Hand Trajectory Segmentation and Classification Using Bayesian Techniques

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Abstract — **This work relies on a probabilistic approach to learn and classify human grasp movements by analyzing reach-to-grasp trajectories that can be used in a future work as general grasp movement for an initial stage in imitation-learning tasks. This research focuses on the development an automated system using Bayesian techniques for human grasping interpretation. The proposed learning phase allows the classification of reach-to-grasp movements in order to recognize the way that humans grasp a specific object. The 3D positions of the hand movement are acquired by markers of an electromagnetic motion tracking system [13], and afterwards by segmenting the observed data by applying the second order derivative will allow us finding changes in direction (i.e., curvatures) for characterization and learning of the movements. The classification step is based on Bayes rule using the learned probability distribution of each class of movement. These reported steps are important to understand some human behaviors before the object manipulation and can be used to endow a robot with autonomous capabilities, e.g., how to reach and grasp some object for manipulation or displacement.**

I. Introduction

Trajectories segmentation is an important issue for researches in different fields, such as neuroscience that analyzes reach-to-grasp trajectories of people with Parkinson disease or post-stroke in order to verify their performance and behaviors concerning movement stability, motor coordination and etc. It is also useful in robotics field for imitation learning or gestures recognition towards human-robot interaction. In this work, we developed an automated system for trajectories segmentation and classification of reach-to-grasp movements. By analyzing these movements we are able to understand some human behaviors during the hand journey to reach and grasp an object. This information can be used as initial step in imitation-learning tasks in order to endow a robot with human-like actions, i.e., using specific movements before the object manipulation. Beside of reach-to-grasp analysis to understand some human behavior, this work is useful for gesture recognition. We address steps such as data collection for learning stage, features extraction to use them for estimation and classification adopting a probabilistic approach.

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II. Related Work

Grasping movements have been the focus of interest of many researches, including neuroscientists, roboticists, and others. Objects can be grasped in different ways, and somehow the chosen grip depends on the properties of the object acquired by visual cues. In a series of studies reported in [1], we can realize that the information transmitted by hand posture about object shape increases gradually and monotonically as the hand approaches the object, reaching a maximum at the time the object is in the grasp of the hand. When the maximum aperture of the hand is reached, hand posture has only partially moulded to the object's contours.

Bayesian models are used in [2] for recognizing gestures from image sequences from a monocular camera. Tracking of human movements (hands and head) is performed based on skin-color features. These features are used to detect movement atoms of direction and they are learned given few gesture classes. The gesture classification relies on a probabilistic approach and it is applied for human-robot interaction. The human actions are interpreted by the robot in order to perform some specific actions (navigation). The authors have also contributed with models for Laban Movement Analysis (LMA) that helps to identify useful low-level features and to develop a classifier of expressive actions in a discrete space using more high level features.

Images sequence are used in [3] for hand tracking and hand shape representation when a person is gripping a mug. A proposed method is presented in this work for hand shape representation that characterizes the finger-only topology of the hand using cepstral coefficients. Techniques of speech signal processing are used for that. The authors address hand shape recognition classified as top-grab, side-grab, flat-hand and handle-grab when the hand is close to object.

Robot learning by imitation, also referred to as robot programming by demonstration, explores novel means of implicitly teaching a robot new motor skills [4][5][6]. This field of research takes inspiration in a large and interdisciplinary body of literature on imitation learning, drawing from studies in Psychology, Ethology and the Neurosciences [7][8][9]. To provide a robot with the ability to imitate is advantageous for at least two reasons: it provides a natural, user-friendly means of implicitly programming the robot; it constrains the search space of motor learning by showing possible and/or optimal solutions. Others techniques as motion tracking and gesture recognition are necessary for learning module. Several techniques have been proposed to detect periodical activities, most of them with sequences of images [10]-[12].

III. Scenario and Context

In this work, we have used the Polhemus Liberty tracking device [13] to track the trajectories performed by humans. Five sensors are used, one attached to each finger of a subject to acquire trajectories of reach-to-grasp, also allowing us analyzing the fingers behaviors during their journey. One sensor is placed on the object in order to have a priori knowledge of the object position to know when the trajectory is finished (e.g., it happens when a person grasps the object, when the thumb sensor is close to object sensor). The chosen object for this application was a mug. Two reach-to-grasp movements were defined for our application: top-grasping and side-grasping. The side-grasping happens when a person wants to grasp the mug by its side or by its handle to lift it and take to the mouth in order to drink. The top-grasping happens when someone wants to grip the object just to displace it or to hold the object without some specific task intention. Figure 1(A) shows how humans achieve grasping (general way); (B) shows examples of our defined grasping types.

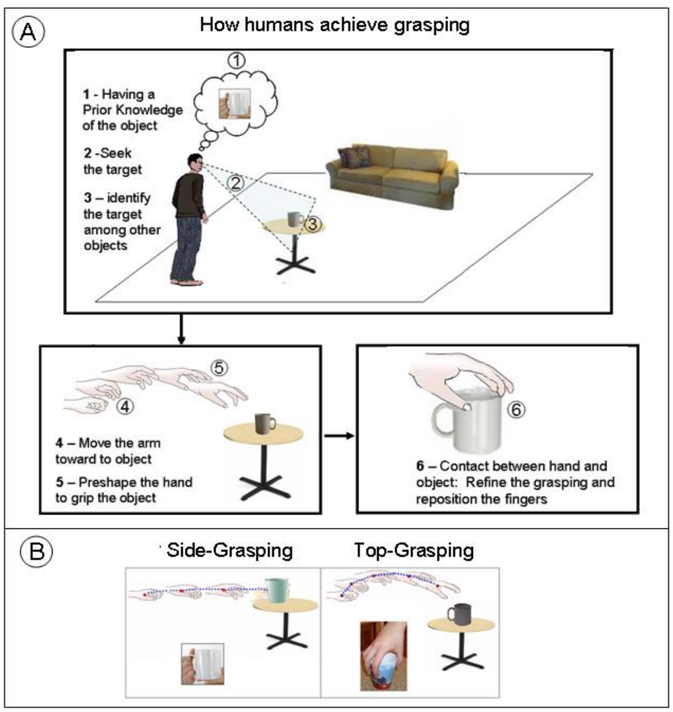


Fig.1. A – How humans achieve grasping, B - Examples of the defined grasping type for our application.

The objectives of this application are acquiring several reach-to-grasp trajectories performed by different subjects to build a dataset of these grasping movements in order to use them for a learning phase. Based on this learning phase the system can estimate and classify grasping movements during an on-the-fly performance. Using these human movements we can analyze behaviours like hand pose and its fingers positions during the movement, and with this information we are able to use it in imitation learning task as a step before manipulation.

IV. Trajectories Segmentation

A. Pre-Processing of the Trajectories

In order to accomplish the goal of features extraction for grasp movement classification, some problems needed to be solved in a pre-processing phase before the trajectory segmentation. One of these problems is depicted in Figure 2. Different subjects can perform reach-to-grasp trajectories in different positions, i.e., vary the distance to the object yielding different scales for the same type of trajectory, which can harm the classification results. To solve this problem, a simple normalization is applied to rescale all trajectories performed in different positions to the same scale, between 0-1, as exemplified in Figure 3.

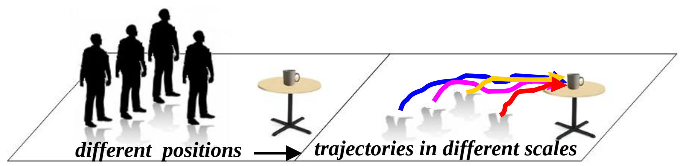


Fig.2. Example of persons at different positions to perform reach-to-grasp trajectories. This implies in trajectories in different scales.

For all trajectory points (in each axis), the following rescale equation is applied:

$$R_a = \left(\frac{X}{\max_a - \min_a} \right) (c_a - \min_a), \tag{1}$$

where R is the rescaled result; a represents a determined axis (x, y or z); X is the desired maximum value; *max* represents maximum value; *min* the minimum value and $\boldsymbol{c}$ the current value that will be transformed.

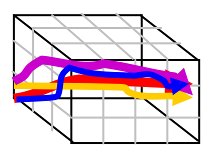


Fig.3. Examples of trajectories after normalization yielding trajectories in the same scale.

Other pre-processing step is the trajectory smoothing. It is used to improve the features extraction - much less noise in the trajectory, the better the detection. A mean filter to smooth each trajectory was used. At each point of the trajectory, the mean value taking into consideration the 8-neighbours (the four previous and four forward points) is computed. Figure 4 shows us small curvatures along the trajectory represented by blue color that can be seen as noise and it might be ignored. The smoothed trajectory is represented with red color where those small variations along the trajectory were smoothed.

B. Trajectory Curvatures Detection

For discrete curvature detection (changes in direction) along the trajectory, we split the trajectory in some slices in order to detect curvatures in each trajectory slice. It is done to accomplish an online classification that happens during some hand displacement (trajectory slice), i.e., to estimate and classify the trajectory that is being performed, updating the classification rate at each slice.

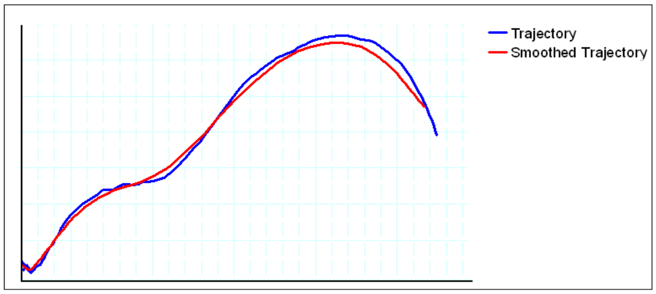


Fig.4. 2D view of a trajectory and its smoothed version after using a mean filter.

Initially, we empirically split the rescaled trajectories in 1/4 and 1/8 of its size to detect the curvatures in each slice. Figure 5 illustrates the idea of splitting the trajectories in 8 equal slices. The colored circles on the trajectory represent some points which are used to detect a curvature type.

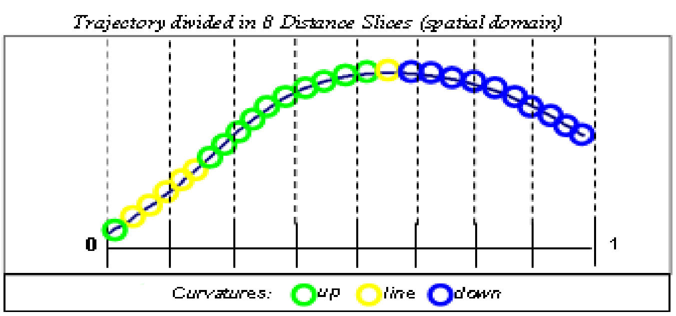


Fig.5. Example of a trajectory divided into 8 equal slices. At each slice can be found ***N*** curvatures between UP, DOWN and LINE (no curvature). The Probability of each type of curvature is computed at each slice.

Using the second order derivative, we are able to detect changes in direction given the points of a trajectory. The curvature is given by three steps as follows:

$$d1 = \begin{cases} \dfrac{(y2 - y1)}{(x2 - x1)}, & (x2 - x1) \neq 0 \text{ and } (y2 - y1) \neq 0; \\ 0, & (y2 - y1) == 0 \text{ or } (x2 - x1) == 0 \end{cases} \quad (2)$$

$$d2 = \begin{cases} \dfrac{(y3 - y2)}{(x3 - x2)}, & (x3 - x2) \neq 0 \text{ and } (y3 - y2) \neq 0; \\ 0, & (y3 - y2) == 0 \text{ or } (x3 - x2) == 0 \end{cases} \quad (3)$$

$$Curvature = d2 - d1, \quad (4)$$

where *d1* and *d2* are the first and second derivative respectively and x_i, y_i represent the coordinates of three points. The curvature value is discretized given a determined threshold:

$$k = \begin{cases} -1, & \text{curvature} < -0.7 \Rightarrow \text{down} \\ 0, & -0.7 < \text{curvature} <= 0.7 \Rightarrow \text{line} \\ 1, & \text{curvature} > 0.7 \Rightarrow \text{up} \end{cases}, \quad (5)$$

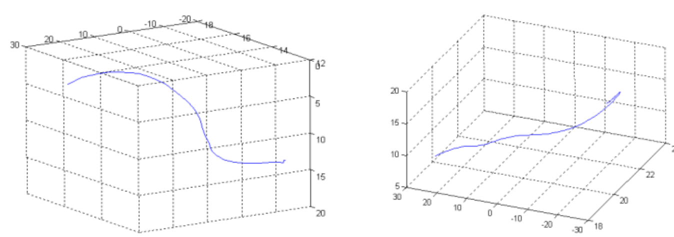
where *k* is the discretized curvature value. The threshold was empirically defined after some tests with threshold values and analyzing the trajectory shape. By now, we are restricting our curvature types as down, up and line using just the x and y coordinates of the trajectory. Our intention in a future work is considering the 3D trajectory to increase our feature types.

C. Fingers Behaviour

In this application beyond of learning and classifying the reach-to-grasp movements, we are interested in analyzing the fingers behaviours which can differentiate during a trajectory being performed. The magnetic markers at the fingers can show us the hand preshapes during their journey to the target, i.e., the kinematics of grasping, the distance of the fingers during the hand aperture. As mentioned in [1], when the maximum aperture of the hand is reached, hand posture has only partially moulded to the object's contours. Using the collected data we can observe whether the maximum distance between the index finger and thumb during the trajectory represents the kinematic key or just a preliminary model of the grasping movement.

D. Experimental Results of the Segmentation Step

The curvatures detection is an important step, because it can differentiate the quality of the results in the trajectory classification. After some tests, we have verified that splitting the trajectory into 8 up to 10 slices, we obtain better characterization of the trajectory. Figure 6 shows reach-to-grasp trajectories performed by a subject and plotted in 3D view. Tables 1 and 2 show the curvature detection and its distribution along the trajectory (top-grasping) presented in Figure 6.



Trajectories measurement unit: ***Inches***

Fig.6. Reach-to-grasp trajectories (raw data). Left image: top-grasping; Right image: side-grasping.

Table 1. Trajectory segmentation (feature extraction): Result of our application for the trajectory presented in Figure 6 (left image).

Slices	Curv. Amount D - L - U	Curv. Probab. D - L - U
1	3 - 2 - 5	0.3 - 0.2 - 0.5
2	3 - 2 - 2	0.43 - 0.285 - 0.285
3	3 - 2 - 1	0.5 - 0.3333 - 0.1667
4	1 - 1 - 3	0.6 - 0.2 - 0.2
5	1 - 1 - 2	0.25 - 0.25 - 0.5
6	1 - 0 - 3	0.25 - 0 - 0.75
7	1 - 0 - 2	0.3333 - 0 - 0.6667
8	3 - 0 - 2	0.6 - 0 - 0.4

Table 2. Trajectory segmentation (feature extraction): Result of our application for the trajectory presented in Figure 6 (right image).

Slices	Curv. Amount D - L - U	Curv. Probab. D - L - U
1	4 - 4 - 6	0.29 - 0.29 - 0.42
2	3 - 0 - 2	0.6 - 0 -0.4
3	3 - 0 - 2	0.6 - 0 -0.4
4	2 - 1 - 1	0.5 - 0.25 - 0.25
5	2 - 1 - 1	0.5 - 0.25 - 0.25
6	2 -1 - 1	0.5 - 0.25 - 0.25
7	2 -1 - 1	0.5 - 0.25 - 0.25
8	2 - 3 - 1	0.333 - 0.5 - 0.167

In this work we verify a reach-to-grasp component, the hand aperture during the journey to the target. As seen in [1] the visual property of the object including object size and location influences the prehension movement. Jeannerod [14] has coded grasping in terms of changing in the hand aperture - the separation between thumb and index finger. The thumb and index finger are the principal fingers during the reach-to-grasp movement and for grip tasks. The index finger is responsible for opening and closing grip, allowing the thumb to maintain stability. Figure 7 shows the fingers trajectories during side-grasping and Figure 8 shows the top-grasping. Comparing the fingers behaviours in the side- and top-grasping, we can see the distance between the thumb and the index finger is bigger in the side-grasping trajectories. The thumb and index finger distance during the trajectories increases until the hand grip the object, where the fingers are re-positioned and adjusted according to the object shape.

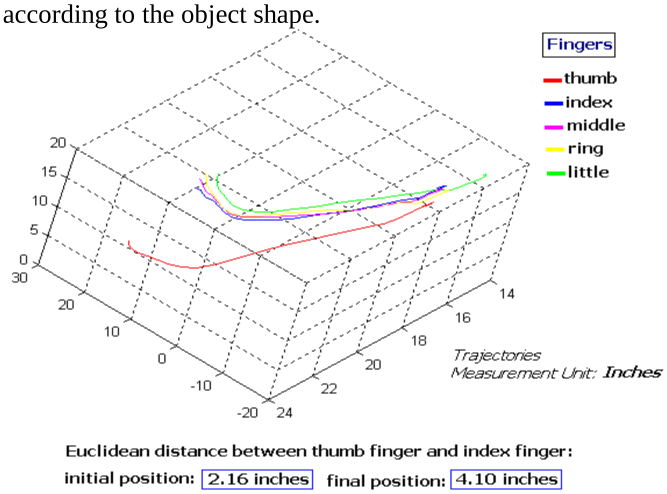


Fig.7. Fingers trajectory: Side-Grasping (raw data).

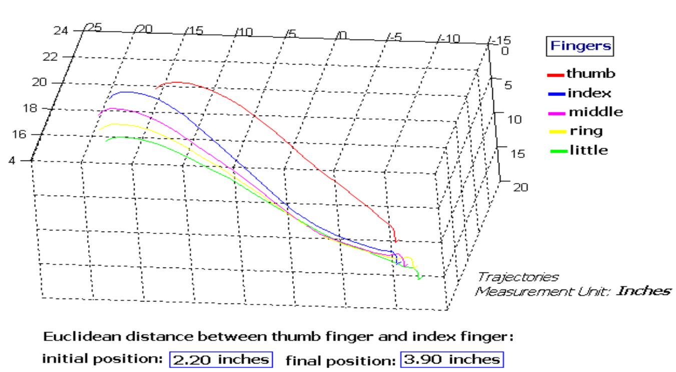


Fig.8. Fingers trajectory: Top-Grasping performance (raw data).

V. Reach-to-Grasp Learning and Classification

Computational models for human perception and action has been explored by researches. Some studies about human brain reports that Bayesian methods have achieved success in creating computational theories for perception and sensorimotor control [15]. These studies have motivated us to adopt Bayesian method for human movement classification. Probability distributions of the features are acquired through histogram techniques allowing the use of Bayesian classification. In the learning phase were collected top- and side-grasping trajectories performed by 10 subjects, 5 times each person.

A. *Grasping Learning Table*

After the feature extraction process, a probability table of the curvatures found in each trajectory is generated. In the learning phase, all trajectories of our dataset is analyzed and then the extraction of curvatures and their probabilities for each trajectory is performed. Given a set of observations to represent a type of grasping *G*, at some displacement *D* (1/8 of trajectory), we have the probability of each type of curvature *C* in each slice of a trajectory represented as $P(C \mid G\ D)$. It is acquired in the segmentation process. The learned table is a mean histogram calculated from all top- and side-grasping probability tables. Each type of grasping has its specific learning table. Figure 9 shows the grasping learning tables obtained after analysing all trajectories of our dataset.
The probability distribution of the features (curvature types) is computed observing their occurrences as follows:

$$P(c = i \mid g) = \frac{c_{i,k}}{\sum_i^n c_{i,k}}, \qquad (6)$$

where c can represent a curvature type i = {*up, down, line*}; g is a specific reach-to-grasp movement top or side-grasping; and k represents the occurrence of a feature c_i in a specific slice of the trajectory.

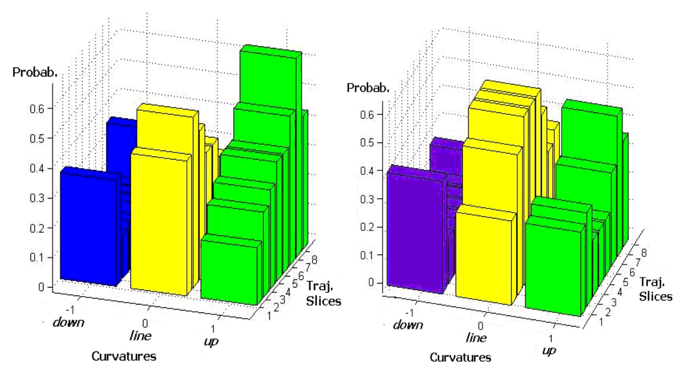


Fig.9. The left image represents the Top-Grasping Learning Table *P(C|GD)*. The probability of the curvature *down* varies between 0.14 and 0.35 along the trajectory slices. The probability of *line* varies between 0.16 and 0.57. The probability of curvature *up* varies between 0.19 and 0.66. The right image represents the Side-Grasping Learning Table *P(C|GD)*. The probability of curvature *down* varies between 0.16 and 0.4. The probability of *line* varies between 0.3 and 0.6. The probability of curvature *up* varies between 0.2 and 0.5. The sum of the *down, line* and *up* in each slice must be 1.

B. Bayesian Classification Model

Bayesian classification models have already proven their usability in gesture recognition systems as demonstrated in [2], thus we are relying on a Bayesian classification.

The estimation and classification of a type of grasping happens along of a trajectory that is being performed by a subject. In each hand displacement (slice), the probability of each type of grasping is updated, i.e., the system informs us which grasping is more probable to happen by the higher probability between top- and side-grasping variables (using the maximum a posteriori).

To understand the general grasping classification model some definitions are done:

1. *g* is a known grasping from all possible *G* (Grasping types);
2. *c* is a certain value of feature *C* (Curvature types);
3. *i* is a given index from all possible slices composed of *a distance D (* 1/8 of a trajectory) of the learned table.

The probability P*(c | g i)* that a feature *C* has certain value *c* can be defined by learning the probability distribution P(*C* | *G D*). Knowing P(*c* | *G i*) and the prior P(*G*) we are able to apply Bayes rule and compute the probability distribution for *G* given the slice *i* of displacement of the learned table and the feature *c*. Initially, the grasping types *G* are a uniform distribution and during the classification their values is updated applying Bayes rule shown below:

$$P(G_{k+1} \mid c_{k+1}, i) = \alpha P(c_{k+1} \mid G, i)\, P(G), \qquad (7)$$

where $\alpha = \dfrac{1}{\sum_j P(c_{k+1} \mid G_j, i)\, P(G_j)}$ is a normalization factor.

We formulate the equation as recursive way. Assuming that at each hand displacement we can find new curvatures, then we can express the online behaviour by using the index *k* that represents a certain displacement performed by the person in the reach-to-grasp movement. The rule for classification is based on the highest probability value being above a certain threshold. We expect that a reach-to-grasp movement that is being performed by a subject to grasp the mug by top or side-grasping will produce a grasping hypothesis with a significant probability.

C. Experimental Results of Learning and Classification

Figure 10 shows a top-grasp trajectory performed by a subject and table 3 shows the answer of our system along this trajectory, classifying it. Our system updates the probability of the variables demonstrating which type of grasp is more probable at each displacement (slice). Figure 11 shows a side-grasping trajectory and Table 4 shows the answer of our application along this trajectory classifying it.

We have asked for 2 subjects performing some reach-to-grasp trajectories (for top- and side-grasping) in order to test our approach. After 10 trials we have observed the top-grasping performance has achieved better classification results than side-grasping performance. This happened due to the side-grasping having more different trajectories inside the dataset, since some subjects started to lift the hand at the beginning of the movement and others started to lift the hand when it was close to the mug. Table 5 shows the performance of 10 trials of top-grasping trajectories and Table 6 trials of side-grasping, highlighting the probability in the classification, the true positive and false negative rates.

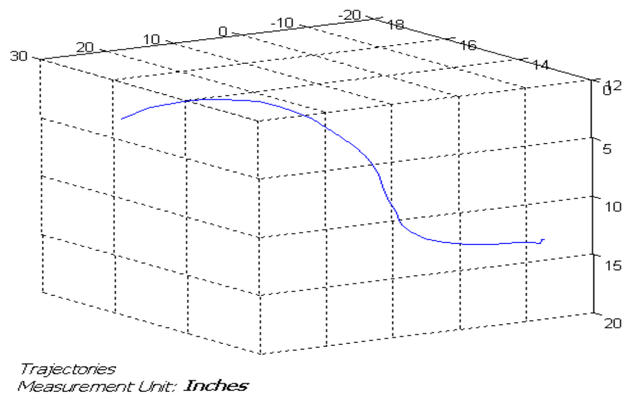


Fig.10. Reach-to-grasp trajectory (Top-Grasping raw data). Along this trajectory our application has returned the probabilities presented in table 3.

Table 3. Result of our approach: This table represents the Estimation/Classification of the trajectory shown in Figure 10. At each slice is shown the probability of the trajectory belonging to top- or side-grasping class. This trajectory was classified with 87.12% as top-grasping.

Slices	Curv. Amount D - L - U	Curv. Probab. D - L - U	TG %	SG%
1	3 - 2 - 5	0.3 - 0.2 - 0.5	47.001%	53.009%
2	3 - 2 - 2	0.43 - 0.285 - 0.285	43.193%	56.807%
3	3 - 2 - 1	0.5 - 0.333 - 0.167	38.787%	61.213%
4	1 - 1 - 3	0.6 - 0.2 - 0.2	55.894%	44.106%
5	1 - 1 - 2	0.25 - 0.25 - 0.5	71.707%	28.293%
6	1 - 0 - 3	0.25 - 0 - 0.75	79.174%	20.826%
7	1 - 0 - 2	0.333 - 0 - 0.667	83.523%	16.477%
8	3 - 0 - 2	0.6 - 0 - 0.4	**87.12%**	12.88%

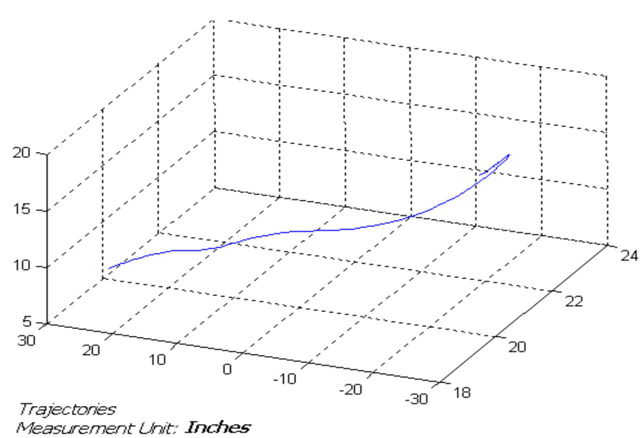


Fig.11. Reach-to-grasp trajectory (Side-Grasping raw data). Along this trajectory our application has returned the probabilities presented in table 4.

Table 4. Result of our approach: This table represents the Estimation/Classification of trajectory shown in Figure 10. At each slice is shown the probability of the trajectory belonging to top- or side-grasping class. This trajectory was classified with 83.70% as side-grasping.

Slices	Curv. Amount D - L - U	Curv. Probab. D - L - U	TG %	SG%
1	4 - 4 - 6	0.29 - 0.29 - 0.42	47%	53%
2	3 - 0 - 2	0.6 - 0 -0.4	43.19%	56.81%
3	3 - 0 - 2	0.6 - 0 -0.4	38.78%	61.22%
4	2 - 1 - 1	0.5 - 0.25 - 0.25	38.78%	61.22%
5	2 - 1 - 1	0.5 - 0.25 - 0.25	38.78%	61.22%
6	2 -1 - 1	0.5 - 0.25 - 0.25	38.78%	61.22%
7	2 -1 - 1	0.5 - 0.25 - 0.25	38.78%	61.22%
8	2 - 3 - 1	0.333 - 0.5 - 0.167	16.30%	**83.70%**

Table 5. Classification Result: 10 trials of top-grasping performed by 2 subjects. Blue color values > 70%; Red Color values < 50%. In the trial 7 the trajectory was classified as Top-Grasping but with small probability (less than the defined confidence threshold).

Trial	Probability	True Positive	False Negative
1	77.17%	x	
2	71.71%	x	
3	85.54%	x	
4	88.38%	x	
5	85.11%	x	
6	38.79%		x
7	55.89%		
8	83.52%	x	
9	87.11%	x	
10	38.06%		x

Table 6. Classification Result: 10 trials of side-grasping performed by 2 subjects. Blue color: values > 70%; Red Color: values < 50%. The trajectories in the trials 3, 5, 7 and 9 were classified as side-grasping with small probability (less than the defined confidence threshold).

Trial	Probability	True Positive	False Negative
1	76.90%	x	
2	78.70%	x	
3	56.81%		
4	28.29%		x
5	54.20%		
6	83.70%	x	
7	52.99%		
8	76.20%	x	
9	59.13%		
10	37.13%		x

We intend to increase our dataset of reach-to-grasp movements and to study with more details the segmentation concerning the threshold to extract the curvatures. We also intend to propose a method for an automatic extraction of slices according to the trajectory geometrical properties, defining a proper slice size in order to achieve better results in the classification. We believe that these two factors can improve our approach towards a better classification.

VI. CONCLUSION

In this work we have presented an automated system for classification of reach-to-grasp trajectories to estimate the way that humans grasp an object. Features extraction by using the second order derivative allows us to find trajectory curvatures along the hand journey to grasp a mug. In this work, we have restricted our curvatures into *down*, *up* and *line*. Our presented approach shows satisfactory results that can be improved adjusting some parameters, such as amount of trajectory slices and increasing our trajectories dataset in order to achieve a better learning. This preliminary work about reach-to-grasp movements will be used in a future work to endow a robot with capabilities of imitation learning. This work allowed us to analyze the fingers behaviour along the trajectory, observing that the thumb and index finger are the principal fingers during the reach-to-grasp movements. The index finger is responsible for opening and closing the hand grip allowing the thumb to maintain stability. In a future work we also intend analyzing the hand behaviour concerning its orientation during the reach-to-grasp trajectory with more details in order to verify the kinematics of grasping. These actions can be learned and mapped to a robot perform these human actions.

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