

## Introduction

### Background

➤ **Gait** is biometrics at a distance.

### Applications:

- Criminal investigation
- Surveillance
- Access control

### Challenges

➤ Intra-class appearance changes

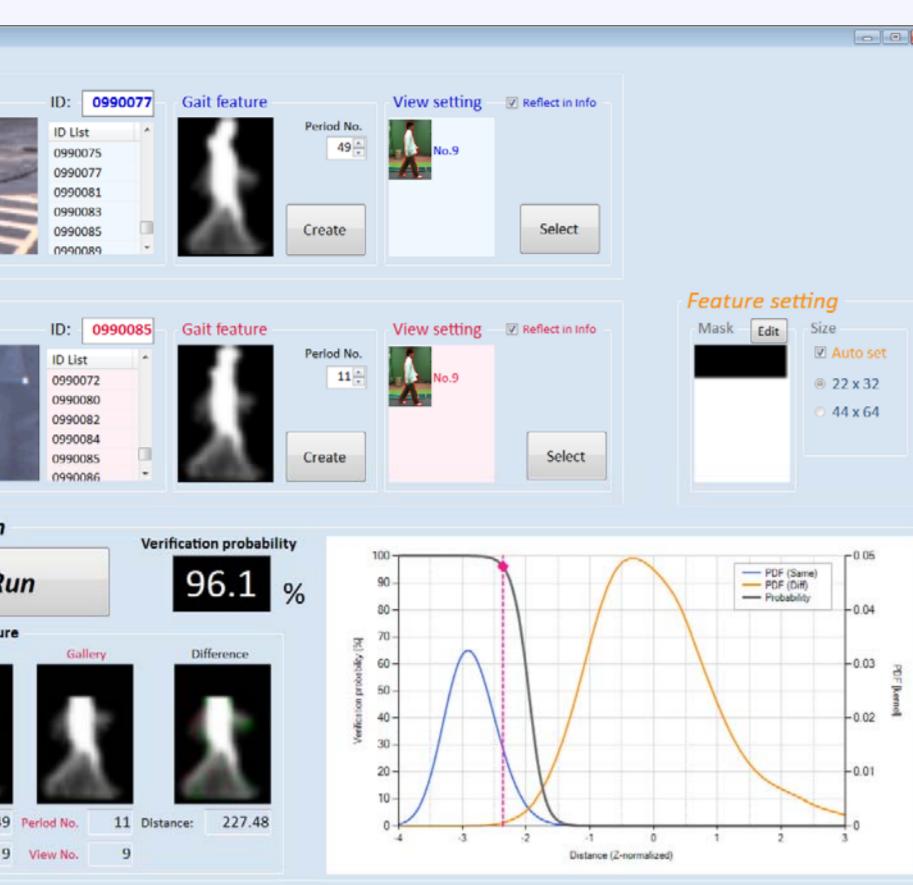
$l_1$ -norm with gait energy image (GEI) [Han+ 2006]



Probe  
(w/ bag)



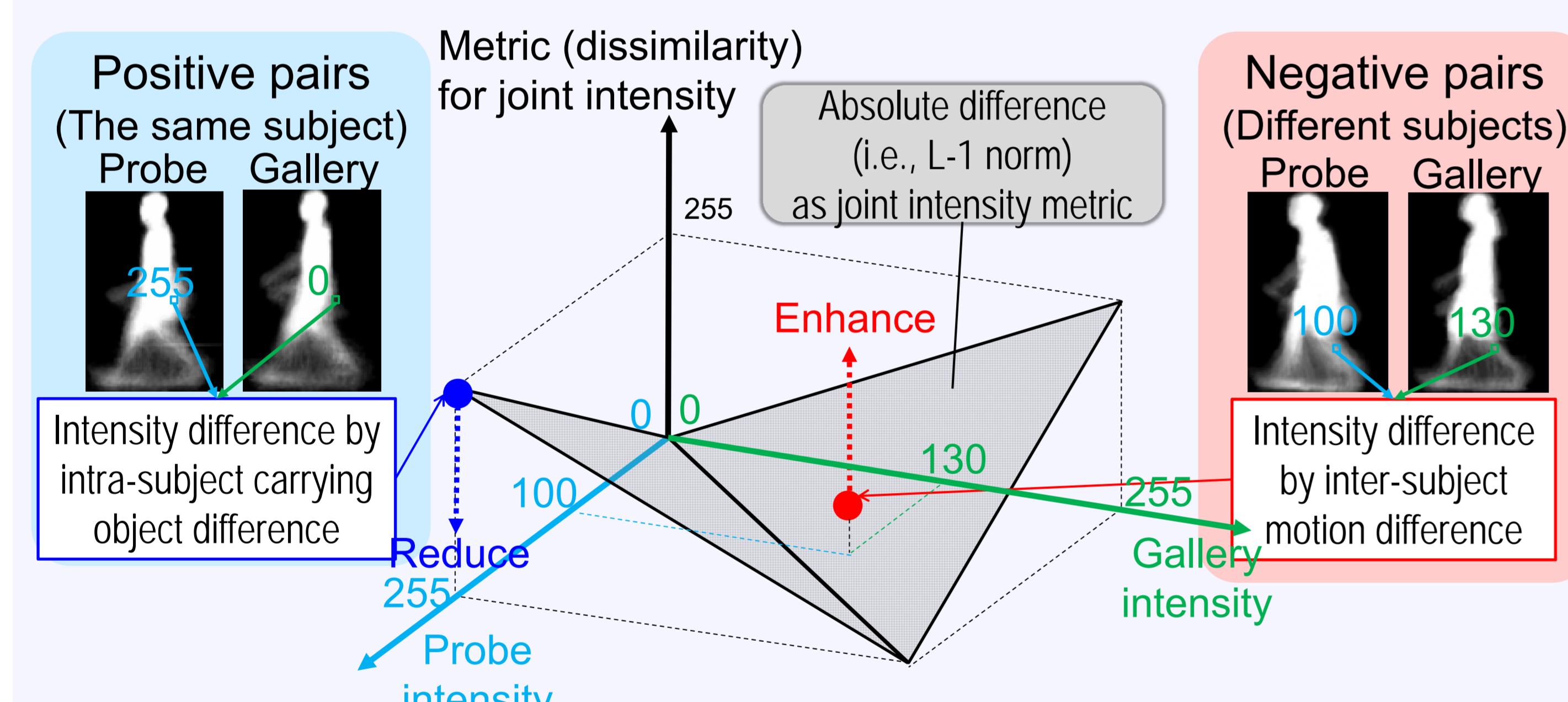
True match gallery  
(w/o bag)



Gait verification system  
[Iwama+ 2013]

### Key idea

➤ Learn a metric for joint intensity for better discrimination



### Related work

➤ Spatial metrics

- Support vector machine (SVM)
- Mahalanobis distance

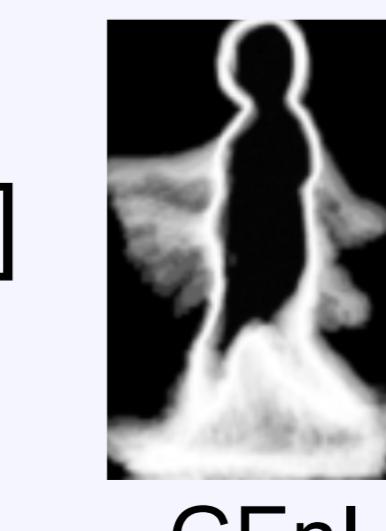
$$d(\mathbf{v}^P, \mathbf{v}^G; \mathbf{w}_S) = \sum_{i=1}^{N_S} w_{S,i} |v_i^P - v_i^G|$$

$$d(\mathbf{v}^P, \mathbf{v}^G; M) = (\mathbf{v}^P - \mathbf{v}^G)^T M (\mathbf{v}^P - \mathbf{v}^G)$$

✓ Subtraction form, monotonic increase

➤ Intensity metrics

- Gait entropy image (GEI) [Bashir+ 2009]
- Masked GEI [Bashir+ 2010]
- Gait energy response function [Li+ 2016]



## Joint intensity and spatial metric learning

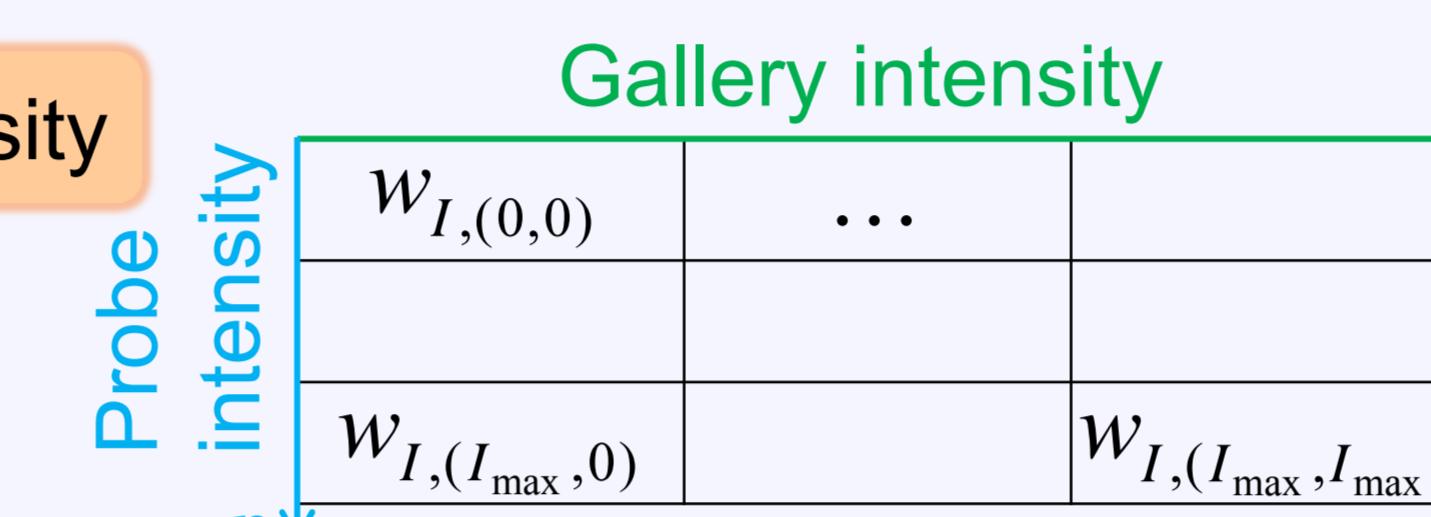
### Representation of dissimilarity measure

$$D(\mathbf{v}^P, \mathbf{v}^G; \mathbf{w}_S, \eta) = \sum_{i=1}^{N_S} w_{S,i} \eta(v_i^P, v_i^G)$$

Spatial weight

Dissimilarity metric for joint intensity  
(e.g.,  $\eta(p, q) = |p - q|$  for  $l_1$ -norm)

$$\eta(p, q) = \mathbf{x}_{(p,g)}^T \mathbf{w}_I$$



Joint intensity metric

Indicator vector

$$\mathbf{w}_I = [w_{I,(0,0)}, \dots, w_{I,(0,I_{\max})}, \dots, w_{I,(I_{\max},0)}, \dots, w_{I,(I_{\max},I_{\max})}]^T$$

$$\mathbf{x}_{(p,g)} = [\delta_{p,0} \delta_{g,0}, \dots, \delta_{p,0} \delta_{g,I_{\max}}, \dots, \delta_{p,I_{\max}} \delta_{g,0}, \dots, \delta_{p,I_{\max}} \delta_{g,I_{\max}}]^T$$

➤ Dissimilarity measure as bilinear form

$$D(\mathbf{v}^P, \mathbf{v}^G; \mathbf{w}_S, \mathbf{w}_I) = \sum_{i=1}^{N_S} \sum_{j=1}^{N_I} w_{S,i} w_{I,j} x_{(v_i^P, v_i^G), j} = \mathbf{w}_S^T \mathbf{X}_{(\mathbf{v}^P, \mathbf{v}^G)} \mathbf{w}_I$$

### Metric learning

➤ Linear SVM

$$J(\mathbf{w}_S, \mathbf{w}_I) = \frac{1}{2} \|\mathbf{w}_S\|^2 + \frac{1}{2} \|\mathbf{w}_I\|^2 + C \sum_{(\mathbf{v}^P, \mathbf{v}^G, t) \in S} l(\mathbf{w}_S^T \mathbf{X}_{(\mathbf{v}^P, \mathbf{v}^G)} \mathbf{w}_I + b, t)$$

Hinge loss function

➤ Alternate optimization

$$J_I(\mathbf{w}_I) = \frac{1}{2} \|\mathbf{w}_I\|^2 + C \sum_{(\mathbf{v}^P, \mathbf{v}^G, t) \in S} l(\mathbf{h}_{(\mathbf{v}^P, \mathbf{v}^G)}^T \mathbf{w}_I + b, t) \rightarrow \min$$

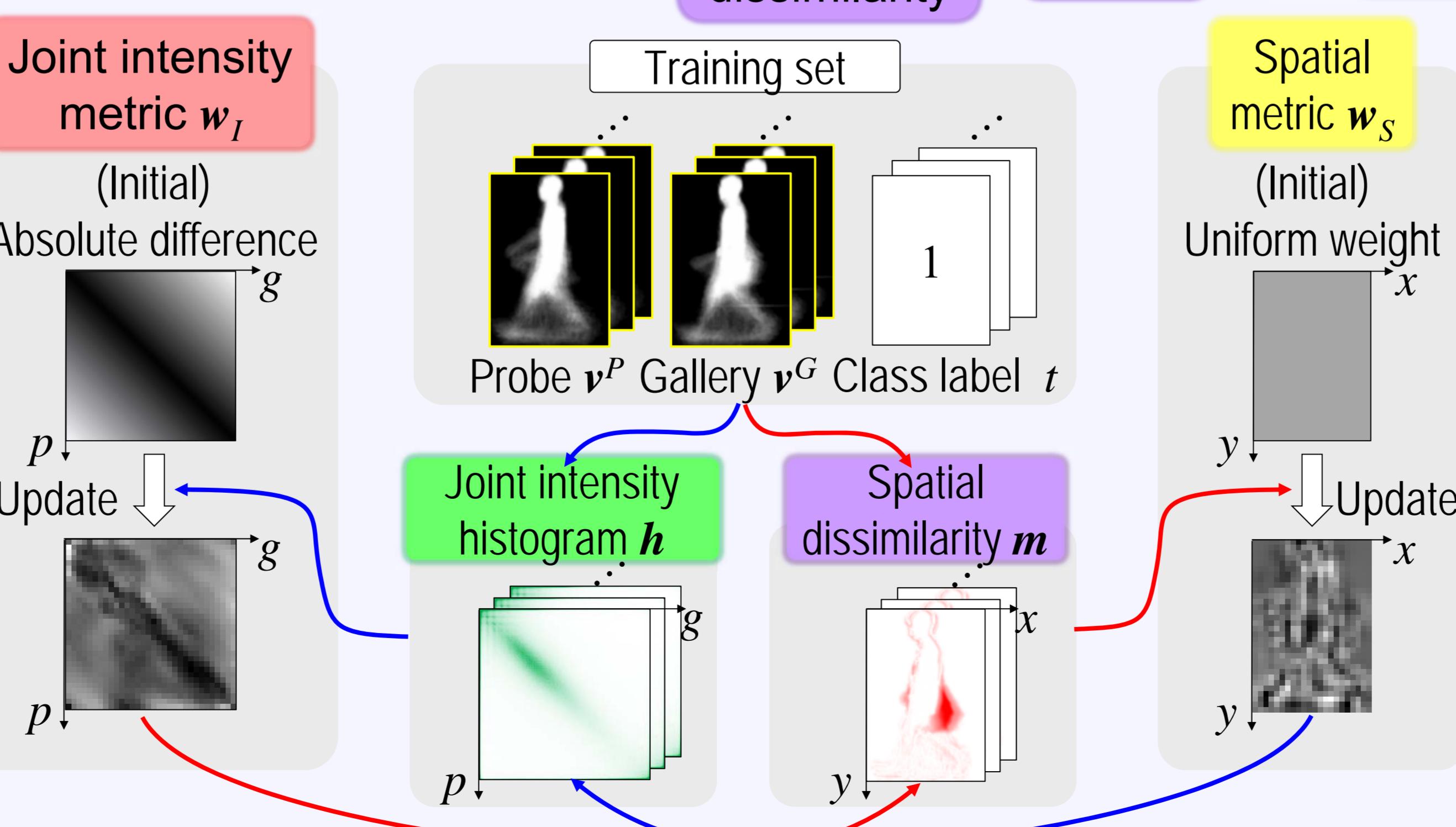
Joint intensity histogram

$$\mathbf{h}_{(\mathbf{v}^P, \mathbf{v}^G)} = \mathbf{X}_{(\mathbf{v}^P, \mathbf{v}^G)}^T \mathbf{w}_S$$

$$J(\mathbf{w}_S) = \frac{1}{2} \|\mathbf{w}_S\|^2 + C \sum_{(\mathbf{v}^P, \mathbf{v}^G, t) \in S} l(\mathbf{m}_{(\mathbf{v}^P, \mathbf{v}^G)}^T \mathbf{w}_S + b, t) \rightarrow \min$$

Spatial dissimilarity

$$\mathbf{m}_{(\mathbf{v}^P, \mathbf{v}^G)} = \mathbf{w}_I^T \mathbf{X}_{(\mathbf{v}^P, \mathbf{v}^G)}^T$$



## Experiments

### Data sets

➤ OUTD-B [Makihara+ 2012]

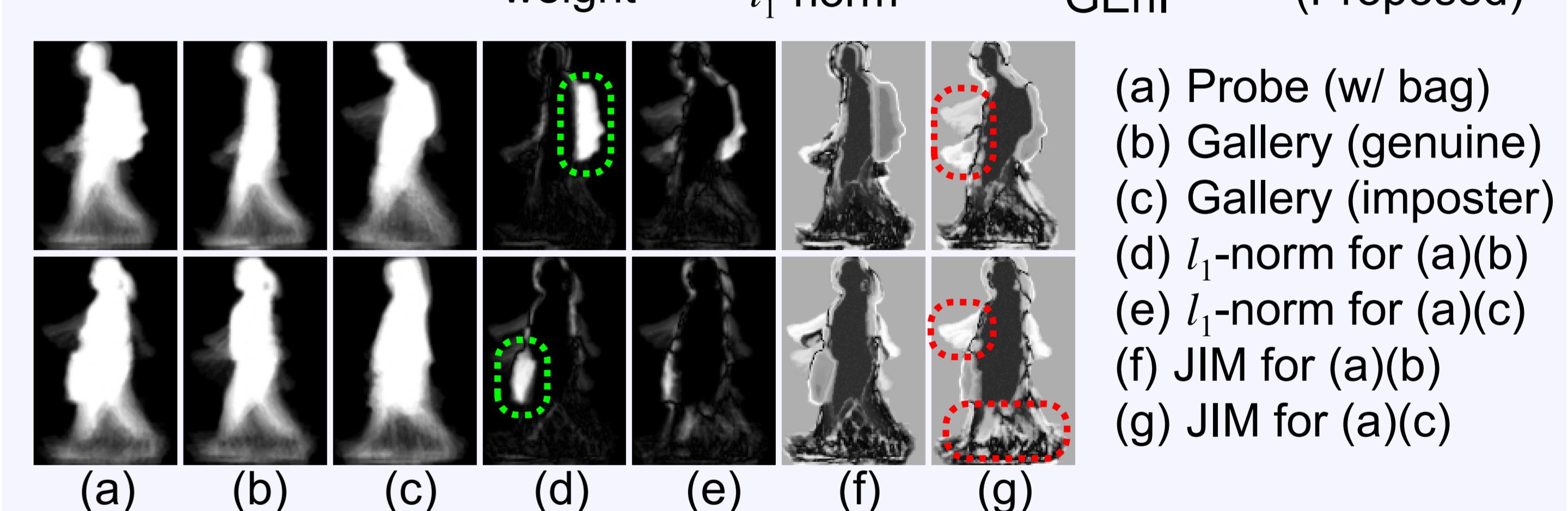
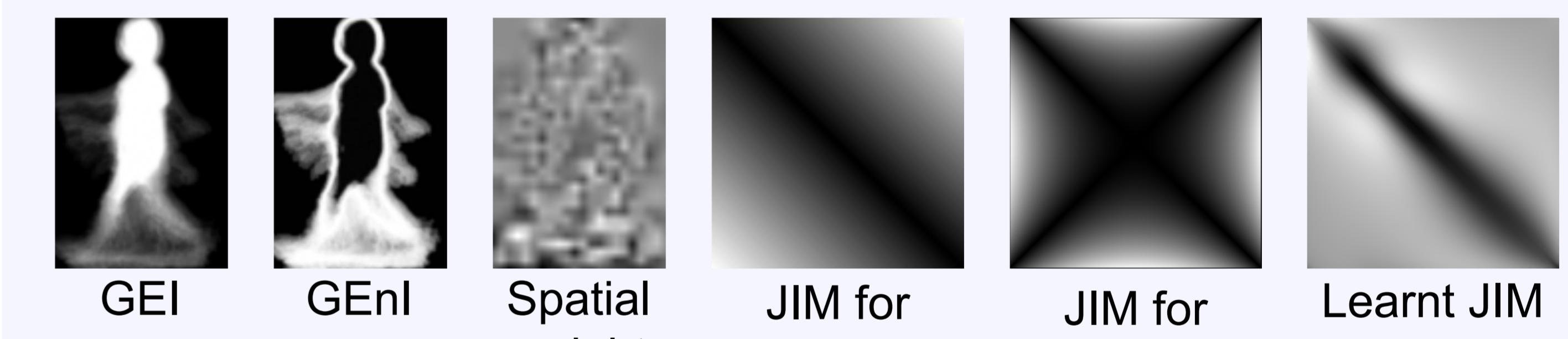
- #Clothes variations: 32
- #Subjects: 68  
(20 for training, 48 for test)

➤ OULP-Bag- $\beta$

- Data collection in long-run exhibition [Makihara+ 2016]
- Carrying status variation in the wild
- #Subjects: 2,070 (1,034 for training, 1,036 for test)

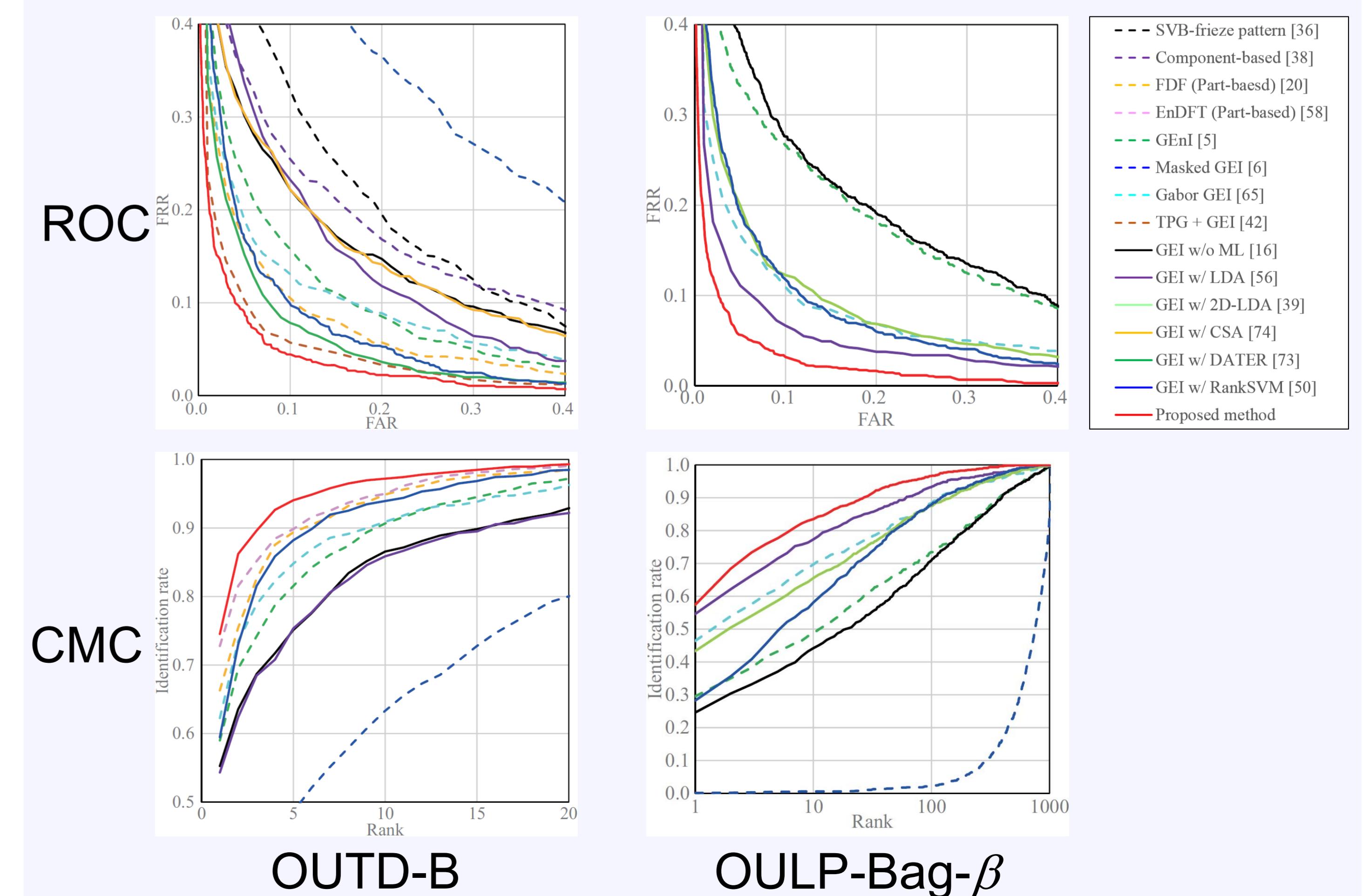


### Learnt metrics and matching examples (OULP-Bag- $\beta$ )



(a) Probe (w/ bag)  
(b) Gallery (genuine)  
(c) Gallery (impostor)  
(d)  $l_1$ -norm for (a)(b)  
(e)  $l_1$ -norm for (a)(c)  
(f) JIM for (a)(b)  
(g) JIM for (a)(c)

### Comparison with state-of-the-art



Available at: