Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

HAPTIC RECOGNITION BASED ON DEEP LEARNING

BY: DONG HAN

TAMS

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Outline

- Motivation
- Haptic Dataset
- Haptic data preprocessing
- Haptic recognition network
- Evaluation
- References

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

- Motivation
- Haptic Dataset
- Haptic data preprocessing
- Haptic recognition network
- Evaluation
- References

◆An intelligent robot should be able to get the unknown environment information by itself.

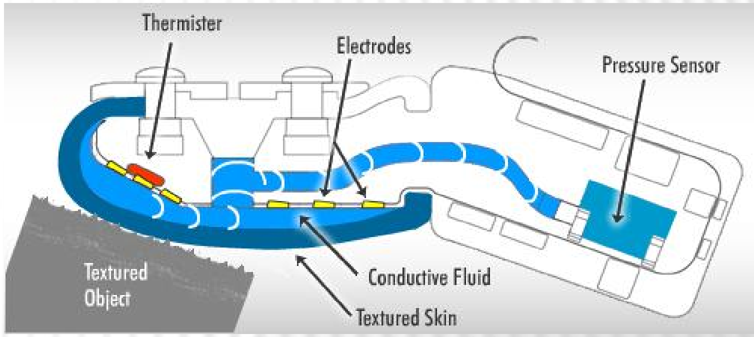
◆Vision is not everything: dark, dusty, or blurry underwater environments, transparent and reflective objects

◆Haptic percption based on multi-model haptic data from Biotac sensor.

- Motivation
- Haptic Dataset
- Haptic data preprocessing
- Haptic recognition network
- Evaluation
- References

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

◆ Biotac sensor: a multi-functional finger sensor that can measure force. temperature and vibration.



Output signals:

◆ PDC signal: pressure

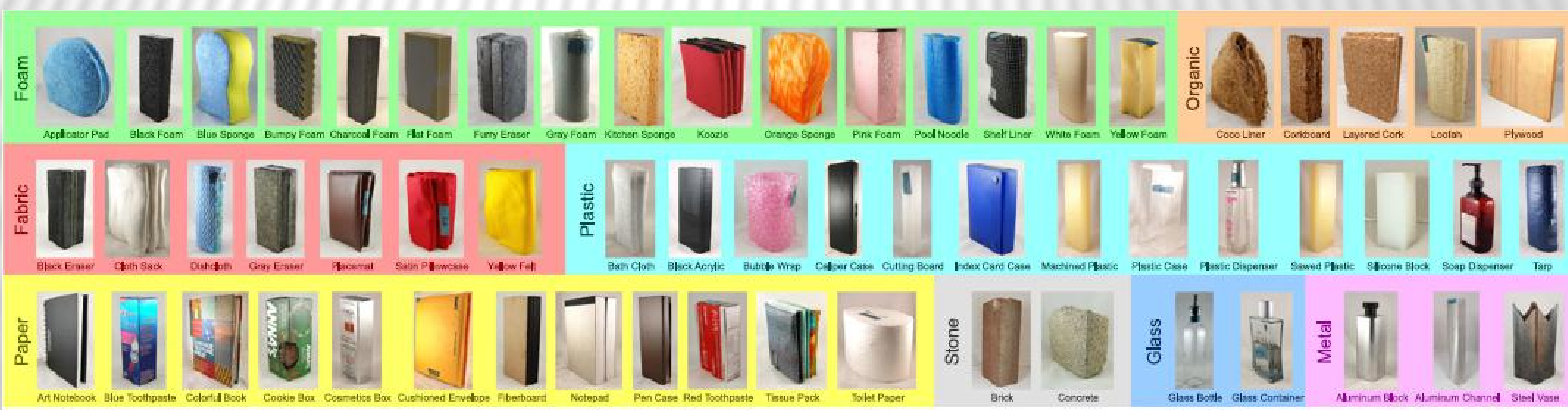
◆ PAC signal: vibration

◆ TDC signal: absolute temperature

◆ TAC signal: temperature change rate

◆ Electrode signals； shape, position, three dimentional force

- Penn Haptic Adjective Corpus 2 (PHAC-2) created by GRASP Laboratory of University of Pennsylvania.
- The haptic data is measured by 2 Biotac sensors
- 60 objects are classified into 8 groups according to their materials.
- The toal data is 60-objects × 2-fingers × 10-trials =1200



There are 4 exploratory procedures in each trial for getting multi-model haptic signals:

- **Squeeze**: squeeze objects at a constant velocity to a specific Pdc value. → Hardness
- **Hold**: hold objects for ten seconds → Thermal
- **Slow Slide**: use a stronger contact with a downward speed of 1 cm/s
- **Fast Slide**: use a lighter contact with a speed of 2.5 cm/s

→ Roughness, Texture

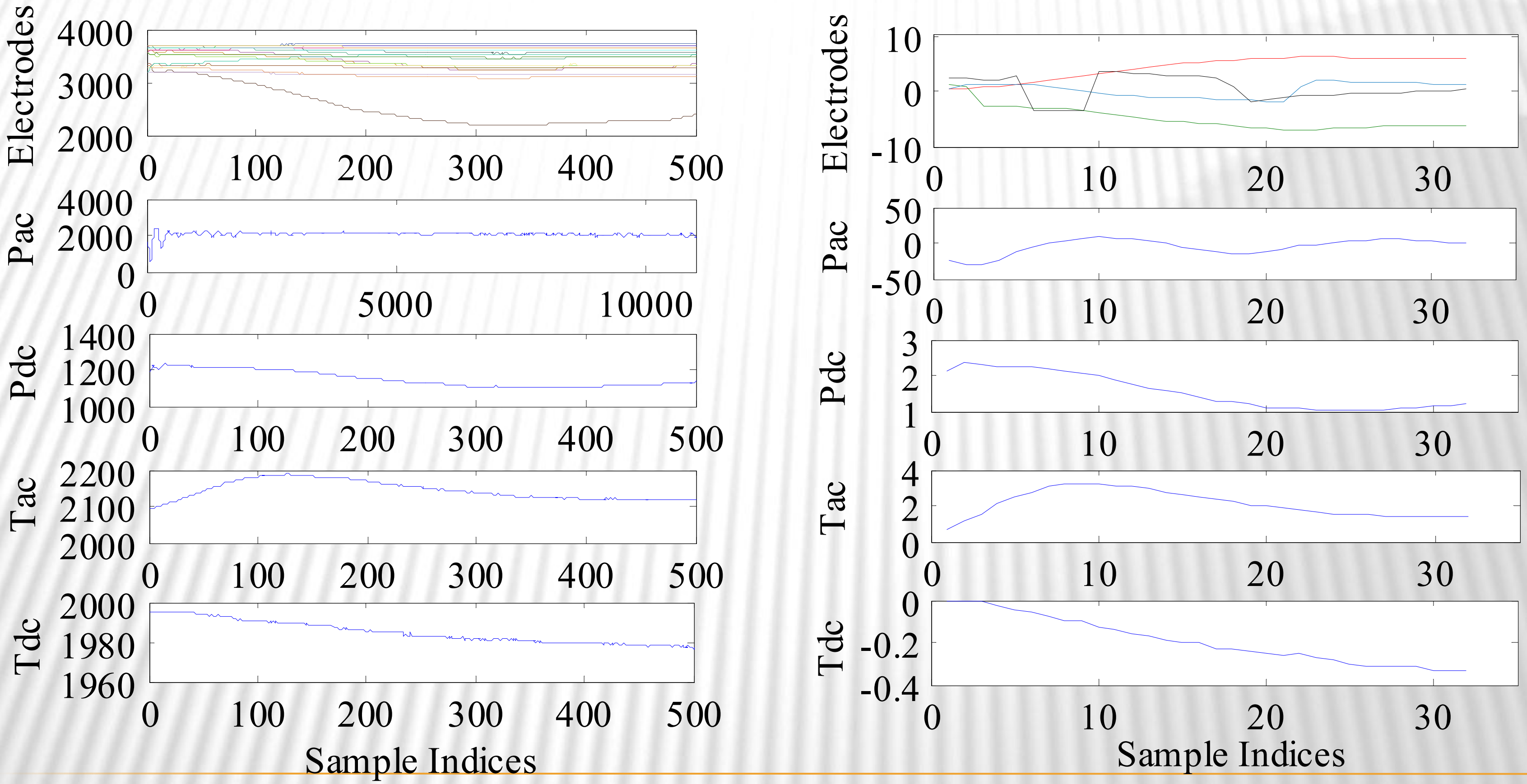
- Motivation
- Haptic Dataset
- **Haptic data preprocessing**
- Haptic recognition network
- Evaluation
- References

- Labels
  - Hardness: 6
  - Thermal conductivity: 6
  - Roughness: 4;
  - Texture: 3
  - Objects: 6

Objects	Organic	Plastic	Paper	Fabric	Foam	Metal
Labels	0	1	2	3	4	5

56 objects

- Normalization
- PCA on Electrode Impedances: 19 dimensions ⇒ 4 dimensions
- Subsampling/Compression
- Haptic data Augmentation: 56-objects × 2-fingers × 10-trials × 5 times =5600



Results of preprocessing

- Train/Test Splits: 46 objects for trainning, the other 10 objects for testing
- The number of each class in Test set is decided by the proportion of this class in the total objects.

Test set

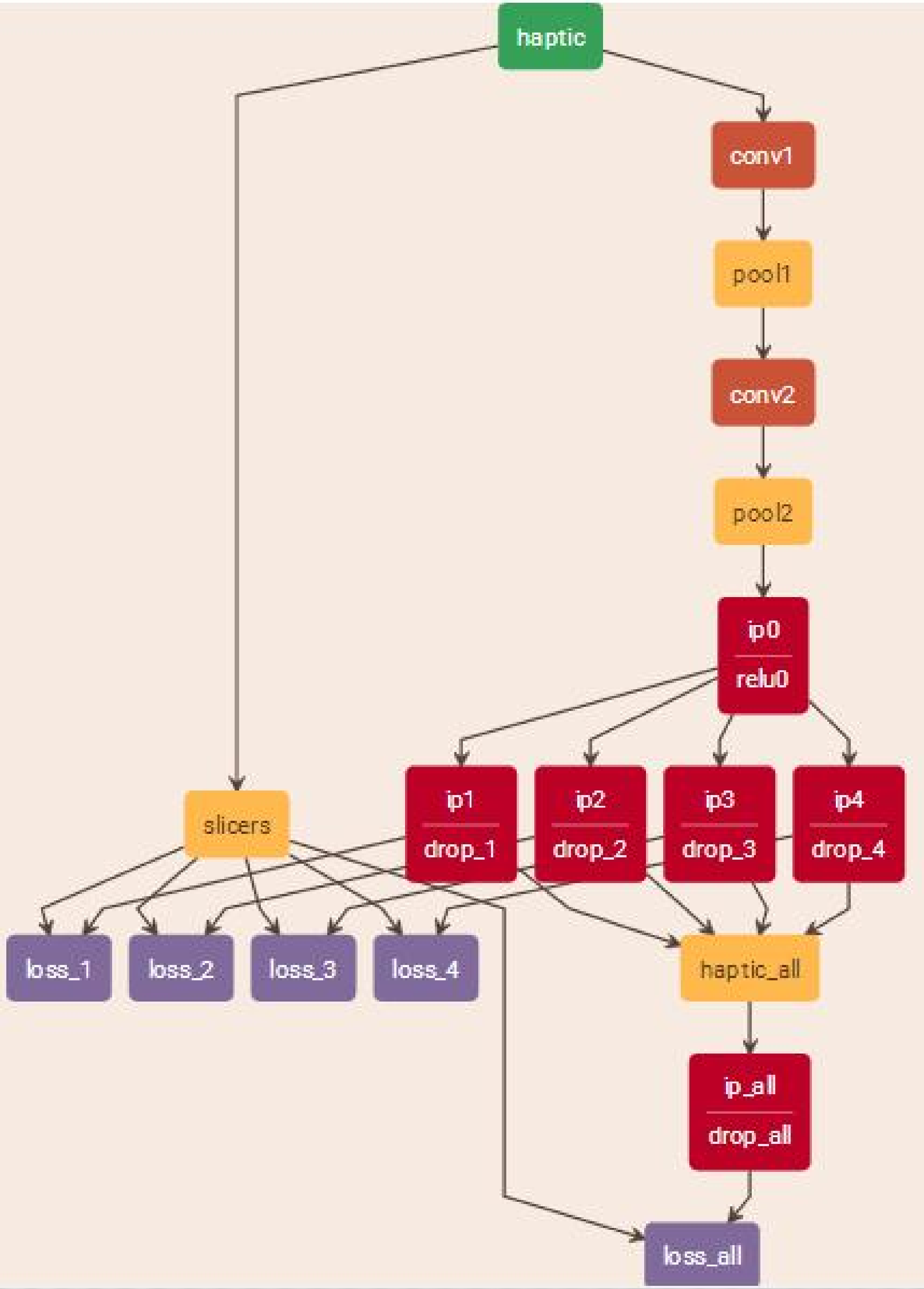
Class Number	Class Name	Object Name
0	Organic	Layered Cork
1	Plastic	Plastic Case
		Sawed Plastic
2	Paper	Colorful Book
		Cookie Box
3	Fabric	Dishcloth
4	Foam	Blue Sponge
		Gray Foam
		Orange Sponge
5	Metal	Aluminum Channel

- All of the processed haptic data and labels are stored in HDF5 files

- Motivation
- Haptic Dataset
- Haptic data preprocessing
- **Haptic recognition network**
- Evaluation
- References

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

- A open source deep learning framework: **Caffe**
- *slicers* layer
  divide the label matrix into five label vectors: hardness, thermal, roughness, texture, object.
- *haptic_all* layer
  combine the haptic features for recognizing objects
- *drop_1,_2,_3,_4,_all* layer
  dropout is an effective method for solving **overfitting** problem.
- A network for **multi-class** and **multi-label** classification



Network trainning

- **Method:** SGD(stochastic gradient descent)

- **Learning rate:**
  lr = base_lr * (1 + gamma * iter) ^ (-power)
  base_lr = 0.01; gamma =0.0001; power=0.75

- **weight_decay = 0.0005**

- **momentum = 0.0005**

- **batch_size = 1000**

- **max_iter = 600**

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

- Motivation
- Haptic Dataset
- Haptic data preprocessing
- Haptic recognition network
- **Evaluation**
- References

- haptic images

8

Squeeze-PDC×1
Hold-TAC×1
Slow Slide-PAC×1
Fast Slide-PAC×1
Squeeze-Electrode×4

8×32

16

Squeeze-PDC×1
Hold-PDC×1
Squeeze-TAC×1
Hold-TAC×1
Squeeze-TDC×1
Hold-TDC×1
Slow Slide-PAC×1
Fast Slide-PAC×1
Squeeze-Electrode×4
Hold-Electrode×4

16×32

32

Squeeze-PAC×1 ; PDC×1 ; TAC×1 ; TDC×1
Hold-PAC×1 ; PDC×1 ; TAC×1 ; TDC×1
Slow Slide-PAC×1 ; PDC×1 ; TAC×1 ; TDC×1
Fast Slide-PAC×1 ; PDC×1 ; TAC×1 ; TDC×1
Squeeze-Electrode×4
Hold-Electrode×4
Slow Slide-Electrode×4
Fast Slide-Electrode×4

32×32; 32×16; 32×8

(PAC+PDC+TAC+TDC+4×Electrode)×4 = 32

Test results for different haptic images

	8×32	16×32	32×32	32×16	32×8
Hardness	58.6	58.8	73.7	55.9	57.0
Thermal Conductivity	62.6	63.5	67.7	68.3	67.0
Roughness	53.8	68.3	69.9	68.9	69.4
Texture	53.5	68.8	77.5	75.6	67.4
Object Recognition	60.5	69.0	74.8	67.6	67.2
Average	**57.8**	**65.7**	**72.7**	**67.3**	**65.6**

- F1-sore is used to evaluate the performance of haptic network
- More haptic imformation can have better performance on haptic recognition if there are enough training data.

	organic	plastic	paper	fabric	foam	metal
organic	0.0	5.0	95.0	0.0	0.0	0.0
plastic	0.0	100	0.0	0.0	0.0	0.0
paper	5.0	22.0	73.0	0.0	0.0	0.0
fabric	0.0	3.0	5.0	45.0	47.0	0.0
foam	0.0	0.0	0.0	0.0	100	0.0
metal	0.0	0.0	0.0	0.0	0.0	100

32×32

	organic	plastic	paper	fabric	foam	metal
organic	5.0	0.0	95.0	0.0	0.0	0.0
plastic	0.0	100	0.0	0.0	0.0	0.0
paper	2.5	30.5	67.0	0.0	0.0	0.0
fabric	0.0	0.0	0.0	5.0	95.0	0.0
foam	0.0	0.0	0.0	0.0	100	0.0
metal	0.0	0.0	0.0	0.0	0.0	100

32×16

	organic	plastic	paper	fabric	foam	metal
organic	10.0	0.0	75.0	15.0	0.0	0.0
plastic	8.5	82.5	9.0	0.0	0.0	0.0
paper	2.5	30.5	67.0	0.0	0.0	0.0
fabric	0.0	11.0	10.0	9.0	70.0	0.0
foam	0.0	0.0	0.0	0.0	100	0.0
metal	0.0	0.0	0.0	0.0	0.0	100

32×8

	organic	plastic	paper	fabric	foam	metal
organic	0.0	0.0	100.0	0.0	0.0	0.0
plastic	0.0	99.5	0.0	0.0	0.0	0.5
paper	0	46.0	54.0	0.0	0.0	0.0
fabric	0.0	3.0	12.0	0.0	85.0	0.0
foam	0.0	0.0	0.0	13.3	86.7	0.0
metal	0.0	0.0	0.0	0.0	0.0	100

8×32

	organic	plastic	paper	fabric	foam	metal
organic	30.0	9.0	60.0	0.0	1.0	0.0
plastic	0.0	92.5	2.5	0.0	0.0	5.0
paper	0.0	35.0	65.0	0.0	0.0	0.0
fabric	0.0	28.0	21.0	11.0	40.0	0.0
foam	0.0	0.0	0.0	13.3	86.7	0.0
metal	0.0	0.0	0.0	0.0	0.0	100

16×32

	organic	plastic	paper	fabric	foam	metal
organic	0.0	5.0	95.0	0.0	0.0	0.0
plastic	0.0	100	0.0	0.0	0.0	0.0
paper	5.0	22.0	73.0	0.0	0.0	0.0
fabric	0.0	3.0	5.0	45.0	47.0	0.0
foam	0.0	0.0	0.0	0.0	100	0.0
metal	0.0	0.0	0.0	0.0	0.0	100

- Organic objects are easily mistaken for paper objects
- Fabric objects are easily mistaken for foam objects

- Objects in organic class and in fabric class have a small number.

- The organic object in test set is similar with some paper objects (layered cork &fiber board); The fabric object in test set is similar with some foam objects (dishcloth&shelf liner)

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

	Roughness			Texture			Object Recognition		
PAC	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
	68.8	67.3	67.4	62.1	61.8	61.4	64.5	67.5	64.2

	Hardness			Object Recognition		
PDC	Precision	Recall	F1-score	Precision	Recall	F1-score
	48.6	51.1	46.9	50.2	55.1	51.4

	Hardness			Object Recognition		
Electrode	Precision	Recall	F1-score	Precision	Recall	F1-score
	51.5	51.1	45.6	68.2	71.9	64.5

	Thermal Conductivity			Object Recognition		
TDC	Precision	Recall	F1-score	Precision	Recall	F1-score
	52.5	61.7	56.4	64.6	63.3	59.3

	Thermal Conductivity			Object Recognition		
TAC	Precision	Recall	F1-score	Precision	Recall	F1-score
	64.0	66.4	64.0	68.3	69.5	68.6

- **For object recognition**
  - The F1-score of TAC signals is the highest, because the objects are classified according to materials
  - The f1-score of PDC signal is smallest, because the objects in one class also have different hardness
- **For feature extraction**
  - TAC signals have a better performance on getting thermal conductivity than TDC signals
  - PDC signals have better performance on hardness recognition than Electrode signals

---

- **The performance of multi-model signal fusion is better than that of single signals**

How can we further improve the performance of haptic recognition.

- use a more complex deep learning network

- increase training data

- provide more reasonable labels for each haptic feature and object

- Motivation
- Haptic Dataset
- Haptic data preprocessing
- Haptic recognition network
- Evaluation
- **References**

Main References

- Gao, Yang, et al. "Deep Learning for Tactile Understanding From Visual and Haptic Data." Computer Science (2015).

- Chu, Vivian, et al. "Robotic learning of haptic adjectives through physical interaction." Robotics & Autonomous Systems 63.P3(2015):279-292.

- Chu, V, et al. "Using robotic exploratory procedures to learn the meaning of haptic adjectives." IEEE International Conference on Robotics and Automation IEEE, 2013:3048-3055.

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Questions? or Suggestions?