Exploiting hand kinematic synergies and wearable under-sensing for hand functional grasp recognition

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***Abstract*—Wearable sensing represents an effective manner to correctly recognize hand functional grasps. The need of wearability is strictly related to the minimization of the number of sensors, in order to avoid cumbersome and hence obtrusive systems. In this paper we present a wearable glove, which is able to provide accurate measurements from three joint angles. These measurements are then completed to reconstruct the whole hand posture, by exploiting *a priori* synergistic information on how human commonly shape their hands in grasping tasks. Results, although preliminary, show the effectiveness of the here described devices and methods and encourage to further investigate this kind of approach.**

***Index Terms*—wearable sensing, hand kinematic synergies, grasp recogniction.**

I. INTRODUCTION

Reliable, unobtrusive and mobile tracking of full body kinematics represents a challenge in supporting physical rehabilitation both in clinics and at patient home. Continuous daily-life monitoring of the patient functional activities in her/his physical interaction with the environment is essential for optimal guidance of rehabilitation therapy by medical professionals and coaching of the patient [1], [2]. Such performance information cannot be easily obtained in daily life conditions with current monitoring systems, because of their cumbersome and sometimes obtrusive architecture.

Previous works [3], [4] described the design, development and preliminary testing of an unobtrusive and modular sensing system for monitoring daily life activities of stroke subjects, evaluating their physical interactions with the environment and training motor function of upper and lower extremities. The system was unobtrusively integrated in clothing (shirt, trousers, shoes and gloves) and included fabric-based and distributed inertial sensing, providing tele-monitoring and adaptive on-body feedback capabilities.

Focusing on hand function and its recovery, the results of the questionnaires and interviews held with professionals and patients [4] indicated the quantification of the frequency and type of grasp of the affected and unaffected arms as the main requirement for a sensing system. In order to fulfill such a requirement, it is hence important to have a minimally obtrusive device: for this reason, wearability and under-sensing can represent the driving principles for system design.

This paper presents an approach to perform hand grasping recognition and classification for healthy subjects through a "smart" glove [5], [6] characterized by a reduced number of sensors (i.e. three) with respect to the total number of hand degrees of freedom (DoFs) (i.e. fifteen, according to the kinematic model we considered [7]). The basic idea is to complete such partial information by exploiting the concept of *kinematic hand synergies* in grasping tasks, i.e. "covariation patterns among digit joints during reach-to-grasp and manipulation tasks" due to both peripheral and central constraints in hand motor control [8]. In other terms, kinematic synergies can be interpreted in terms of statistical *a priori* information on probabilistic distribution of human poses in common tasks.

In [9], [10] authors proposed to collect and organize this information in a database of grasping postures [7] and inter-joint correlation patterns and to fuse it with insufficient and inaccurate measurements provided by a low-cost sensing glove. The objective was to maximize the reconstruction accuracy and get the optimal pose estimation in a Bayesian sense.

In this work, we have applied the aforementioned optimal estimation techniques to the measurements provided by the sensing glove described in [5], [6] for hand functional grasp recognition and based on knitted piezoresistive fabrics (KPF) textile goniometer technology.

Despite the promising results, the KPF goniometer technology still exhibits some drawbacks mainly related to the high number of electrical connections per degree of freedom, which can limit the usage of such technological solution for multi-DOF recording. Additional constraints to the number of used sensors can be due to bandwidth and power consumption requirements, when the glove is used as a module of a multi-sensor wearable platform as in [4].

All these factors push the glove design towards under-sensing: under these condition, it is clear how crucial can be the exploitation of optimal estimation techniques to still guarantee a satisfying posture reconstruction despite the limited number of measurements.

The results we report in this paper, although preliminary and still qualitative, validate our sensing approach for grasp recognition in healthy subjects. Future investigations will be devoted to extend synergy-driven sensing methods and smart glove design for hand functionality assessment in rehabilitative

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applications with stroke patients.

II. MATERIALS AND METHODS

In this section we describe the experimental apparatus and reconstruction techniques used for hand pose reconstruction. One healthy right-handed male participant (age 36) gave his informed consent to participate to the experiment. The participant had no physical limitation that would have affected the experimental outcomes. The participant was instructed to perform grasp poses among the ones described in [11].

More specifically, the goal of the experiment is to correctly recognize the pose among the eight grasp postures referring to common interaction tasks with the external environment [11]: pulp pinch, precision pinch, span grasp, hook grip, power grasp, chuck grip, key pinch and flat hand.

A. Related studies

In this work we report preliminary results on the usage of synergy-based optimal pose estimation techniques applied to the measures provided by the aforementioned “smart” glove. Compared to [10], in this paper we use a completely re-designed sensing glove with only three textile-based goniometers [12] placed on the dorsal side of the hand in correspondence with the metacarpal-phalangeal joints of the index and medium fingers and the trapezius-metacarpal joint of the thumb. The sensors were developed by coupling two piezoresistive layers through an electrically insulating middle layer, as described in [12] and shown in fig. 1.

On the contrary, the glove we used in [10] consisted of twenty “distributed” [13] single layer piezoresisitve sensors running along the five fingers from base to tip. In that case, the glove was able to provide twenty signals related to sensor deformation, affected by non-linearities and hysteresis, but, for grasping recognition purposes, we processed those measurements to achieve an estimation of the five metacarpal joint angles, although partial and non-ideal. Then synergistic information was used to enhance reconstruction performance and complete postural information of the hand.

B. Sensing Glove Structure

The sensing glove employed in this study, produced by Smartex srl and previously described in [6] is one of the main components of a modular prototype conceived for whole body monitoring of stroke patients [4]. The material chosen for the glove is Lycra, a material that satisfies the requirements of adherence to the hand and lightness of the garment. This choice made the sensing glove unobtrusive and comfortable for the subject who wear it. This glove is endowed with three KPF goniometers, developed and characterized in [12], placed on thumb (trapezius-metacarpal joint), forefinger (metacarpal-phalangeal joint) and middle finger (metacarpal-phalangelal joint). Textile based goniometers were developed by coupling two piezoresistive layers through an electrically insulating middle layer, as described in [12] and shown in fig. 1. The sensing layers were made of knitted piezoresistive fabrics, previously employed as single layer strain sensors for measuring local fabric deformations due to joint movements [14], [15] or respiration activity [16]. In [6] authors evaluated KPF textile goniometer technology applied to the sensing glove in comparison with a gold standard instrument (Smart DX 100 produced by BTS Bioengineering [17]). The angular errors were in the order of few degrees [6].

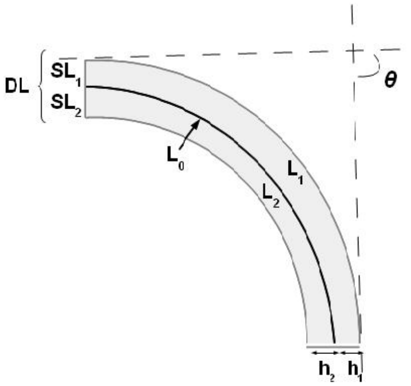


Fig. 1: Representation of goniometer under bending. Two KPF piezoresistive layers SL_1 and SL_2 are attached to the insulating layer L_0. The flexion angle θ is proportional to the resistance difference between the two layers ΔR.

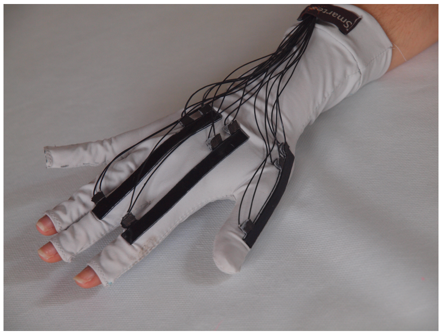


Fig. 2: The sensing glove endowed with three KPF goniometers placed on thumb, index and medium fingers.

As it can be noticed from fig. 2, the long fingers of the glove are uncovered on the fingertip to preserve patient tactile sense.

If the two KPF layers are geometrically and electrically equivalents [12] and considering the electronic front-end described in [6], the voltage output ΔV of the KPF goniometer is proportional to the resistance difference between the two layers ΔR, which is proportional to the sensor flexion angle θ:

$$\Delta V = k\,\Delta R_{DL} = k_1\,\theta. \tag{1}$$

where k_1 depends on the KPF layer dimension, resistivity the electronic front-end parameters (i.e. amplifier gain, supply current and voltage). In practical cases, equation (1) is not verified, due to the unavoidable difference between the two piezoresistive layers. A calibration procedure was hence conceived, based on the following linear approximation of the $\Delta V - \theta$ relation

$$\Delta V \approx S_\theta\,\theta + \Delta V_o \tag{2}$$

where S_θ and ΔV_o represent the device sensitivity and offset, respectively. Considering equation (2), which was verified in [6], the goniometer can be calibrated by measuring its output for two different angular positions. Typically the sensor is calibrated at 0 degrees (i.e. flat open hand, to obtain the offset ΔV_o) and at a second angular position θ_C (i.e. to obtain the sensitivity $S_\theta = \frac{\Delta V_{\theta_C} - \Delta V_o}{\theta_C}$), in our case at 90 degrees. Notice that the angular value of the joint is assumed to be positive while the hand is moving from the open flat position (i.e. 0 degrees) towards the fully closed position.

The sensitivities $[S_\theta^1\ S_\theta^2\ S_\theta^3]$ and offsets $[\Delta V_o^1\ \Delta V_o^2\ \Delta V_o^3]$ (where the index $i = 1..3$ indicates the sensor on the thumb, index and middle, respectively) were hence computed for each of the three sensors. After the calibration, the glove measurement output y and the measured joint angles θs can be expressed as

$$y = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix} = \begin{bmatrix} \frac{\Delta V^1 - \Delta V_o^1}{S_\theta^1} \\ \frac{\Delta V^2 - \Delta V_o^2}{S_\theta^2} \\ \frac{\Delta V^3 - \Delta V_o^3}{S_\theta^3} \end{bmatrix}. \tag{3}$$

C. Hand Pose Reconstruction

For the sake of clarity, let us summarize the definitions and results of [10] used in the following. Let us assume a n degrees of freedom kinematic hand model (fifteen in our case) and let $y \in \mathbb{R}^m$ be the measures provided by a sensing glove (in our case, m is equal to three). The relationship between joint variables $x \in \mathbb{R}^n$ and measurements y is

$$y = Hx + \nu\,, \tag{4}$$

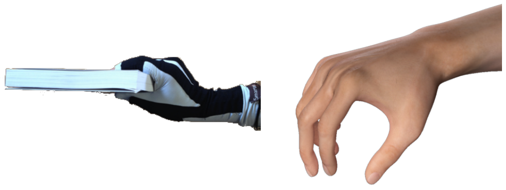
where $H \in \mathbb{R}^{m \times n}$ $(m < n)$ is a full row rank matrix, and $\nu \in \mathbb{R}^m$ is a vector of measurement noise having zero mean and Gaussian distribution with covariance matrix R. In our experiment, the noise covariance was estimated through a 60 s long acquisition performed while the hand was in a known fixed pose corresponding to $\theta_1 = \theta_2 = \theta_3 = 0$ degrees.

Here, the goal is to determine the hand posture, i.e. the joint angles x, from a set of measures y whose number is lower than the number of DoFs describing the kinematic hand model in use.

To improve the hand pose reconstruction, we used postural synergy information embedded in the *a priori* grasp set, which is obtained by collecting, a large number N of grasp postures x_i, consisting of n DoFs, into a matrix $X \in \mathbb{R}^{n \times N}$. The grasp postures were collected by using a highly accurate optical tracking system (Phase Space, San Leandro, CA - USA) and were executed by a right-handed healthy male subject (age 26), different from the one who performed the experiments reported in this work. This information can be summarized in a covariance matrix $P_o \in \mathbb{R}^{n \times n}$, which is a symmetric matrix computed as $P_o = \frac{(X - \bar{x})(X - \bar{x})^T}{N-1}$, where $\bar{x}$ is a matrix $n \times N$ whose columns contain the mean values for each joint angle arranged in vector $\mu_o \in \mathbb{R}^n$.

(a) Credit Card Grasp (pulp pinch)

(b) Reconstruction



(c) Book Grasp (span grasp)

(d) Reconstruction

(e) Hammer Grasp (power grasp)

(f) Reconstruction

Fig. 3: Comparison between real and reconstructed postures from the dataset described in [11].

Based on the Minimum Variance Estimation (MVE) technique, in [10] we obtained the hand pose reconstruction as

$$\hat{x} = (P_o^{-1} + H^T R^{-1} H)^{-1} (H^T R^{-1} y + P_o^{-1} \mu_o)\,, \tag{5}$$

where matrix $P_p = (P_o^{-1} + H^T R^{-1} H)^{-1}$ is the *a posteriori* covariance matrix. (5) can be rewritten as

$$\hat{x} = \mu_o - P_o H^T (H P_o H^T + R)^{-1} (H \mu_o - y)\,, \tag{6}$$

and the *a posteriori* covariance matrix becomes $P_p = P_o - P_o H^T (H P_o H^T + R)^{-1} H P_o$. In our case, matrix R is a 3 x 3 matrix, whose values (in degrees) are

$$R = \begin{bmatrix} 0.2509 & -0.0585 & -0.0404 \\ -0.0585 & 0.0679 & 0.0238 \\ -0.0404 & 0.0238 & 0.0636 \end{bmatrix}$$

D. Preliminary Results

The techniques described in the previous Subsection were applied to the three measurements provided by the glove, The reconstructed poses were then visualized using a 3d rendering software and, finally, qualitatively compared with the reference ones [11]. For the sake of space, we report the reconstruction of only a reduced number of these poses in fig. 3. Preliminary qualitative results show a good agreement between the original poses and the rendered ones. Future works will aim at quantitatively validate the here proposed approach.

III. CONCLUSIONS

This work presents an integrated approach where a wearable hand-pose reconstruction glove was exploited to provide three joint measurements in grasping postures. These three measurements were then completed through synergistic information by applying the optimal estimation techniques described in [10].

Future works will aim to quantitatively evaluate more in depth the reconstruction performance and to design a classifier to properly determine the hand functional grasps performed by a large number of participants. Optimal design techniques for the realization of the glove inspired by synergy information will be also eventually considered [18], [13] to improve sensing performance.

Applications to rehabilitative scenarios with stroke patients will be evaluated, in order to take into account the differences in inter-joint synergistic covariation patterns observable in healthy and stroke subjects. In this manner, reconstructed poses might be profitably used to design and assess the effectiveness of hand rehabilitative therapies.

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