Quantitative Fit Assessment for Smart Gloves

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Abstract

Fit plays an important role in the function and wearability of functional clothing. Smart gloves, or functional gloves with integrated technologies (such as sensors or actuators), rely on fit to create an interaction with the body surface that is needed to afford functionality. For example, glove fit must produce contact between a haptic actuator and the body to enable a haptic sensation. Failure of coupling between body and glove can also cause sensor malfunction, reduced mobility, and user discomfort. High-resolution fit analysis is needed to assess the geometric relationship between gloves and the complicated anatomical structure of the hand. This study developed a high-resolution fit assessment method that provides quantitative information on smart glove fit. The study defined key fit measures, proximity and alignment, to measure smart glove fit, focusing on quantifying the relationship between integrated technologies and the body surface. A quantitative pipeline was developed that included three stages: hand model development, 3D scan analysis, and result translation. The methods provided high-resolution (< 1 mm accuracy) and objective data that can be used to inform smart glove fit improvements and, consequently, improvements to on-body functionality. The results of the fit analysis demonstrate that these methods can effectively quantify glove fit. Adding proximity and alignment measurements to the analysis allows the relationship between the body and integrated technologies to be quantified, providing information to improve smart glove fit. Virtual fitting was explored for expanding the pipeline to reduce prototyping time and costs by simulating gloves virtually.

Keywords: 3D hand scanning, virtual fitting, smart clothing, glove fit

1. Introduction

Smart gloves are functional garments with embedded technologies, such as sensors and actuators, that monitor the user's body and/or physically interact with the user to achieve a functional goal, such as motion tracking, biometric monitoring, or tactile feedback. Smart gloves have been developed for various purposes, such as supporting human-computer interaction in virtual and augmented reality systems, monitoring health, or sensing movement in sports training [1]–[5].

While there are many different types of smart gloves with different functional goals, glove fit is a unifying challenge that has held these devices back from widespread use [1]. For smart gloves, poor fit presents both functional and wearability challenges [6]. For example, poor fit can cause poor on-body performance of sensors and actuators because these technologies often rely on contact with the body surface for functionality, such as sensing and transmission of stimulation [2], [7], [8]. Misalignment between a particular body location and an embedded technology can also cause malfunction [3], [9]. For example, if a bend sensor does not align with a body joint, the sensor cannot track joint angle. Poor fit can also hinder user movement and cause discomfort [10], [11]. Preserving range of motion is particularly important for smart gloves because hands have 27 degrees of freedom used for dexterous manipulations. For optimal functionality and wear comfort, smart gloves must maintain a target fit range without compromising hand dexterity [12]. Prior research has shown that smart glove malfunction can occur even with small changes in glove fit, produced by different wearers and wearer movement [5], [13].

Despite the importance of smart glove fit for enabling on-body performance, a limited number of studies have used quantitative methods to define smart glove fit conditions. Qualitative studies have investigated functional clothing fit, including gloves [14]–[16]. However, perceptual data is difficult to translate into objective and accurate fit information. Fit analysis with 3D scanning produces quantified measures to identify the specific relationship between the garment and the body. However, these 3D scanning studies only visualize overall garment-body distance maps or provide limited cross-sectional garment-body distance analysis [17]–[20]. There are no prior studies that have quantified fit through point-based analysis at the millimeter level, which is required to understand the link between fit and performance of smart gloves.

The purpose of this study was to develop a high-resolution, quantitative fit assessment method that provides detailed information on smart glove fit. We defined key fit measures for smart glove fit analysis (i.e., contact and alignment) to guide point-based analysis, performed advanced fit assessment using 3D technology, and developed a quantitative pipeline that connects smart glove fit evaluation with data-driven fit improvements.

2. Background

Perceptual fit surveys are widely used to investigate functional clothing fit. For example, likert scales are used to rate general garment satisfaction (very satisfied to very dissatisfied) or fit (very tight to very loose) [15], [21]. Mixed method study designs that combine subjective measures with objective measures can mitigate perceptual differences by adding objective indicators of fit. An example of an added objective measure includes time for task performance. While time for task performance is a useful measure, there is not a direct link between a fit condition and hand dexterity to define design changes [22]–[25]. Although perceptual fit surveys combined with objective usability measures result in numerical scores, these scores are easily affected by variation in individual expectations and sensitivities [26], [27]. Advanced fit analysis methods with quantified measures, such as 3D scanning, are required to identify the specific location and magnitude of fit issues [28].

3D scanning is a method used to acquire accurate surface data (size and shape) for the human body, represented as a surface mesh [29]. Common 3D scanning-based fit assessments are conducted by overlaying clothed and unclothed body scans to produce a garment-body distance map, usually visualized as a heat map. These heat maps quantify fit as the garment-body distance offset. Important factors for quantified fit assessment include (1) scan data accuracy, (2) scanning strategy, (3) landmark strategy, and (4) body posture.

(1) *Scan data accuracy:* The accuracy of 3D scanning-based fit assessments is driven by the accuracy of the 3D scanner. Scan accuracy is measured in terms of dimensional accuracy and visual/texture accuracy. Dimensional accuracy refers to the accuracy of the dimensions of the 3D mesh volume produced by the 3D scanners while visual/texture accuracy refers to the accuracy of the visual surface pattern, which can include landmarking, applied to the 3D mesh. Measurement tool validation is often conducted prior to fit assessment to quantify 3D scanner accuracy and differentiate scan error from fit conditions [30], [31].

(2) *Scanning strategy:* In addition to 3D scan hardware, the scanning strategy, including the data collection procedure and the environment, also impacts 3D scan accuracy. Piloting a scanning strategy prior to data collection allows time for troubleshooting, resulting in more consistent and reliable fit assessment data. Scanning strategy considerations include a) scanner locations and support apparatus, b) the direction/angle of scanning, c) tools and jigs for body positioning support, and d) lighting [32], [33].

(3) *Landmark strategy:* Landmarks are visual references, often points, across the body surface that describe and quantify the dimensions and geometry of the body [34]. Landmarks and the distance between landmarks provide the foundation for investigating the physical relationship between hands and gloves (body and wearable product) [35], [36]. Landmark locations can be chosen based on anatomy (bone, muscle) or a product's target wearing location [37]–[39].

(4) *Body posture:* To investigate garment fit, researchers study body shape and measurement changes across static and dynamic postures [40]. Dynamic anthropometry, or the study of the human body's dimensional and geometric changes with movement, quantifies the dynamic garment-body relationship, or the dynamic nature of fit [41]. Quantifying dimensional changes between the body and the wearable product during movement allows researchers to make data-driven changes to wearable product fit [42].

While early 3D scan-based fit analysis was limited to qualitative, morphological visualizations [43], quantitative distance measurements between the garment and the body have been developed by overlaying clothed and unclothed body scans [18]. Previous studies have used clothed/unclothed scan overlays to measure the distance between functional clothing and the body surface using cross sectional analysis and mesh deviation analysis, which quantifies the garment-body dimensional offset, or air gaps [17], [19], [20]. Researchers have validated mesh deviation analysis methods by scanning wet clothing with distinguishable contact areas [44] and by exploring air gaps in specific areas, or 'zones,' referred to as zone analysis [17], [20]. The major limitation of mesh deviation and zone analysis methods is that they only provide overall air gap distributions and are unable to produce quantitative, point-to-point fit data. Consequently, we introduce a new 3D scan-based fit assessment method, point-based analysis, that leverages landmarks to increase the resolution of quantitative fit assessments and specific fit changes needed to improve functionality and wearability of smart gloves.

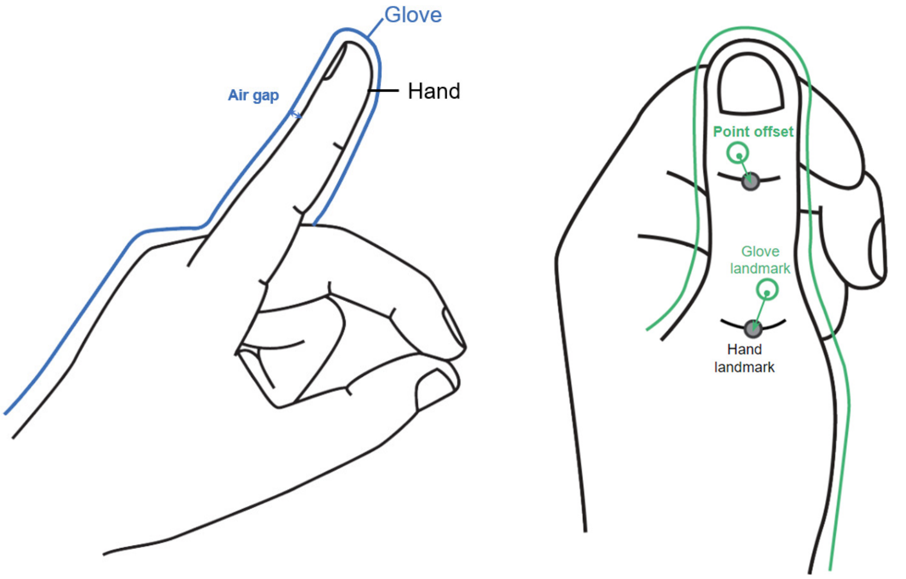
3. Quantitative Fit Assessment

3.1. Fit measures for smart glove

Fit is the physical (kinetic and kinematic) relationship between a garment and the body surface. Previous research has defined traditional measures of fit, by external garment characteristics, such as (1) grain, (2) set, (3) line, (4) balance, and (5) ease [45]. Smart gloves require a revised set of fit measures to quantify the dimensional relationship between the garment and the body. Prior research identified contact and interface pressure between the hand and embedded technologies throughout movement as important considerations for on-body functionality [2], [10]. Alignment between the hand and embedded technologies [3], [4], [47], [48] have also been noted as key to enabling on-body functionality and improved sensor calibration. Based on this prior work, we define proximity and alignment as two key fit measures for the quantified fit assessment of smart gloves (Fig. 1). Kinetic measures, such as interface pressure, cannot be quantified with 3D scan-based methods and require further method development.

Proximity is a kinematic measure of garment fit that captures the relative distance (air gap) between the garment surface and the body surface at any point along the garment-body interface. There have been several studies that have analyzed air gaps through mesh deviation analysis [17], [20]. However, these methods have not been applied to smart gloves for the purpose of improving functionality. Proximity measurements equal to 0 indicate 100% garment-body contact. A proximity measurement greater than 0 quantifies the dimensional offset, or air gap, between the garment and the body. This proximity measurement is dynamic and body posture dependent.

Alignment is a kinematic measure of garment fit that captures the relative offset of a particular point on a garment and a particular body landmark location. Alignment can be an indicator of a) whether the anatomical landmarks of the glove pattern design match the target position of the hand or b) whether the important components of the glove (e.g., sensors or actuators) are correctly positioned relative to the body. Quantified alignment, or point offset, has not previously been part of fit assessment.



a) Proximity measures air gap b) Alignment measures point offset

Fig. 1. Quantified fit measures; a) Proximity and b) Alignment

3.2. Glove Fit Assessment Pipeline

In this study, we developed a quantitative, point-based fit assessment pipeline that leads to data-driven fit improvement for smart gloves. The fit assessment pipeline (Fig. 2) was largely divided into three stages: hand model development, point-based fit analysis, and glove pattern/fit adjustment. After producing revised prototypes that reflected the results of fit analysis, the same fit analysis process was repeated to evaluate fit improvements.

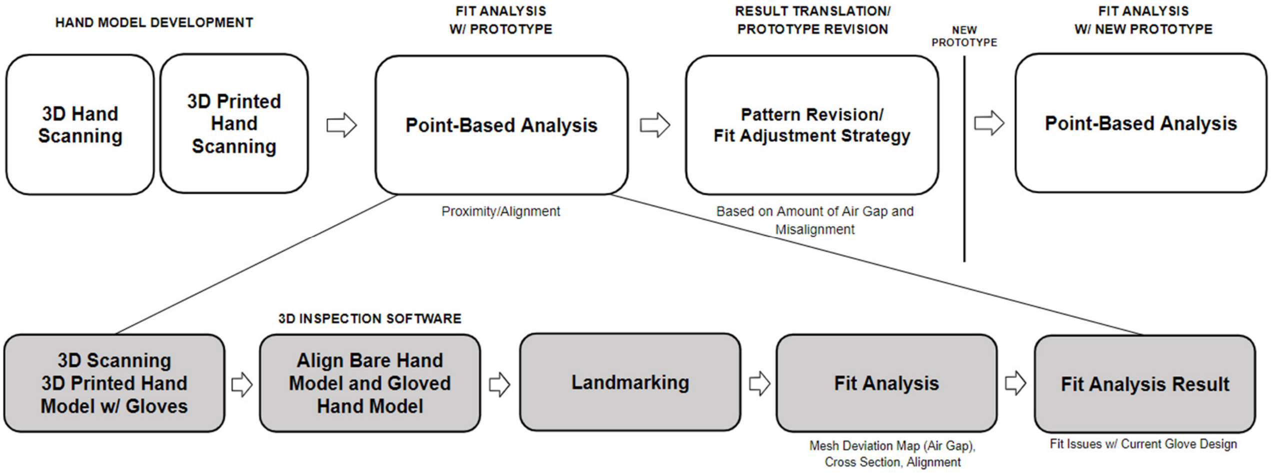


Fig. 2. Quantitative glove fit assessment pipeline

The first step of the fit assessment pipeline was to generate 3D hand models. Hand models were used in place of human hands because it is not possible to pose and repose human hands (for gloved and ungloved scans) with accuracy less than 1 mm, which is required to prevent hand pose from confounding fit assessment results. 3D printed hands enable high accuracy fit analysis by producing consistent/reliable hand poses between gloved and ungloved scans. Hand model development involved (1) placing landmarks at key anatomical locations, (2) scanning human hands, (3) post-processing scans to produce cleaned mesh, and (4) 3D printing the hand mesh to produce 3D hand models. Preexisting hand models could also be used in this fit assessment pipeline.

The second step, fit analysis, included four sub-steps. (1) Both ungloved and gloved 3D hand models were scanned using an Artec Eva 3D scanner (Artec 3D, Luxembourg, Luxembourg). (2) The scans were imported into a 3D mesh inspection software and registered using landmarks. (3) Glove fit was then analyzed using point-based analysis. Point-based analysis was divided into two parts: a) proximity measurements, which quantify the distance between glove and hand surfaces, and b) alignment measurements, which quantify the point offset between specific hand and glove landmarks using a coordinate axis. This point-based fit assessment is discussed further in subsequent sections. (4) The individual measurements were quantified and reported in a table of results.

The third step in the fit assessment pipeline translated fit assessment summary data into actionable design guidance to improve the fit of the glove. Glove fit improvements were implemented through revisions to glove patterns.

4. Point-Based Analysis

Point-based fit analysis is reliant on visual landmarks to enable proximity and alignment measurement. The landmark set (Fig. 3) was developed by selecting major anatomical points of the hand, including fingertips, finger joints, and finger webs. Additional landmarks were distributed across the palm, dorsal, and wrist areas. Each landmark was assigned a coordinate axis (Fig. 3, right) to enable point offset, or alignment measurement between glove and hand landmarks that were intended to align. Landmarks were color coded according to their specific coordinate axis.

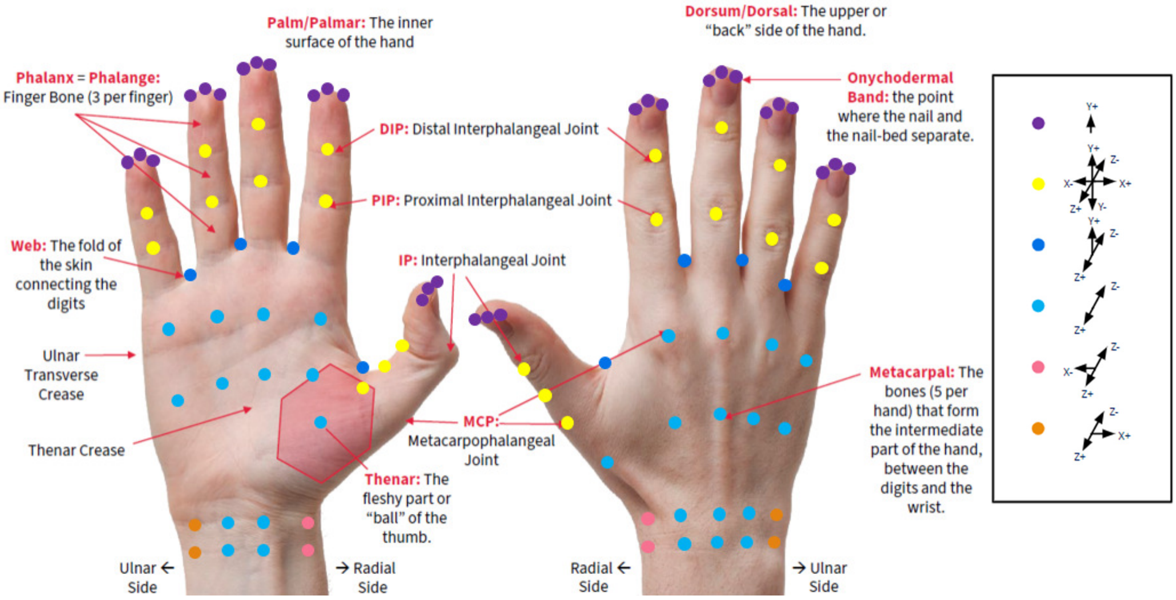
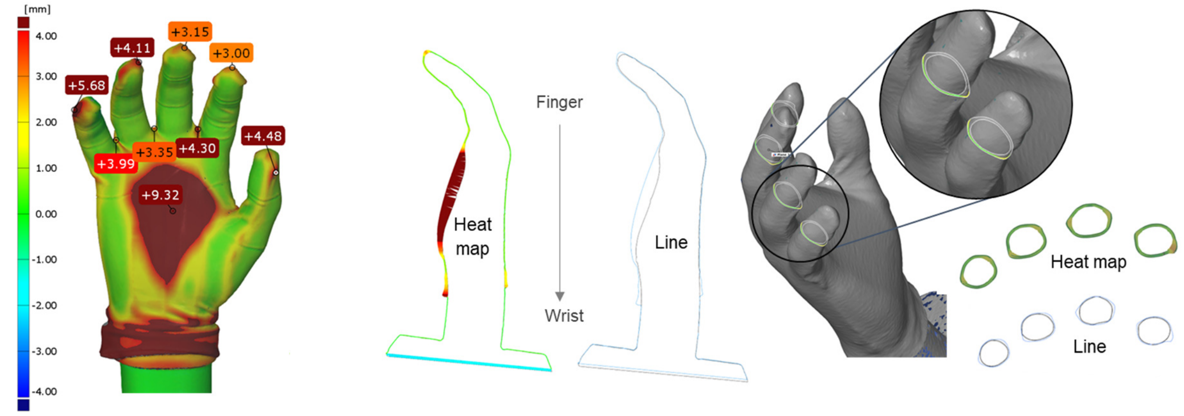


Fig. 3. Landmarks for point-based analysis

Point-based fit analysis can be performed in any 3D CAD or inspection software that is capable of creating mesh deviation maps, measuring distances between points, and generating point coordinates. We analyzed proximity and alignment measures using GOM inspect (GOM Metrology, Braunschweig, Germany) software. Ungloved and gloved hand scan registration was accomplished through pre-alignment and local best-fit functions using wrist landmarks that were visible in both scans. Digital landmarks were created by referencing these physical landmarks.

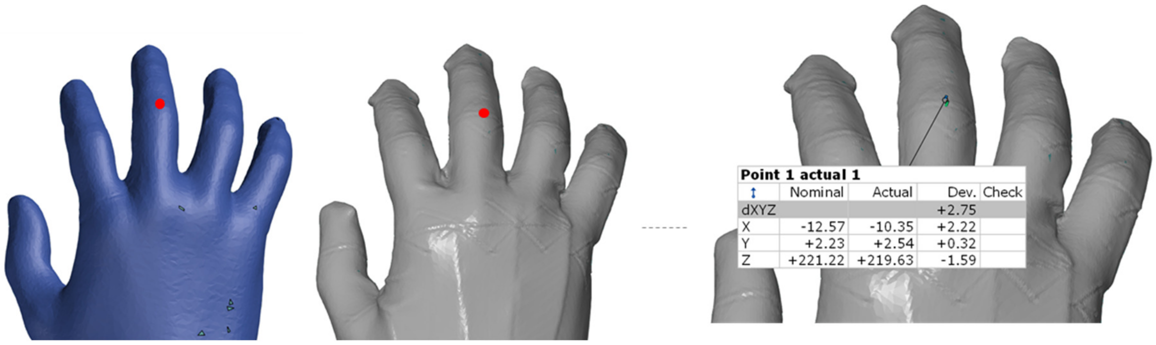
1. *Proximity measures:* Proximity measures were quantified using mesh deviation analysis and cross sectional analysis (Fig. 4). Mesh deviation analysis was conducted by developing mesh deviation maps (Fig. 4a) that visualize the dimensional difference between ungloved and gloved hands. A deviation label was added to the mesh deviation map in specific locations to quantify the garment-body distance, or air gap, at specific locations. Cross sectional analysis was conducted by dropping a vertical or horizontal plane through the mesh deviation map to extract cross sectional slices with clearly visible garment-body distance offsets (Fig. 4b). Quantifying the specific distance, or air gap, in millimeters required consideration of glove construction details, such as seam location, seam thickness, and fabric thickness. Specifically, local glove thickness was quantified and removed from any original garment-body distance measure to produce a proximity measure. Using these proximity measures, it was possible to identify areas of the glove with poor fit.

2. *Alignment measures:* Alignment measures were quantified with coordinate analysis, which was conducted by comparing glove and underlying hand landmarks. Point misalignment can occur in many directions, therefore, coordinate axes were used to quantify the dimensional offset in X, Y, and/or Z axes. Specifically, the Y axis was used to track misalignment in glove length, the X axis was used for checking misalignment between the finger panels and the palm/dorsal panels, and the Z axis was used to track misalignment in glove width. Fig. 4c visualizes the coordinate analysis process that outputs quantitative alignment measures.



a) Mesh deviation analysis

b) Cross sectional analysis



Point 1 actual 1	Nominal	Actual	Dev.	Check
dXYZ			+2.75	
X	-12.57	-10.35	+2.22	
Y	+2.23	+2.54	+0.32	
Z	+221.22	+219.63	-1.59	

c) Alignment measures guided by coordinate axes

Fig. 4. Point-based fit analysis combines traditional a) mesh deviation analysis and b) cross sectional analysis to quantify garment-body proximity with c) coordinate analysis to quantify garment-body alignment

Table 1 describes the key results of point-based analysis. We quantified proximity and alignment measures for a glove prototype, revised the glove pattern in response to proximity and alignment measures, and built a second glove prototype to demonstrate fit improvements. As an example, we focused the point-based assessment on the finger regions. To quantify fingertip proximity, the distance between the finger edge to the glove edge was measured in the Y+ axis (see Fig. 3) at the midpoint and at each side of the finger (ulnar and radial). Glove fingertips were shown to be too long overall, with measured air gaps between 0.5-3.6 mm. We revised the glove pattern to remove these specific excess glove dimensions to produce a more conformal fit at the fingertips. Fingertip air gaps for the revised glove prototype were reduced to 0.0-0.4 mm. We quantified this fit improvement as a percent change between first and second prototype distance measures. The percentage of proximity fit improvement ranged from 39% to 100%.

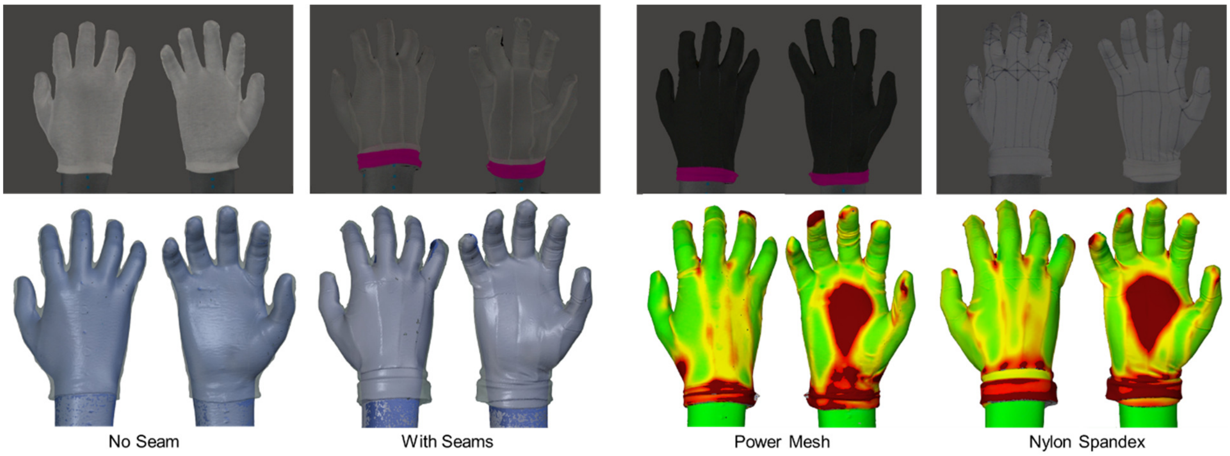
To quantify alignment between specific points on hand (here, distal interphalangeal joints) and specified points on the glove (that could be the location of embedded technologies), we used local coordinate systems to guide data collection. Table 1 reports the misalignment measured in glove length only, captured by the Y axis, because misalignment was most pronounced in glove length. For the first prototype, misalignment ranged from 4.8-6 mm. Based on the measured misalignment value of the first glove prototype, we moved the anatomical landmarks within the glove pattern for the second prototype. As a result, the misalignment in the second prototype was reduced to 0.9-2.7 mm, which was an improvement of 43% to 83%. The results confirmed that the developed point-based fit assessment pipeline can be effectively utilized to improve glove fit.

In order to investigate the method, process, and application of fit assessment pipeline, we performed the assessment with a range of gloves with different designs, fabrics, and embedded technologies. Specifically, we investigated three case studies: (1) gloves made with different pattern designs, (2) gloves made with different fabrics, and (3) gloves with non-functional components to mimic the added mass/volume of embedded technologies. Figs. 5-6 depict 3D scans of hand models wearing each of these case study gloves. Fig. 5a demonstrates that glove patterns constructed without seams fit differently than glove patterns constructed with many seams. Fig. 5b demonstrates that constructing the same glove pattern with different fabrics, here power mesh or nylon spandex fabrics, also produces glove fit differences. While fit differences are visualized qualitatively here, our point-based fit assessment procedure could be used to quantify fit differences between all case study gloves.

Table 1. Key results of point-based analysis (mm). T = thumb, I = index finger, M = middle finger, R = ring finger, P = pinky finger, IP = interphalangeal.

Fit Measure	Area		Landmark	Direction	1st Glove Prototype	2nd Glove Prototype	Fit improvement (%) (A - B)/A*100
					Distance, A (mm)	Distance, B (mm)	
Proximity	Fingertip	T	Midpoint	Y+	0.7	0.0	100%
			Radial	Y+	2.5	0.2	91%
			Ulnar	Y+	2.4	0.0	100%
		I	Midpoint	Y+	0.5	0.3	39%
			Radial	Y+	2.0	0.3	85%
			Ulnar	Y+	3.2	0.1	96%
		M	Midpoint	Y+	1.0	0.0	100%
			Radial	Y+	2.5	0.0	100%
			Ulnar	Y+	2.6	0.0	100%
		R	Midpoint	Y+	1.1	0.4	66%
			Radial	Y+	1.6	0.0	100%
			Ulnar	Y+	3.6	0.0	100%
		P	Midpoint	Y+	1.5	0.0	100%
			Radial	Y+	2.2	0.0	100%
			Ulnar	Y+	2.2	0.4	84%
Alignment	Finger joint	T	IP joint	Y	4.8	2.7	43%
		I	Distal IP joint	Y	5.0	1.2	76%
		M	Distal IP joint	Y	5.6	0.9	83%
		R	Distal IP joint	Y	5.0	0.9	82%
		P	Distal IP joint	Y	6.0	2.2	64%

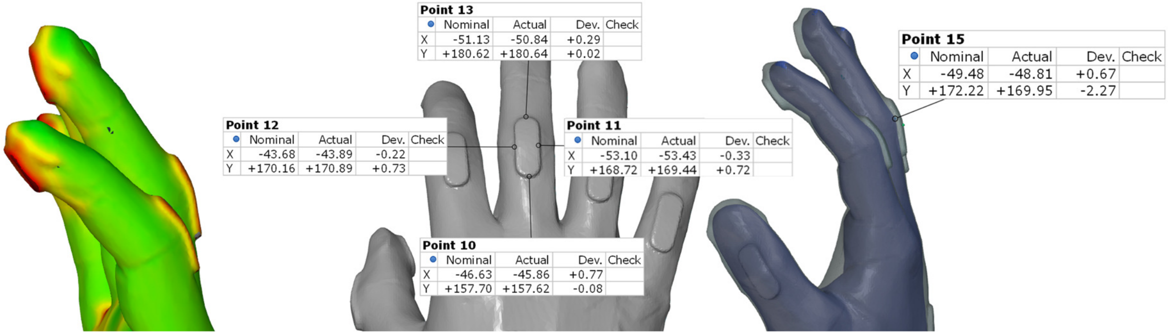
The third case study glove, the component glove, had 3 mm foam rectangles added to the intermediate phalangeal joints and to the fingertips to mimic the embedded technologies that characterize smart gloves (Fig. 6). These nonfunctional components were attached to the base textile glove with a heat bonding sheet. Point-based fit analysis demonstrated that component locations were aligned with their intended anatomical location (intermediate interphalangeal joint) based on the center point and the four edge points of the component. Although Fig. 6 only demonstrates the hand in relaxed posture, this point-based analysis could be conducted in various postures.



a) Different pattern designs
(Superimpose)

b) Same pattern design with different fabrics
(Mesh comparison map)

Fig. 5. Various applications of point-based analysis



Point 13

●	Nominal	Actual	Dev.	Check
X	-51.13	-50.84	+0.29	
Y	+180.62	+180.64	+0.02	

Point 12

●	Nominal	Actual	Dev.	Check
X	-43.68	-43.89	-0.22	
Y	+170.16	+170.89	+0.73	

Point 11

●	Nominal	Actual	Dev.	Check
X	-53.10	-53.43	-0.33	
Y	+168.72	+169.44	+0.72	

Point 10

●	Nominal	Actual	Dev.	Check
X	-46.63	-45.86	+0.77	
Y	+157.70	+157.62	-0.08	

Point 15

●	Nominal	Actual	Dev.	Check
X	-49.48	-48.81	+0.67	
Y	+172.22	+169.95	-2.27	

a) Proximity b) Alignment

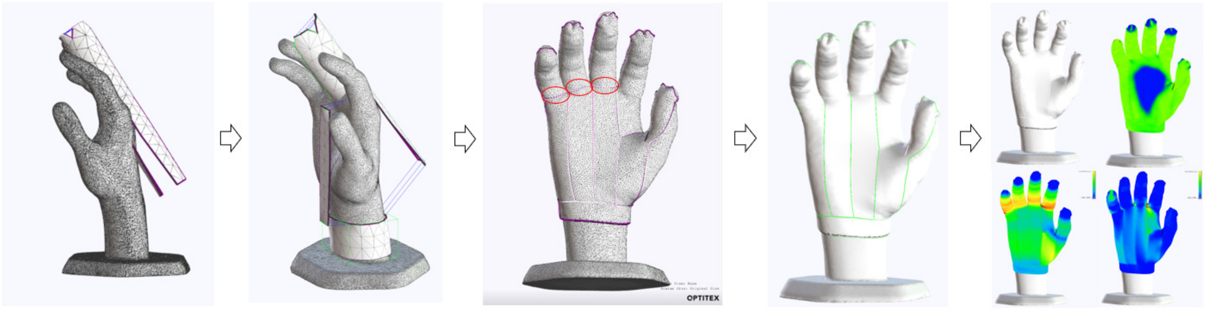
Fig. 6. Point-based analysis for component glove; a) Proximity and b) Alignment

5. Future Outlook

3D body scan-based fit assessment is a useful tool for quantifying fit for smart gloves, but only if there is a physical prototype. To address this constraint, the quantitative fit assessment pipeline can be expanded to incorporate virtual fitting. Virtual fitting has the potential to reduce prototyping/production time and costs by simulating glove fit. Fit assessment using virtual fitting can be advantageous when considering the time and cost of producing smart clothing prototypes, including smart gloves [49].

However, there are still areas to be explored and validated. Unlike the mechanical models used for engineering simulations, new challenges arise from the highly versatile nature of cloth. While virtual simulation tools have matured over the last decade, the accuracy of virtual simulation should be assessed before fit assessment is performed. Simulation assessment can be validated by comparing their results to 3D scan-based fit assessments of physical prototypes. Researchers have compared virtual simulation results with 3D scan-based fit assessment results [50]–[52]. However, these studies presented only qualitative heat map images. One study conducted a quantitative analysis to compare virtual simulations with 3D scans of physical garments and reported that there was a maximum dimensional difference of 3.5 mm or less between virtual and physical prototypes [50]. Several studies have simulated gloves on hand scans for fit assessment [36], [40], however, 3D scan-based fit has not yet been compared to virtual simulation for gloves and quantitative fit analysis has not been conducted due to the complexity of hand anatomy.

To explore the possibility of virtual fitting, we performed glove fitting simulation with Optitex software (Fig. 7). Virtual fitting required several pre-stages to properly simulate the glove on the hand to prepare for fit analysis. Hand scan data was imported as a 3D custom avatar. The hand scan data was cleaned and normal vertices were checked to avoid errors that could affect the simulation. The glove pattern pieces were imported into Optitex in PDS or DXF format. For virtual fitting, textile mechanical properties are a key contributor to glove fit. Therefore, we measured and imported key fabric mechanical properties, such as stretch, friction, and thickness, into the simulation software.



Original piece

Cutting piece
to arrange properly

Initial simulation

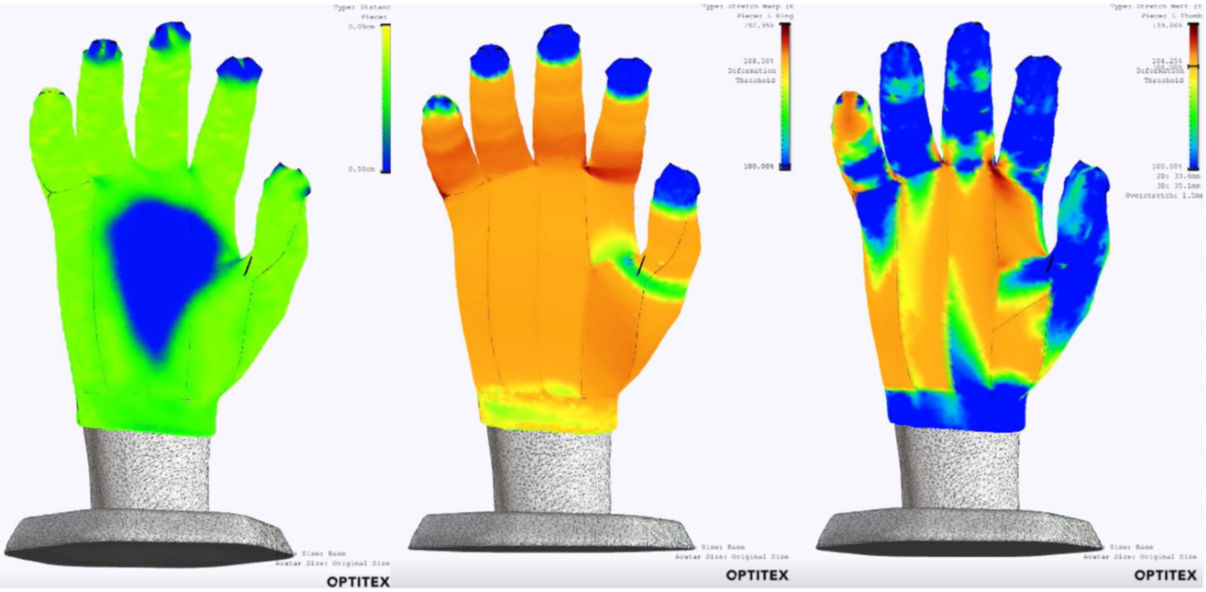
Removing the physical effect
of the fake seam

Fit analysis

Fig. 7. Virtual fitting simulation procedures

Once the preliminary setup was completed, the glove was virtually assembled using a virtual sewing tool. Since the hand has an anatomically complex structure and small, segmented joints compared to other parts of the human body, virtual fitting strategies are required to prevent each piece from overlapping or pinching the avatar during the simulation process. To solve the issue of pattern pieces getting pinched by digging into the avatar, we developed a method of dividing pattern pieces and rejoining them around the avatar. Artificial seams were subsequently removed from the simulation.

Virtual fit simulation software considers fabric mechanical and surface properties to output built-in fit assessments [52], [53]. These fit assessments include (1) a fit/distance map, which shows the relative distance of a 3D garment from the body surface, (2) a stretch map, which shows the garment's engineering strain produced by the garment-body dimensional relationship, and (3) a pressure map, which shows fabric stress produced by the applied strain [51]. Several studies also have qualitatively analyzed the relative distance between the garment and the body by converting a 3D garment to a wire mesh or adjusting the transparency of panels [41], [53]. Fig. 8 shows the fit analysis features (the fit/distance map and stretch map) of Optitex which can be possibly utilized for glove fit assessment.



Distance Stretch - Warp Stretch - Weft

Fig. 8. Types of virtual fitting simulation results

6. Discussion and Conclusion

We demonstrated that point-based analysis, which includes proximity and alignment measures, can accurately quantify air gaps and glove misalignment at the millimeter scale. To replicate these results and trust the dimensional accuracy of the scan data, high accuracy 3D scanners must be used. Additionally, 3D software that can process scan data and analyze mesh deviation is required to perform the analysis. The full analysis process takes approximately 1 hour. Further research to develop an automated process for landmarking and creating deviation labels would reduce the analysis time. This study performed fit analysis using only a relaxed hand posture as a methodological introduction, but the developed pipeline is also applicable for various dynamic hand postures to analyze change in glove fit according to posture.

Virtual fitting was introduced as a technique to virtually assemble digitized clothing patterns, implement material properties, and fit them to an imported avatar. Virtual fitting is a promising technique for predicting the fit of a product under development and correcting fit problems without live models and physical prototypes. This study demonstrated the possibility of virtual fitting for quantitative fit analysis. However, there are some limitations in the current use of virtual fitting software, including Optitex, for advanced fit assessment. For example, fit simulation results can change based on the arrangement and locations of pattern pieces. Additionally, there is little research validating the reliability of built-in fit assessment functions, such as distance and stretch maps. While fit/distance maps can be used to quantify garment-body proximity, existing virtual fitting software does not include point-to-point distance measurement features to quantify alignment, or point offset. Lastly, there are software limitations to accurately simulating multi-material gloves with varying thicknesses and mechanical properties. Virtual fitting is a highly promising technique for quantifying fit issues without real prototypes, which can save on prototyping time and cost. Research on the accuracy of virtual fitting technologies is the first step towards achieving this goal.

In this study, we developed a fit assessment pipeline to quantitatively assess smart glove fit, which had not been studied in previous literature. While fit is important for most functional clothing, smart gloves fit is required to enable on-body functionality. High-resolution fit assessment allows wearable technology researchers to develop better wearable devices, such as smart gloves. While previous research has been limited to subjective measures or qualitative analysis of mesh deviation maps, this study provides precise and objective fit assessment methods for gloves that drive data-driven fit improvements.

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