Identifying Objects from Hand Configurations during In-hand Exploration

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***Abstract*— In this work we use hand configuration and contact points during in-hand object exploration to identify the manipulated objects. Different contact points associated to an object shape can be represented in a latent space and lie on a lower dimensional non-linear manifold in the contact points space which is suitable for modelling and recognition. Associating and learning hand configurations to specific objects by means of Gaussian mixture models, later by identifying the hand configuration during the in-hand object exploration we can generate hypotheses of candidate objects to be identified. This process selects a set of the most probable objects from a database. The accumulated set of contact points (partial volume of the object shape) during the object in-hand exploration is matched to the set selected from the database (most probable candidate objects). Results are presented for human manipulation of objects, but this can also be applied to artificial hands, although we have not addressed the hand control, only the object identification.**

I. INTRODUCTION

The perception acquired by human hands (haptic: kinaesthetic, cutaneous, thermal) plays an important role in human life during the everyday tasks when performing prehensile and manipulation activities. In this work, cues from the hand kinaesthetic stimuli (e.g. distal fingers segments positions and movements) are used for retrieving object intrinsic information as well as to find the object identity. There are different exploratory movements for object haptic perception such as contour following to extract the global shape of the object, lateral motion to perceive the texture, pressure movement to extract the softness characteristics of an object, static contact to perceive the temperature, enclosure (e.g. grabbing a glass by side power-grasp), and unsupported holding to perceive the object weight [1] [2]. By adopting a probabilistic representation model of the object and contact points on the object surface generated during in-hand exploration, some characteristics of object shape associated to the hand configuration can be learned. The learning of hand configurations associated for specific daily objects is achieved through mixture distribution-based representation. Acquiring a compact representation that describes and associates hand configuration to candidate objects shapes improves the hypothesis belief for object identification.

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II. RELATED WORK

Typically, the planning of robotic object identification and recognition tasks start by estimating an initial model of the object, from data obtained from a vision system. Other approaches are dedicated to the estimation of the surface characteristics of the object such as texture and stickiness [3], others to find the object global shape with the human hand [4] or a robotic hand [5]. In this work we are pursuing the second group of approaches, not only for object's intrinsic information extraction, but also for identification.

In [6] an algorithm for surface frictional properties estimation is proposed to classify objects, while the surface is explored by a robotic finger equipped with a force/torque sensor. The authors in [7] presents an approach for haptic object recognition using an anthropomorphic robot hand which identify objects from palpation sequences.

Canonical grasps from human demonstrations are presented by [8] to learn grasp affordances by modelling the hand pose with mixture distributions. Human hand action representations for programming grasping actions is the goal of the approach presented by [9]. A hand posture space is represented by a low dimensional space. Gaussian Process Latent Variable Models were used to model the lower dimensional manifold of human hand motions during object grasping which is useful for grasping actions modelling, mapping and recognition. We are basing our work on these mentioned works regarding mixture distributions, in our case to learn and associate hand configurations to object identities.

In order to achieve our goals, and to propose more efficient and solid ways of object identification using dexterous manipulation through kinaesthetic stimuli, we are adopting probabilistic methods. The benefit of the proposed approach is the belief acquired to search for the object candidates from the possible hypotheses stored in the database.

III. REPRESENTING CONTACT POINTS FROM IN-HAND EXPLORATION

The geometry of an object plays an important role in robotic applications, where its representation is also valuable for identification into a class of known objects, and to search for regions on the object surface proper for a stable grasp. We are adopting the strategy of our previous work [10] to map the contact points into a workspace (occupancy grid based method) that is used to represent the object shape. Here, differently of our previous work, we are just using the probabilistic volumetric map to represent the locations (ocuppied voxels in the grid) of the contact points that are also partial volume of the object surface to assist in the object identification.

A. Probabilistic Modelling of Partial Volume of the Object

In this work, the object and contact points are represented in a 3D map, a grid comprised of a set of cells denoted as voxels, wherein each voxel is a cube with edge $\varepsilon \in \mathbb{R}$. The occupancy of each individual voxel is assumed to be independent from the other voxels' occupancy and thus O_c is a set of independent random variables: $c \in M$ representing the index of a cell on the Map; $O_c \in |0,1|$ which is a binary value describing if the cell C is empty or occupied; Z_c defining the in-hand exploration measurement that influences the cell c; $P(O_c)$ as the probability distribution of preliminary knowledge describing the occupancy of the cell c, initially, it is an uniform distribution and $P(Z_c|O_c)$ defining the probability density function corresponding to the set of measurement that influences the cell C taken from the in-hand exploration measurements. This distribution is computed from the contact points modelling.

To update the 3D probabilistic representation of the manipulated object shape upon a new measurement Z_k (contact points) means updating the probability distribution function $P([O_c=1]|Z_k^c)$ of the voxel c influenced by the measurement Z. Voxels are influenced by a measurement Z_k if the location associated to the sample computed from the sensor model $P(Z_k^c|[O_c=1])$ is contained in that voxel c. In the same manner that demonstrated in [11], for each voxel c, the set of measurements Z_n^c contains the n measurements Z_k^c influencing a voxel c. The probability density function of the object shape representation of voxel c given the Z_n^c measurements influencing that voxel c is represented by $P(Z_n^c|[O_c=1])$. Assuming that consecutive measurements Z_k are independent given the cell occupancy, and applying a Bayesian formulation, we can represent the map updating through:

$$P([O_c=1]|Z_n^c) = P([O_c=1]) \prod_{k=1}^{n} \frac{P(Z_k^c|[O_c=1])}{\sum P(O_c)P(Z_k^c|O_c)}. \quad (1)$$

The cells occupancy in the map are probabilities that is updated over time as long as the sensors measurements are active. In the end of the in-hand exploration of the object, the cells are allowed to represent only two states: full or empty, $O_c \in \{0,1\}$, so that a threshold is used for each cell to consider one of the two states:

$$O_c = \begin{Bmatrix} 0, & P(O_c|Z_n^c) < 0.7 \\ 1, & P(O_c|Z_n^c) \geq 0.7 \end{Bmatrix}. \quad (2)$$

Figure 1 shows examples achieved using the probabilistic volumetric map for partial representation of a mug when the object shape is explored partially and also when the object shape was fully explored as well as the contact points in red color demonstrating the fingers position during a specific grasp.

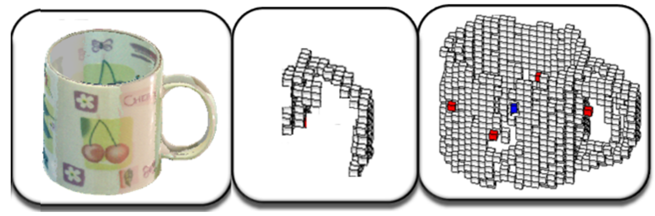

Fig. 1. Example achieved using the probabilistic volumetric map to represent the partial and full representation of an object as well as the contact points on the object surface overlaid on the map when a subject grasped the object.

B. Modelling Contact Points from Sensors Measurement

The contact points are provided during the object in-hand exploration. The sensors measurements are acquired by a magnetic sensor (Polhemus Liberty system). One sensor is attached to each fingertip to acquire the shape of an object by the contour following procedure. During the data acquisition, a workspace ($35cm^3$) is defined in the experimental area for mapping. The grid space is divided in equally sized voxels with $0.5cm^3$ of resolution. During the displacement of each finger on the object surface, it is possible to identify in which grid cell that measurement is inserted.

The model attempts to ensure that, upon receiving a measuring from the sensor attached to the fingertip, the closer the finger position is to the center of a specific cell of the map, the more probable that cell is occupied. The probability that a measurement belongs to a cell is given by a normal distribution using the known sensor position error as standard deviation ($\sigma = 0.3cm$) and the sensors positions relative to the center of each cell in the map as follows:

$$P(Z_k^c|O_c) = \exp\left(-\frac{(x-u_x)^2+(y-u_y)^2+(z-u_z)^2}{2\sigma^2}\right), \quad (3)$$

where (x,y,z) are the coordinates of the 3D point on the object surface and u is the central coordinate of the cell (for each axis).

IV. Learning Hand Configurations for Daily Objects

The key idea of this work is whilst a subject is manipulating an object by means of kinaesthetic sensory modality, the artificial system generate and update candidate objects identities for the presented contact points. For that, a learning phase is performed to associate possible taxonomies of grasp types (i.e. hand configurations formed by contact points) to object shapes. Previous information of these grasps taxonomies are demonstrated by human individuals. The next subsection presents the strategy of the demonstration.

A. Human Demonstrations

A deeply study in which several grasp taxonomies were analysed (robotics, biomechanics and medicine) has been carried out by [12] and then some grasp taxonomies were evaluated. Based on the taxonomies proposed in that work, we are considering some of the taxonomies in this study to learn and associate some hand configurations to object shapes.

Humans demonstrators (five male right handed individuals) participated to provide examples of some grasp taxonomies for some objects. The intention was to build a knowledge repository of contact points (fixed/static hand configuration) for some specific objects. Each individual has attached six Polhemus magnetic sensors to the hand, one on each fingertip to record the 6DoF (position and orientation) $\{x, y, z, yaw, pitch, roll\}$ of each sensor and another in the wrist to compute the relative position of each fingertip with respect to the wrist. The pose of the hand is defined as the fingers position relative to the palm. Each set of contact points are then represented in a 18 dimensionality space (6 sensors, each one $\in \mathbb{R}^3$).

Tactile sensors are also used here to assist the Polhemus sensors in a simple way, using only the positional data that are acquired when the tactile sensors are active (touching the object). We can easily do that since our data acquisition process is distributed and with synchronized time stamps for the data. The tactile sensing device consists of 360 sensing elements (Tekscan Grip System sensor) which are distributed along the hand palm and fingers surface. The sensing elements are grouped in 15 regions as presented in Figure 2, corresponding to different areas of the hand. Each of these regions can be defined as activation level states, $R \in \{NotActive, LowActive, HighActive\}$.

Some daily objects with simple shapes were used for the hand configurations demonstrations, such as mug, bottle, Rubik cube, tennis ball and a ladle. We have asked for each subject to perform the in-hand exploration of the object using seven hand configurations for each object.

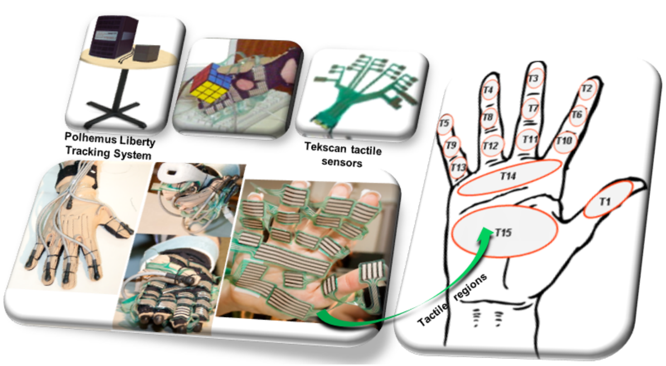

Fig. 2. Sensors used in our experimental setup: Polhemus Liberty Magnetic Tracking System and Tekscan Tactile sensor.

B. Mixtures of Contact Points Models

The contact points space is built from the human demonstrations of contact points $P(Z_n^c|[O_c = 1])$ for daily objects. Features in the latent space is extracted to find signatures of possible hand configurations associated to object shapes. Multiples clusters is computed given the observations using Gaussian Mixture Models (GMM) distributions. Each cluster represent possible hand configurations for a specific object. Each specific distribution of contact points for a specific object is represented by a density function. Furthermore, the use of multiple density functions stores any covariance that may exist between hand configurations and objects. In this work is employed, therefore, the mixture distribution-based representation by means of GMM. Here, the density function of the mixture g is defined as follows:

$$g(\mathbf{x}|\Psi) = \sum_{j=1}^{K} w_j c_j(\mathbf{x}, \mu_j, \Sigma_j|\theta_j), \tag{4}$$

$$\Psi = (w_1 ... w_K, \theta_1 ... \theta_K), \tag{5}$$

and

$$w_j > 0 \text{ and } \sum_{j=1}^{K} w_j = 1, \tag{6}$$

where $\mathbf{x} \in \mathbb{R}^3$ containing the contact points model, K denotes the number of Gaussian densities and c_j is one of the possible density functions describing the contact points of the hand configurations for each object. Each element of the mixture is weighted by w_j. In this work, Ψ represents the K dimensional vector containing all parameters of the Gaussian mixture and $\theta_j = (\mu_j, \Sigma_j)$ represents a vector containing all the contact points coordinates of the means μ_j and all the entries of the covariance matrix Σ_j. The conditions presented in (6) guarantee that g is indeed a density function.

The estimation of the parameters of each individual density function and the weight variables is accomplished by means of the well known Expectation Maximization (EM) algorithm. In this work we define the number of maximum components K (clusters) and by adopting Bayesian Information Criterion (BIC) we can select the proper number of clustering given the input data. The choice of maximum amount of Gaussian density functions is defined to be a fixed number $K = 4$ representing possible categories of hand configurations used for specific objects based on studies of grasp taxonomies as [12] and available also on the website of the GRASP project [13].

Figure 3 shows examples of the clustering process which is associated the demonstrated hand configurations to the objects for later being generated a signature for each object resultant from the hand configurations. Each cluster enclose demonstrations of one or more hand configuration (similar taxonomy) during the in-hand exploration.

C. Signatures Extraction from Contact Point Space

Measure of similarity between the contact points is achieved by using mixture density functions. Since we have a probabilistic model through GMM in the latent space, we can extract contact points signatures by a generalisation process achieved by GMR. Then, a specific trajectory (signature) is generated based on the demonstrated hand configurations for a specific object achieved by using the different clusters generated by GMM.

The GMR over a stochastic retrieval process provides suitable way of reconstruct sequence from a Gaussian model.

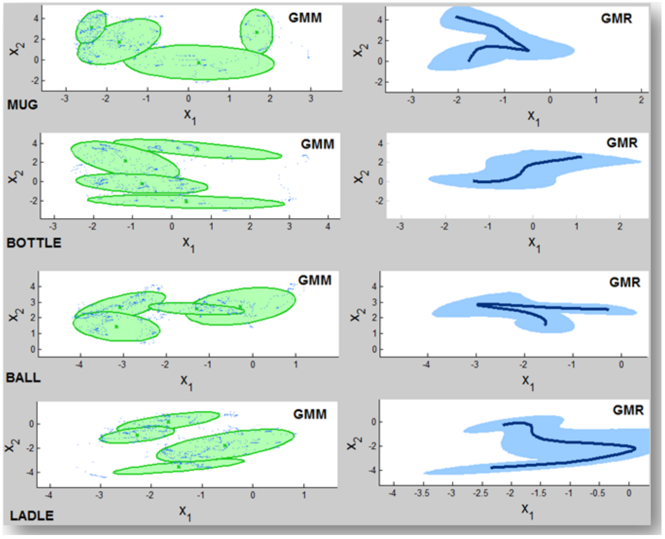

Fig. 3. GMM and GMR process. Each cluster encloses demonstrations of hand configurations. A signature of the transitions between the hand configurations on the object surface is generated using the features in the latent space when is applied GMR. The inputs are data from in-hand exploration (magnetic tracker): fingertips positions relative to the wrist frame of reference. The raw data are in inches units.

Works in different fields such as robotics and machine learning have used the statistical models (mixture distribution-based and local weighted regression) for learning, representation and generalisation of data [14], [15].

The regressor relies on modelling the predictor joint density of the vector $\mathbf{x}$ respect to the target y, so that $u = [y;\mathbf{x}]$. The mean vector μ and the covariance matrix Σ of the j^{th} Gaussian density function is respectively given by:

$$\mu_j = (\mu_j^y, \mu_j^x), \tag{7}$$

and

$$\Sigma_j = \begin{pmatrix} \Sigma_j^{yy} & \Sigma_j^{yx} \\ \Sigma_j^{xy} & \Sigma_j^{xx} \end{pmatrix}. \tag{8}$$

The Minimum Mean Square Error (MMSE) regression function $\hat{g}$ is the conditional expectation of the target variable given the GMM parameters and the predictor variables as demonstrated in [16] and [17]:

$$\hat{g} = E[y|\mathbf{x}] = \sum_{j=1}^{K} w_j(\mathbf{x})[\mu_j^y + \Sigma_j^{yx}(\Sigma_j^{xx})^{-1}(\mathbf{x} - \mu_j^x)]. \tag{9}$$

The weighted sum of linear models is represented by the function $\hat{g}$ with mixing coefficients $w_j(\mathbf{x})$ representing the probability that the j^{th} Gaussian density function produced the regression vector $\mathbf{x}$. The weights $w_j(\mathbf{x})$ are achieved through:

$$w_j(\mathbf{x}) = \frac{\frac{\alpha_j}{|\Sigma_j^{xx}|^{\frac{1}{2}}} e\left(-\frac{1}{2}(\mathbf{x} - \mu_j^x)^T(\Sigma_j^{xx})^{-1})(\mathbf{x} - \mu_j^x)\right)}{\sum_i^M \frac{\alpha_i}{|\Sigma_i^{xx}|^{\frac{1}{2}}} e\left(-\frac{1}{2}(\mathbf{x} - \mu_i^x)^T(\Sigma_i^{xx})^{-1})(\mathbf{x} - \mu_i^x)\right)}. \tag{10}$$

The main idea here is to extract from the latent space a generalised representation of hand configurations (formed by contact points) for each object for later the closest similarity between the input and the the generalised hand configuration signature can be found.

D. Similarity Measure for Contact Points

The similarity measure is verified by comparing how likely is the new observation (set of contact points forming a hand configuration) to the mixture distribution-based representation achieved by GMM and GMR. This way, we can identify in which class the demonstrated contact points belongs to. Here, the class is defined as hand-object, that is, the possible hand configurations for an object shape. For that, we are basing on the approach presented in [9] adapting for our specific case.

The new set of points is then modelled with mixture coefficients (weighted mixture of Gaussians). We can compute the probability of the contact points of a hand-object being generated by the model ζ similar to a signature ξ. Based on the probabilistic model of GMM, then each point $\mathbf{x}$ in the space is generated by a hand-object ζ following the steps:

$$P(\mathbf{x}|\xi) = \sum_{j=1}^{K} w_j^{\xi} \mathcal{N}(\mathbf{x}|\mu_j^{\xi}\Sigma_j^{\xi}), \tag{11}$$

$$P(\zeta|\xi) = \prod_{\forall x \in \xi} P(\mathbf{x}|\xi), \tag{12}$$

then the similarity function $\hat{s}$ is computed by averaging the two entities:

$$\hat{s}(\zeta,\xi) = \frac{P(\zeta|\xi) + P(\xi|\zeta)}{2}, \tag{13}$$

so that the minimum distance between the result of $\hat{s}$ to a specific class of hand-object ξ point to a class that the new observation belongs to. It is needed to compute (13) between the new observation to all possible signatures. The minimum distance is achieved by $min f(\hat{s})$. The distance between the result of $\hat{s}$ and all possible hand-object ξ_i signature is computed as follows:

$$\min_{i \in \{1,\dots,N\}} f(\hat{s}) = |\hat{s} - P(\xi_i|\zeta)|. \tag{14}$$

Equation (11) states that the probability of contact points $\mathbf{x}$ belonging to a hand-object class is modelled as weighted mixture of Gaussians represented following (4) to (6). The mixture of probabilities of the contact points $\mathbf{x}$ forming a hand configuration ζ is generated by the model ξ as presented in (12). The probability of a new hand configuration being generated by a GMR model is computed following these equations above. By comparing those probabilities we can estimate which is the most likely hand-object class that generated that contact points to try to find the most probable object shape for that hand configuration.

V. Object Identification

The process of object identification starts with demonstration of contact points forming a hand configuration whilst the object is being explored. At each hand configuration demonstrated we can search for possible objects candidates identities. As long as the in-hand exploration of object is increasing, the list of possible objects (from the database) is updated based on candidate objects with high occurrence (those objects associated to a hand configuration). The hand configuration during in-hand exploration is compared with the learned signatures by the similarity measure. This process reduce the hypotheses of object identity avoiding to match the partial point cloud formed by contact points with all objects in the database.

The object database is composed of a set of daily objects models as mentioned before. Each object is represented by the 3D Cartesian coordinates in the frame of reference of the sensor that acquired the object model. The 3D object models were acquired by a 3D laser scanner (Konica Minolta Vivid 910) and also acquired with fully in-hand exploration of the object. The idea of having two representations of the object is to guarantee that if not fitted to the object model with a high degree of reliability (generated by the laser scanner) we have the approximated model achieved by the in-hand exploration.

In this work, the identification is an estimation process to find the most probable object. For the selection process of candidate objects, we process the raw data from in-hand exploration into the wrist frame of reference to find invariance to compute and identify the hand configurations.

The set of contact points that represent partial volume of the object surface is matched to the 3D models from the database that was pre-selected during the hypotheses generation. The matching is done using the classical algorithm Iterative Closest Point (ICP) first introduced by [18]. By minimizing the difference between two clouds of points we can achieve the best match. We are computing the Root Mean Square Error (RMSE) to estimate the best matching by choosing the minimum RMSE resultant from all matching.

VI. Experimental Results

Few sequence of contact points that form the hand configurations are presented in Figure 4. The sequence are overlaid in the full volume of the object computed in the object volumetric map. The four sequences presented are identified by using the contact points in the wrist frame of reference as explained previously. The examples presented show the potential of the probabilistic volumetric map applied for in-hand exploration of objects as well as for human demonstration of stable grasp.

We state that using five sequence of hand configurations for the objects that we are dealing within our database, we can achieve the hypotheses to identify correctly the object that is being explored. In the example given in this work (mug), after observing some in-hand exploration performed by five subjects, the most common hand configuration detected for the mug is presented in Figure 5. This figure represents the result after using the similarity measure to identify possible candidate objects associated to each hand configuration. We can select more than one object for each hand configuration. Afterwards the probability of occurrences of all objects listed during the in-hand exploration is computed as shown in Figure 5. The probability distribution for each object is independent from each other.

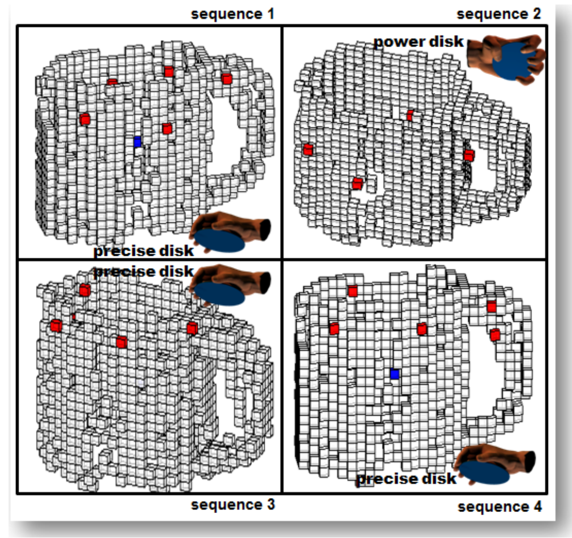

Fig. 4. Sequences of contact points overlaid on the 3D map of the object during the demonstrations of hand design while the in-hand exploration was performed by an individual. For each sequence, the hand-design (grasping taxonomy) is identified given the contact points.

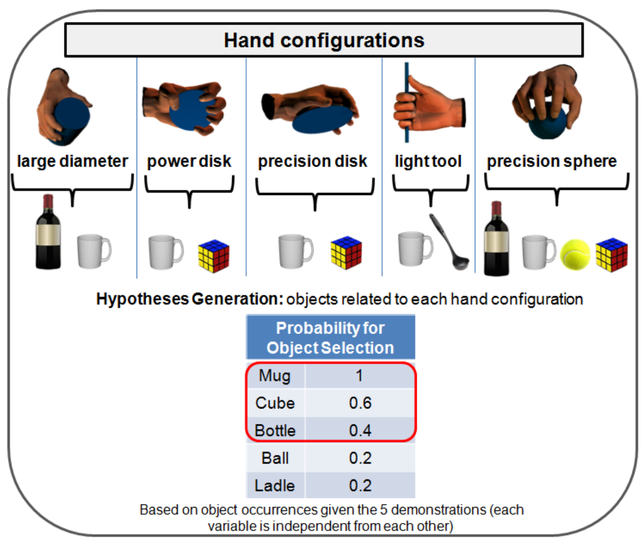

Fig. 5. Most common hand configurations identified for the mug during the in-hand exploration. The grasps presented are following the taxonomy shown in the Human Grasping Database developed inside the GRASP project [13].

Figure 6 shows the result of the matching of the new observation (partial volume of a mug) to the pre-selected objects based on hand configurations. The gray point clouds are the 3D models stored in the database. The green color is the partial volume acquired during the in-hand exploration. The objects in the top row are the selected objects from the

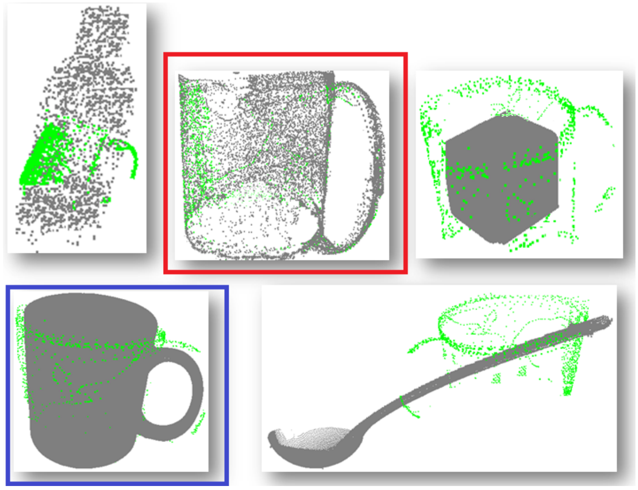

Fig. 6. Matching between object models using ICP method. The best matching between the new observation and the object stored in the database after the selection of candidates is the object in the red box (mug), RMSE = 0.0044. The best matching between the the laser scanner models was the object in the blue box (mug), RMSE = 5.5247.

similarity measure using the signatures achieved during the learning phase. The bottom row presents the most probable object model (mug) acquired from laser scanner and the less probable model (ladle) acquired from the laser scanner. In the top row we can see that selected objects models are full models from in-hand exploration as well as from laser scanner (rubik cube). The object model, mug (in-hand exploration) in the red box indicates the best match between all models. The object model (mug, laser scanner) in the blue-box is the matching between all model acquired from laser scanner. The RMSE for all objects, from left to right, top to down: bottle-mug = 0.2730; mug-mug = 0.0044; mug-cube = 14.2485; mug-mug (laser scanner) = 5.5247; mug-ladle = 22.5571.

Results show that even using different models for the same object in the database (acquired from different sensors), the identification is still successfully performed (i.e. matching between the object model acquired from in-hand exploration and the model of the same object acquired from laser scanner).

VII. Conclusion and Future Work

From human demonstrations of in-hand exploration of objects we can learn (using mixture distributions) hand configurations associated to objects shapes to derive suitable models to identify the manipulated objects. Later by a similarity measure we can compute the probability of a new observation (contact points) being associate for object shapes. This process allows a selection of candidates object identities to reduce the amount of objects for matching. The object identification is achieved by the matching between point clouds (in-hand exploration of object and the selected models from the database). The preliminary results show the methodology adopted has potential and it is possible to acquire satisfactory results using cues from kinaesthetic stimuli. In the future we intend to improve this work increasing the database of daily objects to guarantee that the results are good for object identification. Tactile data can be addressed in the future to assist in the object identification. We also intend to perform tests using a dexterous robotic hand to identify objects.

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