Virtual Shape Recognition using Leap Motion

EC 520: Digital Image Processing and Communication

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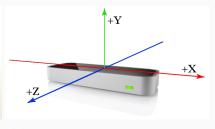
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Problem Statement

To develop a robust algorithm to extend Leap Motion capabilities to recognize hand drawn gestures of various 2D shapes (e.g. circle, ellipse, square, triangle, etc.)



(a) Leap Motion [2]



(b) Coordinates axes of Leap Motion

Data Acquisition

- · Leap Motion SDK Python
- · x,y,z coordinates of the tip of the index finger
- · Store it in .json file

Assumption: The shape is drawn in a plane perpendicular to the Leap Motion (|| to XY plane in Figure:1b) and only using the index finger.

Shape	Data
Circle	50
Rectangle	50
Triangle	50

Table 1: Generated Data

Shapes will not be on a plane \parallel to XY plane of Leap Motion so we find a hypothetical plane z which has the least squared error with the data points provided [4].

$$z = Ax + By + D \tag{1}$$

The coefficients of plane are given by

$$c_{x}=-\frac{A}{D};$$
 $c_{y}=-\frac{B}{D};$ $c_{z}=\frac{1}{D}$

The normal vector of plane is

$$n_p = \left[-\frac{A}{D} - \frac{B}{D} \frac{1}{D} \right] \tag{2}$$

Normal vector to X-Y plane

$$n_{XY} = [001]$$

Rotation Vector (u):

$$u = \frac{n_p}{\mid n_p \mid} \times n_{XY} \tag{3}$$

Rotation angle (θ):

$$\theta = \sin^{-1}(\mid n_p \mid) \tag{4}$$

Using the rotation vector and the angle we calculate rotation matrix R we get the transformed data

$$[x_{new}, y_{new}, z_{new}]^{T} = R[x, y, z]^{T}$$
(5)

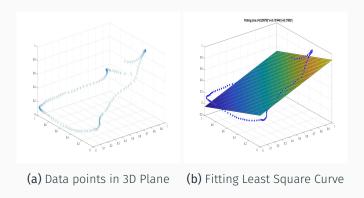


Figure 2: Planner Fitting of 3D points

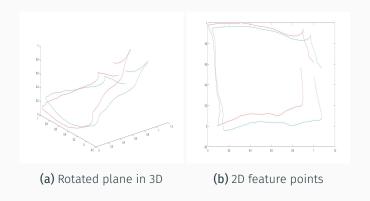


Figure 3: Planner Fitting of 3D points

Feature Extraction: Fourier Descriptor

Fourier Descriptor: We define

$$s[n] = x_n + iy_n$$

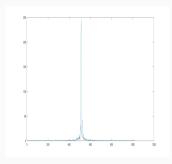
Taking the DFT of s[n]

$$a[k] = \frac{1}{N} \sum_{n=0}^{N-1} s[n] e^{\frac{-j2\pi nk}{N}}$$
 (6)

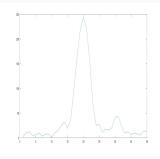
and coefficients can be recovered by

$$s[n] = \sum_{k=0}^{N-1} a[k] e^{\frac{i2\pi nk}{N}}$$
 (7)

Feature Extraction: Fourier Descriptor



(a) Fourier Descriptor: Taking DFT of s[n]



(b) Considering only 40 high energy points

Classification: k-NN

For a Data set $\mathfrak{D}=(\mathbf{x}_1,y_1),\cdots(\mathbf{x}_n,y_n)$ with \mathbf{x} as 20 point feature vector from feature extraction and test point \mathbf{x} Let $(\mathbf{x}_1,y_1),\cdots(\mathbf{x}_n,y_n)$ be reordered such that

$$d(x,x_1) \leq d(x,x_2), \cdots d(x,x_n)$$

where $d(x, x_i)$ can be l_p distance

$$|| x - x_{test} ||_p := (\sum_{i=1}^d |x_i - x_{test}|^p)^{\frac{1}{p}}$$

For our project we are considering the Euclidean distance (l_2)

$$h_{k-NN} = \underset{y=1 \cdot n}{\operatorname{argmax}} \sum_{j=1}^{k} 1(y_{(j)} = y)$$
 (8)

where $1(y_{(i)} = y)$ is the number of k-NNs of **x** with label =y [5]

Classification: k-NN

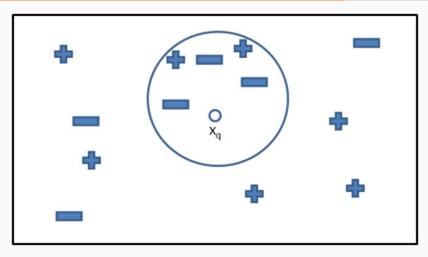


Figure 5: k-NN Example [1]

Classification: k-NN

CCR: 86.67%

	Ground Truth			
ict	10	0	0	
red	0	9	3	
Ь	0	1	7	

Table 2: 80:20 Split

CCR: 88.33%

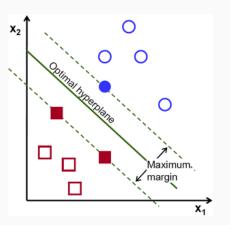
	Ground Truth			
ict	19	1	1	
red	1	18	3	
Ы	0	1	16	

Table 3: 60:40 Split

Classification: SVM

For multiclass classification we extend binary SVM, using One v/s All (OVA) or One v/s One (OVO) approach.

Figure 6: SVM Example [3]



Classification: SVM

One v/s One:

CCR: 73.33%

	Ground Truth			
ict	8	0	0	
redi	2	10	6	
ď	0	0	4	

Table 4: C=16, σ 16

CCR: 90%

	Ground Truth		
ict	10	0	0
red	0	9	2
Ы	0	1	8

Table 5: C=16, σ 32

One v/s All:

- Mean CCR = 71.11% (C = 2, σ = 16)
- Mean CCR = 88.9% (C = 2, σ = 32)

Thank You

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