3D Hand Trajectory Segmentation by Curvatures and Hand Orientation for Classification through a Probabilistic Approach

Diego Faria, Jorge Dias

ISR – Institute of Systems and Robotics
University of Coimbra - Portugal
diego@isr.uc.pt, jorge@isr.uc.pt

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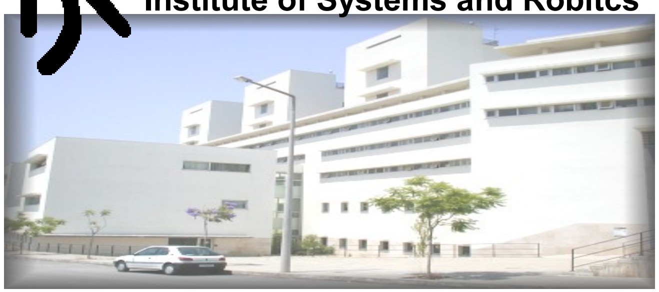

This work is partially supported by the European project Handle ICT-23-16-40. Diego Faria is supported by Portuguese Foundation for Science and Technology (FCT). Diego Faria and Jorge Dias are with Institute of Systems and Robotics – University of Coimbra – Polo II, 3030-290 Coimbra, Portugal (diego, jorge)@isr.uc.pt.

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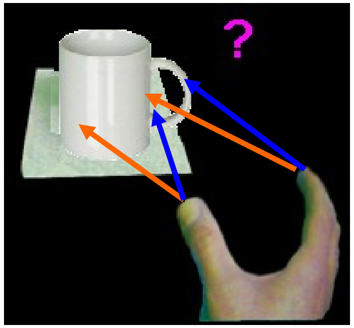
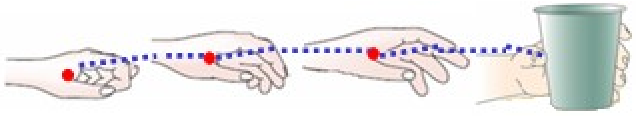
Introduction

Grasping movements have been the focus of interest of many researches, including:

- Neuroscientists: Analysis of movements concerning stability, motor coordination …
- Robotics Field: Imitation Learning or Gestures recognition (human-robot interaction)



- How to grasp an object?
- Where should you place your fingers when grasping an object?



- Hand Trajectory Analysis;
- Hand shape;
- Fingers behaviours during the journey to the target

Main Objectives

- Analysis of 3D trajectory behavior before the object manipulation
- Automated System for Classification of reach-to-grasp trajectories.
- 3D Hand Trajectory Segmentation by curvatures detection in a 3D space (r, θ, h) and by hand orientation by approximating the hand plan.
- Classification by a Probabilistic Approach: Bayesian model to classify trajectories by curvatures and hand orientation.
- Entropy as uncertainty measure for confidence level giving weights for both classification to fuse them.
- Database of grasping movements (hand trajectory)

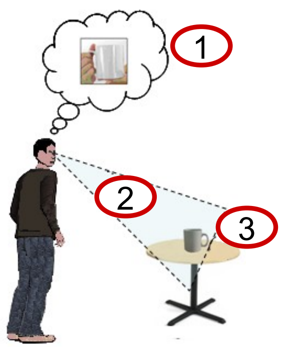
Analysis of Human Grasping

Steps analyzed in our work

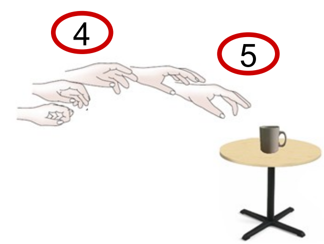
1 -Having a prior knowledge of the object

2 -Seek the target

3 -Identify the target among other objects



4 -Move the arm towards the object



5 -Preshape the hand to hold the object

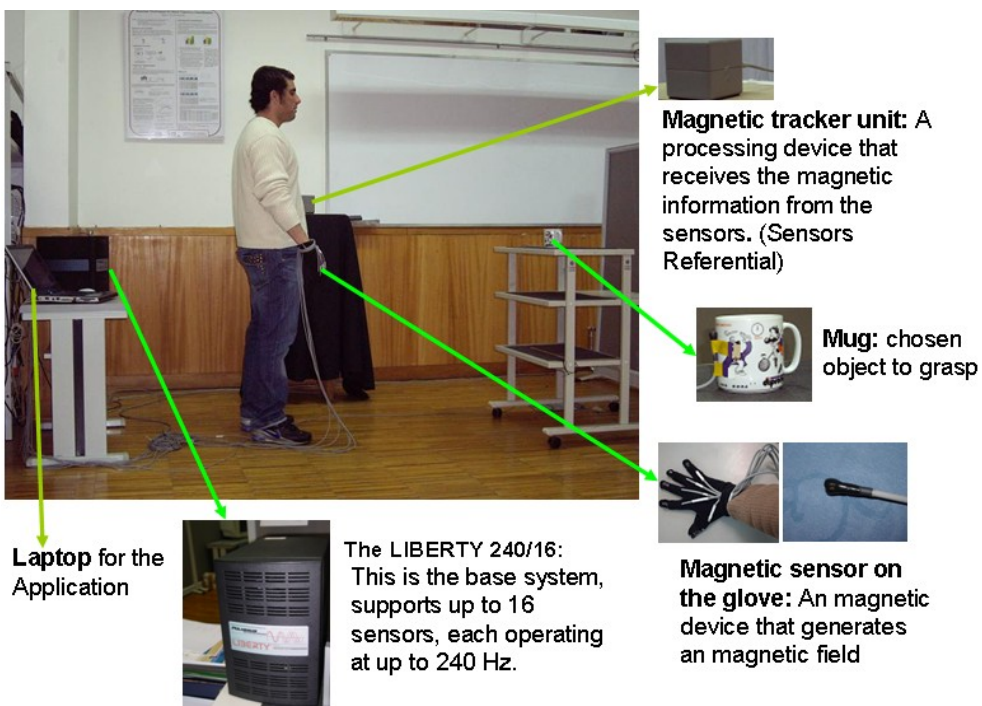
6-Contact between hand and object

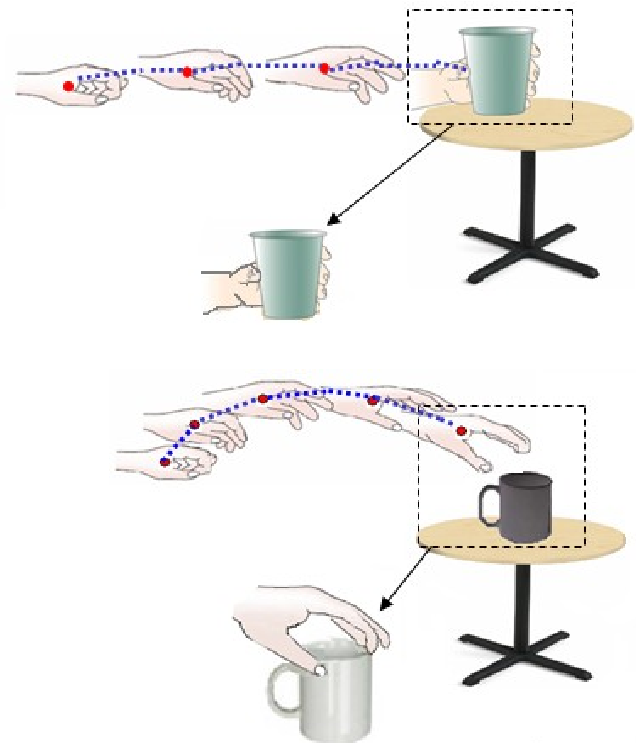
7-Refine the grasping and reposition the fingers

Successful grasp achieved

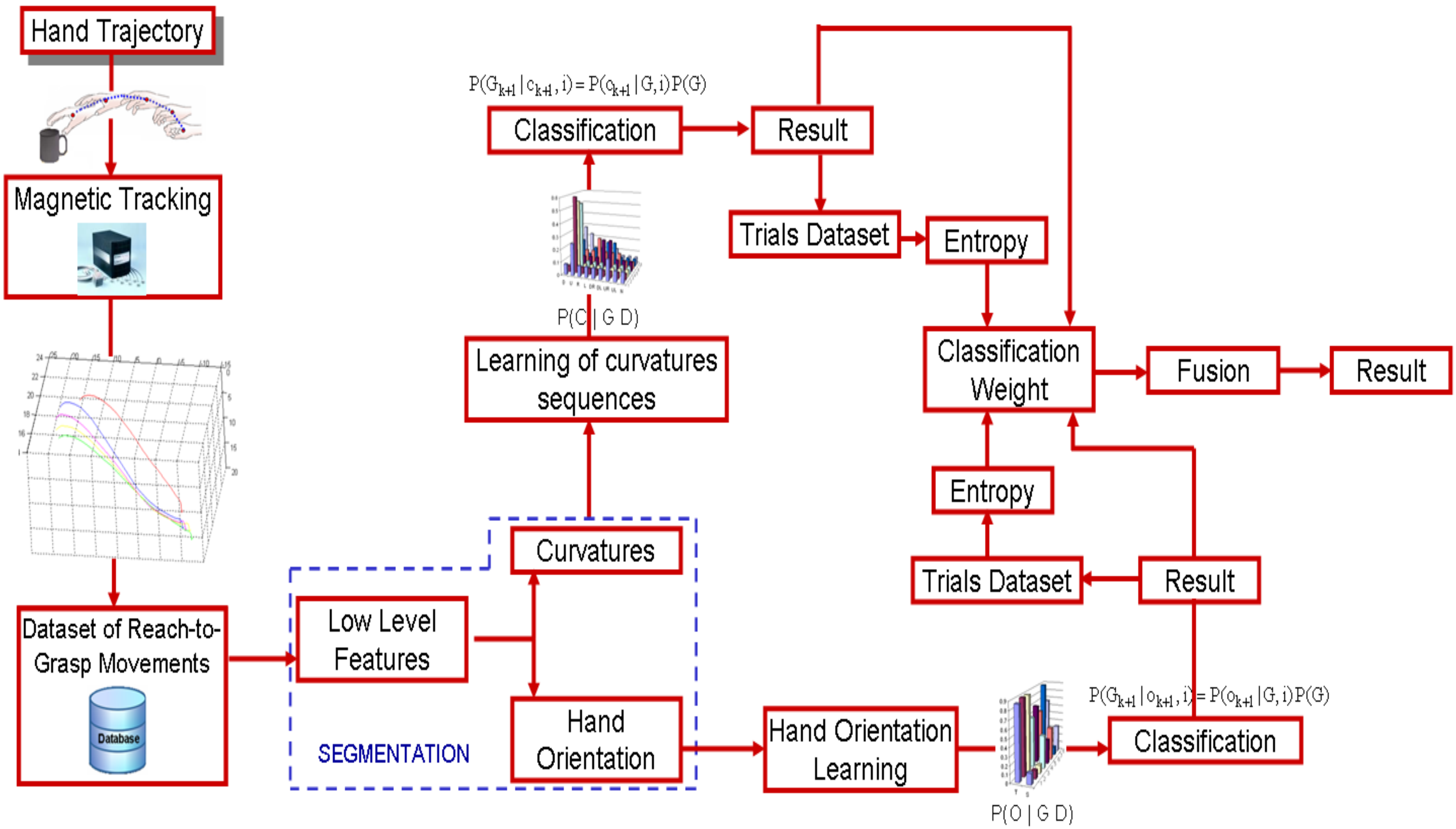
Scenario and Context

- Polhemus Liberty tracking device to track the 3D trajectories;
- Five markers are attached on a glove for tracking of hand trajectory;
- 1 marker on the object to know a priori the object position and the distance size for trajectory normalizartion.
- 2 reach-to-grasp movements were defined for our application: Top-Grasping and Side-Grasping





Implementation



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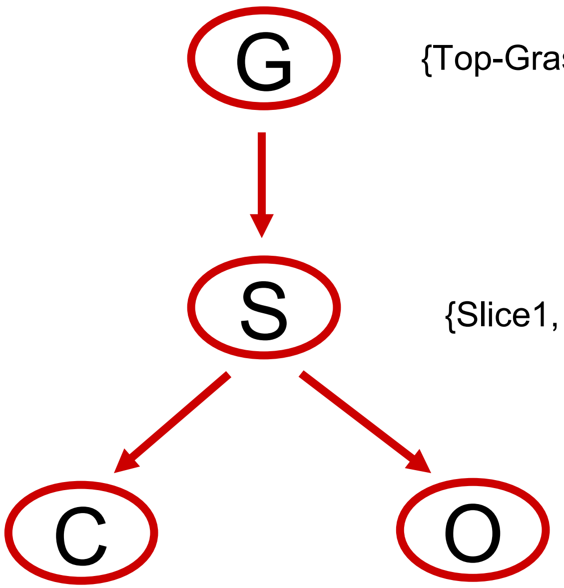
Bayesian Network

Definitions

1. ***G*** is a known grasping from all possible types;
2. ***S*** is a certain displacement, represents a Trajectory Slice;
3. ***C*** represents the curvatures: up, down, line;
4. **D** represents a certain direction concerning Backward or Forward movement.
5. **O** hand Orientation



{Top-Grasping; Side-Grasping}

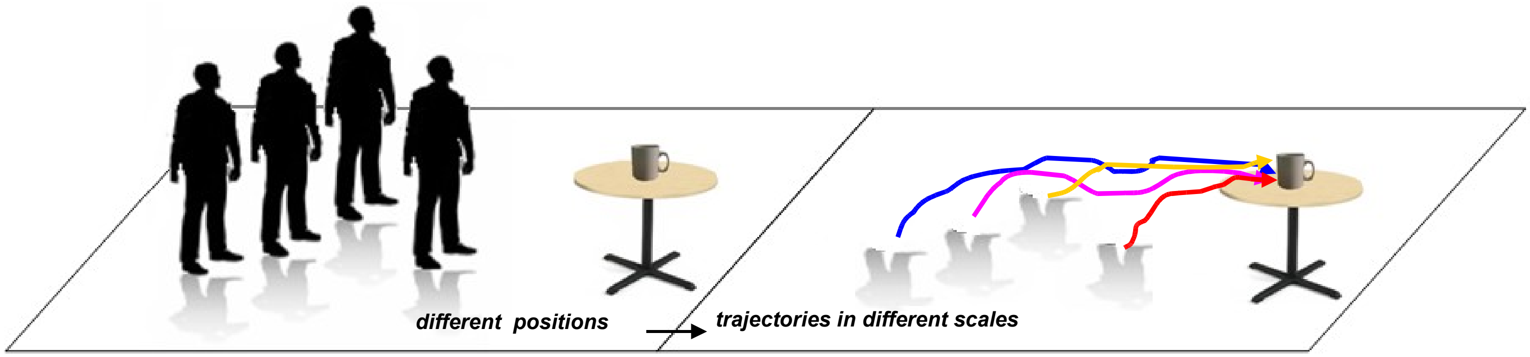
{Slice1, …, Slice8}

{**C**: Down, Up, Left, Right, Upright, UpLeft, Downright, DownLeft;non-movement; **O**: hand pose/orientation}

Phase 1: Hand Trajectory Segmentation

Pre-processing steps are necessary to improve the trajectory segmentation:

- Some problems need to be solved:

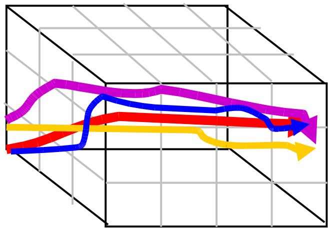


-Solution: Normalization - rescale all trajectories to the same scale (between 0-1).

For all points of each axis:

$$R_a = \left(\frac{X}{\max_a - \min_a}\right)(cur_a - \min_a)$$

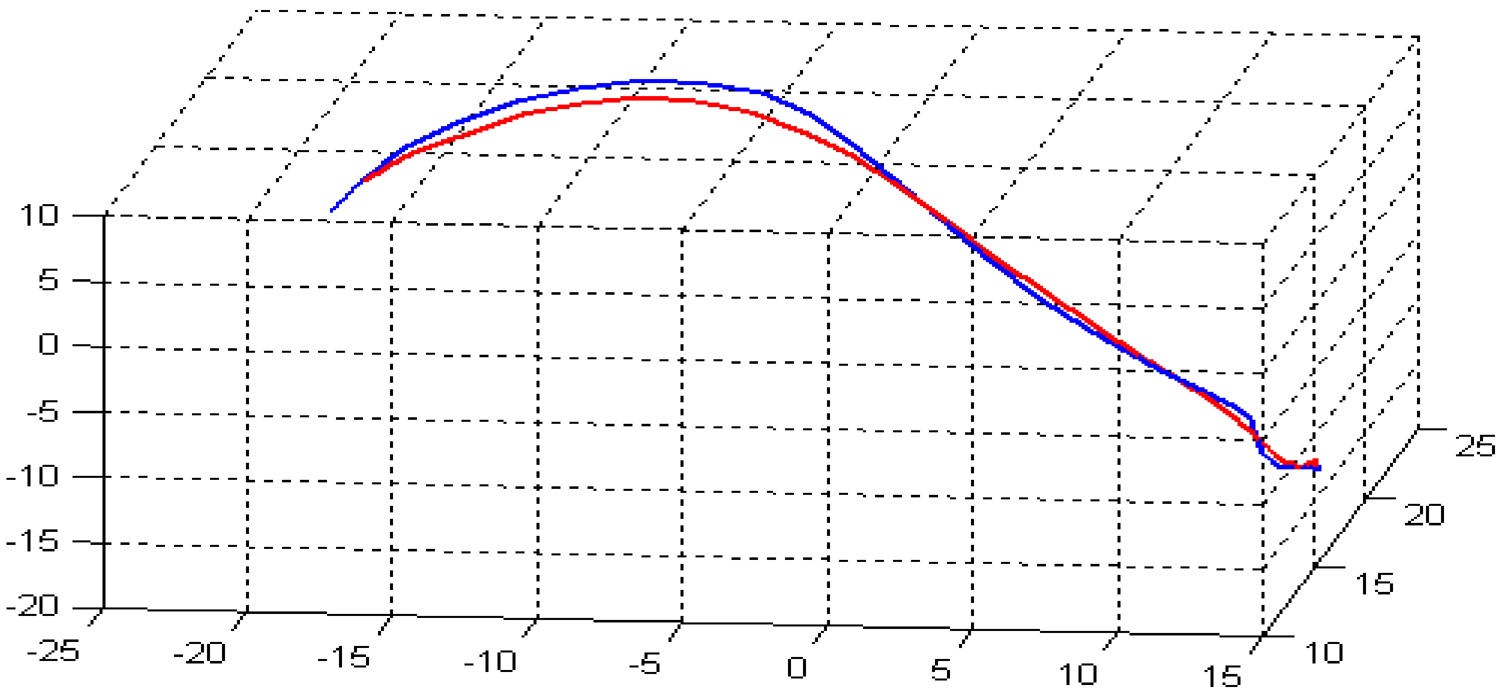
R *- rescaled result;* ***a*** *represents an axis (x, y or z);* ***X*** *- Desired maximum value;* ***max*** *- maximum value of a axis;* ***min*** *- minimum value of a axis,* ***cur*** *–* current value that is being rescaled.



Trajectories normalization

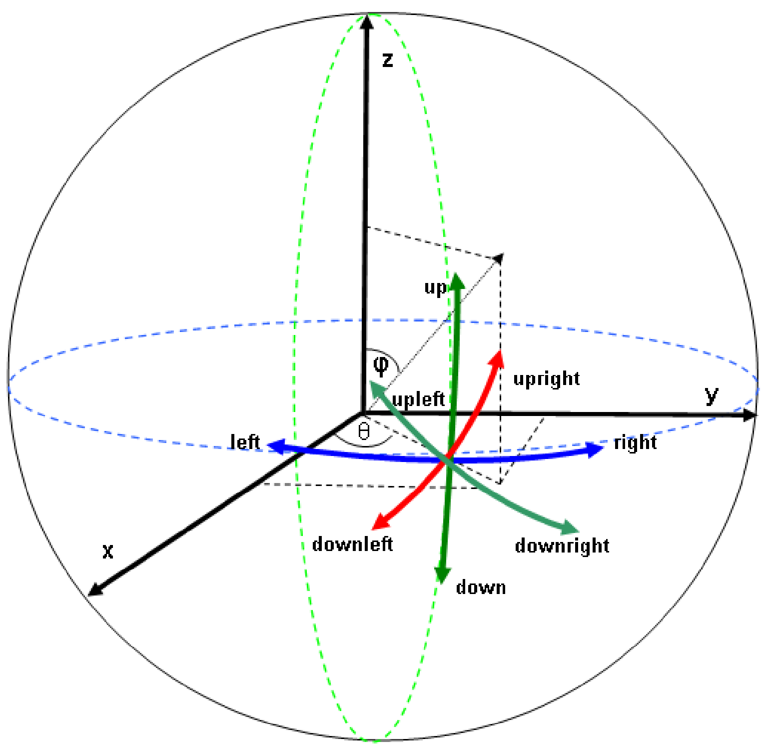
Phase 1: Hand Trajectory Segmentation

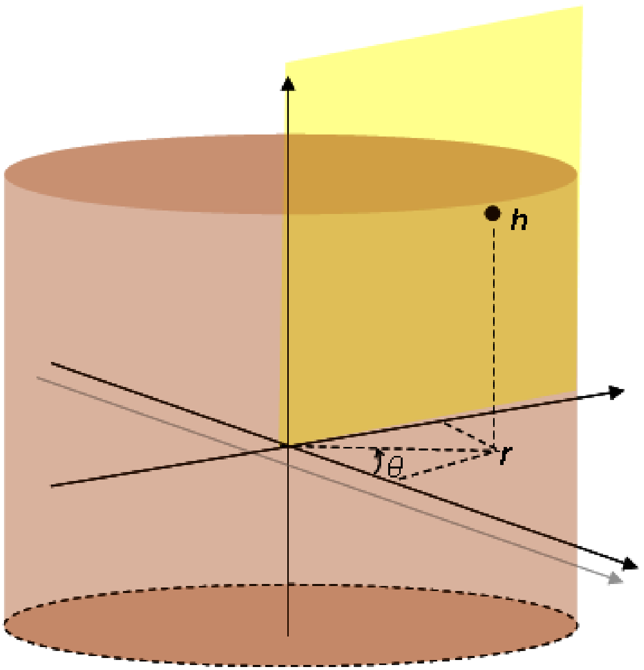
Other necessary pre-processing step is the trajectory smoothing. It is necessary to improve the features detection, as less noise in the trajectory as better will be the detection. It was used a mean filter to smooth each trajectory.



Phase 1: Hand Trajectory Segmentation

Segmentation in a spherical coordinate or cylindrical coordinate system:





- At 2 points of the trajectory is we have the vector representation in 3D space.
- We can estimate the trajectory direction by (r, φ, θ) or by (r, θ, h) .

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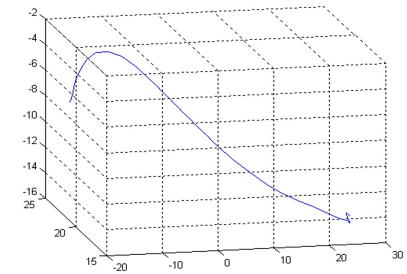
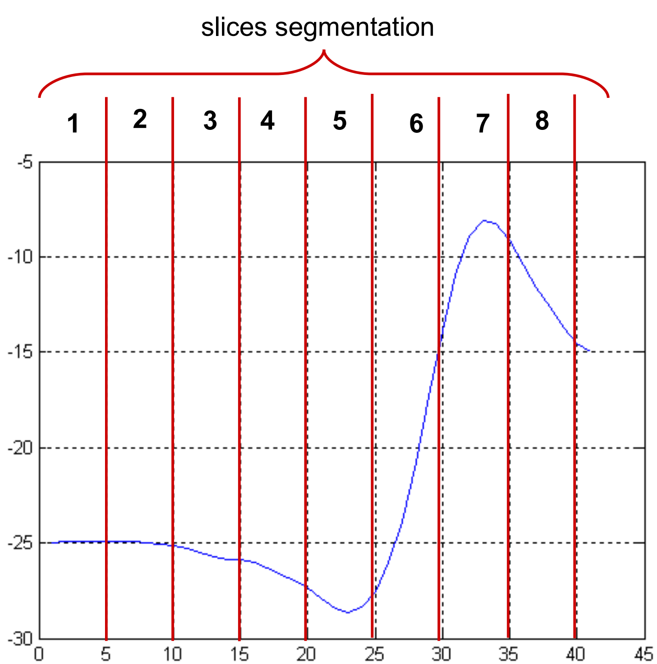
Phase 1: Hand Trajectory Segmentation

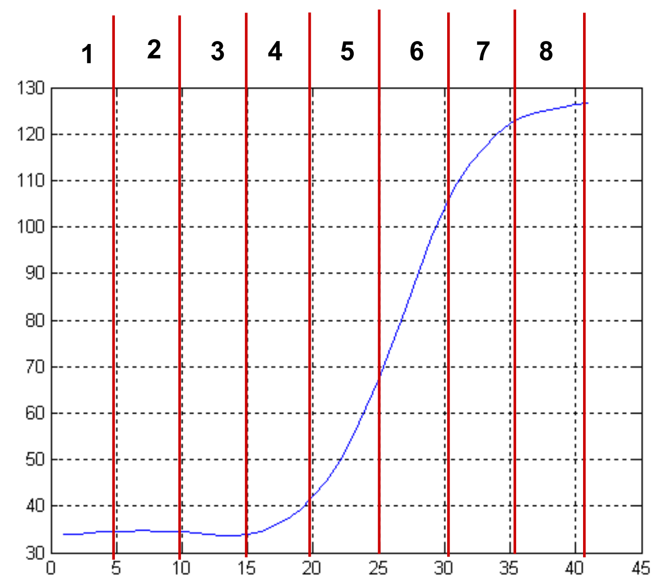
- Trajectory split in 8 parts to estimate and classifying the trajectory that is being performed at each hand displacement,
- At each trajectory slice is verified the θ angle and the height information, Combining height information and the angle in x,y plan we can detect thecurvatures.



3D Trajectory: Cartesian Space



2D view of φ



2D view of θ

Phase 1: Hand Trajectory Segmentation

The curvature segmentation is performed at each two points of the trajectory. The next steps demonstrated by the following equations show us how to reach **(*r, θ, φ*)** in spherical coordinate system:

Spherical coord. system

$$v_1 = \begin{pmatrix} x_1 \\ y1 \\ z_1 \end{pmatrix} \qquad v_2 = \begin{pmatrix} x2 \\ y2 \\ z_1 \end{pmatrix}$$

$$r1 = \sqrt{x_1^2 + y_1^2 + z_1^2} \qquad r_2 = \sqrt{x_2^2 + y_2^2 + z_2^2}$$

$$\sin\varphi = \frac{\sqrt{x_1^2 + y_1^2}}{r1} \qquad \sin\varphi = \frac{\sqrt{x_2^2 + y_2^2}}{r_2}$$

$$\cos\varphi = \frac{z_1}{r1} \qquad \cos\varphi = \frac{z_2}{r_2}$$

$$\varphi_1 = \arctan 2(\sin\varphi, \cos\varphi) \qquad \varphi_2 = \arctan 2(\sin\varphi, \cos\varphi)$$

$$h = z_2 - z_1$$

$$r_{1(x,y)} = \sqrt{x_1^2 + y_1^2}$$

$$r_{2(x,y)} = \sqrt{x_2^2 + y_2^2}$$

$$r_{(x,y)} = r_{2(x,y)} - r_{1(x,y)}$$

cyilindrical coord. system

$$\varphi = r_2 \cos\varphi_2 - r_1 \cos\varphi_1$$

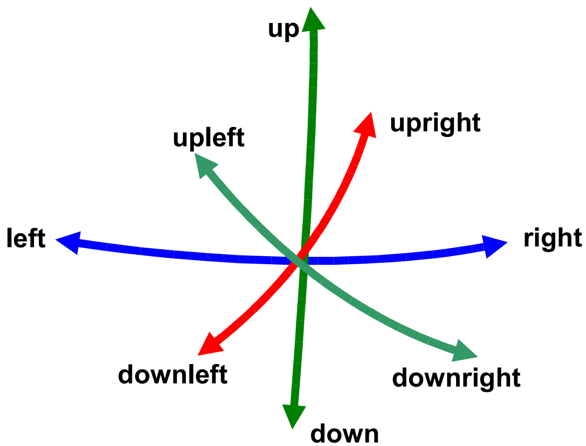
$$\cos\theta = \frac{x_1}{\sqrt{x_1^2 + y_1^2}} \qquad \cos\theta = \frac{x_2}{\sqrt{x_2^2 + y_2^2}}$$

$$\sin\theta = \frac{y_1}{\sqrt{x_1^2 + y_1^2}} \qquad \sin\theta = \frac{y_2}{\sqrt{x_2^2 + y_2^2}}$$

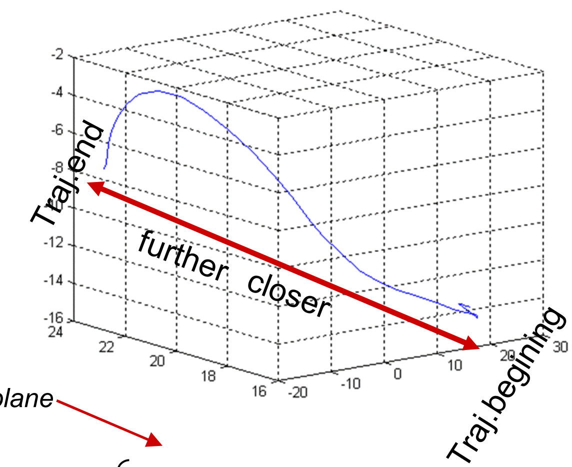
$$\theta_1 = \arctan 2(\sin\theta, \cos\theta) \qquad \theta_2 = \arctan 2(\sin\theta, \cos\theta)$$

$$\theta = \theta_2 - \theta_1$$

Phase 1: Hand Trajectory Segmentation



Possible Directions



*Projection of **R** in x,y plane*

$$r = \begin{cases} \text{Positive = further} \\ \text{Negative = closer} \end{cases}$$

$$\boldsymbol{c} = \begin{cases}
height > 0 \ \text{and} \ \theta \sim 0 \ \text{and} \ r_{(x,y)} \sim 0 & \text{Up} \\
height < 0 \ \text{and} \ \theta \sim 0 \ \text{and} \ r_{(x,y)} \sim 0 & \text{Down} \\
height = 0 \ \text{and} \ \theta > 0 \ \text{and} \ r_{(x,y)} = 0 & \text{Right} \\
height = 0 \ \text{and} \ \theta < 0 \ \text{and} \ r_{(x,y)} = 0 & \text{Left} \\
height > 0 \ \text{and} \ \theta > 0 \ \text{and} \ r_{(x,y)} \sim 0 & \text{UR} \\
height > 0 \ \text{and} \ \theta < 0 \ \text{and} \ r_{(x,y)} \sim 0 & \text{UL} \\
height < 0 \ \text{and} \ \theta > 0 \ \text{and} \ r_{(x,y)} \sim 0 & \text{DR} \\
height < 0 \ \text{and} \ \theta < 0 \ \text{and} \ r_{(x,y)} \sim 0 & \text{DL}
\end{cases}$$

Phase 1: Hand Trajectory Segmentation

After curvatures detection is computed the probability distribution of the curvatures in each slice. For each feature is computed its probability as follows:

$$P(c_i) = \frac{c_i}{C}$$

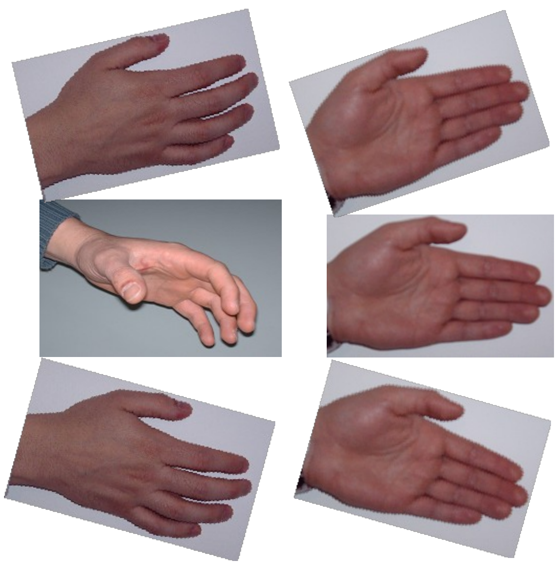
Where ***ci*** represents the amount of a specific curvature in a specific slice and ***C*** is the total of curvatures found in each slice, i.e., the summation of the total of occurrence of all ***ci***.

Phase 1: Hand Trajectory Segmentation

Segmentation of Hand Orientation

3 Parallel fingers used to find the hand orientation.

Side Grasping

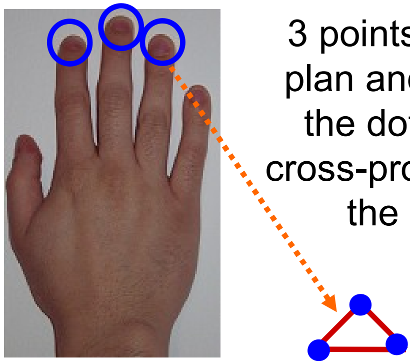


Using 3 points is possilbe to approximate hand plan to know the hand orientation

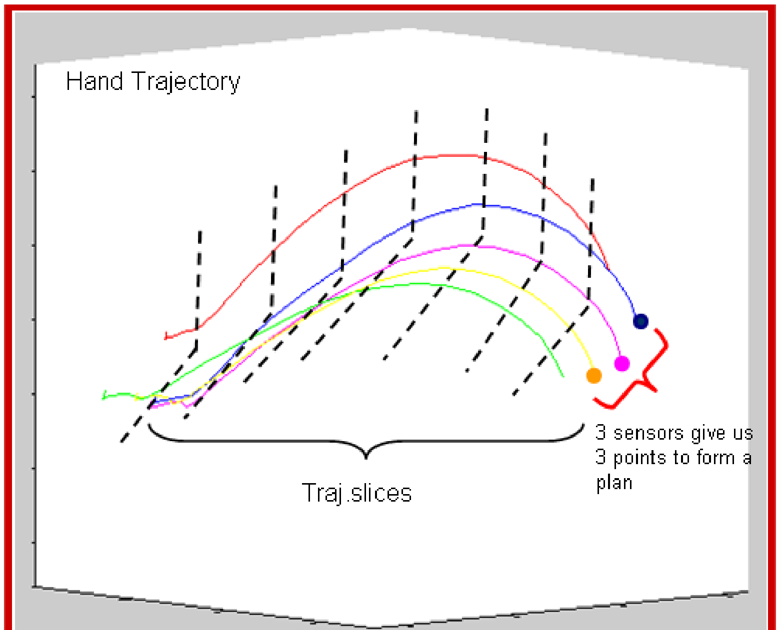
Top Grasping

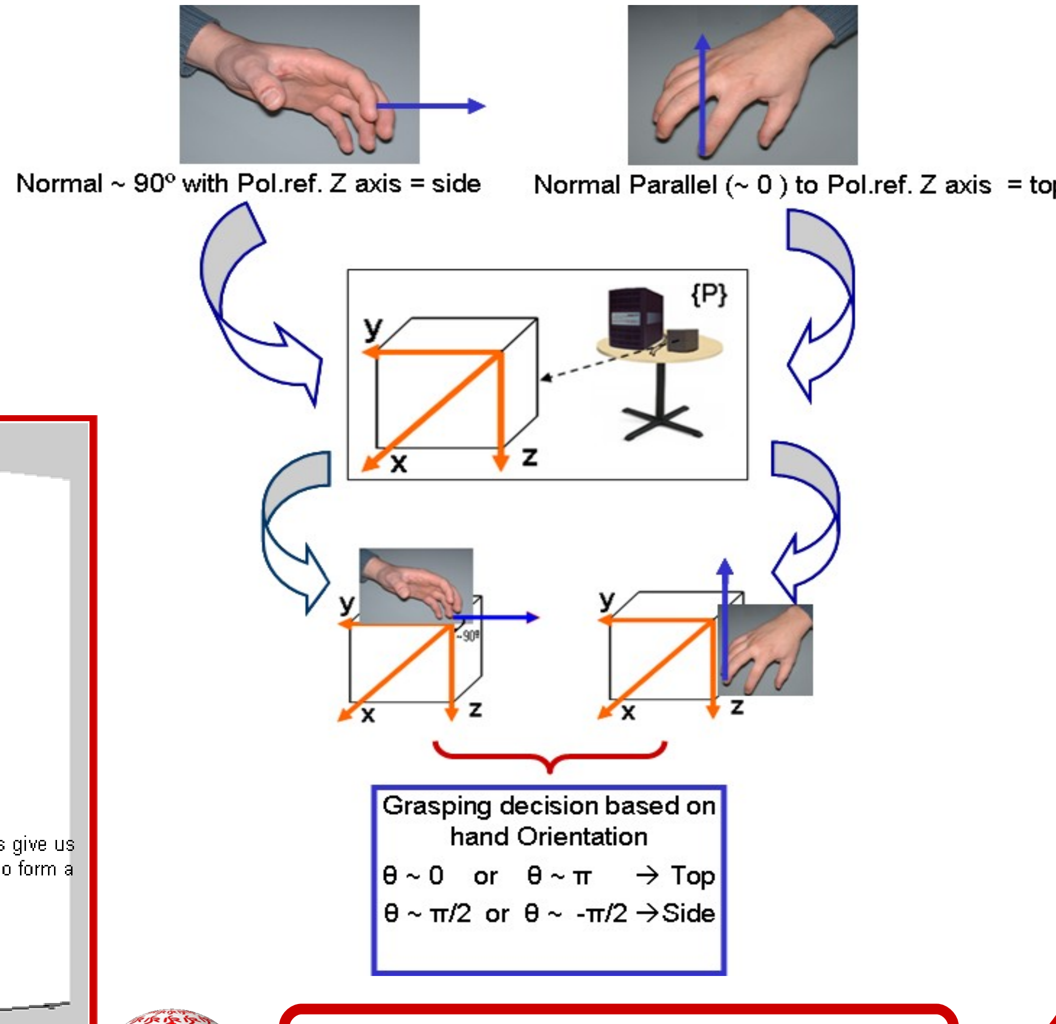
Phase 1: Hand Trajectory Segmentation

Hand Orientation



3 points to have a plan and calculate the dot-product, cross-product to find the normal





Grasping decision based on hand Orientation

θ ~ 0 or θ ~ π → Top

θ ~ π/2 or θ ~ -π/2 → Side

Phase 1: Hand Trajectory Segmentation

In each slice is found the amount of hand orientation for side and top-grasp. The probability of each one is computed as follows:

$$P(o_i) = \frac{o_i}{O}$$

Where ***oi*** represents the amount of a kind of hand orientation (side or top grasp) in a specific slice and ***O*** represents the total of all occurrences of all hands orientation found in a specific slice.

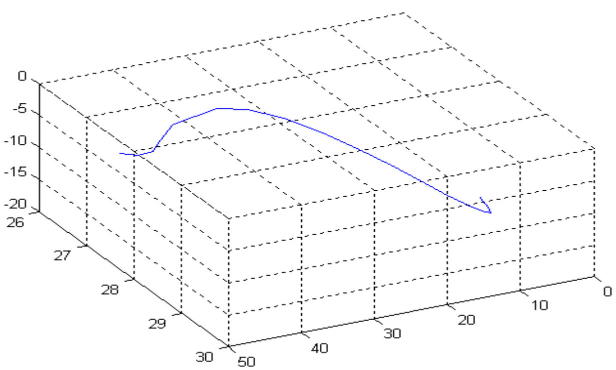
Phase 1: Segmentation Results

- For each observation is created a xml file for curvatures segmentation and a file for hand orientation segmentation.
- All Observation are stored in a database of reach-to-grasp movements

Curvatures Detection:

Slices	Curv. Amount D-U-L-R-UL-UR-DL-DR-N	Curv. Probab. D-U-L-R-UL-UR-DL-DR-N
1	1 - 2 - 0 - 0 - 0 - 3 - 1 - 1 - 0	0.12 - 0.26 - 0 - 0 - 0 - 0.38 - 0.12 - 0.12 - 0
2	1 - 4 - 0 - 0 - 2 - 4 - 1 - 1 - 0	0.08 - 0.30 - 0 - 0 - 0.15 - 0.30 0.08 - 0.08 - 0
3	1 - 5 - 0 - 0 - 2 - 3 - 0 - 1 - 0	0.08 - 0.42 - 0 - 0 - 0.16 - 0.25 0 - 0.08 - 0
4	1 - 1 - 0 - 0 - 1 - 6 - 1 - 1 - 0	0.09 - 0.09 - 0 - 0 - 0.09 - 0.54 0.09 - 0.09 - 0
5	1 - 1 - 0 - 0 - 1 - 4 - 0 - 1 - 0	0.125 - 0.125 - 0 - 0 - 0.125 0.5 - 0 - 0.125 - 0
6	1 - 1 - 1 - 2 - 0 - 1 - 1 - 4 - 0	0.09 - 0.09 - 0.09 - 0.18 - 0 0.09 - 0.09 - 0.36
7	3 - 0 - 1 - 0 - 1 - 0 - 2 - 3 - 0	0.3 - 0 - 0.1 - 0 - 0.1 - 0 - 0.2 0.3 - 0
8	5 - 3 - 2 - 1 - 3 - 1 - 1 - 2 - 1	0.26 - 0.15 - 0.1 - 0.05 - 0.15 0.05 - 0.05 - 0.1 - 0.05

Top-Grasping



Hand Orientation Detection:

Slices	Hand Orientation Side - Top	Hand Orientation. Probab. Side - Top
1	5 - 4	0.56 – 0.44
2	3 - 8	0.28 – 0.72
3	4 - 7	0.37 – 0.63
4	3 - 8	0.28 – 0.72
5	2 - 10	0.17 – 0.83
6	1 - 11	0.08 – 0.92
7	1 - 13	0.07 – 0.93
8	1 - 16	0.06 – 0.94

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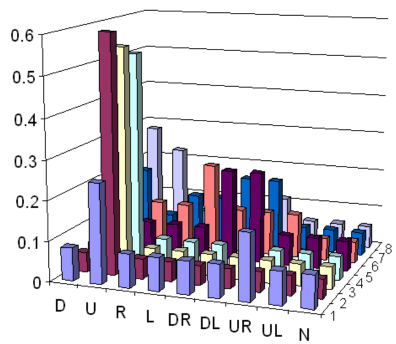
Phase 2: Learning

- The learning phase is based on histogram of the segmented features. *The curvature learning table is given by **P(C | G D)***. It's a mean histogram calculated from all Top-Grasping and Side-Grasping probability tables.

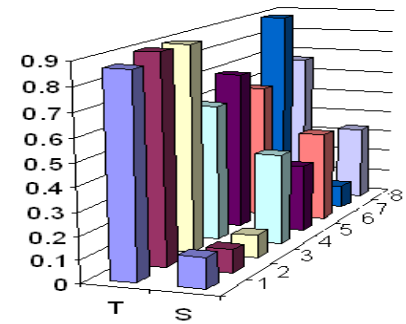
__G__: set of observation of a grasping type; *__D__: a determined displacement (trajectory slice);* **C**: *probability of each curvature in each slice.*

- The same rule is used for hand orientation learning so that we have ***P(O| G D)*** where ***O*** represent all possible hand orientation.

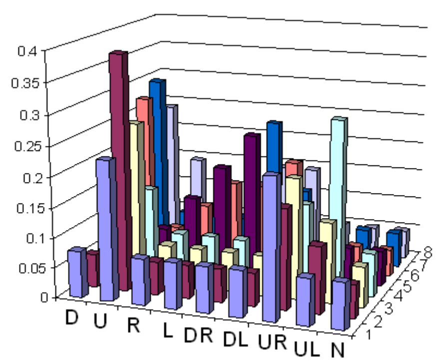
Curvatures



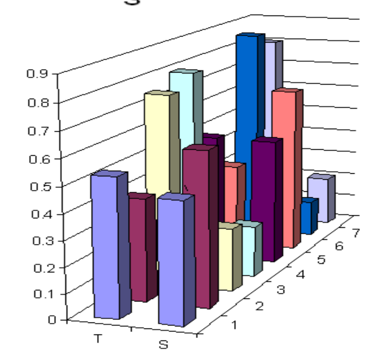
Top-Grasping



Hand Orientation



Side-Grasping



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Phase 2: Learning

- Due the learning be achieved through histogram is possible some features might have zero probability, because they never have been observed. Whenever these features with zero probability occur in the classification step the correspondent hypothesis(es) will receive also a zero probability.

- Our classifier is continuous, based on multiplicative update of beliefs and this situation leads to definite out-rule of the hypothesis. To avoid this problem we are using the ***Laplace Succession Law***, i.e., producing a minimum probability for non-observed evidences by the equation below:

$$P(F = i) = \frac{n_i + 1}{n + [F]}$$

Where ***F*** represents the features (e.g. curvatures = 9, orientation = 2); ***ni*** represents total of occurrence of this feature; ***n*** represents the total of all features occurrence.

Phase 3: Classification

The General Grasping Classification Model

Classification by Curvature

Definitions

1. ***g*** is a known grasping from all possible *G* (Grasping types);
2. ***c*** is a certain value of feature *C* (Cuvature types);
3. ***i*** is a given index from all possible slices composed of displacement ***D*** of the learning table.

Used in a recursive way

$$P(G_{k+1} \mid c_{k+1}, i) \,\alpha\, \overbrace{P(c_{k+1} \mid G, i)}^{\text{Likelihood}} P(G) \longrightarrow$$

Prior: Top and side Grasping Variables: uniform distrib.

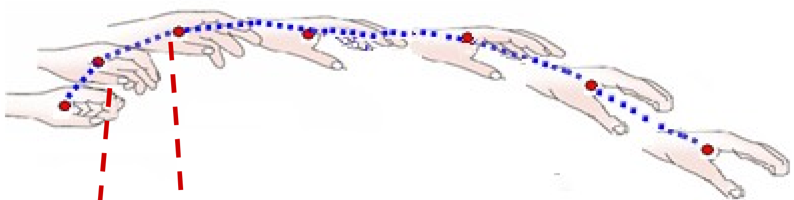
Classification by Hand Orientation

Definitions

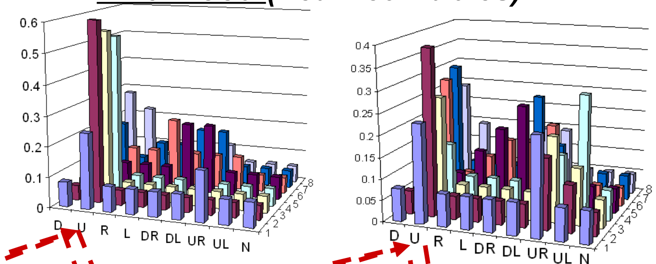
1. ***g*** is a known grasping from all possible *G* (Grasping types);
2. ***o*** is a certain value of feature *O* (Hand Orientation);
3. ***i*** is a given index from all possible slices composed of displacement ***D*** of the learning table.

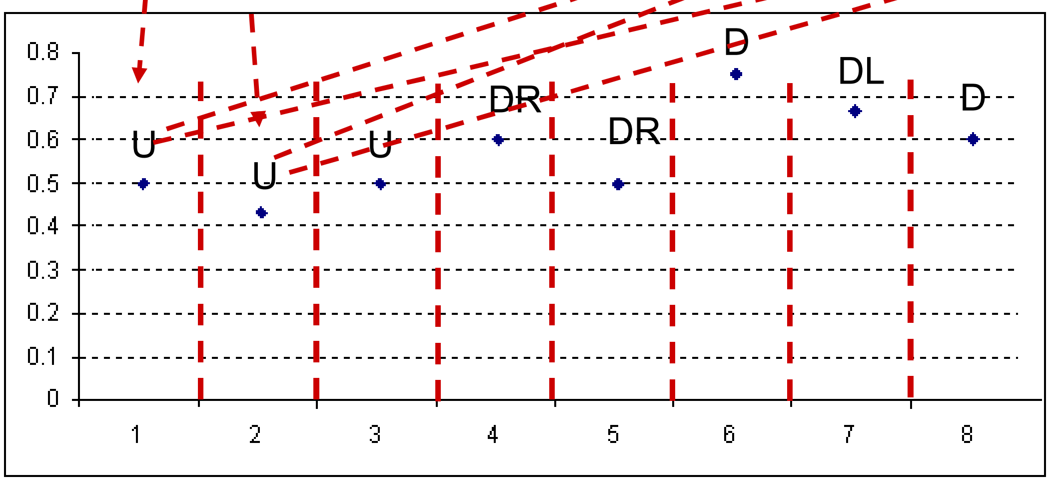
$$P(G_{k+1} \mid o_{k+1}, i) \,\alpha\, P(o_{k+1} \mid G, i)\, P(G)$$

Phase 3: Classification



***Likelihood* (Learned Tables)**





PRIOR:

TG ***SG***

Initialy uniform distribution, it's updated at each interaction with the result of the last interaction

And So on … The same process is done for all slices.

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Phase 3: Classification

Entropy as Confidence Level for Classification Fusion

- ***Goal:*** improving and reach a better classification based on results of previous classification.

After analyze the classification results of trajectory classification based on hand orientation and curvatures, we can apply entropy to verify the best classification between both.

- Confidence variables will be used as weight w Є {w1 , …, wN} for each model of classification.

- For each model of classification we can compute the entropy of the posterior probabilities as follows:

$$H(P(G \mid F\ D)) = -\sum_i P(G_i \mid F\ D)\log(P(G_i \mid F\ D))$$

P(G| F D) represents the posterior probability of each model of classification. ***F*** (curvatures or hand orientation) ; ***D*** the hand displacement (trajectory slice); ***i*** index of each classification results.

$$w = 1 - \left(\frac{Hc}{\sum_{i=0}^{n} H_i} \right)$$

Where ***w*** is the weight result; ***HC*** is the current value of entropy that is being transformed in a weight***;*** ***i*** represents the index for each entropy value.

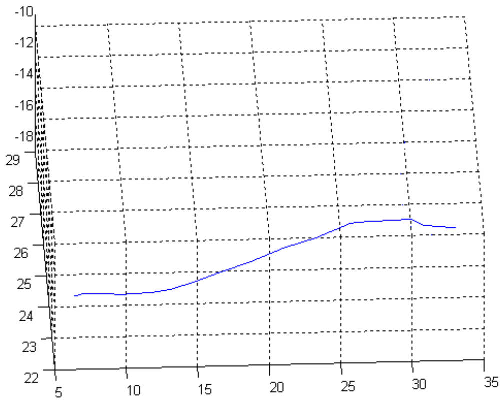
$$P(G \mid F\ D) = \sum_{j=1}^{n} P(w_j)P(g_j \mid f\ i)$$

Classifications Fusion

Phase 3: Experimental Results

Side-grasp

3D trajectory



Slices	Curv. Type / highest probability	Top%	Side%
1	UR: 0.60	34	66
2	UR: 0.90	34	66
3	UR: 0.90	34	66
4	U: 0.90	0.68	99.32
5	U: 0.90	0.68	99.32
6	D: 0.70	0.68	99.32
7	DR: 0.90	0.68	99.32
8	U: 0.35	**1.68**	**98.32**

Slices	Hand Orientation / highest prob.	Top%	Side%
1	S: 0.90	19.10	80.90
2	S: 0.67	4.76	95.24
3	T: 0.90	4.76	95.24
4	T: 0.90	4.76	95.24
5	T: 0.90	4.76	95.24
6	T: 0.90	8.25	91.75
7	T: 0.67	10.83	89.17
8	S:0.80	**8.00**	**92.00**

Phase 3: Experimental Results

We have asked for 2 subjects performing some reach-to-grasp trajectories (top and side grasp) to test our application. The result table shows 10 trials of *side grasp* by curvatures and hand orientation.

Trial	1 - Curvatures Classification Probability	1 - False Negative	2 - Hand Orientation Classification Probability	2 - False Negative
1	98.32 %		92.00 %	
2	86.63 %		76.93 %	
3	21.67 %	✓	91.53 %	
4	84.69 %		61.12 %	
5	5.78 %	✓	82.53 %	
6	99.33 %		51.22 %	
7	99.68 %		90.43 %	
8	99.97 %		91.53 %	
9	88.98 %		95.69 %	
10	78.67 %		55.98 %	

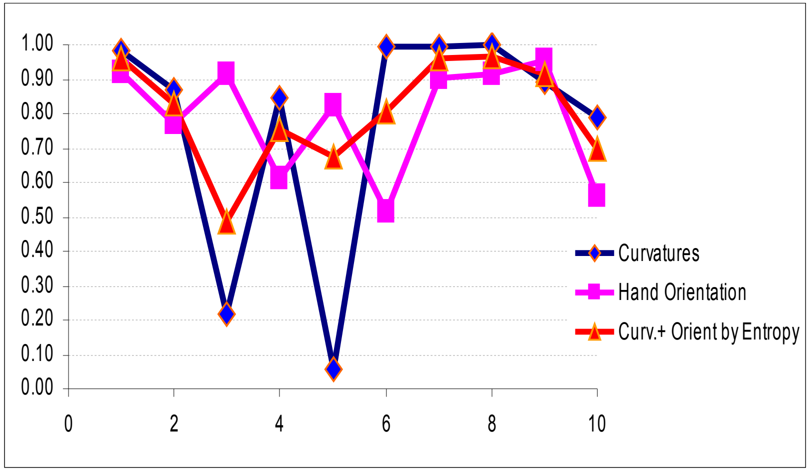
A deep study and tests performing much more trials need to be done with this classification model by curvature and hand orientation to confirm that one method is really better than another.

Phase 3: Experimental Results

To reach an uncertainty measurement and give weights, for each type of classification we reached the following weights: ***P(w_curv)*** **= 0.611367** and ***P(w_hor)*** **= 0.38863252.**

Figure below shows a comparison graphic among these 3 methods. The results show us that the result reached by the entropy belief is a kind of balance between both methods for the trials showed in the previous slide.

Trial	1 - Curvatures Classification Probability	2 - Hand Orientation Classification Probability	3 -Classification Probability using entropy as confidence Level
1	98.32 %	92.00 %	**95.86 %**
2	86.63 %	76.93 %	**82.86 %**
3	21.67 %	91.53 %	**48.81 %**
4	84.69 %	61.12 %	**75.52 %**
5	5.78 %	82.53 %	**67.41 %**
6	99.33 %	51.22 %	**80.63 %**
7	99.68 %	90.43 %	**96.08 %**
8	99.97 %	91.53 %	**96.68 %**
9	88.98 %	95.69 %	**91.58 %**
10	78.67 %	55.98 %	**69.85 %**



Conclusion and future work

- Features detection in 3D space: trajectory curvatures; hand orientation.
- Trajectory Classification by Curvature, Hand Orientation;
- Entropy as Confidence Level to give weights for each type of classificaton for fuse them.
- Automated system for 3D hand trajectories Segmentation and Classification.
- Database of human grasping movements available at::

Future work

- All these information acquired by segmentation process can be used as initial step before the manipulation in robotics field. These actions can be learned and mapped to a robot perform these human actions.
- Detect and classify Grasping concerning Precision Grip and Power Grip

3D Hand Trajectory Segmentation by Curvatures and Hand Orientation for Classification through a Probabilistic Approach

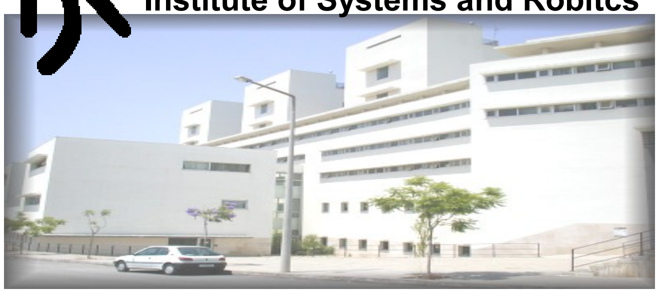
Thank you For your Attention!

Diego Faria, Jorge Dias

ISR – Institute of Systems and Robotics
University of Coimbra, Portugal
diego@isr.uc.pt, jorge@isr.uc.pt

FCTUC

Institute of Systems and Robitcs



This work is partially supported by the European project Handle ICT-23-16-40. Diego Faria is supported by Portuguese Foundation for Science and Technology (FCT). Diego Faria and Jorge Dias are with Institute of Systems and Robotics – University of Coimbra – Polo II, 3030-290 Coimbra, Portugal (diego, jorge)@isr.uc.pt.

http://www.paloma.isr.uc.pt

Mobile Robotics Laboratory
Institute of Systems and Robotics
ISR – Coimbra