 10 workstation (Intel Core i7-10700K, 3.8 GHz; 16-GB RAM; NVIDIA GeForce RTX 1070). A custom Python script enabled simultaneous acquisition of hand kinematics from the LMC and MOS. The LMC was placed beneath the participant hand, with MOS cameras arranged to avoid interference with the LMC infrared sensing. The systems were synchronized via UDP messages triggered by LMC recording events. The setup was positioned as follows: the LMC was placed under the participant's hand and MOS cameras were positioned so as not to interfere with the LMC infrared camera (Fig. 2).

To enable temporal alignment of joint angle data, the two systems were synchronized: when the LMC started and stopped recording, a UDP message was sent to the MOS workstation. In addition, three static trials with the hand at rest were recorded, to estimate offset values.

B. Experimental Protocol

The experimental protocol consisted of two experiments. In the first one, each participant, seated comfortably with all fingers extended, was asked to perform three different trials: one with the hand in resting position to estimate static offset values, one involving F/E movements of the four long fingers and another involving F/E movements of the thumb. For A/A movements, the same initial hand posture used for the F/E trials was adopted, but, in this case, participants were asked to perform the A/A of the MCP joints of all the fingers. Each task was repeated three times for both the movements.
In the second experiment, participants were asked to perform F/E movements of all the fingers, paying attention to cover the full ROM. As in the first experiment, movements of the long fingers and the thumb were acquired in two separate trials, each repeated once. In both the experiments, 24 retroreflective markers (2-mm diameter) were placed on the dominant hand of the volunteers according to the kinematic protocol proposed in [3] (Fig. 3).

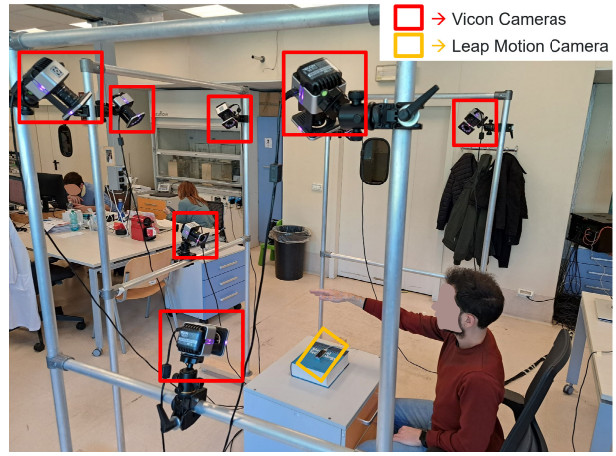

Fig. 2. Experimental setup including the LMC, the MOS cameras, and a participant performing the required tasks.

C. Ethical Considerations and Sample Size

The Ethics Committee of the Universitá Campus Bio-Medico di Roma approved the experimental protocol under application Prot. N. 41/17 OSS ComET CBM.

A total of ten healthy participants with no history of musculoskeletal or neuromuscular disorders were recruited for each experiment. The average age of participants was 28 ± 2 years (five males, five females) in the first experiment and 26 ± 2 years in the second (five males, five females). The difference between ages was due to the fact that the experiments were conducted on different days, and some participants from the first experiment were no longer available for the second.

III. DATA ANALYSIS

A. Application of the Kinematic Protocol on LMC Data

An initial postprocessing was performed on the MOS data using the Vicon Nexus software, where marker trajectories were reconstructed and labels were assigned.

The kinematic protocol [3], [20] used to validate the accuracy of the LMC uses 24 markers (Fig. 3) to reconstruct 21 hand joint angles by determining XYZ Euler angle sequences between the distal and proximal local reference frames at each joint. F/E angles are identified as the rotation around the z-axis of the proximal reference frame, while A/A angles are defined as the rotation around the y-axis. Thus, the protocol enables the calculation of A/A angles of the carpometacarpal (CMC) and MCP joints as well as F/E angles of the CMC, MCP, IP, PIP, and DIP joints.

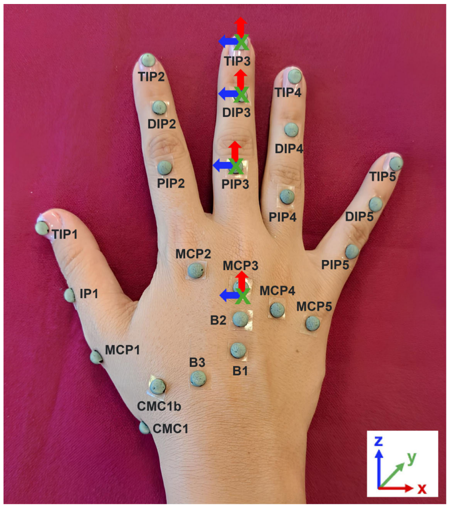

Fig. 3. Markers positioned according to the kinematic protocol reported in [20].

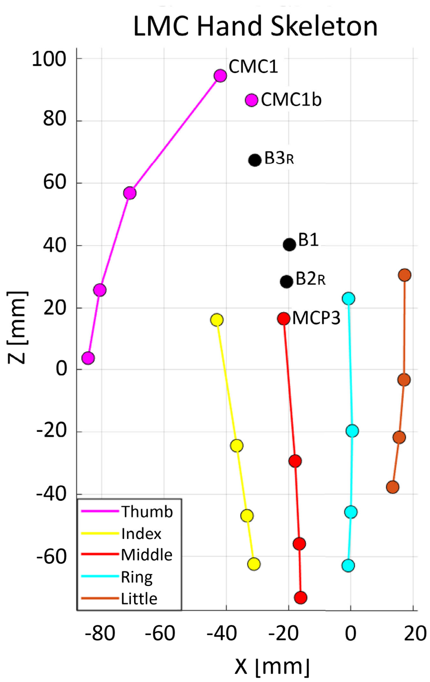

Fig. 4. LMC hand skeleton. $B2_R$ and $B3_R$ stand for the reconstructed virtual positions of $B2$ and $B3$, respectively.

In the LMC hand skeleton, the B2 and B3 markers are absent. Therefore, their position is estimated since they are necessary to reconstruct the hand frame centered in B1. In particular, the positions of the markers B2 and B3 are reconstructed (Fig. 4) by considering the mean position between B1 and MCP3 and of B1 and CMC1, respectively. Once the trajectories of the LMC and MOS markers were obtained, the kinematic protocol proposed in [3] and [20] was applied to reconstruct the hand joint angles. To mitigate the effects of skin artifacts [22] in the MOS and tracking errors in the LMC, a two-stage filtering approach was adopted. The Hampel filter with a 30-sample window was used to detect and remove sudden spikes, while a moving average filter, also with a 30-sample window, was applied to smooth high-frequency noise. These filters, and the corresponding window sizes, were selected based on a previous study [3].

B. Resampling and Segmentation

To enable comparison of LMC and MOS joint angles over time, the LMC data, characterized by a variable acquisition rate [23], were resampled in MATLAB to match the fixed acquisition frequency of the MOS (100 Hz). The MATLAB *resample* function was used, which performs up- and downsampling by applying an anti-aliasing finite impulse response (FIR) filter followed by interpolation. The resampling induced distortion, assessed by comparing pre- and postresampling joint angles, was negligible (mean rms difference $0.16^\circ \pm 0.45^\circ$ across subjects and trials).

To isolate F/E and A/A movements, each recording was segmented by identifying the start and end points as the first and last frames in which the angular velocity of the MCP2 joint exceeded 10% of its maximum value [3].

C. Static and Dynamic Offset Estimation

Previous literature studies have highlighted that LMC data are affected by both static and dynamic angular offsets [16]. Therefore, to determine how to remove these offsets in F/E and A/A measurements, the following analyses were conducted. First, the existence of a statistically significant difference between the static and dynamic offsets was assessed. These offsets were computed using the median of the differences between MOS and LMC joint angle data, to minimize the influence of outliers. As the data did not follow a normal distribution (assessed using the Shapiro–Wilk test) and originated from the same subjects performing different tasks, a Mann–Whitney test was applied. A second statistical analysis was then performed to determine whether the offsets were subject-dependent. Since the data did not follow a normal distribution, a Kruskal–Wallis test was used to assess whether statistically significant differences in offsets across subjects existed.

Finally, a third statistical analysis was conducted to evaluate the presence of a statistically significant difference among the joints. The same considerations of the second statistical analysis were adopted, but in this case the comparison was made across joints rather than subjects.

D. Evaluation Metrics

Data from the first experiment were considered to comprehensively evaluate the LMC ability to reconstruct the hand joint angles. In particular, the following metrics were considered.

1) RMSE to assess the accuracy of adopting the LMC to estimate the hand joint angles over time, i.e., the entire joint angles' curve

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{\left(\theta_{\mathrm{MOS}_i} - \theta_{\mathrm{LMC}_i}\right)^2}{n}} \tag{1}$$

where n, θ_{MOS}, and θ_{LMC} are the number of samples of the trial, the MOS, and LMC reconstructed angles, respectively. A lower RMSE indicates higher accuracy and better agreement between the two measurement methods.

2) The Spearman correlation coefficient (ρ) [24] to assess the correlation between LMC and MOS angles given the nonnormal distribution of the data (Shapiro–Wilk test). A ρ value close to 1 indicates a strong positive correlation and good agreement between the two measurement methods, while values near 0 suggest weak or no correlation.
3) Bland–Altman plots were used to assess the agreement between the LMC and MOS in measuring hand joint angles. When the differences between measurements were normally distributed, the limits of agreement were defined as the mean difference ± 1.96 times the standard deviation [25]. For nonnormally distributed differences, the limits of agreement were defined as the median difference ± 1.45 times the interquartile range (IQR) [26]. A good result is indicated by narrow limits of agreement, indicating that most differences fall within an acceptable range of measurement error.

The Spearman coefficient and Bland–Altman plots were obtained using the default MATLAB functions.

Data of the second experiment were used to estimate subjects' intrafinger couplings, useful in prosthetic hand design [21]. For each long finger, the proximal (K_{PC}) and distal (K_{dc}) couplings were computed as the linear relationship during flexion between PIP–MCP and DIP–PIP, respectively,

$$\begin{aligned}\theta_{\mathrm{pip}} &= K_{\mathrm{PC}}\theta_{\mathrm{mcp}}\\ \theta_{\mathrm{dip}} &= K_{\mathrm{dc}}\theta_{\mathrm{pip}}.\end{aligned}\tag{2}$$

For the thumb, K_{PC} and K_{dc} were calculated as the linear relationship, during finger flexion, between MCP–CMC, and IP–MCP joints

$$\begin{aligned}\theta_{\mathrm{mcp}} &= K_{\mathrm{PC}}\theta_{\mathrm{cmc}}\\ \theta_{\mathrm{ip}} &= K_{\mathrm{dc}}\theta_{\mathrm{mcp}}.\end{aligned}\tag{3}$$

The intrafinger couplings were calculated considering only the flexion phase of the movement. Specifically, the movement onset for each finger was identified as the instant when the MCP joint velocity reached 10% of its peak value. The end of the movement was defined as the time step at which all the three joints of that finger reached at least 80% of their ROM [21]. For intrafinger couplings, a good result is a smaller discrepancy between LMC and MOS data.

Signal processing, metric calculations, and statistical analyses were performed using MATLAB software (version 2023b; MathWorks, Natick, MA, USA).

IV. Results and Discussion

This section presents the results of the comparative evaluation between the LMC and MOS. The findings are interpreted in relation to the main aim of this study: assessing the validity of the LMC, after offset compensation, in reconstructing hand joint kinematics and performance parameters such as intrafinger couplings. The results are also compared with the findings obtained in previous literature studies.

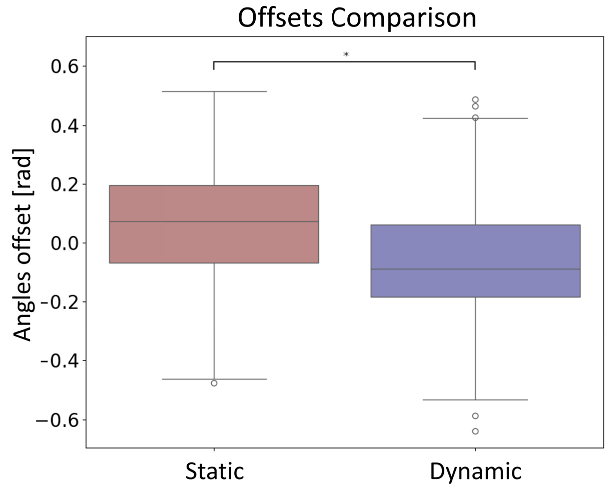

Fig. 5. Dynamic and static offset comparison. The statistically significant difference is outlined with a *.

The boxplots of the offset between the angles obtained with the LMC and the MOS during static and dynamic trials are shown in Fig. 5. The statistical analysis pointed out a significant difference (p-value $\ll 0.05$) between the offsets obtained in the two trials.

To verify whether an offset common to all subjects and specific to each joint could be applied, two statistical analyses were conducted. With respect to the first analysis, aimed at assessing whether offsets were subject-dependent, the results of the comparative analysis of subjects' dynamic offsets are shown in Fig. 6. Only Subject 3 exhibited statistically different offset values compared with the other subjects. This discrepancy was caused by a tracking error in the LMC, which mistakenly identified thumb movements as those of the index finger. Consequently, this subject was considered an outlier and excluded from further analyses. A new Kruskal–Wallis test performed without Subject 3 revealed no statistically significant differences among the remaining subjects (p-value $=$ 0.59), thereby supporting the application of the same offsets to the remaining subjects.

The last statistical analysis investigated whether dynamic offsets differed significantly between joints. The Kruskal–Wallis test showed that joint-specific differences were present (p-value $\ll 0.05$). Based on the outcomes of the three statistical analyses, the dynamic offsets were computed for each joint using data from the dynamic trials of all subjects (excluding the outlier) and applied to correct the LMC data of the nine remaining subjects.

In Fig. 7, the LMC accuracy in reconstructing joint angles during F/E movements of the long fingers is reported. The results show that the RMSE values were consistently below 0.17 rad across all joints, with errors lower than 0.12 rad observed specifically for PIP joints. Instead, in thumb F/E movements, the RMSE values of the IP1 joint occasionally exceeded the 0.17 rad value. Fig. 8 presents the Spearman correlation coefficient results for long finger F/E. A strong correlation was obtained in most of the cases ($\rho > 0.9$), while distal joints generally had lower correlation values. Similarly, for the thumb, CMC1 and MCP1 joints showed $\rho > 0.7$,

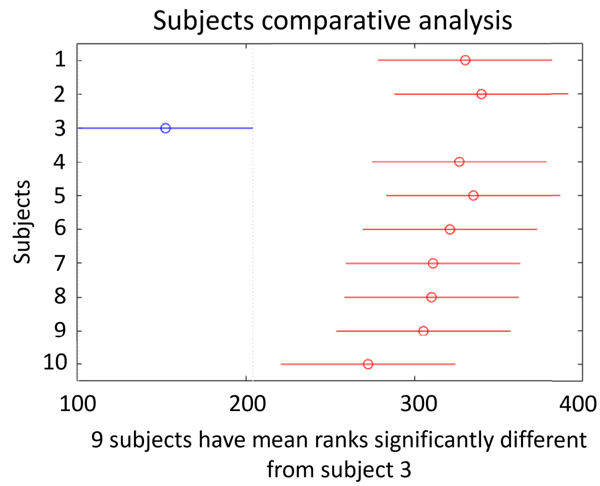

Fig. 6. Outcome of the *post hoc* analysis on the dynamic offsets of all joints across ten subjects.

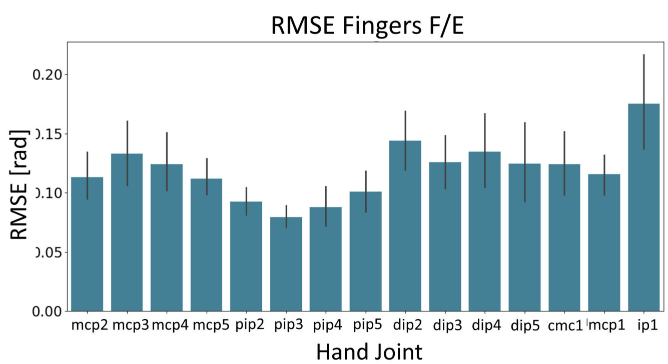

Fig. 7. Bar plot showing the RMSE of F/E angles of all hand joints across the nine subjects.

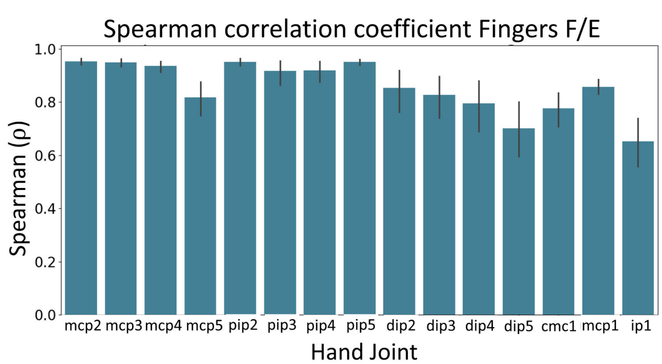

Fig. 8. Bar plot showing the Spearman correlation coefficients of F/E angles computed for all hand joints across the nine subjects.

whereas IP1 correlations were lower but still acceptable ($\rho < 0.7$), indicating strong correlation.

These results demonstrate that the application of dynamic offsets enhances the accuracy of the LMC in hand joint angle reconstruction during F/E movement and outperforms literature approaches [16], [18]. In 95% of cases, RMSE values remained below 0.17 rad, while previous works reported errors exceeding 0.27 rad [18] for most joints (except PIP4). Furthermore, in 85% of cases, a Spearman correlation coefficient

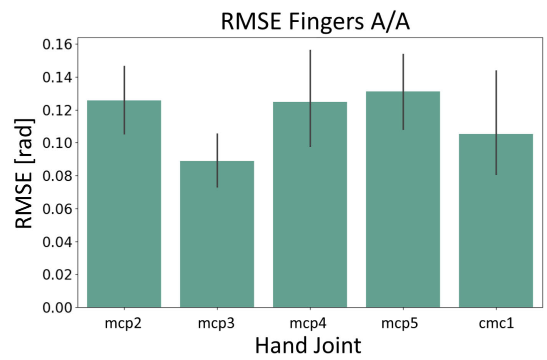

Fig. 9. Bar plot showing the RMSE of A/A angles of CMC1, MCP2, MCP3, MCP4, and MCP5 across the nine subjects.

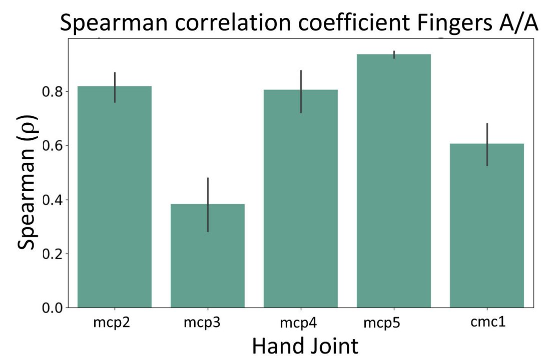

Fig. 10. Bar plot showing the Spearman correlation of A/A angles of CMC1, MCP2, MCP3, MCP4, and MCP5 across the nine subjects.

above 0.7 was achieved, compared with the state-of-the-art methods that only showed improvements for the little finger.

Therefore, the implementation of dynamic offsets that are not subject-specific but defined as global values common to all participants has been demonstrated to be an effective strategy for reducing the angular reconstruction error of the LMC. These findings suggest that this correction enables a higher level of accuracy than the one reached in previous studies, in which systematic offset compensation was not implemented or more sophisticated approaches were adopted, such as the fusion of the information coming from three LMC.

Using the kinematic protocol reported in [20] and [27], it was also possible to reconstruct the A/A angles. In Fig. 9, the accuracy of the LMC in estimating the A/A finger joint angles is provided. The obtained RMSE values were lower than 0.17 rad. High Spearman correlation coefficient values ($\rho > 0,7$) were obtained for MCP2, MCP4, and MCP5 joints (Fig. 10). However, the same considerations could not be made for CMC1 and MCP3 joints, in which values lower than 0.7 and 0.4 were found, respectively. For MCP3, these results are explained by limited ROM during A/A movements. Subjects were instructed to start with a closed hand and then maximally spread the fingers, which constrained MCP3 motion, resulting in very low ROM. Although this limited movement led to a low RMSE (<0.1 rad), it caused a low Spearman correlation coefficient due to the LMC difficulty in detecting the beginning and the end of such small movements.

The LMC showed better performance in measuring A/A compared with F/E angles. This is likely because A/A

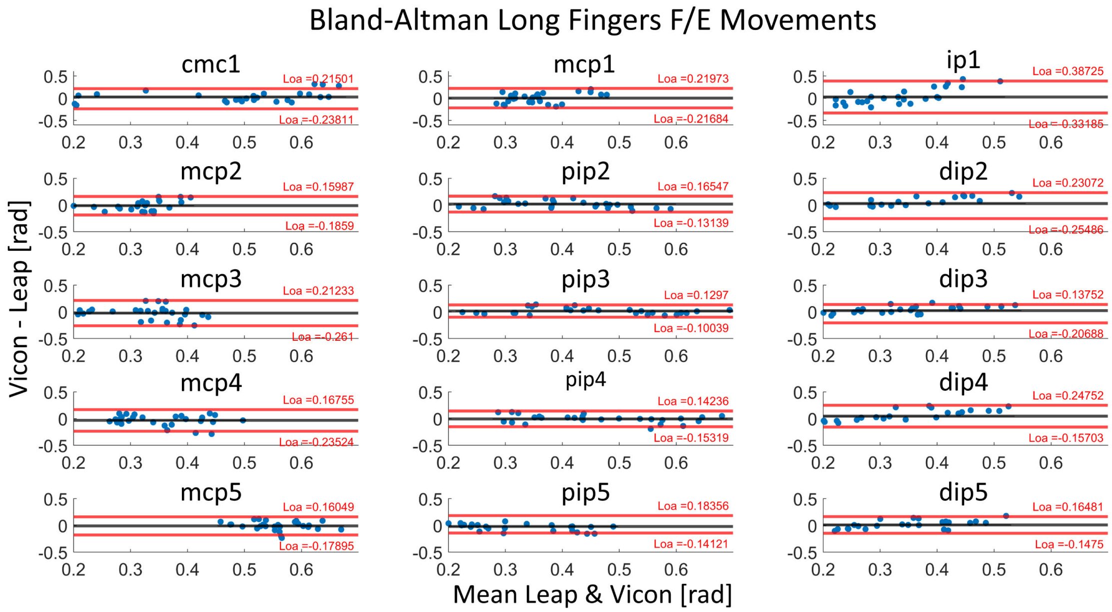

Fig. 11. Bland–Altman plot of all fingers' F/E movement.

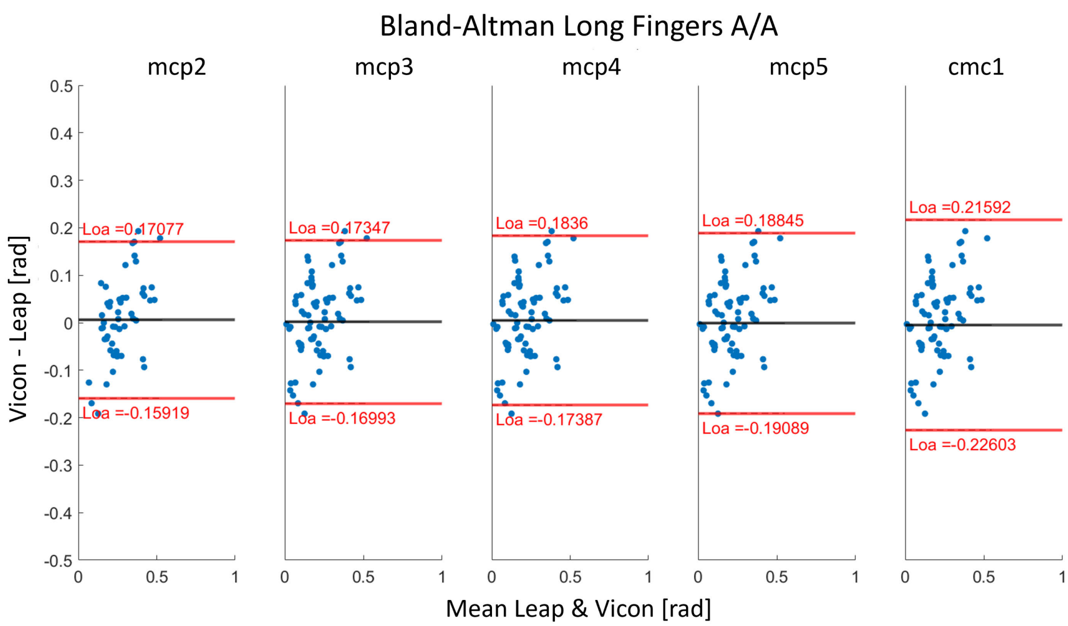

Fig. 12. Bland–Altman plot of A/A movements.

movements occur primarily in a plane parallel to the LMC sensor, reducing occlusions that typically arise during F/E movements where finger segments can hinder each other.

While RMSE and Spearman coefficients help quantify device performance, they do not fully address the question: "Can the LMC device replace optoelectronic systems?"

To answer this question, Bland–Altman plots were used to evaluate the agreement between LMC and MOS. This analysis provides insights into whether the LMC could serve as a reliable substitute of MOS in reconstructing joint kinematics. In Figs. 11 and 12, the Bland–Altman plots about the reconstruction of the F/E and the A/A joint angles are shown, respectively. Each plot was obtained by considering LMC and MOS median values of each trial. Due to offset correction, the bias (black line) is generally close to zero. Limits of agreement were within ± 0.17 rad in most joints, with the exception of the thumb IP1, which exceeded 0.30 rad.

These findings suggest that the possibility of using Leap as an alternative to MOS while maintaining the same quality of kinematic analysis depends on the level of precision that the intended application requires. In clinical settings or rehabilitation, where high precision is critical to assess physical conditions and design therapeutic interventions, the LMC remains insufficient, as its limits of agreement exceed clinical standards [28]. However, in domains such as human–robot interaction, virtual environments, and coarse gesture detection,

TABLE II
COMPARISON OF INTRAFINGER COUPLINGS BETWEEN LMC AND MOS

	Proximal Coupling		Distal Coupling	
Finger	MOS	Leap	MOS	Leap
Thumb	1.40	0.58	1.14	0.68
Index	1.50	0.80	1.00	0.43
Middle	1.70	0.82	0.90	0.39
Ring	1.70	0.86	0.90	0.37
Little	1.60	0.89	1.10	0.41

where compactness, ease of use, and speed are more important than high precision, the LMC offers a valuable alternative.

In addition to joint angles, intrafinger couplings, useful in prosthetic hand design [21], were evaluated. The average values of the proximal and distal couplings are shown in Table II. The estimation of the LMC couplings showed errors around 50%, making this device unsuitable for applications that require precise biomechanical modeling, such as prosthetic hand design. This poor performance can be attributed to two main factors.

1) Errors in angle estimation are reflected more in the calculation of intrafinger couplings.
2) Internal constraints in the LMC skeleton tracking algorithm limit realistic joint behavior, as they are designed to avoid anatomical collisions between joints rather than reflect actual motion.

These results serve to further substantiate the preceding assertions, namely, that the LMC is only appropriate for scenarios characterized by a minimal level of precision and accuracy. Although the device under discussion provides a cost-effective and user-friendly solution for a range of applications, including gesture recognition, human–computer interaction, and virtual reality, it is important to acknowledge its limitations in applications that require detailed biomechanical evaluation, such as prosthesis design. The substantial discrepancies observed in intrafinger couplings, which are key features for biomimetic prosthesis design, highlight that the LMC is not a reliable tool for capturing the complexity of hand fine motor coordination. Consequently, despite its potential in low-precision contexts, the LMC cannot be considered a viable replacement for MOS in domains that demand high-resolution kinematic data and accurate modeling of joint behavior.

V. CONCLUSIONS AND FUTURE WORKS

In this article, we present methods to enhance the accuracy of the LMC in estimating hand joint angles and investigate its potential for extracting additional metrics beyond joint angles, such as intrafinger coupling. This analysis is intended to assess the validity of using the LMC in applications beyond motor assessment, including prosthetic design. To reduce estimation errors, both dynamic and static offsets were computed and applied to the LMC data. The obtained results demonstrate that incorporating these offsets leads to improved performance compared with existing literature [18]. In fact, in 95% of the cases, errors were lower than 0.17 rad. In addition, improvements in the Spearman correlation coefficients were also observed, with $\rho > 0.7$ in 85% of the cases. However, Bland–Altman analysis showed that the LMC and MOS systems are not yet interchangeable in clinical scenarios. High precision is essential in such contexts to accurately assess patients' physical conditions and to develop effective rehabilitation protocols. In addition, due to limitations in angle reconstruction accuracy and kinematic constraints in skeleton tracking, the LMC is currently unsuitable for reliably estimating intrafinger couplings.

Future works will be devoted to assess the usability of the LMC in alternative domains, such as robot teleoperation and training in virtual environments.

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