Comparison and Improvement of CyberGlove III Calibration Methods

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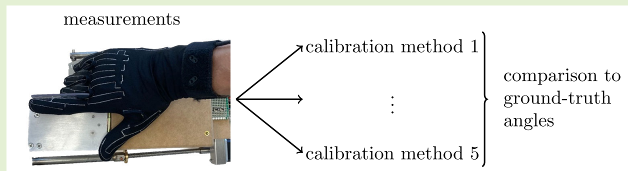
***Abstract*—We investigate the accuracy of different calibration methods for the CyberGlove III for objective hand function assessments. The accuracy is evaluated by means of root-mean-squared errors (RMSE) between ground truth and angles estimated by the glove. Additionally, we propose two improvements. The first increases standardization capabilities for the measurement of pure thumb carpometacarpal joint flexion. The second increases the accuracy by extending an existing calibration method to all thumb and distal interphalangeal (DIP) joints. The best calibration method is identified and compared to an across-subject calibration by means of RMSEs, highlighting the tradeoff between the number of necessary measurements and the accuracy. Our proposed improvements both reduce the measurement effort, while only the second improvement reduces the RMSEs substantially. The best calibration method yields RMSEs below 10° for most joints, while the across-subject calibration has RMSEs that are approximately 5°–10° higher. We conclude that the CyberGlove III is a suitable tool for objective monitoring of hand movement and function, and the across-subject calibration has the potential to track the range of motion or frequency of joint movements. With this work, we provide an overview for researchers to choose calibration methods suitable for their application depending on necessary accuracy and possible extent of calibration measurements. This work further highlights potential obstacles, when such a glove is used with patients.**



***Index Terms*— Biomechanics, calibration, data glove, hand function monitoring, joint angles, kinematics.**

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I. Introduction

Measuring hand kinematics is an important topic in clinical research, for example, in the context of rheumatoid arthritis [1], to monitor hand motions objectively during different tasks, or in general biomechanical research [2] to investigate hand movements. The gold standard for movement analysis in experimental biomechanics is marker-based optical motion capturing, which is extensively used for gait analysis. However, it has several disadvantages if applied to the hand, for instance, time-consuming preparation, occlusion of markers, and influence on the motion of the attached markers. While marker-less motion capturing is increasingly available for gross body movements [3], it is not well established for hand motion [4].

An alternative method is the use of sensorized gloves that are available with different technologies [1]. They allow for flexible application in different settings independent of complex laboratory setups and cause less interference during activities of daily living, such as grasping objects, which makes them more suitable for the clinical routine. Additionally, wearing a glove is a more familiar situation for most people than having markers taped to the skin and several cameras directed at them. Among the more commonly used sensor gloves is the CyberGlove series by CyberGlove Systems LLC [5], [6], [7], [8], [9], [10], [11], [12]. They are strain-gauge-based gloves, that measure joint angles via electrically resistive wires. Their dependence on extensive calibration for accurate angle estimation as well as limitations measuring DIP joint angles has been reported previously [6], [7]. It was shown that hands should be at least 184 mm long to record DIP joint angles properly [7]. The DIP joint angles are often either not analyzed or not even recorded by using the 18 sensor version of the CyberGlove, due to the difficulties in obtaining high quality and reliable measurements [8], [9], [10].

Such gloves are not yet used to assess hand function in clinical routines or clinical trials with larger cohorts. However, several studies are using these gloves for different use cases, for example, to measure joint angles in sign language [6], to detect osteoarthritis from functional tasks [8], [9], [10] or to measure joint movement during general functional tasks [11], [12], [13], [14].

We see a potential benefit in the implementation of sensor gloves in the assessment of hand function in inflammatory joint diseases, such as rheumatoid and psoriatic arthritis, that are characterized by swelling and pain of the hand and finger joints [15]. Current tools for the evaluation of the functional status are mainly based on patient-reported outcome measures that lack objectivity [16]. One of the many available tests to assess hand function in clinical studies is the Sollerman hand function test [17], where 20 activities of daily living are evaluated by a physician regarding the duration and quality of the movements. Using a sensorized glove during this test, similar in [9] for osteoarthritis, would increase the objectivity of the assessment. We also see a potential benefit for this field to easily measure the range of motion in all joints [12], or to simply track the usage of certain joints during everyday life and relate this to structural damage in the finger joints.

To reach the long-term goal of using such gloves for objective hand function analysis, we investigate the capabilities and usability of the aforementioned sensor glove, the CyberGlove III. Accuracy and the potentially increased duration due to the glove-based assessment are important factors influencing the acceptance of monitoring hand function in studies, clinical routines, or monitoring hand function at home. One important factor influencing the accuracy and duration of such an assessment is the calibration, which has to be done each time the CyberGlove III is put on. There are numerous approaches to calibrate the CyberGlove III focusing on different applications, such as animating hands in virtual and augmented reality, or games requiring only plausible hand postures [18]. Other applications include controlling robots [19] and biomechanical analyses [6], [11]. We focus this comparison on calibration methods for the latter as they are the most suitable to be used in a clinical setting. Methods that depend on black-box machine-learning approaches [20], [21] are excluded from the comparison.

The following approaches are considered in our work: the affine (linear plus offset) relationship between the sensor value and the joint angle used in the CyberGlove software, and two calibration procedures including parameter fitting (using more measurements than parameters to identify) and second-order polynomials that account for interdependencies between certain sensors (called crosstalk) [6], [11]. Additionally, the concept of an across-subject calibration [11] is considered, as it reduces the number of measurements required for the calibration with each person, making it suitable for large clinical studies or even regular clinical routines. Another approach worth mentioning is the concept of dimensionality reduction, that is, kinematic synergies that establish a relation between joint angles [22]. This approach has to be used with care, as it deduces all joint angles by measuring only a reduced number after kinematic synergies were found. This means that the individual application and used kinematic synergies have to be taken into account, and it has to be taken care of so that the assumptions do not affect the assessment negatively. Therefore, we exclude this approach here.

This work aims to investigate the accuracy of several calibration methods, by comparing angle estimations, based on these calibrations, with ground-truth angles, using data from healthy controls and patients with rheumatoid or psoriatic arthritis. Furthermore, changes to the calibration, improving accuracy and repeatability and reducing the complexity of the calibration process, are proposed. Additionally, difficulties and limitations in the application with patients with rheumatoid or psoriatic arthritis are reported. The results are then discussed to determine suitability for different use cases in clinical hand function assessment.

II. Methods

All processing and data collection steps are implemented using Python 3.8, as the standard CyberGlove software has proven to be too limited and hard to use. The communication is based on a list of glove-specific commands via TCP/IP [23] and was realized in two previous works [24], [25]. We published the code for the communication on GitHub [26]. The data transmission rate with the implemented code is approximately 50 Hz, which we estimate to be high enough for various calibration procedures. We advise using the data streaming function of the glove for continuous measurements, especially when faster movements occur. With this function, measurement frequencies up to 120 Hz (as promised by CyberGlove Systems LLC, [5]) should be achievable.

Note: In this work, the term separation is used for the abduction of the metacarpophalangeal (MCP) joints of the index, middle, ring, and little finger, as the sensors measure the relative angle between two fingers. Also, we use the joint name interchangeably with the sensor at that joint.

A. Participants

Healthy, nonarthritic subjects and patients recruited from the Internal Medicine 3 outpatient clinic, Universitätsklinikum Erlangen, Germany, were enrolled in this study after giving written informed consent. The study protocol was approved by the ethics committee (21–288 B). Subject characteristics (age, sex, hand size, and disease) were recorded. Patients underwent a standardized joint count (28 joints) for tender and swollen joints, filled out the Health Assessment Questionaire (HAQ) [27], and the Disease Activity Score (DAS)-28

(a) (b)

Fig. 1. Hand poses for both neutral pose measurements. (a) Neutral pose 1 for the thumb carpometacarpal joint. (b) Neutral pose 2 for the remaining joints.

[28] was calculated. Inclusion criteria for the patients were either a diagnosis of rheumatoid arthritis, according to the American College of Rheumatology/European League Against Rheumatism 2010 criteria [29], or psoriatic arthritis, according to the Classification Criteria for Psoriatic Arthritis [30].

B. Measurements

Data for the calibration and evaluation were collected using a right-handed CyberGlove III with 22 sensors [5]. The sensors at the wrist were excluded from this analysis, as the calibration methods compared in this work do not consider the wrist sensor [6], [11]. The measurements were chosen such that existing calibration methods [6], [11] can be executed and a comparison of the accuracy over the full range of motion of the hand is possible. These measurements include multiple continuous tasks over the full range of motion and static postures as instantaneous snapshots.

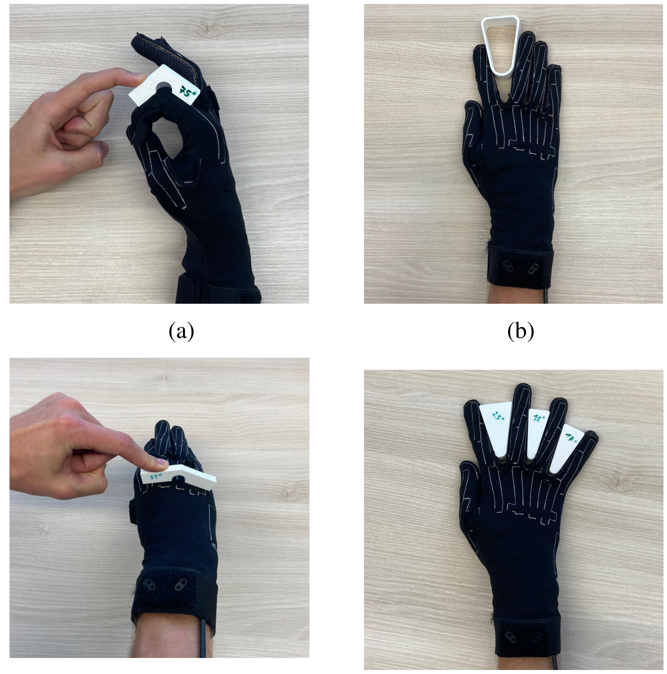
1) Static Measurements: Neutral pose 1: hand with the fingers straight and together on the table [Fig. 1(a)]. *Neutral pose 2*: as neutral pose 1, but the thumb was fully extended pointing away from the digits [Fig. 1(b)].

Static flexion for distal and proximal interphalangeal (DIP and PIP) and MCP joints: 10° increments in the range from −40° to 130° and additionally at 15°, 35°, and 75° collected using 3-D printed wedges [Fig. 2(a)] [6], [11]. Not all participants reached the full range of joint angles in all joints.

Static palm arch: At 35° using a 3-D printed wedge [Fig. 2(c)] and eight measurements using a goniometer, placed in the same way as the wedge [11]. Seven of these measurements with the goniometer were taken in the range of 0°–60° with 10° increments and one at the maximum possible arch. The angle during the maximum arch measurement was read from the goniometer.

Static separation (MCP joints) for each pair of fingers: 10° increments in the range of 0°–40° using 3-D printed angles [Fig. 2(b)]. **Simultaneous static separation** for all MCP joints at once [Fig. 2(d)]: with 25° for the leftmost, 16° for the middle and 17° for the rightmost separation sensor [11].

Static thumb CMC 1 (pure abduction between the thumb and index finger): 10° increments in the range of 0°–80° using 3-D printed wedges in the sagittal plane of the hand between the index finger and thumb as in Fig. 3(a). **Static thumb CMC 2** (pure thumb CMC flexion): 10° increments in the range of



(a) (b) (c) (d)

Fig. 2. Static measurements with 3-D printed wedges. (a) Flexion measurement. (b) Separation measurement. (c) Palm arch measurement with the 3-D printed wedge. (d) Simultaneous separation measurement.

(a) (b)

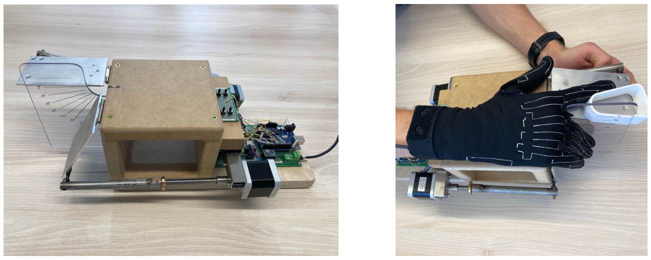
Fig. 3. Static measurements for the thumb CMC joint. (a) Abduction measurement static thumb CMC 1. (b) Flexion measurement static thumb CMC 1.

0°–80° using 3-D printed wedges with the hand placed on the table as in Fig. 3(b). Note that the hand is kept floating for Static thumb CMC 1, while the hand is placed flat on the table for static thumb CMC 2.

2) Continuous Measurements: A ramp tool [6] was used, to prescribe static flexion and separation angles for one finger, while the neighboring finger moved continuously. Our ramp tool is equipped with two stepper motors to adjust the plates [Fig. 4(a)] [24]. The subjects were instructed to place their hand on the device and move the finger through the whole range of motion at a self-selected steady speed.

Continuous flexion 1 (each MCP joint of the four digits): Three flexion-extension cycles, while the neighboring fingers remained in 0°, 40° and 80° flexion, and 0° separation [11].

Continuous flexion 2 (six measurements per separation sensor): One flexion-extension cycle while the finger on the left of the corresponding separation sensor was fixed on the ramp tool with a flexion angle of 20° and 80° and a separation angle of 0°, 20° and 30° [Fig. 4(b)] [6].



(a) (b)

Fig. 4. Ramp tool with stepper motors to prescribe flexion and separation angles and its application for simultaneous prescription of flexion and separation angle [6], [24]. (a) Motorized ramp tool for the MCP joint sensor (flexion and separation) calibration. (b) Simultaneous prescription of static flexion and separation angles.

(a) (b)

Fig. 5. Start and end positions of the closed-loop movement for the thumb CMC joint calibration. (a) Start position. (b) End position.

(a) (b)

Fig. 6. Vertical thumb movement [11] and newly proposed alternative for the thumb CMC flexion. (a) Vertical thumb motion. (b) New thumb flexion.

Closed-loop motion (thumb CMC joint): Three repetitions with constant contact between the fingertips as in Fig. 5 [11]. **Horizontal thumb motion** (pure abduction of thumb CMC joint): Thumb moved horizontally on top of the closed fist as far as possible [11]. **Vertical thumb motion** (pure flexion of thumb CMC): Thumb extended as in Fig. 6(a) [11].

We propose to adjust the vertical thumb movement to simplify the execution, as we observed issues in executing this motion with 0° abduction. **Adjusted vertical thumb motion**: hand placed flat on a table and the thumb extends from the index finger followed by a flexion while the thumb and hand stay in contact with the table [Fig. 6(b)].

C. Calibration Methods

We omit additional indices in equations to ensure better readability whenever possible (e.g., we write g instead of g_i for the gain of the ith joint). Greek letters are used as follows: α for generic angles, θ for flexion angles (including the palm arch angle), ϕ for separation angles, ψ for angles from the thumb CMC joint, and δ for the distance between fingertips.

1) Calibration Method 1: The CyberGlove software allows the calibration of all sensors of the glove by adjusting two parameters for each sensor. A gain g to scale the sensor value s and an offset o for all angles α (1) are calculated from two static postures with known angles [Fig. 2(a) and (d)]

$$\alpha(s) = g\, s + o. \tag{1}$$

We used the following measurements: **neutral pose 1** for the 0° measurement for the thumb CMC joint and **neutral pose 2** for the remaining joints. Furthermore, we used from **static flexion** 75° for the PIP and MCP joints, 50° for the DIP joints, from **static palm** 35°, from **static thumb CMC 1** 60°. The thumb CMC flexion sensor is not considered here.

2) Calibration Method 2: This method uses two measurements for each flexion sensor, seven measurements for each separation sensor and three measurements for the two sensors at the thumb CMC joint [11]. A general difference compared to other calibration approaches is that relative sensor values $\hat{s}$ are used. These are obtained with s_{neutral} from the **neutral pose 1** measurement in (2). The flexion sensors are calibrated using two measurements with (3), which can be directly related to (1). Additionally, this method accounts for crosstalk between each separation sensor and its neighboring flexion sensors, as well as both thumb CMC joint sensors, and utilizes continuous motions for the calibration of these

$$\hat{s}(s) = s - s_{\text{neutral}} \tag{2}$$

$$\theta(\hat{s}) = g\, \hat{s}. \tag{3}$$

The flexion angles are calibrated with the nonzero flexion measurement as in method 1 [Fig. 2(a)]. Also, the thumb MCP joint is calibrated with the 35° measurement from **static flexion**, and the palm is calibrated with the maximum arch measurement (**static palm arch**).

The separation sensor angles are calculated using the second order polynomial in (4) with the separation sensor value $\hat{s}$ and the flexion sensor value on the left and right $\hat{s}_l$ or $\hat{s}_r$, respectively,

$$\phi(\hat{s}, \hat{s}_l, \hat{s}_r) = g\, \hat{s} + C_1\, \hat{s}_l + C_2\, \hat{s}_r + C_3\, \hat{s}_l^2 + C_4\, \hat{s}_r^2 + C_5\, \hat{s}_l\, \hat{s}_r. \tag{4}$$

The gains are calculated with the **simultaneous static separation** and **neutral pose 2** measurements. Thereafter, the correction terms C_i for each sensor are obtained from a least-squares problem with the six measurements associated with each separation sensor from **continuous flexion 1**.

The least-squares problems in method 2 are solved in Python, using the SciPy package and the Levenberg–Marquardt algorithm. We use the default settings and an initial guess of one as changes in the guess did not affect the results. The objective functions for the minimization problems are defined in (5) depending on a known quantity $\overline{x}_i$ at time step i of T total time steps and the calculated quantity x depending on calibration parameters g and o (if absolute sensor values are used), and possibly correction terms $\boldsymbol{C}$. Depending on the relationship of x and the beforehand recorded sensor values $\boldsymbol{s}_i$ at this timestep, some parameters are not needed or the sensor values can be replaced by their relative counterpart, depending on the used relation between sensor value and angle

$$J(g, o, \boldsymbol{C}) = \sum_{i=1}^{T} \frac{1}{2}(x_i(g, o, \boldsymbol{C}, \boldsymbol{s}_i) - \overline{x}_i)^2. \quad (5)$$

The thumb CMC joint is calibrated with a continuous motion to obtain the parameters in (6) and (7). First, the correction terms for flexion C_{flex} (with **vertical thumb motion**) and abduction C_{abd} (with **horizontal thumb motion**) are calculated with least-squares fitting under the assumption of $\overline{\psi} = 0°$ for both flexion and abduction

$$\psi_{\text{abd}}(\hat{s}_{\text{flex}}, \hat{s}_{\text{abd}}) = g_{\text{abd}}\,(\hat{s}_{\text{abd}} + C_{\text{flex}}\,\hat{s}_{\text{flex}}) \quad (6)$$

$$\psi_{\text{flex}}(\hat{s}_{\text{flex}}, \hat{s}_{\text{abd}}) = g_{\text{flex}}\,(\hat{s}_{\text{flex}} + C_{\text{abd}}\,\hat{s}_{\text{abd}}). \quad (7)$$

As the last step of the calibration procedure, the gains for (6) and (7) are calculated using the previously obtained calibration parameters for the thumb and index finger, the **closed-loop motion**, and a hand model with the assumption that the fingertips of index finger and thumb remain in contact. The relation between DIP and PIP joint angles, $\theta_{\text{DIP}}(\theta_{\text{PIP}}) = 0.87\,\theta_{\text{PIP}} - 25.27°$, are taken from the corresponding calibration method [11].

We use a hand model developed for the open-source software OpenSim, which is available on SimTK [31]. To calculate the distance between the fingertips δ, we define points on the tips of the index finger and thumb, respectively. During the closed-loop motion, the distance between the fingertips is assumed to be zero. The gains are obtained from the least-squares problem, with an objective function as in (5), with the optimization variables g_{abd} and g_{flex}. The correction terms C_{flex} and C_{abd} are known. The objective function is comprised of the distance of the fingertips at each timestep $\delta_i(g_{\text{abd}}, g_{\text{flex}})$ and the actual distance $\overline{\delta}_i = 0$.

3) Calibration Method 3: This calibration method [6] uses least-squares fitting to calculate all calibration parameters and accounts for crosstalk between MCP flexion and separation, with a different polynomial compared to method 2. The flexion sensors of the eight MCP and PIP joints are calibrated using the **static flexion** measurements at 10°, 30°, 50° and 70° with a linear relation between sensor value s and angle θ via parameters a and b

$$s(\theta) = a\,\theta + b. \quad (8)$$

Each separation sensor is calibrated with nine measurements and (9) to account for crosstalk due to flexion of the neighboring fingers θ_l and θ_r using constants C_1 and C_2

$$s(\phi, \theta_l, \theta_r) = a\,\phi + C_1\,(\theta_l - \theta_r)^2 + C_2\,(\theta_l - \theta_r) + b. \quad (9)$$

Three measurements from **static separation** at 10°, 30° and 50° (assuming $\theta_l - \theta_r = 0°$) and the six measurements from **continuous flexion 2** are used.

Both, the flexion and separation sensor parameters are calculated by solving the least-squares problem associated with $\boldsymbol{s} = \boldsymbol{\Theta}\boldsymbol{p}$, with a rectangular matrix containing the angles $\boldsymbol{\Theta} \in \mathbb{R}^{N\times M}$, parameter vector $\boldsymbol{p} \in \mathbb{R}^{M}$ and measured sensor value vector $\boldsymbol{s} \in \mathbb{R}^{N}$, with the number of measured frames N and the number of parameters M (i.e., two for flexion and four for separation).

4) Improved Calibration Procedure: We propose two improvements to increase accuracy and reduce the complexity of the required measurement and therefore the whole calibration process.

a) Improvement 1—adjusted thumb flexion: We propose to replace the vertical thumb motion measurement in method 2 (Section II-C2) with the new measurement shown in Fig. 6(b). Due to the execution with the hand placed on the table, the subject can perform the pure flexion motion more easily and reliably. The calibration procedure and used polynomial for the thumb CMC abduction remain as in method 2.

b) Improvement 2—least-square problems for more joints: Additionally, we propose to transfer the affine approach from method 3 (8) to the thumb joints, and all DIP joints. This reduces the complexity of the measurements for the thumb CMC joint. We use four measurements from **static flexion** at 10°, 30°, 50° and 70° (Fig. 2(a) for the DIP, thumb MCP, and IP joints and Fig. 3 for the thumb CMC joints).

D. Across-Subject Calibration

In contrast to performing a whole calibration procedure with each individual, it is possible to use an across-subject calibration to obtain a somewhat average calibration for many individuals [11]. This approach uses previously obtained calibration parameter sets from different persons. These sets have to be calculated with the same calibration method, however, the approach works with every relationship between angle and sensor values. The gains and correction terms from these sets are averaged and only two neutral pose measurements are needed from the individual [11]. Depending on the calibration method chosen, the neutral pose measurements are used to either calculate relative sensor values (as in method 2) or to obtain an offset (as in methods 1 and 3 or improvement 2).

We use this approach with the combination of the most accurate calibration methods for each sensor group determined in Section III-B (Table I). The results obtained with the across-subject calibration are also compared to the best individual calibration method.

III. Results

A. Recruited Participants

Eight healthy subjects (three males, five females; age 31.5 ± 14.6) and six patients (five males, one female; age 62.2 ± 5.1 years) were included. Disease characteristics for the patients were disease activity according to the visual analog scale of 32.5 ± 22.5 mm, disease duration of 6.6 ± 8.3 years, tender joint count 3.0 ± 6.3, swollen joint count 2.0 ± 2.65, HAQ 0.79 ± 0, 47, DAS28 2.7 ± 1.3, and C-reactive-protein of 9.8 ± 7.7.

Both groups were asked to execute all motions. Patients could not perform all motions and two subjects had to be excluded as their hands did not fit the glove.

B. Comparison of Different Calibration Methods

The accuracy of the different calibration methods is rated with a root-mean-squared error (RMSE) between ground-truth angles and the estimated angles of each subject. We used the

21 **static flexion** angles per joint, seven **static palm arch** angles excluding the maximum possible arch measurement, five **static separation** angles for each pair of fingers, and the nine **static thumb CMC 1** and nine **static thumb CMC 2** angles. To prevent artificial reduction of the RMSE values, we excluded measurements that would lead to an angle estimation error of 0 by definition. (This is the case for exact affine relationships, calculated from two measurements.)

Due to limitations in wearing the glove and executing the necessary motions, the comparison of calibration accuracy is only done for the healthy group. Furthermore, the fingers of one of the healthy subjects were too short (hand length 15.3 cm) to reach the DIP sensors, agreeing with the minimal hand size necessary estimated previously [7]. This resulted in RMSEs between 89° and 397°. The measurements of this subject's DIP joint angles were, therefore, discarded.

We also exclude individual RMSEs, if they can clearly be identified as outliers. The outlier criterion is that the RMSE value is greater than 45°. Such deviations can be easily detected after the calibration and before usage by comparing hand poses with a visualization of the measured joint angles. It is, therefore, possible to notice such a calibration error and repeat the calibration of a specific joint. With this criterion, 11 out of 438 measurements are identified as outliers.

The RMSEs at each sensor are listed as mean values over the eight subjects in Table I. They are also arranged in sensor groups, for which the mean RMSEs are given. The best result, and, therefore, the best method for a specific group or joint is highlighted by a bold font.

Most sensor groups achieved mean RMSEs of 10° or lower for the most accurate calibration method. However, the RMSEs for individual joints vary strongly both within a sensor group and between different subjects. According to our study, the most accurate calibration is achieved with method 3 for the flexion sensors, improvement 2, and method 2 for the separation sensors.

TABLE I
AVERAGE RMSES, EXCLUDING OUTLIERS AND ERRONEOUS MEASUREMENTS, OF THE DIFFERENT CALIBRATION METHODS. THE LOWEST RMSE FOR EACH GROUP IS HIGHLIGHTED WITH BOLD FONT. ALL VALUES ARE GIVEN IN DEGREE

	Method			Improvement	
sensor	**1**	**2**	**3**	**1**	**2**
MCP flexion					
thumb	17.03	25.33			**10.94**
index	5.17	7.47	6.25		
middle	15.66	17.11	14.05		
ring	5.89	8.07	5.56		
little	7.10	9.56	6.81		
mean	10.17	13.51	**8.17**		
PIP					
thumb	9.73	16.46			**4.79**
index	5.54	6.29	6.23		
middle	11.03	12.74	9.98		
ring	14.88	12.73	13.86		
little	6.72	12.41	7.72		
mean	9.58	12.13	**9.45**		
DIP					
index	6.85				4.71
middle	12.06				11.82
ring	7.46				6.79
little	22.01				19.80
mean	12.29				**10.78**
separation					
$MCP_{2,3}$	10.23	10.15	13.35		
$MCP_{3,4}$	11.32	10.89	12.09		
$MCP_{4,5}$	14.69	10.64	14.83		
mean	12.08	**10.56**	13.42		
CMC					
flexion		22.66		22.71	**13.20**
abduction	10.26	28.11		27.61	**9.01**
palm arch	22.66	**17.32**			

TABLE II
AVERAGE RMSES FOR THE SENSOR GROUPS OF THE BEST CALIBRATION METHOD AND THE ACROSS-SUBJECT CALIBRATION IN DEGREE

sensor group	Best method	Across-subject
MCP flexion	8.72	13.82
PIP flexion	8.52	17.14
DIP flexion	10.78	19.62
separation	10.56	16.38
CMC flexion	13.20	23.97
CMC abduction	9.01	16.78

C. Across-Subject Calibration

The across-subject calibration is obtained using the best calibration results according to the RMSEs in Table I, excluding the palm arch, as we deem the RMSE of 17.32° too high in comparison to the range of motion to be used for an objective assessment. The coefficient of variation (ratio between one standard deviation and its mean) ranged between 5% and 53% (two exceeded 25%) for the gains and between 24% and 1510% for the correction terms.

The accuracy of the across-subject calibration is compared to the best calibration approaches for each sensor group in Table II. For most joints, an increase of the mean RMSE by 5°–10° can be observed, compared to the best method.

D. Feasibility Study With Patients

We observed that not all patients were able to perform a complete calibration procedure as intended. Therefore, we report the observations made during the attempt to use the CyberGlove III with patients.

All patients had swollen and tender hands, with two cases of severe swelling, such that the glove did not fit. All patients complained about discomfort leading to a limited duration of the measurements. They had reduced ranges of motion for flexion, most of them had ranges below 60°. The static separation measurement with multiple wedges at once was not possible for some of them. However, taking one separation measurement at a time was still possible. Even though issues with limited ranges of motion, tender hands, and exhaustion from the procedure were observed for all of them, the nature of the limitations seems highly individual.

IV. DISCUSSION

In summary, we compared different calibration methods by means of RMSEs, advanced existing calibration methods to be more accurate and easier to execute, and identified the best individual calibration to reach RMSEs below 10°. We simplified with improvement 1 the measurement to calibrate the thumb CMC based on method 2 without reduced accuracy. Additionally, we reduced with improvement

2 the RMSEs for the thumb and DIP joints substantially, by transferring a known procedure that uses four static measurements and a least-squares fitting. The number of necessary measurements for these calibrations ranges from two static measurements for the across-subject calibration, 22 static measurements for method 1, up to 66 static plus 18 continuous measurements for the best calibration method. The RMSEs show a clear advantage for methods using fitting, that is, more measurements than parameters to identify. This highlights the need for researchers to choose a calibration approach with an appropriate balance between high accuracy and the extent of the calibration process.

We cannot compare our determined accuracy to previously reported results, since we did not find prior investigations using ground-truth angles. According to the manufacturer, the sensors have a resolution of $<1°$ [5], which represents the physical limit that can be reached with a perfect calibration and perfectly fitting glove. Calibration method 2 was originally validated by having three measurements of static postures from distinct sessions and comparing them among each other [11], which highlights the repeatability of the method but does not directly allow conclusions on its accuracy. This leads to smaller deviations than in our comparison, showing that the repeatability is even better than the accuracy. Method 3 is rated by means of the variance accounted for (VAF) of estimated angles with respect to ground-truth angles, where 100% equals a perfect fit of the calibration [6]. For flexion and extension, the mean VAF was 97.9% and higher, while it was 92.6% and higher for the separation angles. Yet, these values are difficult to compare to absolute accuracy as can be done with RMSEs. The across-subject calibration was compared by the angle difference to an individual calibration yielding precision errors between 1.34° and 10.39° [11]. These errors cannot directly be compared to our RMSEs in Table II, but they show a similar increase in error. This means that our investigation supports the feasibility of an across-subject calibration for the CyberGlove III.

The individual calibration methods compared in this work show different advantages regarding the extent of the calibration process and achieved accuracies shown in Table I. The RMSEs of calibration method 1 (affine relationships (1) for all sensors) are surprisingly low, compared to more sophisticated methods, especially for the separation sensors, where no correction for flexion in the neighboring MCP joints is considered. This method has the advantage of using the lowest number of measurements for individual calibrations. Method 2 uses rearranged equations for the flexion sensor values (2) and (3). Yet, the RMSEs are higher than for method 1. With a consistent choice of the neutral and 0° measurements during the calibration, the same RMSEs as in method 1 would render similar accuracy, but with a higher number of measurements. The separation sensors [using (4)] yield the lowest RMSEs for this sensor group, using a second-order polynomial and a least-squares fitting. Method 3 uses multiple static poses with a least-squares fitting for the flexion sensors, which reduces the RMSEs substantially for the MCP and PIP flexion, compared to the other methods. The separation sensors show higher RMSEs compared to method 2, which might be caused by the polynomial with lower number of parameters to correct for crosstalk [two in (9)] compared to five in (4). All calibration methods that use a fitting procedure (e.g., least squares) can be expected to be more robust regarding single outliers in the measurements. This robustness may even be further increased using the one-norm instead of the two-norm for the parameter fitting.

Improvement 1 (Fig. 6) shows similar accuracy as method 2, meaning that the expected increase due to a more standardized motion was not achieved. However, the here proposed calibration is easier to standardize, as it uses the table as a support to perform a pure abduction without flexion. Improvement 2 transfers the robust and accurate calibration for the flexion sensors in method 3 to the remaining joints. The RMSEs show that this indeed provides an improvement regarding the accuracy of angle estimation in all joints it is applied. The most noticeable decrease in RMSE is achieved for the thumb MCP and IP joints. But also the DIP joint angle estimates benefit from improvement 2. The reduction in RMSE, compared to the lowest RMSEs of the three methods, is between 2° and 9° (12%–50%). Additionally, the calibration of the thumb CMC joint with this improvement is independent of a hand model and uses easily executed static measurements.

The across-subject calibration based on our best calibration method shows increased RMSEs compared to the individual calibration based on this best calibration method. We deem this increase to be expected and acceptable. This calibration method is meant for reduced assessment time or monitoring at home rather than for the highest accuracy since it only needs two static neutral poses of the hand. However, the high variability of the correction terms raises the question of whether they should be obtained individually, which would increase the number of measurements for the calibration.

We observed, for all calibration approaches, that the RMSEs varied substantially between subjects and between different fingers and joints within one subject. Meaning the individual accuracy can be better or worse than the mean RMSEs. It was not possible to identify reasons for the variability in accuracy, suggesting that more investigations are needed.

It was observed that the palm arch sensor was the most inaccurate. This is plausible as there is not one distinct point to measure the palm arch angle but a whole area, the accurate calibration difficult. Additionally, the range of motion is rather small, making small deviations more influential. We also observed issues with the calibration of the DIP sensors, which resulted in partially good, but also unrealistic calibration results (see Section III-B). A clear cause was not found, but we suspect that the position of the joints with respect to the sensors caused these problems, as the subject whose DIP measurements had to be discarded, did not reach the DIP sensors with its fingers and had the smallest hand length.

We advise visualizing the estimated hand postures after calibration to check for severe calibration errors. This can be done using the Python API in OpenSim [32] and any hand model without extending the calibration process considerably.

We suggest using the gloves for objective analyses of the range of motion and to quantify the usage of a joint by counting how frequently it reaches certain angles. These quantities can be obtained objectively and efficiently using the across-subject calibration. While the best calibration methods can be used in sophisticated studies, it has to be investigated for the specific use case whether the accuracy is high enough to distinguish small differences in movement patterns. Our feasibility study showed that using the glove in a clinical setting or clinical study introduces additional challenges. We observed, for example, that the degree of limitation differed between joints and individuals, and it was not possible to conclude from hand size or disease duration that the glove might not fit. This emphasizes the need for more research in realistic scenarios with patients and for a flexible calibration procedure that can be done by patients with different limitations. Furthermore, an adjustable glove that can be put on without discomfort even with swollen joints would be helpful, especially for clinical settings where the acceptance of such a device is highly important. Monitoring at home might also add additional difficulties, such as ensuring a high-quality calibration without supervision. Therefore, an easy-to-execute across-subject calibration becomes even more important for this use case. It is an especially promising technique, as successful calibrations of healthy subjects could be used to calculate the across-subject calibration parameters. This would mean that patients only have to execute the neutral pose measurements for the calibration. Eventually, one has to decide for each application individually whether the accuracy of the glove is high enough.

More studies with more subjects, especially with a focus on patients, would be helpful to draw stricter and more thorough conclusions on the usage of such gloves in a clinical setting. On the one hand, a number of different subjects are important to ensure that the whole population can use these gloves with a certain accuracy. On the other hand, calibration methods need to be developed and validated, which are not sensitive to reduced ranges of motion.

V. Conclusion

We conclude that the CyberGlove III and the investigated calibration methods are accurate enough to monitor hand movements, excluding wrist and palm arch movements. We did not investigate the wrist sensors and the palm arch has shown to be difficult to calibrate. Even though the findings in this work need to be confirmed for arthritis patients as well, it already shows that using the CyberGlove III for objective hand monitoring of healthy subjects is feasible, supporting previous findings ([2], [6], [8], [11], [12], [22]). Furthermore, the CyberGlove III was already used to discriminate between healthy individuals and patients suffering from osteoarthritis with an accuracy of 80% [8]. This highlights the promising capabilities of such gloves insofar as the glove fits the patient.

Nonetheless, with our achieved accuracy for healthy subjects, many questions can be investigated. For instance, determining the frequency of joint movement and the range of motion and exploring strategies to reduce pain during certain tasks (e.g., adapted movement patterns). Most importantly, with the help of easily executed calibrations such as the across-subject calibration, this monitoring can be implemented at home during everyday life instead of in laboratory and clinical settings. Yet, there are still investigations to be made. For instance, the across-subject calibration, while being a useful method, should be developed further. It might be beneficial to investigate the potential of a more personalized across-subject calibration, where the calibration parameter sets are clustered in different groups depending on certain characteristics of the hand, such that accuracy increases. To do this, many calibration results are needed and as the calibration is glove-specific, it is currently impossible to share the calibration of one CyberGlove III with another. Therefore, another question to be investigated is, whether a transfer of these parameters between gloves can be realized.

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