The Influence of Segmentation On Individual Gait Recognition

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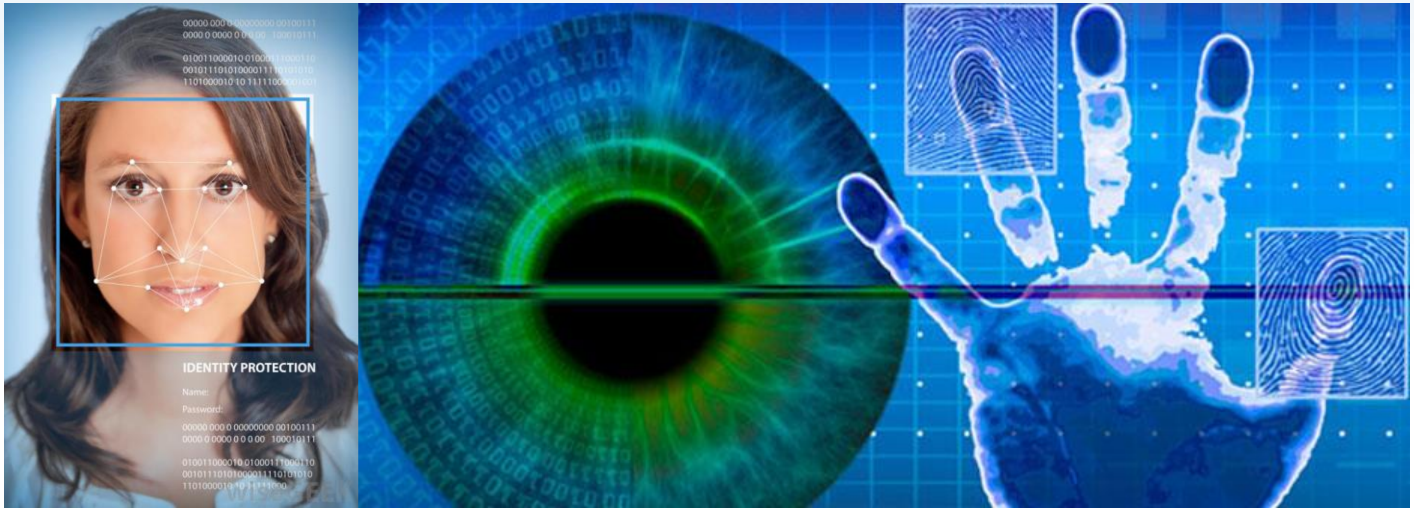
OVERVIEW

- PROBLEM STATEMENT
- GAIT BASELINE ALGORITHM
- DATASET PREPARATION
- EXPERIMENT DESIGN
- RESULT AND ANALYSIS
- CONCLUSION

PROBLEM STATEMENT

Gait as biometric trait:

- Pros: Acquired from a distance
- Cons: Not as reliable as face, iris, fingerprint, etc.



PROBLEM STATEMENT

Factors hinder the performance of gait recognition algorithms:

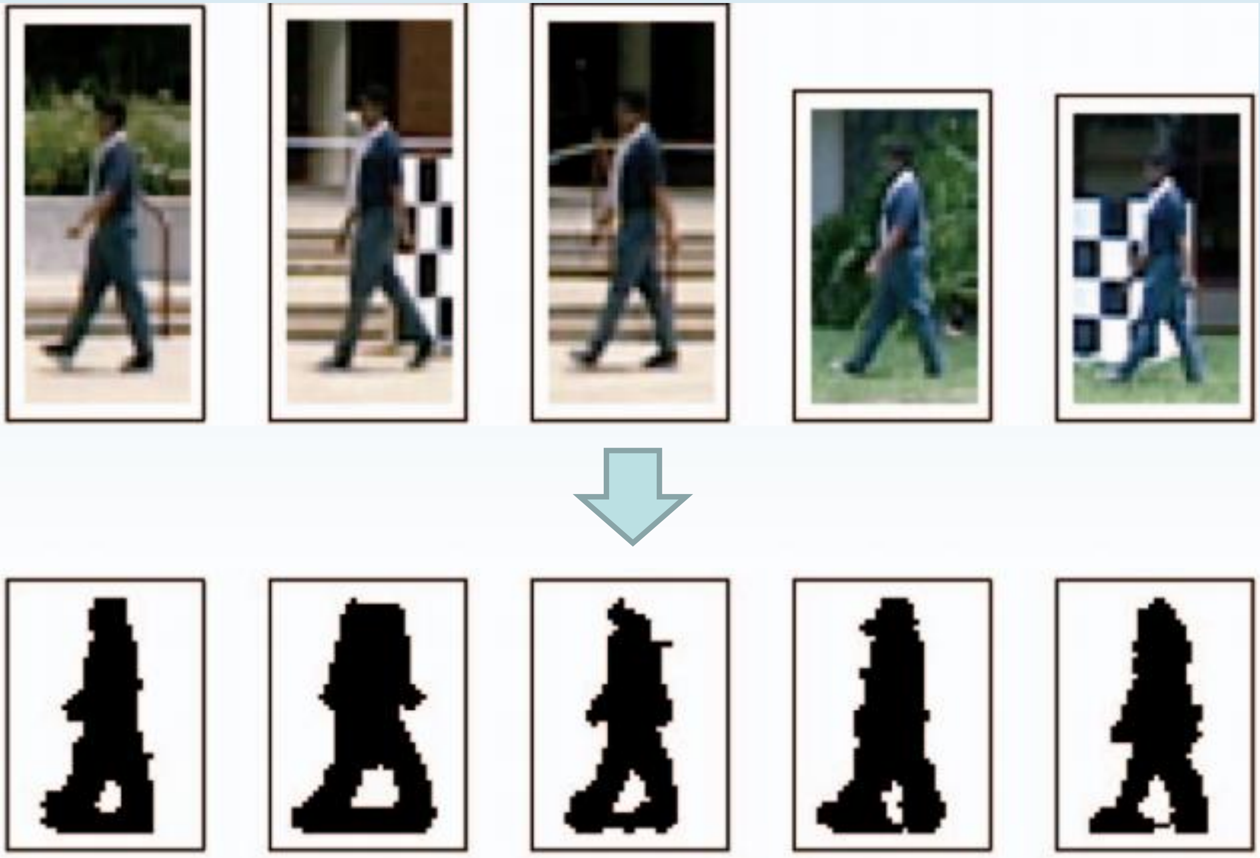
- age, clothes, walking surfaces, viewing angles, health condition, segmentation error

THE BASELINE ALGORITHM

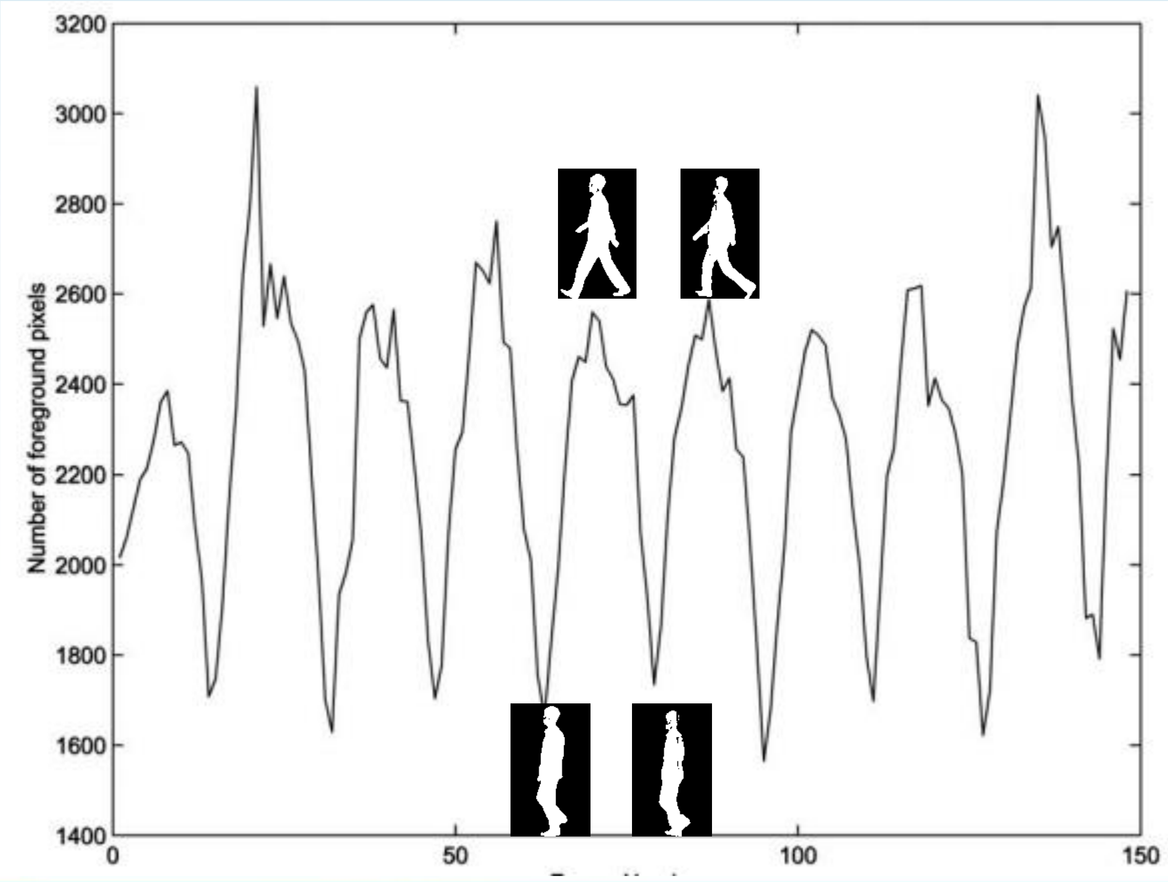
Silhouette Extraction → Gait Period Detection → Similarity Computation

S.Sarkar, et.al., ‘The HumanID Gait Challenge Problem: Data Sets, Performance and Analysis’ , *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 27, no.2, pp. 162 – 177, Feb. 2005.

SILHOUETTE EXTRACTION



GAIT PERIOD DETECTION



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SIMILARITY COMPUTATION

- Similarity Score $Sim(P_i, G_i)$ between probe P_i and the full gallery set $\{G_1, \dots, G_n\}$: ($s.d.$ Is the standard deviation)

$$Sim(P_i, G_i) = \frac{Sim(P_i, G_i) - Mean_j Sim(P_i, G_i)}{s.d._j \, Sim(P_i, G_i)}$$

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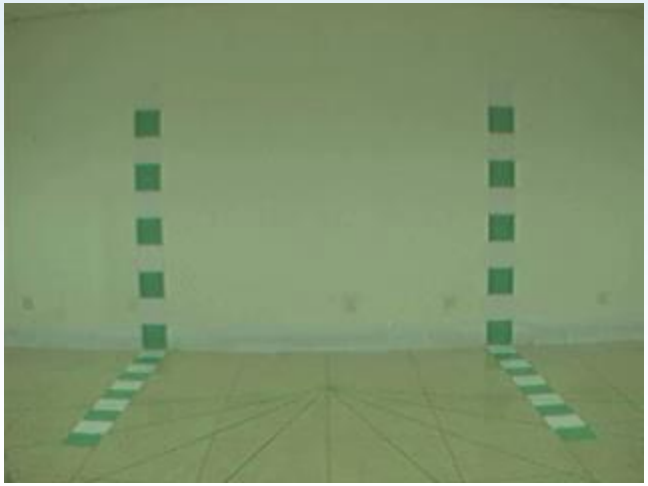
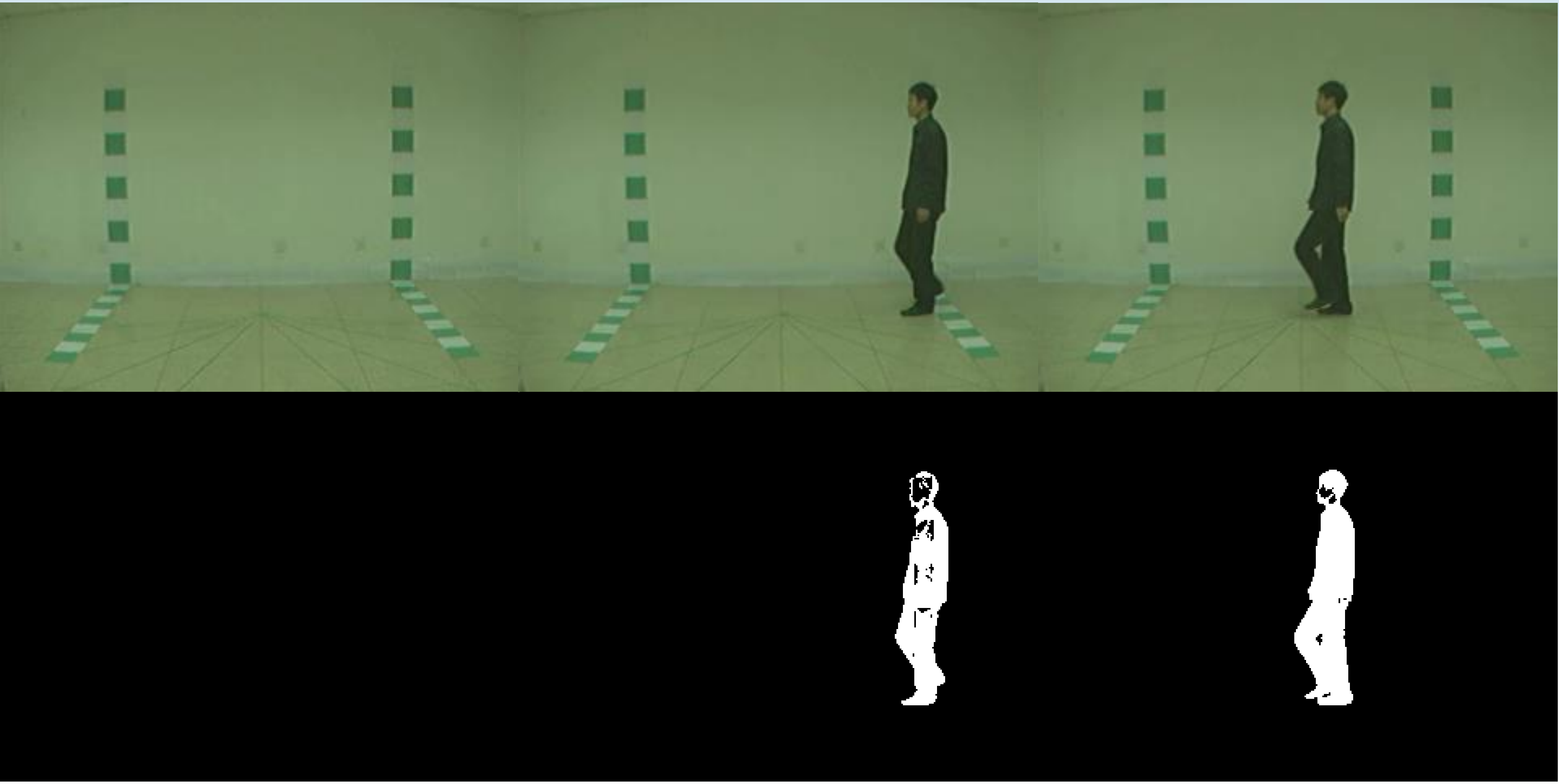
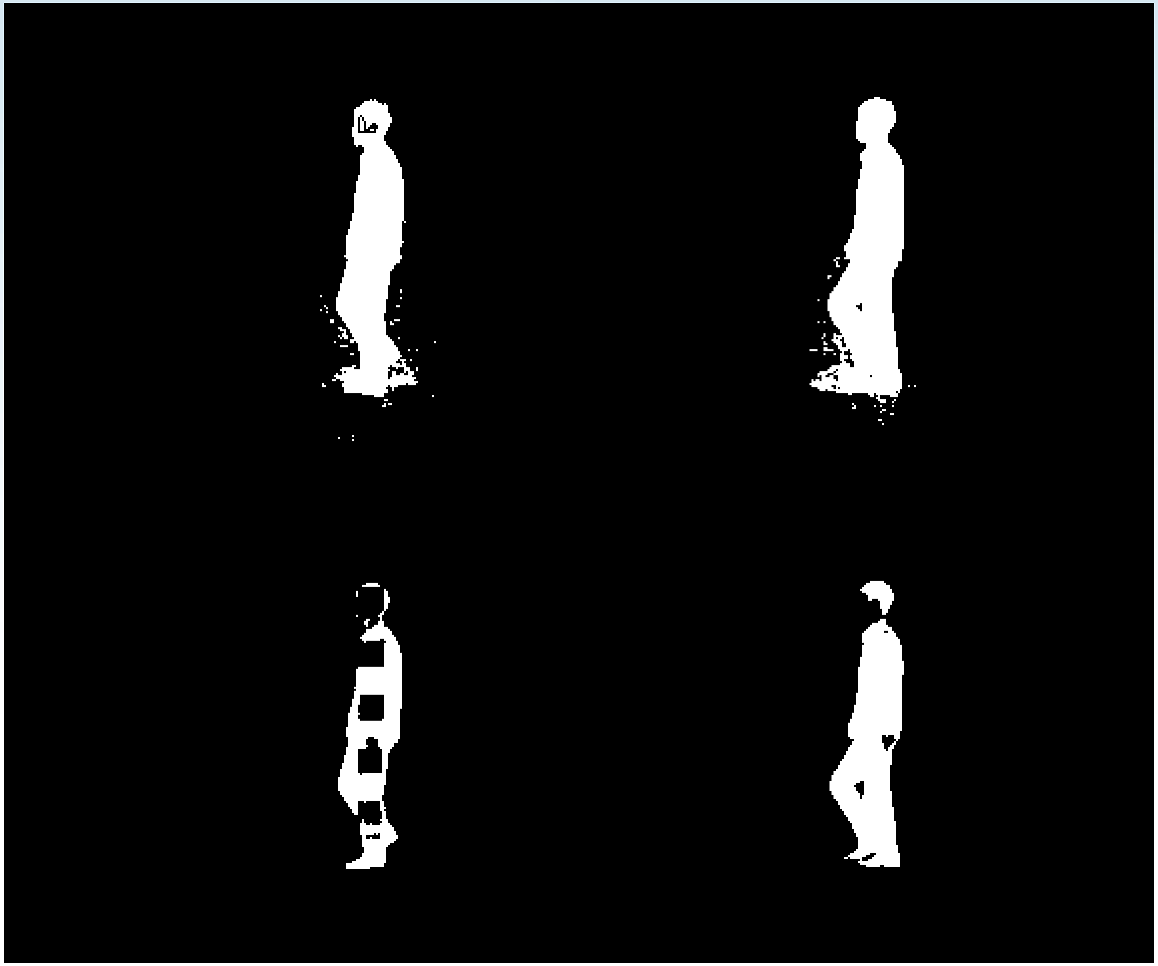
DEMO: BACKGROUND SUBTRACTION



DEMO: BACKGROUND SUBTRACTION



DEMO: SEGMENTATION ERROR



METHODOLOGY

- Template: Gait Energy Image (GEI)
- Singularity: Principle Component Analysis
- Discriminant Learning Method: Local Fisher Discriminant Analysis (LFDA)
- Least Square QR Decomposition Based Feature Fusion (LSQR Fusion) + Voting

GEI

- A representation model containing spatial-temporal information for one gait cycle.

$$G = \frac{1}{c}\sum_{k=1}^{c} I_k$$

- G refers to GEI, I_k is the kth silhouette image, where the total number of silhouettes in one gait cycle is denoted as c.
- Reform GEI data matrix into G vector x, as the input of discriminant learning.

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LFDA

- Local within-class and between-class scatter matrices:

$$\tilde{S}^{(w)} = \frac{1}{2}\sum_{i,j=1}^{n} \tilde{W}_{i,j}^{(w)}(x_i - x_j)(x_i - x_j)^\top, \; \tilde{W}_{i,j}^{(w)} = \begin{cases} 1/n_\ell & if y_i = y_j = \ell, \\ 0 & if y_i \neq y_j, \end{cases}$$

$$\tilde{S}^{(b)} = \frac{1}{2}\sum_{i,j=1}^{n} \tilde{W}_{i,j}^{(b)}(x_i - x_j)(x_i - x_j)^\top, \quad \tilde{W}_{i,j}^{(b)} = \begin{cases} 1/n - 1/n_\ell & if y_i = y_j = \ell, \\ 1/n & if y_i \neq y_j. \end{cases}$$

- Transformation matrix

$$W_{LFDA} = \underset{W \in \Re^{d\times r}}{\arg\max} \left[tr\left(\frac{W^\top \tilde{S}^{(w)} W}{W^\top \tilde{S}^{(b)} W}\right) \right]$$

LSQR FUSION

- Calculate weight: $\arg\min_w ||G * w^{\mathsf{T}} - p||$
- The dimension of gallery feature matrix G and probe feature vector p are very small after dimension reduction and subspace learning, thus avoid the computational cost issue during the iteration computation of weight set w.
- Gallery feature fusion: $G_f = \sum_{i=1}^{n} g_i * w_i$

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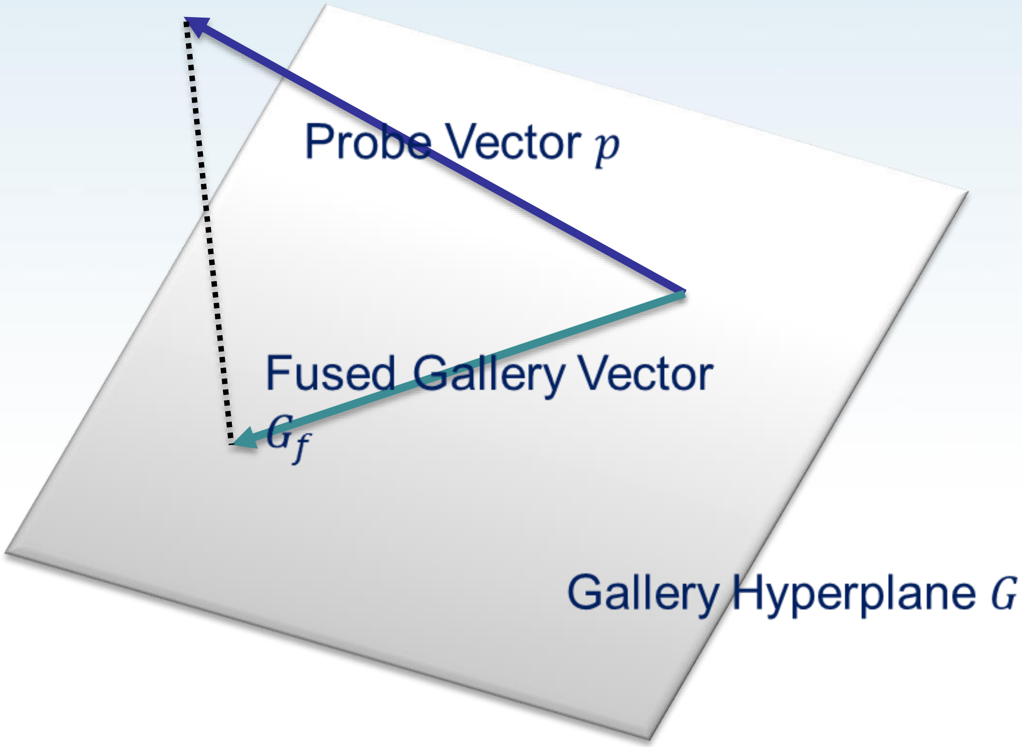
LSQR FUSION



Probe Vector p
Fused Gallery Vector G_f
Gallery Hyperplane G

MAJORITY VOTING

- Assume probe set $X = \{x_1, \dots, x_n\}$. For each subject from probe set $x_i, i \in \{1, \dots, n\}$, there will be p outcomes from p classifiers. Denote m_j as the count of output label j,

$$assign\ x_i \to l_j\ if\ n_j = \max(M),$$
$$M = \{m_1, \dots, m_p\}.$$

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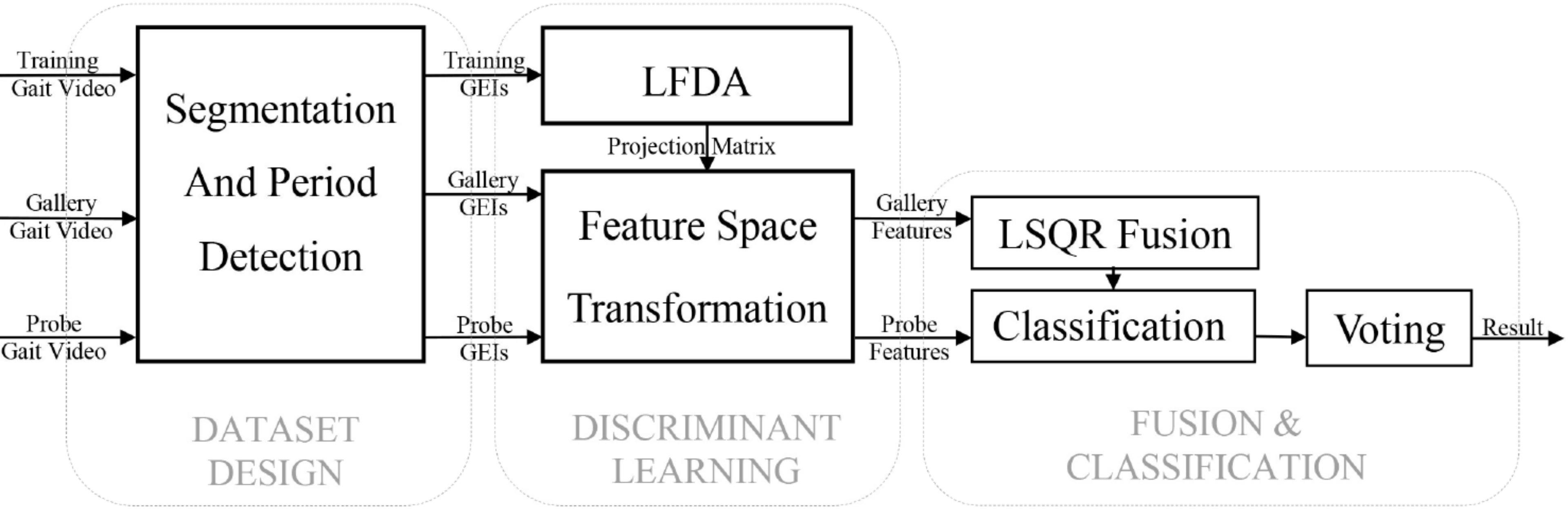
EXPERIMENT DESIGN



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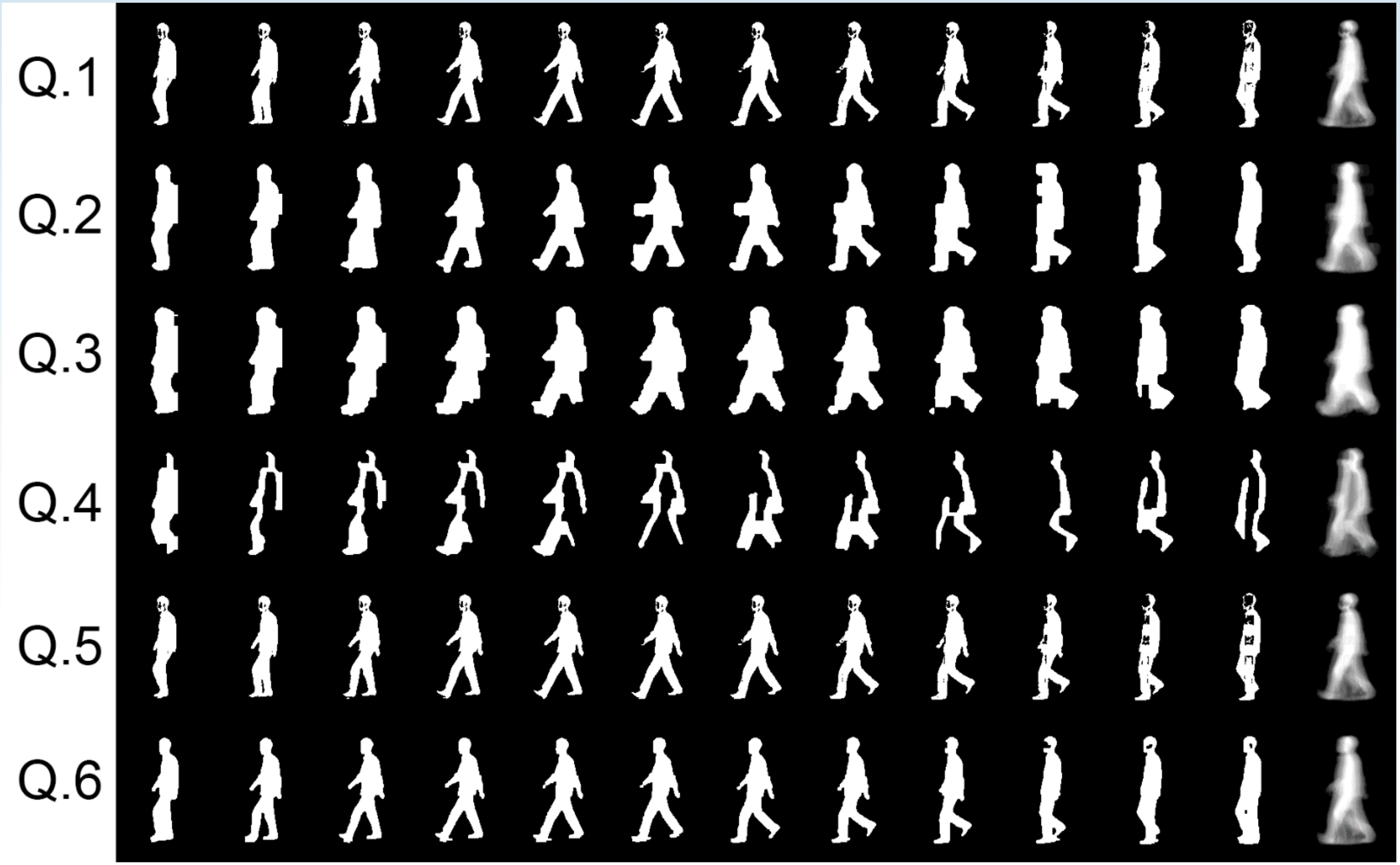
DATASET PREPARATION

- CASIA Dataset B: 124 subjects, 62 for training and 62 for testing.
- Each subject has 6 gait sequences, 1-4 is considered as gallery set and 5-6 as probe set.
- Frame size: 240*320; Normalised silhouette size: 128*88.
- Only normal gait sequences are chosen

DATASET PREPARATION



DATASET PREPARATION

Quality	Segmentation Approach
Q.1	Approach 1: BS with Otsu's threshold
Q.2	Approach 2: Normalised BS plus dilation & erosion
Q.3	Approach 3: BS with small threshold (1/3 of Otsu's)
Q.4	Approach 4: FD plus dilation & erosion
Q.5	Approach 5: GMM & EM method
Q.6	Approach 6: LMedS method

RESULT AND ANALYSIS

Recognition without discriminant learning

G \ P	Q.1	Q.2	Q.3	Q.4	Q.5	Q.6
Q.1	**85**	12	7	10	80	70
Q.2	12	**67**	17	8	10	35
Q.3	17	15	**78**	5	17	8
Q.4	15	8	5	**38**	18	15
Q.5	83	12	7	13	**83**	63
Q.6	58	25	5	10	43	**97**

Recognition after applying LFDA

G \ P	Q.1	Q.2	Q.3	Q.4	Q.5	Q.6
Q.1	**95**	75	63.3	20	93.3	95
Q.2	85	**85**	83.3	30	78.3	91.7
Q.3	68.3	75	**95**	33.3	66.7	81.7
Q.4	48.3	46.7	70	**61.7**	56.7	68.3
Q.5	95	75	56.7	21.7	**95**	96.7
Q.6	88.3	66.7	65	23.3	85	**100**

Comparison between methods

	Probe						
Alg.	Q.1	Q.2	Q.3	Q.4	Q.5	Q.6	Avg.
DL-A	80	70.6	72.2	31.7	76.3	87	**68.3**
DL-H	95	85	95	61.7	95	100	**88.6**
FDL-S	90	78.3	83.3	33.3	88.3	96.7	**78.3**
FDL	95	85	90	58.3	95	98.3	**86.9**
FDL-I	95	76.7	73.3	23.3	93.3	95	**76.1**

G: Gallery data; P: Probe data; Q.1:Q.6: gait data under different quality levels;
LDA: gait data after LDA learning; LDAF: gait data after LDA learning and fusion.

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CONCLUSION

- Gait recognition is indeed affected if the quality of the probe data set differs from that of the gallery data set.
- Important improvements in matching rate may be attained when subspace learning methods are used, since the feature subspace finds the best projection to match probe with gallery features of the same quality level.
- The LSQR based fusion can further improve matching rates.

THANK YOU