Data-Driven Human Grasp Movement Analysis

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***Abstract*— The description of human hand motions is very complex, and methods to reduce this complexity have attracted much attention in the motor control literature. Important implications in robot hand design and programming have also generated a wide interest in the robotics research community. Early studies prevalently used direct analysis methods such as visual inspection to define grasp taxonomies. More recently, analytical methods have been employed to perform grasping data dimensionality reduction. In this paper, we present a methodology to reconcile these two distinct and apparently incompatible approaches under a unified framework: this allows us to obtain a data-generated grasp taxonomy along with low-dimensional representations which could be used for human grasping data classification and posture reconstruction, as well as for simplifying grasp planning algorithms and robotic hands programming.**

Keywords: Human Grasp Movement; Grasp Taxonomy; Posture Reconstruction; Multiple Eigenspaces

I. Introduction

In the past 60 years, attempts made towards the generation of a grasp taxonomy (such as [1] in the 50s and [2] in the 80s) have mostly relied on direct visual inspection. Still recently (see e.g. [3] and [4]), the most successful approaches to classify human grasping postures and movements apply the same method.

On an apparently separate side, a large number of models and techniques for dimensionality reduction have lately been applied to postural and grasping data. Santello et al. [5] asked subjects to grasp a large number of imagined objects and used Principal Component Analysis (PCA, [6]) to extract the so called *postural synergies*; the more recent work from Vinjamuri and co-workers [7], [8] extended the concept to *temporal* and *kinematic* postural synergies; Thakur et al. [9] analyzed hand posture data obtained from a motion capture system during an unconstrained haptic exploration task still applying the same technique, which to date remains the most largely used; this type of reduction was then exploited in many areas, from robotic hands programming (see e.g. [10]), sensing (see e.g. [11] and [12]), and building of simpler, underactuated hands (e.g. [13] and [14]).

Fig. 1: An example of a 1-dimensional linear space in hand posture space obtained using the kinematic model from [20] and the technique from [21] adapted for postural data analysis. Subject ED, spherical grasp movement.

Other types of dimensionality reductions have been used too: e.g., Bernardin et al. [15] approached the problem of fusing data glove and tactile sensor information applying an Hidden Markov Model (HMM, [16]) recognizer to distinguish among different grasp types; the same technique was used by Ekvall et al. [17] to recognize grasp types based on entire grasping timeseries; on different data types, Jenkins et al. [18] extended the concept of ISOmaps to spatio-temporal ISOmaps in order to approach more general human data analysis; Peternel and Leonardis [19] showed that even movements as complex as human locomotion can be modeled by a small number of Degrees of Freedom (DoFs), i.e. 15 Gaussian Mixture Model (GMM) in 4-D space.

All these automatic techniques have been applied to show that there is an underlying structure in the way humans perform any action, in particular grasping, which seems to be an apparently irreconcilable topic with respect to the generation of a grasp taxonomy.

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Some attempts at automating the procedure of data segmentation have been made in the last decade (e.g., [22], [23]), and even very recently (see [24]): still they start by performing dimensionality reduction on the full dataset, and then look for a valid segmentation in the reduced dimensional space which is, indeed, affected by the population employed. Specifically, [24] uses functional PCA (fPCA, [25]) to analyze grasping motions which are first projected over 3 PCs, and then each PC is decomposed along 2 fPCs to obtain movement 6-D representations: the grasping movements, generated on instruction from a subset of Cutkosky's grasp taxonomy, are then clustered using K-means (see [26]) into a new grasp taxonomy.

This work aims to find a systematic, data-driven way to explain grasp taxonomy from generic grasping data, which could then be used for automatic movement classification, hand-posture database indexing (see e.g. the DB at [27]), and as a way of reducing grasp planning algorithms and robotic hands programming complexity, moving towards the unification of human grasp movement analysis and robotic grasp synthesis procedures.

Although global dimensionality reduction techniques are well-suited for building simpler, underactuated robotic hands and to more easily program fully actuated hands, different approaches can be exploited which can benefit from the locally low-dimensional structure of the data to be used (see e.g. the work by Ciocarlie et al [10] on dexterous robotic grasping with a variety of hands, or [28] for a recent application of Programming by Demonstration, PbD [29]). A low number of DoFs is desirable for these methods, and a technique which automatically groups together similar movements could relieve the programmer from most of the pre-processing of a suitable dataset for the task at hand.

As a means to our goal, we borrow form computer vision the technique of Multiple Eigenspaces (originally from [21], see Section III), and adapt it to our data. The reason behind this choice is that Multiple Eigenspaces are a generalization of PCA, which can be viewed as a single eigenspace which tries to explain the whole dataset. Using more than one eigenspace the dataset is automatically clustered and, differently from other clustering techniques like K-means, each cluster can have a different dimension. Moreover, the used approach gives lower dimensional subspaces w.r.t. PCA, which means that they can be used for interpolation (the whole space is meaningful, which is not true when a single high order space is considered): we thus try not to neglect the low dimensional local structure of the data, which is instead usually ignored.

The paper is organized as follows: in Section II we report the data collection procedure for obtaining a test bed dataset, along with a brief explanation of the fully parameterized hand model we use to reconstruct the postures from those data; in Section III the technique of Multiple Eigenspaces is briefly recalled, with some advantages highlighted over global dimensionality reduction techniques, and a specialization of the algorithms for our type of data is illustrated; in Section IV we show qualitatively and quantitatively how our approach fits in between a taxonomy-generation problem and a human grasp movement dimensionality reduction problem for analysis and synthesis of grasping behaviors. Finally, conclusions and ongoing research are presented in Section V.

II. Hand Model Description and Postural Data Gathering

To test the algorithm which we will fully describe in the following Section, the grasping movement data are obtained from timed sequences of postural data constructed with the procedure described in [20]. In particular:

- a volunteer (*subject*) has his/her hand prepared with active markers (LEDs) placed on the skin;
- a motion capture system (Phase Space, San Leandro, CA - USA) is used to record the 3-D movement of the markers; the recording frequency is 480 Hz;
- upon timed intervals (every 12 sec), a random image from a set of possible objects is shown to the subject for 3 seconds (see Table I for a partial list of the objects used, or [5] for a full list of the 57 objects);
- as a correspondence to the experiment performed in [5], after each image disappears the subject is asked to perform the grasp as if the object just shown was in front of them.

1. Bucket	11. Hammer
2. Calculator	12. Ice cube
3. Chalk	13. Jar lid
4. Cherry	14. Light bulb
5. Computer mouse	15. Pen
6. Dinner plate	16. Rope
7. Espresso cup	17. Telephone handset
8. Fishing rod	18. Tennis racket
9. Frisbee	19. Toothpick
10. Hair dryer	20. Wrench
$21 \div 57 \cdots$	

TABLE I: A partial list of objects used for data gathering.

The marker position data are then used to reconstruct joint movements of the subject via a fully parameterized 26 DoFs kinematic hand model which includes a mechanism to compensate for movements of the markers positioned close to joints due to movements of the skin relative to the bones (the so called "soft-tissue artifact"). The procedure, applied for computational time reasons to a version of the data downsampled to 15 Hz, goes as follows:

- a calibration phase estimates the geometric parameters of the specific subject hand to adapt the general model; these parameters are mainly bone lengths and position of the markers with respect to bones;
- keeping constant the calibration data, an identification with an Extended Kalman Filter is performed on the whole movement data.

From the 26 DoFs data, which includes also 2 wrist DoFs, only the remaining 24 "inner-hand" DoFs are considered. A visual example of how the model looks like when a posture is reconstructed is shown in Fig. 1, which represents the extrema of a 1-DoF movement in joint space reconstructed using the procedure highlighted in Sec. III.

To reduce the computational burden of the following analyses, only 20 frames of each interval, which contain in full the grasping movement, are considered. No other pre-processing is performed.
Data from two subjects (ED and VB, both right handed and unimpaired, between 20 and 30 years old), each performing the full experiment twice, have been used: the full dataset for each subject contains twice the full experiment consisting of 57 grasping movements, lasting 20 frames, i.e. $2 \times 57 \times 20 = 2280$ datapoints.

III. Multiple Eigenspaces Technique

In order to proceed towards our goal of finding a data-driven way to explain grasp taxonomy, we decide to use the technique of Multiple Eigenspaces [21].

The word *Eigenspace* stands for a representation of a subset of the data which consists of a mean datapoint and a certain number of linear directions, taken as the direction of maximum variance in the data: this number is called *dimension* of the eigenspace.

The problem of generating the eigenspaces is twofold, i.e. has to consider these two aspects:

- which datapoints belong together in the same eigenspace
- what should the dimension of each eigenspace be.

We will now illustrate the original technique as proposed in [21], along with its advantages over more classical approaches, and necessary modifications which have been applied to the algorithm to work with our different type of data.

A. Original Algorithm

In [21] the procedure of generating multiple eigenspaces is structured as follows:

- generate a large number of *seeds* with a certain amount of datapoints (DP's) in the dataset (Sec. III-A.1)
- apply a cyclical growing procedure
  - grow them independently of each other (Sec. III-A.2.a)
  - prune the eigenspaces using a selection procedure (Sec. III-A.2.b)

  which terminates when no eigenspace can further be grown.

1) Seeds generation: Seeds, which are the initial stage of the eigenspaces, are generated from the dataset with a proximity criterion, to have a good set of seeds, based on spatial or temporal proximity in the acquisition: once the initial scope of the seeds has been chosen (being the scope the number of DP's in the eigenspace), corresponding DP's are incorporated in an eigenspace which, at the beginning, simply represents their mean value (i.e., has dimension *zero*).
Notice that the scope has to be chosen small enough to let the seeds be free to evolve in the best possible direction as dictated by the data. Notation: in the following, the j-th eigenspace at stage t will be denoted by E_j^t, thus the seeds are denoted by E_j^0.

2) Eigenspace cyclical formation: The eigenspaces are then obtained with a cyclical procedure, which terminates when they cannot be further grown.

a) Eigenspace independent growing: Each eigenspace is independently grown inserting the DP's which are more closely related to it, sorted considering their reconstruction error δ. The δ_{ij}^t error of the i-th DP w.r.t. eigenspace j at stage t is simply the norm of the distance between the DP $\mathbf{x}_i$ and its reconstruction $\hat{\mathbf{x}}_{ij}^t$ obtained in E_j^t

$$\delta_{ij}^t = \|\mathbf{x}_i - \hat{\mathbf{x}}_{ij}^t\| \tag{1}$$

where the reconstruction $\hat{\mathbf{x}}_{ij}^t$ is the projection of $\mathbf{x}_i$ onto the eigenspace.

An allowable error level σ (see Table II), has to be chosen depending on the data at hand (i.e., what we consider to be an average level of error in a group of DP's). The δ error has thus to be below a pre-specified threshold δ_{th} to avoid inserting in the eigenspace DP's which are too far from it, still trying to expand the scope; a value of $\delta_{\text{th}} = 2.0\,\sigma$ is used.

At every iteration, the maximum number of DP's allowed to enter an eigenspace is equal to its scope. If for an eigenspace there are no DP's which respect the threshold on δ error, the growing of that eigespace is terminated.
When a certain set of DP's is considered compatible with an eigenspace (based on δ error), it is temporarily included in E_j^{t+1}, and the overall reconstruction error ρ is computed

$$\left(\rho_j^t\right)^2 = \frac{1}{\#E_j^t} \sum_{\mathbf{x}_i \in E_j^t} \left(\delta_{ij}^t\right)^2 , \tag{2}$$

where the symbol $\#$ means the number of postures in E_j^t, i.e. its scope.
This error is used to decide whether an eigenspace is expanding correctly, and when it would be useful to increase its dimension; this is achieved using two thresholds $\rho_{\text{th1}} \leq \rho_{\text{th2}}$ (chosen as in Table II) and the following procedure:

- *if* the eigenspace E_j^{t+1} is already a good representation for the postures in it, i.e. $\rho_j^{t+1} < \rho_{\text{th2}}$, accept the eigenspace and make the inclusion permanent

- *otherwise* try increasing the dimension of E_j^{t+1} by one (generating $\hat{E}_j^{t+1}$) and compute again its error $\hat{\rho}_j^{t+1}$
  - *if* the error of this new eigenspace is significantly reduced, i.e. $\hat{\rho}_j^{t+1} < \rho_{\text{th1}}$, accept this new eigenspace
  - *otherwise* discard the last set of inserted DP's, revert the eigenspace to its previous stage (assigning $\hat{E}_j^{t+1} = \hat{E}_j^t$) and stop growing it.

b) Eigenspace selection: The selection procedure is the step used to take some eigenspaces out during the cyclical growing, to make it computationally feasible. Which eigenspaces have to remain is decided based on a Minimum Description Length (MDL) principle considering the following cost function

$$F(\mathbf{h}) = \mathbf{h}^{\mathrm{T}} C \mathbf{h} = \mathbf{h}^{\mathrm{T}} \begin{bmatrix} c_{11} & \cdots & c_{1r} \\ \vdots & & \vdots \\ c_{r1} & \cdots & c_{rr} \end{bmatrix} \mathbf{h} \qquad (3)$$

where each c_{jj} is the *saving* associated with leaving the eigenspace j in, and each c_{jk} is the *saving* associated to leaving in both eigenspaces j and k; finally, h is a vector whose i-th entry is 1 if E_i is included, 0 otherwise. Notice that, for the sake of readability, all superscript t are omitted in the following equations. c_{jj} have the structure

$$c_{jj} = K_0(\#E_j) - (K_1 d_j + K_2(\#E_j) d_j + K_3(\#E_j)\rho_j), \quad (4)$$

where d_j is the dimension of E_j, while K_0, K_1, K_2, and K_3 are constant (see Table II). K_0 is related to the cost of encoding one DP in the absence of the eigenspace, and K_1 to the cost of encoding each eigendirection: these costs are considered to be equal, being all images in the original work of the same size, and will be kept equal as all postures have 24 DoFs. K_2 is the cost related to encoding the coefficients of each DP in the eigenspace, and is neglected as much smaller than the others. Finally, K_3 is related to the average cost due to the error, and is a parameter which have to be chosen appropriately. c_{jj} is thus simplified to

$$c_{jj} = K_0(\#E_j - d_j) - K_3(\#E_j)\rho_j. \qquad (5)$$

Elements c_{jk} out of the diagonal are elements which are used to consider that savings only occur only once even when the DP's are inserted in more than one eigenspace.

$$c_{jk} = (\#E_{j\cap k})(-K_0 + K_3\rho_{jk}), \qquad (6)$$

where $E_{j\cap k}$ represent the datapoint intersection of E_j and E_k, and ρ_{jk} is the maximal error of the DP's in $E_{j\cap k}$ w.r.t. E_j and E_k.
For the choice of these out-of-diagonal coefficients, the procedure work well when the overlaps of each DP are mainly pairwise (each DP is at most present in 2 eigenspaces), but does not generalize well for higher order overlaps.

The sub-optimal choice of h is performed via greedy search, as the optimal cost (3) would require the solution of a binary search problem which is computationally unfeasible as soon as the number of eigenspaces exceeds few entries.

Parameters	Description	Value
σ	level of allowed error	N.A.
δ_{th}	threshold: allow a datapoint in	2.0σ
ρ_{th2}	threshold: request a dimension upgrade	$> 1.2\,\sigma$
ρ_{th1}	threshold: accept a dimension upgrade	$< 1.0\,\sigma$
K_3/K_0	relative cost of the reconstruction error	1.1

TABLE II: Parameters and their values in the original algorithm. Notice that the value of σ was chosen based on normalized image errors and is thus not meaningful for our analyses.

B. Advantages Over Global Techniques

Global dimensionality reduction techniques can generally be very effective in representing the data, but usually do not consider the locally low-dimensional structure of the data. Clustering methods such as K-means [26], on the other hand, force all clusters to have an a priori fixed dimension.

In terms of ability to explain the data, a global technique may give poor results, even if the error in reconstructing each DP is very low. As an example to illustrate this concept, we use in Fig. 2 a Figure from [5] for an example of a space (the first 2 PCs of hand postures) which is mainly meaningful only along two lower dimensional (1-D) subspaces.

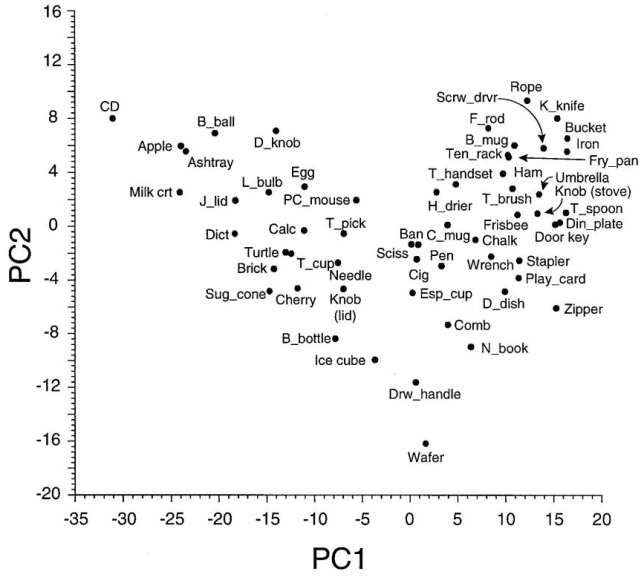

Fig. 2: Distribution of hand postures in the plane of the first two principal components. Note the distributions of the coefficients along two main axes. Reproduction from [5].

C. Modifications for Postural Data Analysis

The technique illustrated so far, although working well on images, does not give meaningful results when applied to postural data: the main reason for this is the fact that the selection procedure shown in Sec. III-A.2.b cannot handle high order overlaps, which happen rather frequently in human grasping data.

In order to overcome this issue, we include the following modifications:

- before the selection, include a *datapoint reduction* phase to avoid high order overlaps (Sec. III-C.1)
- change the coefficients c_{jk} because, from an MDL point of view, the cost of encoding the coefficients is in these data not negligible (Sec. III-C.2)
- at the end of the growing phase, increase the specificity of the eigenspaces performing an additional reduction step in order to keep each posture in no more than one eigenspace (Sec. III-C.3).

1) Datapoint reduction: After all eigenspaces have passed a stage of growing, a datapoint reduction procedure is performed to keep each posture in at most two eigenspaces. This is done keeping each posture in the two eigenspaces which best reconstruct it, i.e. selecting the two lowest δ errors amongst all possible ones across the various eigenspaces which include that posture. After reducing the datapoints in each eigenspace, if the dimension of the changed eigenspaces can be lowered still respecting error threshold, we do so.
Again, this step serves as a preparation to the selection procedure (Sec. III-A.2.b), which can handle well pairwise overlaps, but suffers when much higher order overlaps exist.

2) New savings coefficients: Because the dimensionality of the data we use, the cost K_2 of encoding coefficients is not negligible. We thus use c_{jj} as in (4) and

$$c_{jk} = (\#E_{j\cap k})(-K_0 + K_2\, d_{jk} + K_3\, \rho_{jk}), \qquad (7)$$

with $K_2/K_0 = 1/24$ as one posture has 24 elements (see Table III).

Moreover, the choice of σ is related to the covariance of the dataset X used for generating the eigenspaces.

Parameters	Description	Value
σ	level of allowed error	$0.75\sqrt{\|\mathtt{Cov}(X)\|}$
K_2/K_0	cost of a coefficient	$1/24$

TABLE III: Parameters and their values in the modified algorithm. In this case, K_2 is not negligible, and σ is chosen based on the dataset covariance.

3) Final selection and unification: When the eigenspaces reach a steady state and, thus, the growing procedure terminates, we unify the eigenspaces, allowing each posture to belong to no more than one eigenspace: this step reduces the overlaps to zero.
Moreover, as we are interested in movements rather than just static posture classification, before performing this merging, we kill all the eigenspaces which have an order of zero (i.e., the postures in those are represented only by a mean value).

IV. Results

The technique described in the previous Section has then been applied to each subject dataset obtained as explained in Section II.

A. Qualitative results: Grasp taxonomy classification of eigenspaces

Eigenspaces resulting from this procedure have been directly inspected to assess their similarity to a classical grasp taxonomy entries. Most similar grasps from the taxonomy in [2] are as follows:

ED: medium wrap (see Figure 3), tripod, light tool (see Figure 4), thumb - 4 finger, sphere (see Figure 1);
VB: tripod, lateral pinch, medium wrap, thumb - 2 finger, large diameter, thumb-index, prismatic with adducted thumb, light tool (see the attached video for a graphic representation of these movements).

Given their similarity to entries in a classical grasp taxonomy and their inherent low-dimensional nature, eigenspaces are great candidates as basic components of robotic hands programming as in [10], human grasping sequence classification from noisy data as in [11], and low-dimensional grasp planning as in [30].

About Programming by Demonstration side, and especially w.r.t. [24] in which the authors reduce the dimensionality of a 14 DoFs hand movements first to 3 Principal Components and then to 6 functional PCs, our algorithm does not need any pre-processing nor extra clustering and is able to reduce 24 DoFs hand motions in few 1-D or 2-D simple linear spaces which could then be used as training sets for the robot.
Of course, fPCA is a more powerful tool compared to PCA and, thus, its application inside a Multiple Eigenspaces framework remains of interest for future work.

B. Quantitative results: Parallel with PCA

As the multiple eigenspaces algorithm here used is somehow a generalization of PCA, a fair comparison of the results is with the application of simple PCA. A number of 5 or 7 Principal Components is used when employing PCA in order to show results which are of a comparable order w.r.t. the results of this work. An analogous comparison could be done with a different number of PCs, and would give expected results, which are thus not reported for the sake of space.

In Table IV, a comparison of explained variance across the postures included in each eigenspace are reported. The first columns indicates the subject to whom the data belong, then the second column says whether we consider a PCA or an eigenspace, and the third column shows the number of PCs (or eigenspace dimension). Fourth and fifth columns are, respectively, number of postures and explained variance, in

Fig. 3: Subject ED: medium wrap grasping; hand closing from left to right.

Fig. 4: Subject ED: light tool grasping; hand closing from left to right.

percentage over total variance, of the corresponding dataset. Finally, last column, inserted for completeness, displays how many PCs coming from a PCA on the full dataset would be needed to explain the same amount of percentage variance on all the postures: notice that this measure can be misleading, as averaging effects can take place when considering a dataset which is much broader than the ones of each eigenspace.

A fairer comparison can be made using reconstruction error (δ error) of each posture. In Figure 5, histograms of δ error using, from left to right, multiple eigenspaces, 5 PCs, and 7 PCs respectively, are shown. It is possible to see that, using multiple eigenspaces, the amount of postures reconstructed with an error up to 0.5 is similar to a PCA in which 5 PCs are considered. Using more PCs obviously leads to better results about reconstruction. Still, interpretation is a total different matter. Also notice that, in the first of these images, there are no postures with a δ error as high as in the other two, and this is because datapoints with such a high error, if any, get automatically discarded by the procedure.

Subject(s)		dim.	# postures	variance	# of corr. PCs
VB + ED	PCA	5	4560	75%	-
VB + ED	PCA	7	4560	84%	-
VB	E_1	1	191	66%	4
VB	E_2	1	293	67%	4
VB	E_3	1	243	57%	3
VB	E_4	1	369	58%	3
VB	E_5	1	166	63%	3
VB	E_6	1	373	63%	3
VB	E_7	1	307	66%	4
VB	E_8	1	129	79%	6
ED	E_1	1	287	70%	5
ED	E_2	2	1302	60%	3
ED	E_3	1	236	61%	3
ED	E_4	1	210	40%	1
ED	E_5	1	182	44%	2

TABLE IV: Comparison of percentage explained variance values using PCA or Multiple Eigenspaces. PCA is performed on the whole dataset, while eigenspaces are generated on separate subjects as they become clustered from the very beginning. Number of Principal Components (PCs) used, or dimension of the eigenspace, are shown, along with number of datapoints included and percentage of total variance in the data explained. In the last column, the corresponding number of PCs required to explain the same amount of total variance across the whole dataset is reported.

V. Conclusions and Future Work

In this work, the problem of conciliating direct, data-driven human grasp movement analysis towards classification and taxonomy generation, and analytical analysis for obtaining low-dimensional representation of grasping data has been considered.
To do this, the algorithm of Multiple Eigenspaces from [21] has been adapted and applied to a dataset of imagined grasping movements obtained following the procedure from [20]. Noteworthy, grasping movements analogous to classical grasp taxonomy entries (from, e.g., [2]) are automatically found from the data, as shown in Figures 1, 3, and 4, and in the video attachment.

The presented procedure builds in the direction of increasingly automating classification of movements, and using its

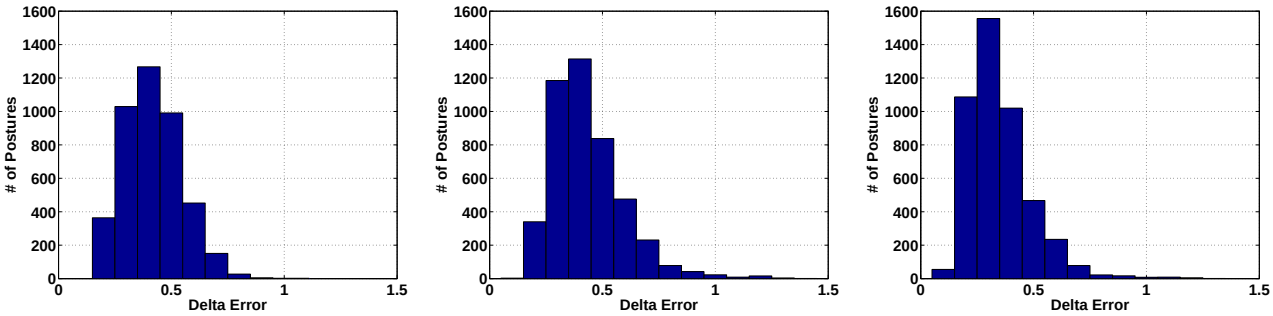

Fig. 5: Histograms of delta error across datapoints. From left to right: delta error obtained with a Multiple Eigenspace representation; delta error with 5 PCs from PCA; again PCA, taking into account 7 PCs. Notice that the total of postures in the first (left-most) figure is lower than the other two, as only postures represented by the selected eigenspaces are considered.

results for speeding-up grasp planning algorithms (given the great advantages of searching in more than one smaller spaces w.r.t. a single, higher dimensional space - see e.g. [30] for an example of grasp planning with 1-DoF motion), for Programming by Demonstration dataset generation, for human grasping movement classification, and for data-driven posture database indexing.

Ongoing research involves the implementation of the automatically generated taxonomy-like grasping movements in a grasp planner to control a fully actuated robotic hand.
Moreover, future work also includes the idea of using Multiple Eigenspaces procedure, which is based on PCA, building upon more complex (maybe nonlinear) dimensionality reduction techniques, finding a principled way to change error thresholds in order to deal with different levels in the grasp taxonomy hierarchy, and using parabolic mirrors in order to make the imagined grasp experience closer to reality by having the object to be grasped shown exactly where it should be.

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