Data-Driven Human Grasp Movement Analysis

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Abstract

Humans tend to simplify the space of possible grasps they can perform. Yet, 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 Analysis; Robotic Grasp Synthesis; Robot Hand Design; Grasp Taxonomy; Posture Reconstruction.

1 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]).

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. [19] to recognize grasp types based on entire grasping timeseries; on different data types, Jenkins et al. [20] extended the concept of ISOmaps to

Figure 1 An example of a 1-dimensional linear space in hand posture space obtained using the kinematic model from [17] and the technique from [18] adapted for postural data analysis. Subject ED, spherical grasp movement.

spatio-temporal ISOmaps in order to approach more general human data analysis; Peternel and Leonardis [21] 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.

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 [18], see Section 3), 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 2 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 3 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 4 we show 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 5.

2 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 [17]. 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 1** 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 1 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 **Figure 1**, which represents the extrema of a 1-DoF movement in joint space reconstructed using the procedure highlighted in Sec. 3.
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 preprocessing 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.

3 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 [18].
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 [18], 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.

3.1 Original Algorithm

In [18] 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. 3.1.1)
- apply a cyclical growing procedure
  - grow them independently of each other (Sec. 3.1.2.1)
  - prune the eigenspaces using a selection procedure (Sec. 3.1.2.2)

  which terminates when no eigenspace can further be grown.

3.1.1 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.

3.1.2 Eigenspace cyclical formation

The eigenspaces are then obtained with a cyclical procedure, which terminates when they cannot be further grown.

3.1.2.1 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 2**), 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 $\#E_j^t$ indicates 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 2) 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.

3.1.2.2 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

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

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

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

where d_j is the dimension of E_j, while K_0, K_1, K_2, and K_3 are constants (see Table 2). 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 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 2 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.

3.2 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] and J-linkage [30], on the other hand, force all clusters to have an a priori fixed dimension.

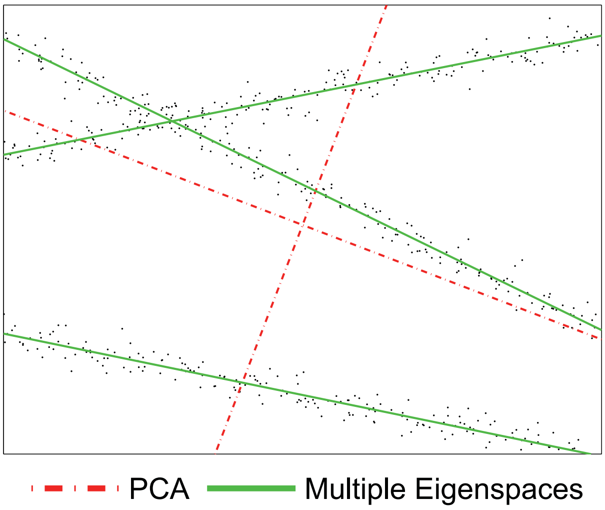

Figure 2 When data are along multiple low dimensional subspaces, a global dimensionality reduction technique may give poor results in terms of ability to explain the data, even if the error in reconstructing each datapoint is very low.

In terms of ability to explain the data, a global technique may give poor results, even if the error in reconstructing

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each DP is very low. To illustrate this concept, in **Figure 2** an ad hoc dataset is reconstructed with both PCA and Multiple Eigenspaces algorithms. The reconstruction error of the PCA using two principal components (PCs, red-dashed lines) is exactly zero, which is not true for the Multiple Eigenspaces (green solid lines), nonetheless this latter representation can be clearly seen to be more meaningful and representative of the data.
Although this is an oversimplified example, similar situations may arise in higher dimensional data analysis: see e.g. Figure 8 and 9 in [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.

3.3 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. 3.1.2.2 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. 3.3.1)
- 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. 3.3.2)
- 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. 3.3.3).

3.3.1 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. 3.1.2.2), which can handle well pairwise overlaps, but suffers when much higher order overlaps exist.

3.3.2 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

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

with $K_2/K_0 = 1/24$ as one posture has 24 elements (see **Table 3**).

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	$0.75\sqrt{\lVert \mathtt{Cov}(X) \rVert}$
K_2/K_0	cost of a coefficient	$1/24$

Table 3 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.

3.3.3 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 discard all the eigenspaces which have an order of zero (i.e., the postures in those are represented only by a mean value).

4 Results

The technique described in the previous Section has then been applied to each subject dataset obtained as explained in Section 2.

4.1 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 video [31]).

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 [32].
Moreover, an interesting application of this methodology is represented by the possibility of using such sub-spaces to have a simplified, task-driven hand design approach for building simple robot hands (such as e.g. [14]).
About Programming by Demonstration, 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

Figure 3 Medium wrap grasping; hand closing from left to right.

Figure 4 Light tool grasping; hand closing from left to right.

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.

4.2 Quantitative results: Parallel with PCA

As shown in Sec. 3.2, even if global dimensionality reduction techniques can reconstruct the data well, they do not necessarily lead to an explanatory representation of the data. We here present a parallel on reconstruction error using both Multiple Eigenspaces technique and a PCA with 5 PCs.
In **Figure 5**, histograms of δ error using, from left to right, Multiple Eigenspaces, and 5 PCs, 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, although not necessarily increasing the interpretation capability of the model.

5 Conclusions

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 [18] has been adapted and applied to a dataset of imagined grasping movements obtained following the procedure from [17]. 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 [31].
The presented procedure builds in the direction of increasingly automating classification of movements, and using its results for speeding-up grasp planning algorithms and reducing their complexity (given the great advantages of searching in more than one smaller spaces w.r.t. a single, higher dimensional space - see e.g. [32] for an example of grasp planning with 1-DoF motion), moving towards the unification of human grasp movement analysis and robotic grasp synthesis, while also guiding simple robot hands design.
Ongoing research involves the implementation of the automatically generated taxonomy-like grasping movements in a grasp planner to control a fully actuated robotic hand, as well as extending the Multiple Eigenspaces procedure, which is based on PCA, building upon more complex (maybe nonlinear) dimensionality reduction techniques.

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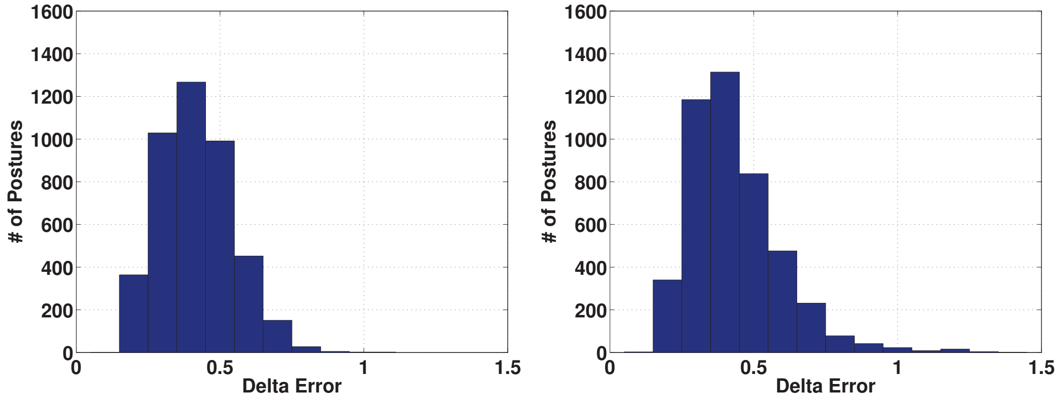

Figure 5 Histograms of delta error across datapoints. From left to right: delta error obtained with a Multiple Eigenspace representation; delta error with 5 PCs from PCA.

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