Proceedings of the 2010 IEEE
International Conference on Information and Automation
June 20 - 23, Harbin, China

Study of Coordinated Motions of the Human Hand for Robotic Applications

Shao-Chun Sun
National Lab of Mechatronic Engineering and Control
Beijing Institute of Technology
Beijing, 100081, China
sunshaochun66@gmail.com

Carlos Rosales, Raúl Suárez
Institute of Industrial and Control Engineering
Universitat Politècnica de Catalunya
Barcelona, Catalonia, Spain
{carlos.rosales-gallegos, raul.suarez}@upc.edu

***Abstract* –This paper presents an acquisition method that comprehensively looks for the mimic configurations of the human hand. The data obtained through this process is further analyzed, transformed, and then used to synthesize a reduced configuration space of a robot anthropomorphic hand. The method rely on a dimensionality reduction technique that provides a new basis of the full configuration space, from which one can select a subset of the vectors forming that basis, and finally obtaining a simpler configuration subspace. These vectors are called Principal Motion Directions, and represent the coordinated motions captured by a sensorized glove on a human hand and transferred to the robot hand. The characteristics and limitations of the subspace are discussed, as well as its application in several scenarios within robotics such as the motion planning of robot hands, where the subspace has been successfully implemented and executed.**

Index Terms – hands; motion capture; configuration space; principle component analysis (PCA)

I. Introduction

The desire to accomplish different tasks appearing in everyday activities or industrial processes with a single tool has led to the development of robot hands, pursuing the dexterity and flexibility of the human hand. An anthropomorphic robot hand is a complex mechanism with a large number of degrees of freedom (DOF). Several multi-fingered robot hands have been developed so far, such as the Utah/MIT Hand [1], the DLR Hand [2] and the MA-I Hand [3] with four fingers, and the Shadow Hand [4], the GIFU Hand [5] and the Bolonia Hand 3 [6] with five fingers. Despite the advanced features of these robot hands, the automatic determination of their movements is still difficult, mainly due to the large amount of involved degrees of freedom, which makes the search space (the hand configurations space) to be of a high dimension and therefore checking for collisions and searching for a valid joint path has an extremely high computational cost. Hence, new approaches are necessary in this line, in order to broaden their use by introducing more efficient solutions to this matter.

An interesting contribution is due to Santello et al. [7], who found correspondence between different joints in the human hand when an individual was asked to grasp an object, which suggest that a reduced configuration space could be used for practical applications. Based on this result, Ciocarlie and Allen [8] proposed heuristic low-dimensional posture subspaces for different hands using the concept of Eigengrasps and a simulated annealing based method to generate grasp configurations. Similarly, Tsoli and Jenkins [9] presented a robot hand telemanipulation scheme, where the control was performed using human hand motion capture data embedded in a reduced configuration space. Another proposal is that of Rosell et al. [10] who, based on the coordinated movements of the human hand while moving freely, introduced the concept of Principal Motion Directions to build a configuration subspace where a particular motion planning strategy was developed. These works, among others, endorse the necessity of revisiting how humans perform such complicated tasks, as clearing the right key from a key ring full of keys with a natural finger manipulation, and how these skills could be transferred to artificial hands, to complete the mimicking of one of the most difficult elements within humanoid robotics, the robot hand.

In relation to this perspective, this work continues studying the coordinated motion of the human hand and its application to a robotic hand. This paper focuses on providing a more reliable data acquisition of the human hand movements and performing a Principal Component Analysis (PCA) to build configuration subspace of the mechanical hand using these data, detailed in Section II, choosing and analysing the subspace, exposed in Section III, and applying the analysis for an anthropomorphic robot hand, described in Section IV.

II. Learning Principal Motion Directions

Several researches have proved that there are systematic coordinated motions in the human hand [7] [8] [9] [10], which mean that a dimensionality reduction could be considered when trying to mimic the human hand poses with an anthropomorphic mechanical hand. In [7], the data to analyse are a large number of configurations of the human hand while grasping familiar objects. In [10], the data are obtained by moving all fingers arbitrarily trying to cover all the configuration space of the human hand.

The aim of this work is the determination of a subspace of the mechanical hand configuration space that allow motion planning for different tasks, thus, this subspace must consider a compromise between the dimension (the smaller the better) and the amount of actual hand configurations included in it

This work was partially supported by the CICYT project DPI2007-63665.
Carlos Rosales is also with the Institut de Robòtica i Informàtica Industrial (CSIC-UPC), Barcelona, Spain.

Authorized licensed use limited to: UNIVERSITAT POLITECNICA DE CATALUNYA. Downloaded on July 26,2010 at 17:03:01 UTC from IEEE Xplore. Restrictions apply.

(the larger the better). With this aim, the way in which the human postures are sampled, how they are mapped to the mechanical hand, and how they are analyzed and processed are quite relevant steps. This section deals with the first two steps.

A. Experimental Set-up

A commercial sensorized glove CyberGlove® from Immersion Corporation with 22 sensors is used to obtain the configuration data from the human hand, as shown in Fig. 1. It has three flexion sensors per finger, four abduction sensors, a palm-arc sensor, and sensors to measure the flexion and the abduction of the wrist.

The Schunk Antropomorphic Hand (SAH) [11], with four fingers and 13 joints shown in Fig. 2 is used as the main workbench in this research. A standard PC is used to interconnect the CyberGlove® and the SAH.

B. Design of the Experiments

In this work, a more reliable way of obtaining configuration data is advanced. Based on the observation of the human hand motion and the results frorn [7] and [10], the configurations of human hand are divided into 17 groups, as shown in Table I. In each group, only a subset of hand joints is used to change the hand configuration without collision, while the rest of the joints are steady. For example, for the group 1, the user only moves the joints "thumb abduction," "thumb inner" and "thumb outer" when obtaining the configuration data of the human hand, i.e. only the thumb is moved.

Fig. 1 Human hand with the sensorized glove connected to the mechanical hand simulator used in the data acquisition procedure. This is the "0" configuration, which means all the joint angles are 0 in this configuration.

Fig. 2 Schunk Antropomorphic Hand (SAH).

TABLE I
DIFFERENT COMBINATIONS OF JOINTS IN DATA ACQUISITION

Id	Joints Used	Id	Joints Used
1	Thumb abduction + thumb inner + thumb outer	10	Index + middle
2	Thumb roll + thumb abduction + thumb inner	11	Middle + ring
3	Thumb	12	Index + ring
4	Index	13	Thumb + index + middle
5	Middle	14	Thumb + index + ring
6	Ring	15	Thumb + middle + ring
7	Thumb + index	16	Index + middle + ring
8	Thumb + middle	17	Thumb + index + middle + ring
9	Thumb + ring		

Since the obtained configuration data are used for the construction of the configuration subspace, the number of configurations in each group should be considered. The number of configurations is determined according to the number of joints in each group. It may seem trivial at first sight, since one could just fix a maximum number of data and divide it by the number of groups. However, there are three issues that suggest the use of a more methodic approach. Firstly, we would like to provide a reasonable value for the maximum number of samples, not just an arbitrary one, secondly, we would like to have a good coverage of the hand configuration space which, due to the fact that each group makes use of different joints, is not guaranteed, and finally, it would be desirable that each group have the same importance, in terms of the relative sizes of each group, within the whole data set. The reason behind this can be illustrated with an example: consider a grasp of type A and another of type B, using 2 and 13 joints, respectively. The first issue needs no further explanation; simply, one could not say a priori how many samples are needed. As for the second issue, assume that 100 samples are defined as the maximum number of samples, and then we would have 50 samples per group each. However, 50 samples do not represent the same in a 2D space than in a 13D space. If we consider a uniform covering, the number of samples are obtained by powering the coverage per joint, C, to the number of joints. In the case of the type A grasp, we will have $50 = C^2$, which yields $C = 7.07$ or in other words, an average discretization of 7 values per joint, and in the case of the type B grasp, this value goes down to 1.35, implying a worse coverage of its configuration subspace. Regarding the third issue, it is clear that if 99% of the samples are gathered performing grasps of type A, in the end, the analysis will conclude that the main coordinated motion of a human hand is that of performing grasps of type A. Our assumption when defining the grasp groups is that they are equally important, in the sense that, humans use the grasp types indifferently.

In order to overcome these issues, we propose not to define a maximum number of samples, but a reasonable number of samples per group, which fulfils the second and third issue requirements, and finally, they sum up to a reasonable total number of samples. For this, we observed that the maximum number of joints to be used among all grasp types is 13. It is necessary to find a compromise between a good coverage and a practical number in order to perform the

Authorized licensed use limited to: UNIVERSITAT POLITECNICA DE CATALUNYA. Downloaded on July 26,2010 at 17:03:01 UTC from IEEE Xplore. Restrictions apply.

experiments. A minimal good discretization of one dimension, that is, the values a joint can take, is to have the lower, middle and upper value of such joint, which add up to 3 samples per joint. Repeating the calculation above, it yields $3^{13} = 1.594.323$ configurations. This number is friendly, giving the fact that we have 17 groups, and assuming all of them use 13 joints, we will need at most a data set of 27.103.491 configurations, which is still affordable. Thus, if a grasp uses the thirteen joints, the number of samples should be near this value in order to have a good coverage of the configuration space. The proposed expression to determine the size of group i is the following:

$$d_i = Ne^{-\frac{\alpha}{n_i}} \tag{1}$$

where n_i stands for the number of joints used in the group, N stands for the number of samples required to have a good discretization, and α is a parameter to adjust the relative sizes between groups. Note that $\alpha = 0 \Rightarrow d_i = N \forall i$, hence the relative sizes are 1. And $\alpha \to \infty \Rightarrow d_i = 0 \forall i$, hence the relative sizes are 1, again, but farther from the desired number of samples. Finally, the results in this paper have been obtained using $\alpha = 0.8$ and $N = 3^{13}$.

C. Mapping data from the data glove to the mechanical hand.

Initially, the calibration procedure described in [12] is followed, which leads to the determination of the "0" configuration shown in Fig. 1. In this configuration all joint angles are zero.

Let g_i be a sample data describing the operator hand position obtained with the sensorized glove, and let $\mathbf{G} = (\boldsymbol{g_1} \cdots \boldsymbol{g_i} \cdots \boldsymbol{g_n})$ be the set of data composed of the n samples of the 17 groups of human hand configurations. The samples $\boldsymbol{g_i}$ in $\mathbf{G}$ are mapped to the mechanical hand using the approximate 1-1 mapping method presented in [10], obtaining a set $\mathbf{H} = (\boldsymbol{h_1} \cdots \boldsymbol{h_i} \cdots \boldsymbol{h_n})$ where $\boldsymbol{h_i}$ is a sample describing the mechanical hand position. The mechanical hand has 13 joints, as shown in Table II. Since the data glove measures the abduction angles between the index and the middle fingers and between of the middle and the ring finger relatively to the middle finger, the joint "middle abduction" of the mechanical hand is considered fixed at a joint value equal 0. The values of the other joints of mechanical hand have a direct relation with the corresponding joints of the glove. In particular, the joint "thumb abduction" that was not used in [10] is considered in this mapping.

TABLE II
THE JOINTS OF SAH

Id	Name	Id	Name
1	Thumb roll	8	Middle abduction
2	Thumb abduction	9	Middle inner
3	Thumb inner	10	Middle outer
4	Thumb outer	11	Ring abduction
5	Index abduction	12	Ring inner
6	Index inner	13	Ring outer
7	Index outer		

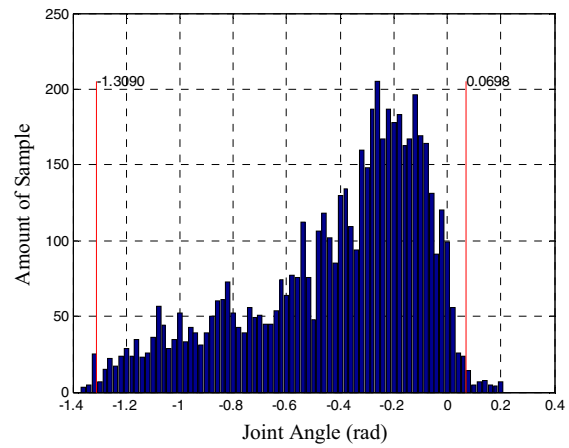


Fig. 3 Data distribution for the joint "Index Inner" of the mechanical hand. The two vertical red lines indicate the mechanical limits of the joint.

With this direct mapping most of the obtained configurations of the mechanical hand have the joint values within their mechanical limits. An example of the data distribution for the joint "Index Inner" is shown in Fig. 3. Analyzing the data distribution of all the joints the configuration with higher frequency (the most used one) was identified as $\bar{\boldsymbol{h}}$ = (-0.7, 0.17, -0.2, -0.12, -0.06, -0.2, -0.16, 0, -0.24, -0.2, 0.34, -0.4, -0.2).

D. Gaining Principle Motion Directions

Principle Component Analysis is used to obtain a new base of the mechanical hand configuration space. Let $\mathbf{Q} = (\boldsymbol{q_1} \cdots \boldsymbol{q_i} \cdots \boldsymbol{q_n})$ be there presentation of $\mathbf{H} = (\boldsymbol{h_1} \cdots \boldsymbol{h_i} \cdots \boldsymbol{h_n})$ in this new base. The transformation between these configurations is given by

$$\boldsymbol{q_i} = \mathbf{E}^{-1}\left(\boldsymbol{h_i} - \bar{\boldsymbol{h}}\right) \quad i = 1 \cdots n \tag{2}$$

where $\mathbf{E}$ is the transformation matrix and $\bar{\boldsymbol{h}}$ stands for the origin of the new space [13]. The vectors that define the new base of the hand space are called Principal Motion Directions (PMDs). Each PMD is a linear combination of the former axes of the hand configuration space. The PMDs are ordered such that the first one has the largest variance of the samples and, therefore, contains more information. The sub-space generated by the first m PMDs is called the m-PMD space.

III. ANALYSIS OF THE PMD SPACE

Fig. 4 shows the variance of the first PMDs. The first three PMDs contain 70.54% of the total variance. This percentage is lower than the 84.71% reported in [10], the difference being due to a different selection of samples (of course none of the works fully cover the whole hand configuration space). In any case, this is not critical for the proposed approach.

A. Construction of the 3-PMD space

The 3-PMD space already contains about 70% of the whole information in the data set, which is considered enough for the purpose of this work while the reduction from a space

Authorized licensed use limited to: UNIVERSITAT POLITECNICA DE CATALUNYA. Downloaded on July 26,2010 at 17:03:01 UTC from IEEE Xplore. Restrictions apply.

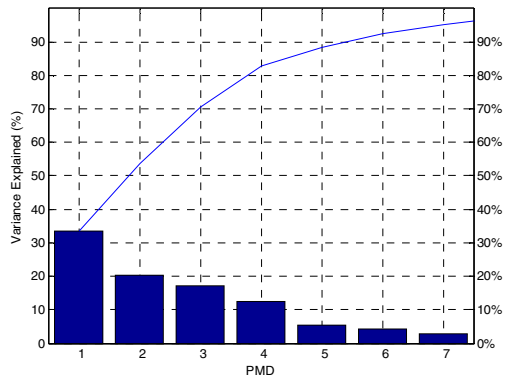


Fig. 4 The variance of each PMDs and the total variance covered when using an increasing number of PMDs.

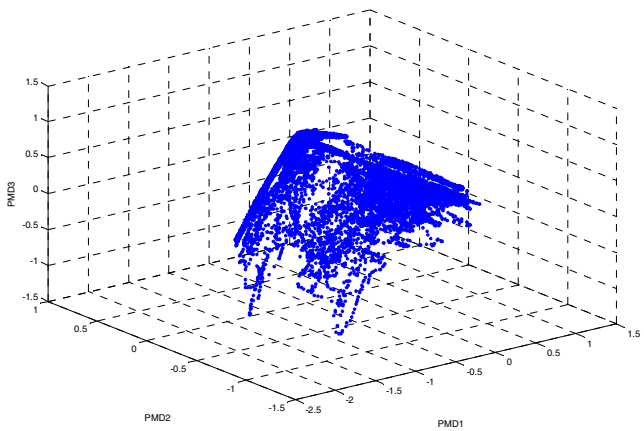


Fig. 5 3-PMD space.

of dimension 13 to one of dimension 3 is significant. Besides, 3-PMD space has the advantage that it can be visualized in a 3D plot. Based on these benefits, the 3-PMD space is chosen as the subspace for this work. 3-PMD space is shown in Fig. 5.

B. Characteristics of the 3-PMD Space

Although there has been some works using the 2-PMD space [7] [9], up to the authors knowledge there is no previous works that analyzes the main characteristics of the 3-PMD space, which is done in this work. As it can be seen in Fig. 5, there are several "lines" in the 3-PMD space, which are the binderies of the space, and the workspace of the mechanical hand looks like a hexahedron. The point of intersection of the "lines" is the (0.1142, 0.6373, 0.3200), which correspond to the "0" configuration shown in Fig.1. Each group of the data is now independently mapped to the 3-PMD space. The points representing the movements of each finger are marked in Fig. 6. The vectors of the lines are listed in Table III and the angles between them are listed in Table IV.

TABLE III
VECTORS OF THE LINES

Id	Name	Color	Vector
1	Thumb	Red	0.4797, -0.5800, -0.3216
2	Index	Green	-0.2351, -0.0270, -0.3195
3	Middle	Black	-0.6871, -0.1497, -0.8064
4	Ring	Yellow	-0.8336, -1.1917, 0.8619

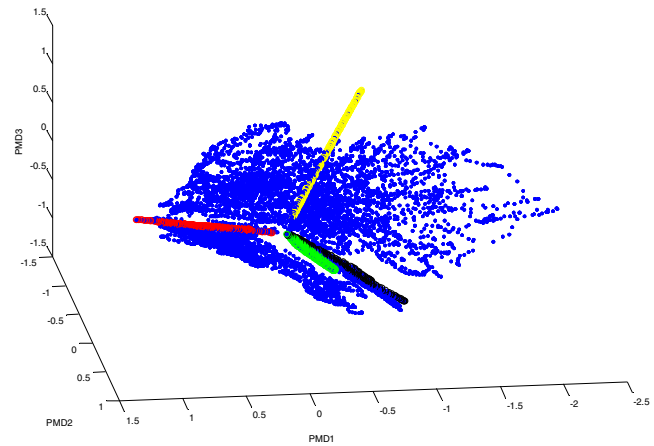


Fig. 6 The lines representing the joints of different fingers.

TABLE IV
INCLUDED ANGLES BETWEEN THE LINES

Included angle	Value (degree)
Thumb and index	89.0090
Thumb and middle	88.9163
Thumb and ring	89.4153
Index and middle	5.8069
Index and ring	85.9714
Middle and ring	88.2218

The contribution of each joint to 3-PMD space can be seen in Fig. 7. The range of variation of each joint is represented by the direction and length of a segment. The joints "thumb abduction (2)," "index abduction (5)," "middle abduction (8)" make little contribution to 3-PMD space, and therefore are not represented. The segments of the thumb joints, 1, 2, 3 and 4, are almost in the same direction, which is the same of the group of data obtained with the movement of the thumb. The same effect happens with the index joints 5, 6 and 7, the middle joints 8, 9 and 10, and the ring joints 11, 12, 13.

The configurations of typical gesture and movement are marked in the 3-PMD space, as shown in Fig. 8.

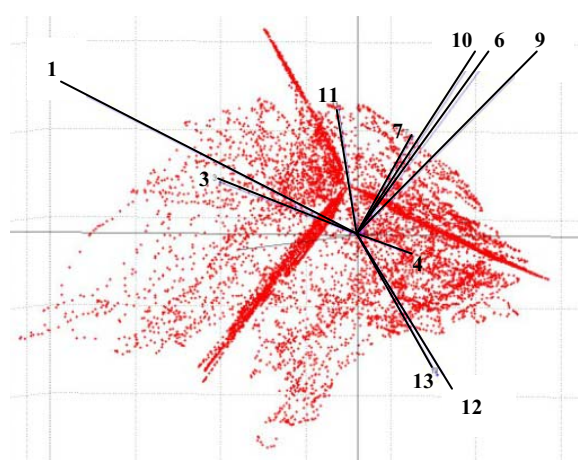
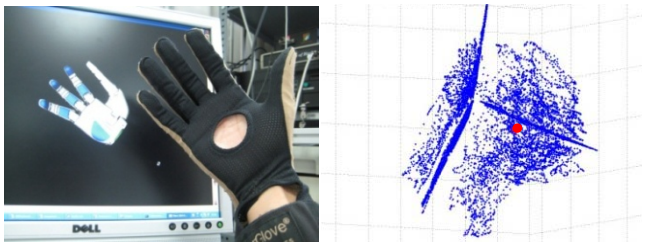
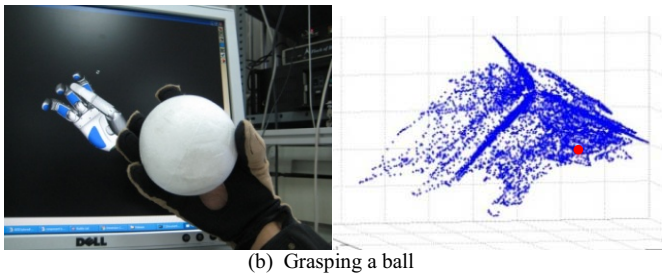


Fig. 7 The contribution of each joint to 3-PMD space.

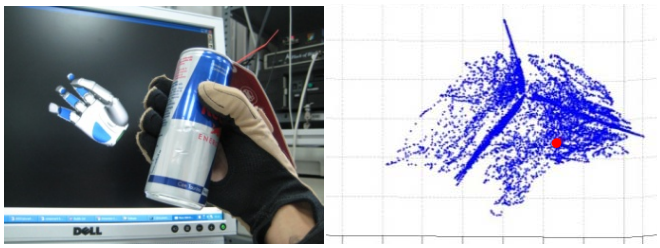
Authorized licensed use limited to: UNIVERSITAT POLITECNICA DE CATALUNYA. Downloaded on July 26,2010 at 17:03:01 UTC from IEEE Xplore. Restrictions apply.



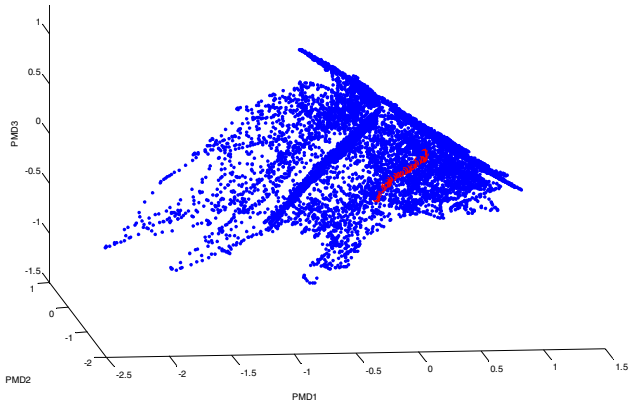
(a) Naturally open



(b) Grasping a ball



(c) Grasping a bottle



(d) Four fingers move together to grasp

Fig. 8 The configurations of typical gesture and movement in the 3-PMD space, marked by the red points.

IV. Robot Applications

This section presents some applications of the resulting 3-PMD space by defining the hand working space within it. The 3-PMD space is a linear space (Subsection III-A), where the lines representing the finger movements are binderies of the workspace of the mechanical hand, while other binderies are related with the limits of the joints and self-collisions. Note that any configuration in the hand workspace can be expressed as a linear combination of the configurations in the lines. The workspace is determined as a box, designed to contain 90% of all the configuration data, as shown in Fig. 9.

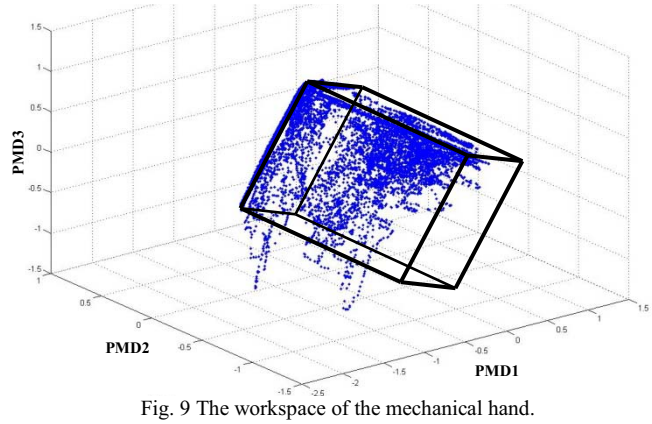


Fig. 9 The workspace of the mechanical hand.

This is done using multiples of the standard deviation of the data to fix the box side lengths.

There is no doubt that using the 3-PMD space we constrain the possible configurations that the mechanical hand can adopt, but it allows a simpler and easy-to-handle configuration space. As application examples, the reduction in the dimension of the configuration space of an anthropomorphic robot hand is applied in two main scenarios: simplify the decision making for autonomous robots and in robot telemanipulation.

A. *Autonomous Robot Scenario*

In this scenario, the goal is to automatically determine the robot movements. This is a complex problem for the case of an anthropomorphic robot hand mounted on an arm with (at least) six additional degrees of freedom. The motion planning of such system can be done using probabilistic sampling techniques to build either roadmaps or exploration trees but, even for these approaches, the dimensionality of the configuration space is too large to allow an efficient application. Thus, in practice, the 3-PMD space can be used instead of the full configuration space. Good results using such a reduced configuration space have been presented in [10] and [14], which motivated the deeper exploration of this work in order to improve the dimensionality reduction process presented there. Fig. 10 shows an example of different intermediate arm-hand configurations obtained with the planner developed at the Institute of Industrial and Control Engineering at the Technical University of Catalonia using the 3-PMD space obtained in this work.

B. *Telemanipulated Robot Scenario*

The objective is to move a robot making it to follow the operator hand movements. An anthropomorphic robot hand may be similar to the human hand, but they are still different (especially if different operators work with the same robot hand). Moreover, in our particular case, we are handling the information (position, velocity and acceleration) of 22 sensors in the user side (sensorized glove) and 13 joints in the robot side (SAH), which means a position mapping problem. These differences may be overcome if both spaces are reduced to a common 3-PMD space. An approach in this line was proposed by Tsoli and Jenkins [9]. These results motivate a further

Authorized licensed use limited to: UNIVERSITAT POLITECNICA DE CATALUNYA. Downloaded on July 26,2010 at 17:03:01 UTC from IEEE Xplore. Restrictions apply.

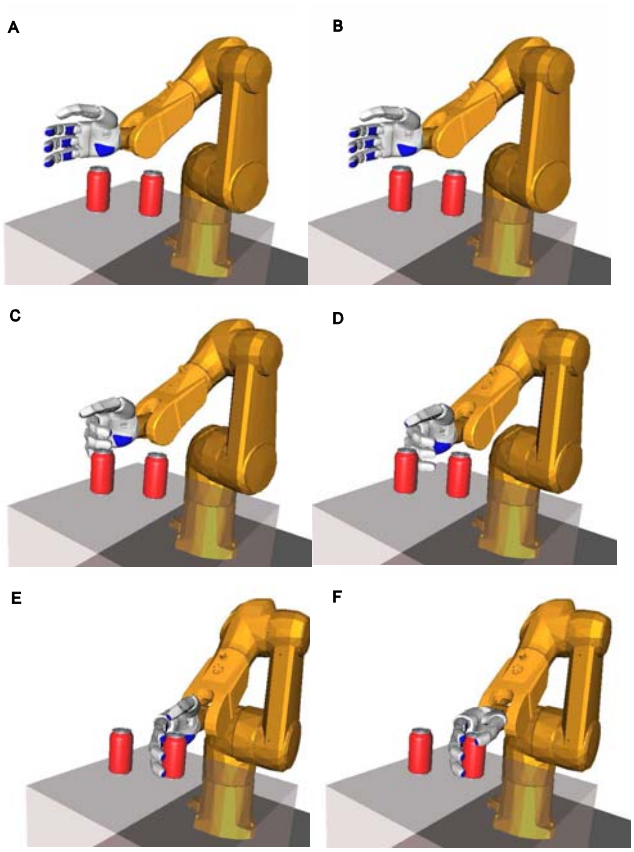


Fig. 10 Example of the planner using the 3-PMD space obtained in this work.

study in the coordinated motions in the human hand.

C. *Other scenarios*

One of the goals in the design of prosthetic hands is the low-weight feature. The heaviest parts are the batteries, followed by the motors used to move all the hand. Usually, these hands are built with 2 or 3 motors at most, often used to open/close all the fingers and move the thumb, respectively. However, this open/close movement does not follow any particular rule, but the joints are frequently coupled in a 1:1 ratio. A more interesting and natural design would be to constrain the joints to move along the principal motion directions.

V. Conclusions

This paper has presented an acquisition method of human hand configurations whose aim is to properly cover all the human hand configuration space. Then, the configuration data are used to construct the 3-PMD space, a subspace of the human hand configuration space, by using PCA. The characteristics of the 3-PMD space are discussed and experimentally tested using hand SAH. The configuration data and analysis of the subspace can be used for further applications of anthropomorphic hands with high number of DOF. Future work includes the developments of a more efficient and accurate calibration method, further and deeper analysis of the 3-PMD space in order to better exploit it, and the development of a potential new application simplifying the use of anthropomorphic robot hands in the telemanipulation scenario.

Acknowledgment

The authors would like to thank Prof. Jan Rosell for his support on the software. The authors also would like to thank Leo Palomo and Jose Fortin for their help in the experiments.

References

[1] S. C. Jacobsen, J. E. Wood, D. F. Knutti, and K. B. Biggers, "The UTAH/M.I.T. dextrous hand: Work in progress," The Int. J. of Robotics Research, vol. 3, no. 4, pp. 21–50, December 1984.

[2] J. Butterfass, M. Fischer, M. Grebenstein, S. Haidacher and G. Hirzinger, "Design and experiences with DLR hand II," in *Proc. of the World Automation Congress*, vol. 15, 2004, pp. 105–110.

[3] R. Suárez and P. Grosch, "Mechanical hand MA-I as experimental system for grasping and manipulation," in *Video Proc. of the IEEE Int. Conf. on Robotics and Automation*, Barcelona, 2005.

[4] Shadow Robot Company, "Design of a dextrous hand for advanced clawar applications," in *Proc. of the Climbing and Walking Robots and the Supporting Technologies for Mobile Machines: CLAWAR*, 2003, pp. 691–698.

[5] H. Kawasaki, T. Komatsu, and K. Uchiyama, "Dexterous anthropomorphic robot hand with distributed tactile sensor: Gifu hand II," *IEEE/ASME Trans. on Mechatronics*, vol. 7, no. 3, pp. 296–303, 2002.

[6] F. Lotti, P. Tiezzi, G. Vassura, L. Biagiotti, G. Palli, and C. Melchiorri, "Development of UB hand 3: Early results," in *Proc. of the IEEE Int. Conf. on Robotics and Automation*, 2005, pp. 4488–4493.

[7] M. Santello, M. Flanders, and J. Soechting, "Postural hand synergies for tool use," *Journal of Neuroscience,* 1998, vol 18, pp. 10105–10115.

[8] M. Ciocarlie and P. Allen, "Hand Posture Subspaces for Dexterous Robotic Grasping," *The International Journal of Robotics Research*, 2009, vol 28, pp. 851-867.

[9] A. Tsoli and O. Jenkins. "2D subspaces for user-driven robot grasping." *RSS Workshop on Robot Manipulation: Sensing and Adapting to the Real World*, Atlanta, GA. 2007

[10] J. Rosell, R. Suárez, C. Rosales, J. A. García and A. Pérez, "Motion Planning for High DOF Anthropomorphic Hands," in *Proc. of the IEEE Int. Conf. on Robotics and Automation*, 2009, pp. 4025–4030.

[11] Schunk GmbH & Co. KG, "Schunk anthropomorphic hand,"http://www.schunk.com/, 2006.

[12] Hu, X. Gao, J. Li, Jie. W and H. Liu, "Calibrating Human Hand for Teleoperating the HIT/DLR Hand," in *Proc. of the IEEE Int. Conf. on Robotics and Automation*, 2004, pp. 4571–4576.

[13] I. Jolliffe, *Principal Component Analysis, Second Edition*, Springer, 2002.

[14] R. Suárez, J. Rosell, A. Pérez, and C. Rosales. "Efficient search of obstacle-free paths for anthropomorphic hands", in Proc. Of the III/RSJ International Conference on Intelligent Robots and Systems, 2009, pp. 1773-1778.

Authorized licensed use limited to: UNIVERSITAT POLITECNICA DE CATALUNYA. Downloaded on July 26,2010 at 17:03:01 UTC from IEEE Xplore. Restrictions apply.