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A Multi-Modal Sensing Glove for Human Manual-Interaction Studies

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Abstract: We present an integrated sensing glove that combines two of the most visionary wearable sensing technologies to provide both hand posture sensing and tactile pressure sensing in a unique, lightweight, and stretchable device. Namely, hand posture reconstruction employs Knitted Piezoresistive Fabrics that allows us to measure bending. From only five of these sensors (one for each finger) the full hand pose of a 19 degrees of freedom (DOF) hand model is reconstructed leveraging optimal sensor placement and estimation techniques. To this end, we exploit a-priori information of synergistic coordination patterns in grasping tasks. Tactile sensing employs a piezoresistive fabric allowing us to measure normal forces in more than 50 taxels spread over the palmar surface of the glove. We describe both sensing technologies, report on the software integration of both modalities, and describe a preliminary evaluation experiment analyzing hand postures and force patterns during grasping. Results of the reconstruction are promising and encourage us to push further our approach with potential applications in neuroscience, virtual reality, robotics and tele-operation.

Keywords: hand pose sensing; tactile/force sensing; wearable sensing; optimal design; human hand synergies

1. Introduction

The human hand is the principal means of interaction with the external world and has a crucial role in many tasks related to common daily life activities. Consequently, numerous neuro-scientific works have focussed their attention on the quantitative analysis of hand kinematics and kinetics to deepen our understanding of the motor control mechanisms underlying the remarkable manipulation skills of human hands and thus paving the way to develop more efficient human-machine interfaces and robotic hands. Many application fields can benefit from these research results, e.g., virtual reality/video-games [1,2], rehabilitation [3,4] and remote manipulation/tele-operation [5,6].

Existing hand pose reconstruction (HPR) systems are visual-based or glove-based devices that track and estimate the hand kinematics, see [7–9] for a detailed review. Visual-based HPR systems, such as the ones described in [1,2,6], are quite accurate, inexpensive and unobtrusive, but they are not suitable for ambulatory monitoring during daily life activities. In contrast, glove-based HPR devices, relying on off-the-shelf flex sensors [3,10], dielectric elastomer stretch sensors [11], optical fibers [12], or inertial measurement units [4], are intrinsically ambulatory, but they are often less usable than visual-based systems due to obtrusive wiring and rigid sensor technology that does not adapt to the dynamically changing hand shape of the users. Indeed, the human body, and the human hand in particular, have a high number of degrees of freedom (DOFs) that act on a continuously compliant structure. For this reason, stretchability and adaptability of the sensing technology are mandatory requirements for efficient and ecological monitoring of the human hand.

In addition to hand pose, tactile sensing and force control play a crucial role for successful manipulation. In an early experiment it was shown, that subjects have severe difficulties in maintaining stable grasps when their sense of touch was eliminated by local anesthesia [13]. Similarly, the lack of tactile feedback in today's robots restricts their use to highly structured environments where contact with unknown objects and humans has to be avoided by external security measures. To endow future service robots with modern tactile sensors, e.g., [14–17], and thus to enable their operation also in unstructured and unknown environments, calls for new tactile-based control approaches [18–20]. To develop those, in turn requires a deeper understanding of the interplay between kinematic and kinetic hand control in human manipulation, i.e., particularly also considering interaction forces, which will open new insights into the overall motor control processes underlying manual intelligence [21].

Several works have dealt with the development of flexible tactile sensors suitable for ambulatory hand monitoring. A common technology employs flexible printed circuit boards (PCBs) [22–24], which can be bent in one direction at a time. Cutting the film carrier, surfaces with two-dimensional curvature can be covered as well [14,25]. However, stretchable material can much better adapt to the variable human hand shape. For example, methods using conductive rubber with interwoven wiring were reported [26]. Using electrical impedance tomography, it is possible to get rid of the wiring and only use electrodes along the circumference of the conductive rubber sensor to reconstruct applied force patterns [27]. However, this method is prone to ghosting and mirroring (detecting spurious tactile locations). Optical sensors, exploiting intensity modulation based on reflection [28] or strain in optical fibers [29], require cumbersome wiring to/from light sources and thus are too bulky for unobtrusive usage. Very high spatial resolution was achieved with a sprayed-on silicone elastomer [30], but this method was restricted to single-time usage. All these tactile sensing technologies present some drawbacks, mainly related to poor robustness, scarce adaptability, or complex electronics design.

To the best of our knowledge, none of the existing monitoring systems can measure at the same time the hand pose and tactile/kinetic information in an ambulatory and unobtrusive fashion. The aim of the current work is to report about the development and preliminary assessment of a multi-modal sensing glove able to provide both kinematic and kinetic information.

The kinematic part of our prototype—the kinaesthetic glove of Section 2.1—relies on our previous achievements on the development of textile-based, flexible and stretchable electro-goniometers, described in [31–33]. Similar sensors were used to estimate the pose of a continuum soft robot [34]. Textile goniometers, besides being stretchable and well adaptable to the different body structures, demonstrated a reliable performance in angular measurement (errors below five degrees [33]). On the other hand, they are quite complex bi-layer devices that need at least six connecting wires per DOF, thus limiting their use in multi-DOF monitoring (such as the human hand). For this reason—to maintain the wearability of our prototype—we combined textile goniometers with synergy-based optimal design and reconstruction techniques, we have described in [35,36]. In particular, we have exploited human hand synergy information, i.e., inter-joint covariation patterns, to design an under-sensing glove able to reconstruct the full hand posture (of a 19-DOF hand model) from only five goniometric sensors. The sensors are placed on the hand joints according to a synergy-based optimal design and the complete hand kinematics is reconstructed leveraging synergistic information again, following the theoretical findings we reported in [36].

The kinetic part of our prototype—the tactile sensing glove described in Section 2.2—is based on our previous developments of fabric-based, flexible and stretchable tactile sensors [37,38]. The sensor is composed of multilayer, conductive and piezo-resistive fabric that allows for multi-taxel measurements. The fabric substrate makes the sensor soft, light, and conformable to natural shapes. The force measurement range is $[0.1 - 30]$ N, thus covering the range of grasping forces observed in human daily-life activities [39]. The multi-taxel sensor design mimics the distribution of mechano-receptors in the human hand, achieving spatial resolutions of less than 1 cm in the fingertips and less than 3 cm in the palm.

In the current work, we integrated the kinaesthetic and tactile sensing gloves to develop a unique hand monitoring interface. In particular, we have conceived grasping experiments where the kinaesthetic glove was worn underneath the tactile one, while both the kinematic and kinetic signals were acquired and interpreted. A dedicated software developed in ROS enables to synchronize data acquisition and implements result visualization through a realistic dedicated hand model. Preliminary experiments performed with one participant show a good level of reliability. In this manner, we also demonstrate the feasibility of the here proposed approach, which encourages us to further proceed towards a more effective hardware integration. At the same time, a thorough quantitative validation and exploration of potential application fields are envisioned.

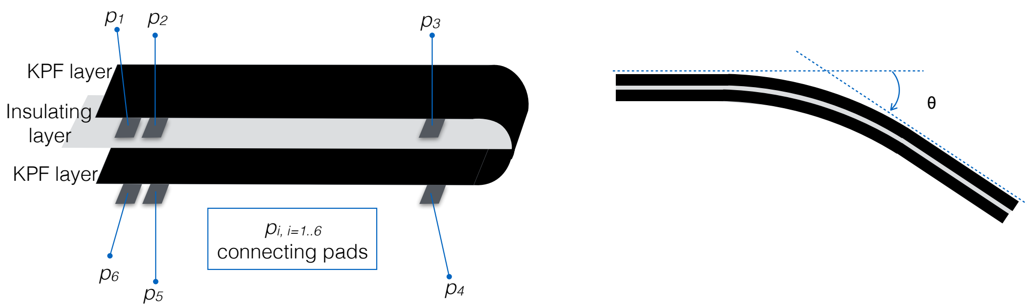
2. Materials and Methods

2.1. Kinaesthetic Sensing

The kinaesthetic sensing glove reconstructs the hand poses associated to daily life grasping activities. The key design objectives were: (i) hand pose reconstruction according to a 19 degrees of freedom kinematic model of the human hand; (ii) real time performance; and (iii) wearability, which is a key aspect to enable the glove employment during daily life activities (e.g., rehabilitation, robotic tele-operation, entertainment, etc.).

2.1.1. Textile-Based Goniometers

We employed "e-textile" goniometers based on knitted piezoresistive fabrics (KPFs). As described in our previous studies [31,32], KPF goniometers are made of two identical piezoresistive layers that are coupled through an electrically insulating textile. As shown in Figure 1a, we fold a single KPF on the insulating layer to obtain the goniometer. The theoretical working principle assumes the flexion angle (θ), defined as the angle between the tangent planes at the sensor extremities (Figure 1b), to be proportional to the difference of the electrical resistance (ΔR) between the two layers.



(a) Layers **(b)** Principle

Figure 1. Textile goniometer made of two knitted piezoresistive fabric (KPF) layers. (**a**) The two conductive KPF layers (in black) are coupled through the electrically insulating stratum (in light gray). The device has six connecting pads for power supply and signal acquisition ($p_i, i = 1, ..., 6$, in dark grey); (**b**) The difference of electrical resistance (ΔR) between the two sensing layers is proportional to the flexion angle (θ), defined as the angle between the planes tangent to the sensor extremities.

As demonstrated in [31], the relationship $\theta(\Delta R)$ can be approximated using the following linear function:

$$\theta = \frac{\Delta R - \Delta R_o}{s}, \tag{1}$$

where s and ΔR_o are the angular sensitivity and offset, respectively, which can be determined in the calibration phase by measuring the sensor output in two known angular positions (0°: flat hand, palm down, 90°: closed hand (fist)). Note, that due to the differential measurement ($\Delta R = R_1 - R_2$), the sensor is agnostic to pressure and stretching, but only measures bending.

As shown in Figure 2, the goniometer can be regarded as the series of six strain-variable electrical resistances (three resistances for each layer). The resistances R_1 and R_2 represent the active layers of the goniometer and their difference $\Delta R = R_1 - R_2$ depends on the flexion angle (θ) through Equation (1). We acquire R_1 and R_2 by means of a 4-wires measuring method (to reduce the influence of the contact resistances at the pads). We supply a constant current I between the pads p_1 and p_6 and we amplify the voltage across consecutive signal pads ($V_1 = V_{p_2} - V_{p_3} = R_1\, I$ and $V_2 = V_{p_4} - V_{p_5} = R_2\, I$) through the instrumentation amplifiers INS_1 and INS_2. We chose instrumentation amplifiers to avoid current loss through $p_2 - p_5$ thanks to the high input impedance. We set both amplifications to the same quantity (A), thus obtaining: $V_{o1} = A\, R_1\, I$ and $V_{o2} = A\, R_2\, I$. Finally, the differential amplifier (*DIFF*) amplifies the difference between V_{o1} and V_{o2} to obtain the final output (V_{out}) that is proportional to ΔR. Note that the proportionality constant depends on well known values: I, A and the gain of *DIFF*. *DIFF* can be also used to perform hardware compensation of the sensor offset.

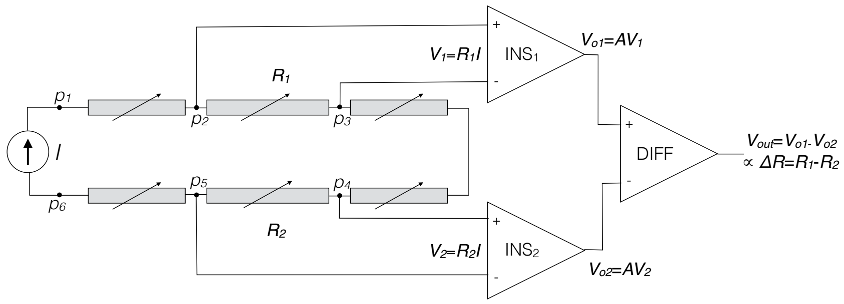
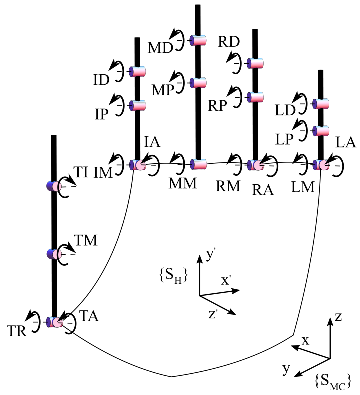


Figure 2. Electrical model of the KPF goniometer and schematic of the front-end of the acquisition electronics. The light grey boxes are strain-variable electrical resistances. A 4-wires resistance measuring method is employed: (i) a constant current (I) is supplied (pads p_1 and p_6); (ii) the voltages across the two sensing layers are measured ($p_1 - p_2$ and $p_4 - p_5$) through the two instrumentation amplifiers (INS_1 and INS_2), and (iii) the difference between the measured voltages—proportional to ΔR—is performed through the differential amplifier ($DIFF$).

In an earlier sensing glove prototype [33], we integrated three KPF goniometers to measure the flexion-extension of thumb (trapezius-metacarpal joint), index (metacarpal-phalangeal joint) and medium (metacarpal-phalangeal joint) fingers. The KPF goniometers exhibit errors below 5 degrees during natural hand opening/closing movements. Despite these promising results, that can be considered a consistent step forward in human motion detection through e-textiles, KPF goniometers cannot be easily employed in multi-DOF measurements due to the high number of connecting wires per DOF (6 pads per goniometer, see Figure 1a).

2.1.2. Glove Design

As a compromise between wearability/comfort and reconstruction performance, we have designed and engineered the kinaesthetic sensing glove, which uses only five KPF sensors optimally placed over the hand to measure five joints according to the optimal design guidelines described in [36]. We chose a five sensor design as a good trade-off between the retrieved kinematic information and the wearability of the prototype. The hand pose reconstruction can then be performed exploiting synergistic information to estimate the full hand kinematics according to a 19 DOF model. The 19 DOF kinematic model (reported in Figure 3) is partially derived from the study described in [40], augmenting the original 15 DOF model with the distal joints of the fingers. Their joint values are computed from proximal joints (P) using the relationship $\theta_D = \frac{2}{3} \cdot \theta_P$ [41].



DoFs	Description
TA	Thumb Abduction
TR	Thumb Rotation
TM	Thumb Metacarpal
TI	Thumb Interphalangeal
IA	Index Abduction
IM	Index Metacarpal
IP	Index Proximal
ID	Index Distal
MM	Middle Metacarpal
MP	Middle Proximal
MD	Middle Distal
RA	Ring Abduction
RM	Ring Metacarpal
RP	Ring Proximal
RD	Ring Distal
LA	Little Abduction
LM	Little Metacarpal
LP	Little Proximal
LD	Little Distal

Figure 3. The 19 degrees of freedom (DOF) kinematic model of the human hand.

The main idea of the synergy-based approach is to exploit joint angle correlations observed in human hand poses during everyday tasks. Performing a principal component analysis (PCA) on those hand poses, it is possible to explain a huge fraction of hand motions using only a few eigen vectors (synergies), which effectively reduces the number of independently controlled degrees of freedom in the human hand. This prior knowledge on how humans most frequently use their hands can be exploited as a prior to reconstruct the most likely hand pose from only a few noisy measurements provided by any HPR device [35,42,43]. In this manner, undersensing, i.e., the usage of a number of sensors ($m = 5$) smaller than the number of DOFs ($n = 19$), becomes feasible, thus ensuring full hand reconstruction from a reduced amount of sensing elements. This aspect is particularly important to increase the wearability of the prototype.

At the same time, hand synergies can be also used to determine the sensor selection that maximizes the knowledge on the actual posture given a limited number of sensors [36,44]. For further details, the interested reader should refer to the mentioned references. However, for the sake of completeness, we will summarize the main equations in the following section.

2.1.3. Synergy-Based Hand Pose Reconstruction

Let us consider an n-DoF hand model to be reconstructed from m sensors. Assuming a linear relationship between joint variables $x \in \mathbb{R}^n$ and measurements $y \in \mathbb{R}^m$ we obtain the model:

$$y = Hx + \eta \tag{2}$$

where $H \in \mathbb{R}^{m \times n}$ is a full-row-rank matrix and $\eta \in \mathbb{R}^m$ denotes Gaussian measurement noise, with zero mean and covariance R. From a kinematic point of view, hand synergies can be defined in terms of inter-joint covariation patterns, which were observed both in free hand motion [40] and object manipulation [45]. Collecting a large number N of hand postures in a matrix $X \in \mathbb{R}^{n \times N}$, the synergy information can be summarized in the covariance matrix

$$C_o = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})(x_i - \bar{x})^T \quad \in \mathbb{R}^{n \times n}, \tag{3}$$

where x_i and $\bar{x} \in \mathbb{R}^n$ are individual hand posture vectors and the mean hand posture vector respectively. According to [42], the hand pose reconstruction can be obtained through the minimum variance estimation (MVE) technique as:

$$\hat{x}(y) = \bar{x} - C_o H^T (H C_o H^T + R)^{-1} (H\bar{x} - y) \tag{4}$$

where the matrix $C_{map} = C_o - C_o H^T (H C_o H^T + R)^{-1} H C_o$ is the "a-posteriori" covariance matrix, that can be used as a measure of how much information an observable variable y_i carries about a joint variable x_j. In [36,44], we explored the role of the measurement matrix H on the estimation procedure and obtained as a result the optimal placement of sensors. Theoretical results were used to devise design guidelines for the kinematic sensing glove, as discussed in the next subsection.

2.1.4. Sensor Layout

Starting from the hypothesis that each goniometer measures a single hand DOF, the optimal design problem is reduced to the choice of the m DOFs (or joints) that ensure the best reconstruction performance. Assuming negligible measurement noise, the theoretical solution described in [36] with five measures (which represent a good trade-off between effectiveness and wearability) proposes to place the sensors at the following joints: TA, MM, RP, LA and LM. Then we engineered the kinaesthetic glove by sewing KPF goniometers on a Lycra glove, positioning them over the chosen joints, as shown in Figure 4. The KPF goniometers were specifically built for the specific application and, in particular, their length was specifically tailored to take into account the subject's anthropometric variability (avoiding cross-talk).

Joint	Sensor Lenght (mm)
TA	82
MM	72
RP	62
LM	60
LA	74

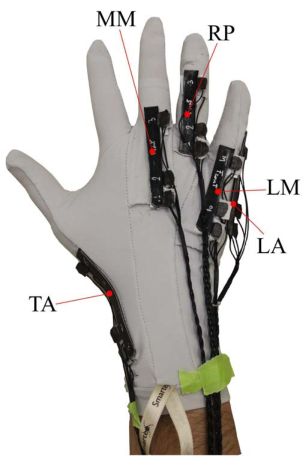


Figure 4. The kinaesthetic glove. According to the optimal design criteria, the five KPF goniometers are placed on TA, MM, RP, LA and LM joints of the hand.

For the acquisition phase, we designed and developed a dedicated acquisition unit. The analog front-end has five channels, one for each goniometer, which replicate the circuit reported in Figure 2. We filtered each channel with a low-pass (anti-aliasing) filter with 10 Hz cut-off frequency. An "Arduino Micro" board was then employed to digitally convert (10 Sa/s) and stream the data to a PC for further processing.

2.2. Tactile Sensing

The tactile sensing glove attempts to acquire contact forces during interaction with objects like everyday grasping and manipulation. Key design objectives during the development of the sensorized glove were: (i) high sensitivity to allow for detection of small first-touch contact forces around 0.1 N;

(ii) coverage of a large range of forces up to 30 N; and (iii) a high degree of wearability and robustness. Particularly, wearability is a very important aspect in order to minimize interference with human motion execution and tactile sensing thus maintaining a manipulation experience that is as natural as possible. Accordingly, we looked for a thin and stretchable fabrics solution, and –after evaluating numerous combinations of conductive fabrics– we decided for a design comprising four layers of fabrics as shown in Figure 5.

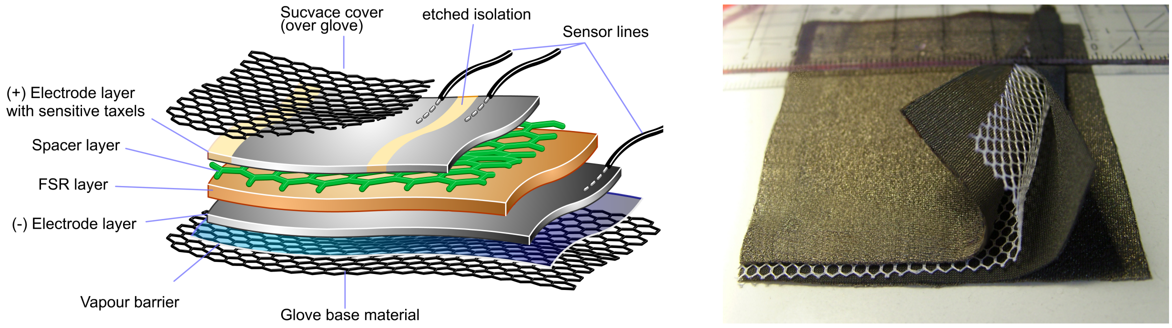


Figure 5. The flexible tactile sensing glove is manufactured from several layers of conductive and piezo-resistive fabrics.

The sensor exploits the piezo-resistive effect, i.e., mechanical pressure applied to the material induces a change of its electrical resistance that can be easily measured. The piezo-resistive material employed here is a highly stretchable knitted fabric (72% nylon, 28% spandex) manufactured by Eeonyx. The individual fibers within the fabric are coated on a nano-scale with inherently-conductive polymers. The material is available at different resistances, determined by the thickness of the applied coating. During experimental testing, we found a material with a surface resistivity of 70–80 $k\Omega/\square$ to be most suitable for our application.

By placing the piezo-resistive fabric between two highly conductive materials, we can measure the change in the resistance between the two outer layers when pressure is applied to the compound. These outer layers constitute the low impedance electrodes that transport current into and out of the sensor with minimal losses. A low impedance is achieved by plating nylon knitted fabric (78% polyamide, 22% elastomer) with pure silver particles.

Wrinkles in the fabrics can generate spurious contact observations. Thus, in order to reduce this effect, we integrated an additional meshed layer between the piezo-resistive layer and an electrode layer, which keeps them insulated as long as too small forces are applied. Obviously, the sensor's first-touch sensitivity, i.e., the smallest measurable force threshold, depends on the thickness of the meshed layer and on the size of its mesh openings: Smaller openings and thicker layers result in a higher force threshold, because more force is required to establish contact between conductive layers. We evaluated meshes with openings in the range of 0.2 to 5 mm and found that a 0.23 mm thick fabric with a honeycomb structure (Figure 5) and openings of ca. 2 mm balances best between high first-touch sensitivity and suppression of spurious contacts. In experiments we measured an initial force threshold of 0.1 N using a 3 mm^2 probe tip.

The more contacts between the conductive layers are established, the more the resistivity decreases. Hence, above the initial force threshold, the sensor can be considered as a parallel circuit of force-sensitive resistors (Figure 6). Hence, as already pointed out in [46], two major factors contribute to the force sensitivity of a piezo-resistive sensor: (i) the increase of contact area between conductive layers and (ii) the piezo-resistive effect in the middle layer.

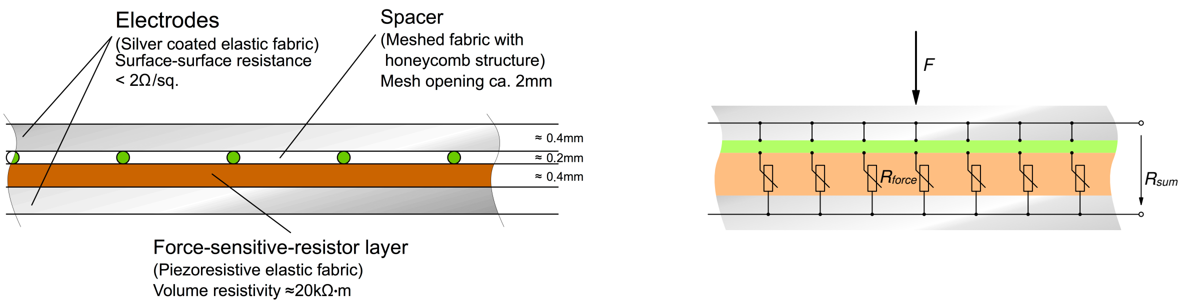


Figure 6. Schematic representation of the fabric-based tactile sensor: Two highly conductive electrode layers (silver) enclose a piezo-resistive layer (orange), measuring changes in its resistivity. The mesh layer, pictured in green, guarantees high resistance (GΩ range) during no-contact idle state. When contacts are established between the electrode and piezo-resistive layer, the sensor acts as parallel circuit of force sensitive resistors.

The high resistance of the sensor in its idle state has the additional benefit of minimizing the current flow through the sensor and thus minimizing the energy loss. This ensures a longer runtime for battery-powered portable systems and also significantly reduces the heat produced by the sensor.

2.2.1. Tactile Sensor Characteristics

To determine the sensor characteristics and to evaluate various fabric materials, we used a measurement bench with a calibrated, strain gauge sensor mounted on a vertical linear axis to measure ground truth forces. A motion performed along the linear axis is transformed into force changes via a coil-spring.

We evaluated the sensor characteristics by first increasing the force from 0 to 10 N and subsequently decreasing back again to 0 N, always measuring the resulting voltage between the electrodes. Between individual measurements, the linear axis was displaced by an amount of 0.1 mm, decreasing or increasing the applied force in a non-linear fashion. Before each measurement we waited for 300 ms for the mechanics to settle, thus reducing transient effects. Each measurement sweep was repeated 5 times to evaluate the repeatability of measurements. The resulting characteristic curves for various sensor materials are shown in Figure 7.

All curves exhibit an hysteresis effect, i.e., measuring smaller voltages (or higher force) during unloading compared to the loading phase for the same applied forces (up to 14% of the measurement range). This hysteresis effect is common to all piezo-resistive materials due to an increasing intertwinement of the material and memorized compression due to the applied load. However, as can be observed from the graphs, the sensor's repeatability is very high, having a standard deviation of less than 0.4% of the measurement range.

We have chosen a fabrics that nicely covers the whole measurement range of 0–5 V within the typical force range of 0–30 N observed in typical human manual interaction [39]. The nonlinear, saturating sensor characteristics is beneficial for measuring forces across several orders of magnitude: While the sensor provides high force resolution for small forces (< 10 N), it can also measure forces up to 60 N. This is in accordance to the human sense of touch, which exhibits a power-law dependency of resolution as well [47].

2.2.2. Taxel Layout and Glove Design

Employing the fabrics-based tactile sensor, we produced a multi-taxel tactile-sensing glove to be worn by humans allowing us to record force interaction patterns during manipulation. To this end, different taxel areas need to be isolated from each other. We employed two different methods to do so: First, individual fabric patches are sewed onto a very thin and breathable support glove. As the seams will disturb the tactile experience of the human operator, we tried to minimize the number of seams. Hence, as a second method to create isolated taxels, we used etching: Employing a $FeCl_3$ acid, the conductive silver coating of the electrode layer is removed along thin paths between individual taxels, thus electrically isolating them from each other. The resulting glove with its individual taxels is shown in Figure 8.

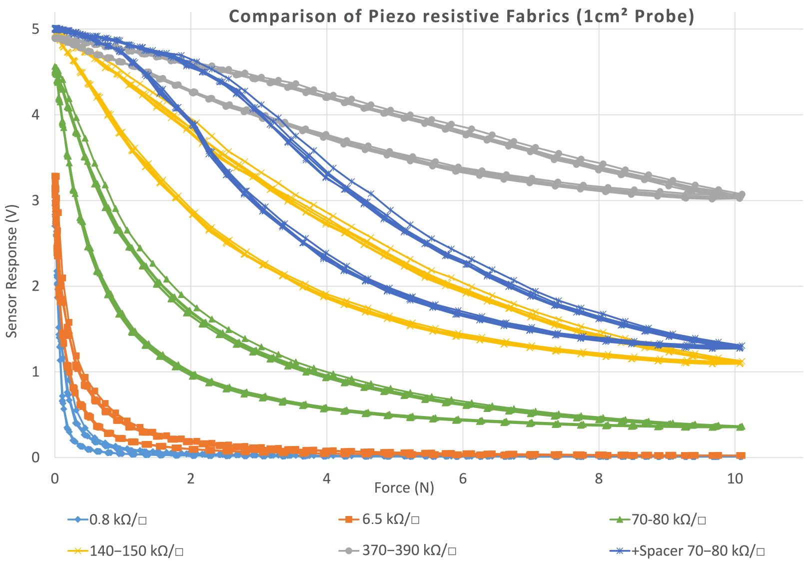


Figure 7. Tactile sensor characteristics was measured using a 1 cm^2 flat probe tip. Curves of like colors represent a measurement sweep of increasing and decreasing force in the range of 0–10 N for a specific material. All curves exhibit hysteresis that is common to piezo-resistive sensors. We have chosen the material that best covers the whole measurement range of 0–5 V, namely the fabrics with a surface resistance of 70–80 kΩ/□ without the spacer layer (Ω/□ indicates the unit of surface resistivity).

Figure 8. Tactile-sensing glove composed from various sensing patches sewed onto a very thin and breathable base glove. Individual sensing patches are further subdivided into taxels by etching away the conductive silver coating. The corresponding insulating gaps are clearly visible as dark lines in contrast to the bright taxels regions.

In order to reduce sensor degradation due to sweat and other moisture (which corrodes the silver coating), the sensing layers are augmented with an additional vapor barrier underneath the lower electrode layer as shown in Figure 5. The individual taxels are connected to the acquisition electronics, which is located in a wrist band, using Teflon coated wires interwoven into the electrode layers. Using a voltage divider circuit and an ADC for each single taxel, a PIC18 micro-controller on the acquisition board collects the sensor data of all taxels and transmits them via USB to the host PC.

The taxel distribution across the palmar side of the glove was chosen to mimick the density distribution of mechano-receptors in the human hand [48]; however, on a much coarser scale. Each finger tip comprises four individual taxels, measuring contact forces at the tip, the central fingertip area, and on the sides. Similarly, the other finger segments are covered by 2–3 taxels. Their sensor area ranges from 34 to 130 mm^2 corresponding to a spatial resolution of 7.2 to 9.6 mm.

For the palm we have chosen much larger taxel areas (195 to 488 mm^2) corresponding to a spatial resolution of 12.4 to 29.7 mm. All sensor patches are designed to minimize wrinkling within individual taxels as this would induce spurious measurement peaks. Consequently, each finger segment is covered by an individual fabrics patch, which is further subdivided by etching into individual taxels. The sensor patches within the palm were separated along typical folds of the human skin. The final tactile-sensing glove comprises 54 individual taxels as shown in Figure 5.

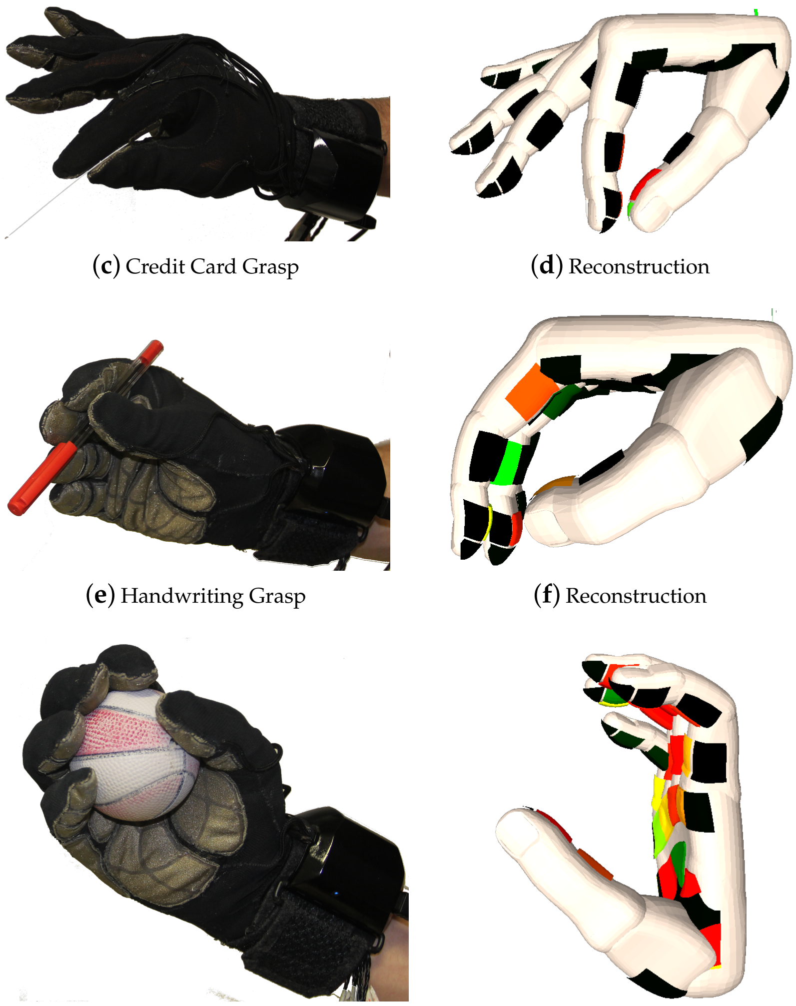
2.3. Experiment Approach

For the experiments, we placed the two types of glove one over the other. A dedicated software was developed based on ROS to enable modular and synchronous data acquisition as well as visualization. More specifically, the data acquisition and processing modules of the two sensing gloves published their time-stamped measurements (joint angle and normal force values) to specific ROS topics, which were integrated by rviz for visualization. For pose visualization we developed a rigid-link 3D model of a human hand, which is available as URDF. Tactile contact forces are rendered on top of this hand model using mesh markers matching the shape of individual taxels and mapping force magnitudes with a color-map from black over green to red, i.e., from zero over medium to maximum force. To specify the tactile sensor configuration, i.e., location and shape of taxels, we augmented URDF with appropriate information. The corresponding software is available on on our repository [49].

For the preliminary experiments, we asked a right handed male participant (28) to grasp the following objects, which are representative of human grasp workspace as we did in [43,50]: hammer, credit card, pen and ball. What is observable is the high kinematic coherence with human biomechanics: at the same time, contact force can be visualized thus providing information on which parts of human hand are the most involved for grasp. Note that the effectiveness of the integration of synergistic information for hand posture reconstruction via Conductive Elastomer (CE) and KPF sensors was already validated in terms of estimation error and pose classification in [35] and in [50], respectively. For further details, the interested reader can refer to these references. In Figure 9 we report the original grasps performed by the subject wearing the integrated glove as well as their reconstructions in a side-by-side manner. As already mentioned, the reconstructions are defined in $\mathbb{R}^{19}$, completing the measurements of the five KPF sensors with synergistic information. For the sake of visualization, in Figure 9 the grasped object is also shown.

(**a**) Hammer Grasp (**b**) Reconstruction

Figure 9. *Cont.*



(**c**) Credit Card Grasp (**d**) Reconstruction

(**e**) Handwriting Grasp (**f**) Reconstruction

(**g**) Ball Grasp (**h**) Reconstruction

Figure 9. Side-by-side comparison of real and reconstructed grasps.

3. Discussion and Conclusions

In this paper, we have reported on the (software) integration between a tactile glove and an HPR under-sensed system based on KPF technology. The latter uses synergistic information, i.e., hand joint covariation patterns observed in grasping tasks, to complete the estimation of the hand pose from only five measures to a set of 19 joint angles. Outcomes of such an integrated sensing can be displayed using a visualization tool, which enables to show both postural and tactile information of the user's hand. Results are very promising and show a high level of consistency with human hand bio-mechanics, under a qualitative point of view. This encourages us to push further our wearable approach that could have numerous applications in different fields, such as neuroscience. For example, the system could be used to investigate how the central nervous system copes the redundancy problem by examining how humans control grasping of hand-held objects in unconstrained grasping tasks, enabling the analysis of anticipatory control in both the position and force/tactile domains [51,52]. Another potential application field could be in rehabilitation for the assessment of hand recovery in post-stroke patients. Indeed, the integrated measurement of both hand posture and force/tactile information on the patient's hand, both jointly recorded in an unobtrusive and ecological fashion, is important for the evaluation of the effectiveness of therapeutic outcomes. Our integrated glove could be also employed to map user's hand kinematics and tactile data onto a slave robotic hand controlled in tele-operation tasks. Finally other potential application fields could be in virtual reality and entertainment. Future works will be devoted to develop our integration also under a hardware point of view, in order to get a more and more unobtrusive sensing system. At the same time, a more thorough quantitative evaluation of our techniques will be performed. Finally, we will also consider the usage of other wearable sensing systems, which could provide additional information on the interaction between the human hand and the external environment (e.g., [53], as well as the integration of the here proposed approach with feedback mechanisms, see e.g., [54,55] to be used in tele-operation applications for the remote control of robotic hands).

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Abbreviations

The following abbreviations are used in this manuscript:

DOF	degree of freedom
HPR	hand pose reconstruction
KPF	knitted piezoresistive fabric
PCA	principal component analysis

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