Gait Recognition by Applying Multiple Projections and Kernel PCA

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Why Gait?

As a biometric, gait is available at a distance and difficult to hide

Biometrics and Gait

- Emerging gait research
- Gait is non-contact and uses sequences
- Advantages: perceivable at distance and hard to disguise
- Potential applications: security/ surveillance, immigration, forensic, medicine?
- Other applications: moving objects
- Related fields: animation, tracking

Clinical Gait Analysis

MIE Medical Research

Overview of the proposed algorithm

Silhouette Extraction

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Gait Pattern Producing

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Gait Pattern Normalization by gait cycle estimation

↓

FFT to achieve translation invariant

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Kernel PCA Egienspace Computation

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Projection in Egienspace

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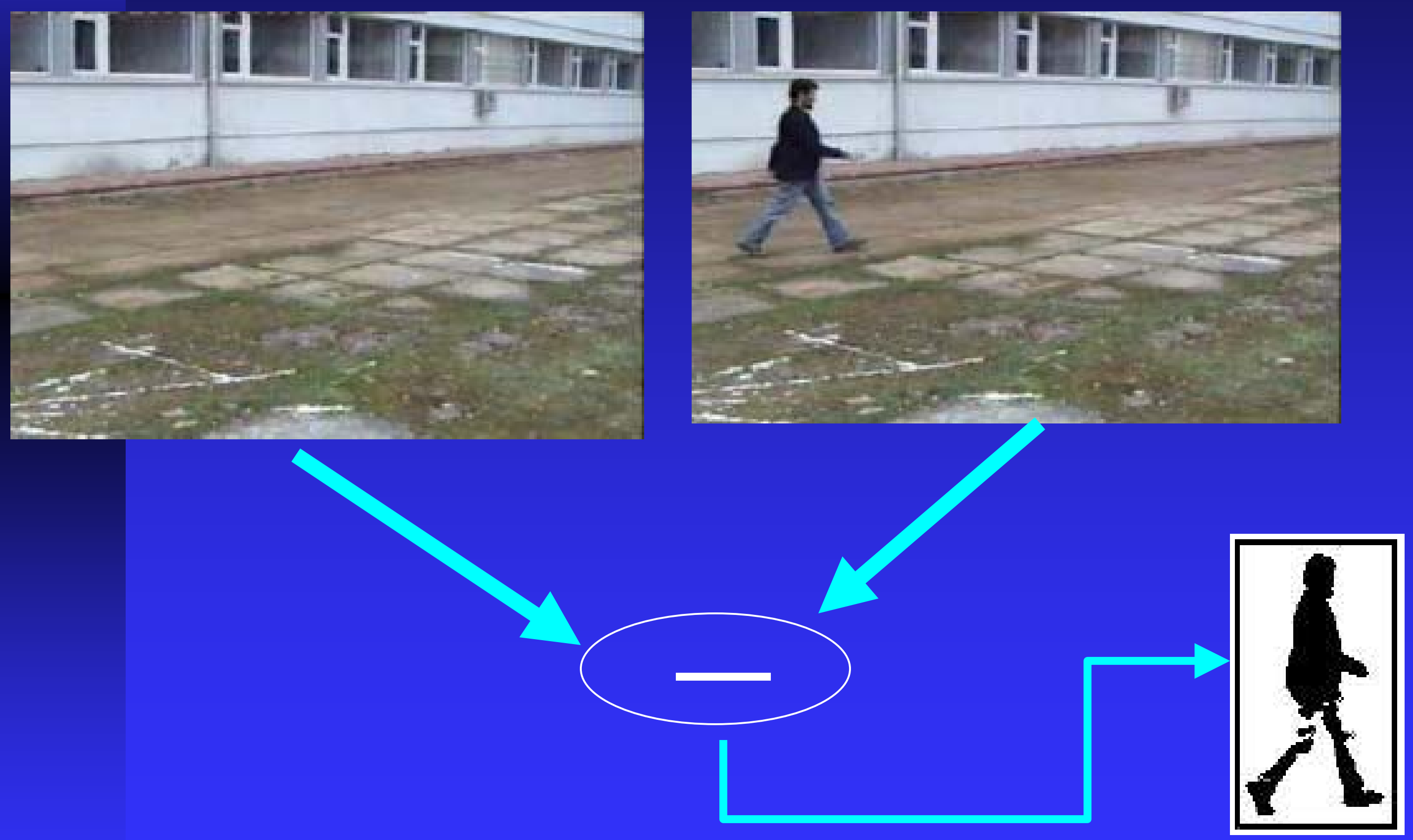
Recognition

Automatic Silhouette Extraction

Background Subtracted

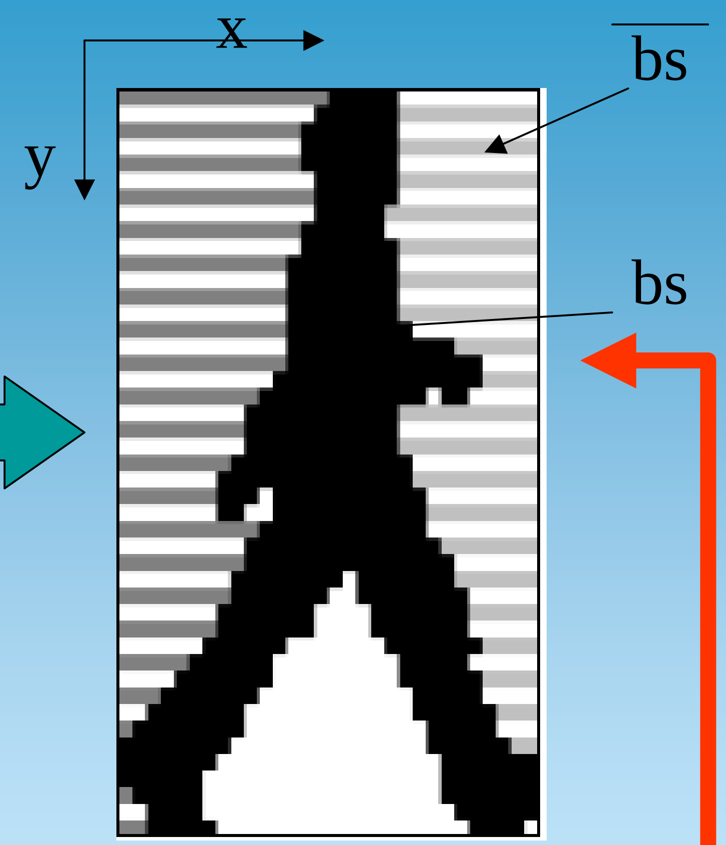
Current Frame



Left & Right Projections

- Left projection is represented by a 1D signal. The size of 1D signal is equal to the height of the bounding box. The values in the signal are computed as the differences between bounding box and silhouette, that is number of columns in a given row. $F_L(y,t) = \sum_x \overline{bs}(x,y,t)$
- Right projection is also similar to the left projection.

$$F_R(y,t) = \sum_{-x} \overline{bs}(x,y,t)$$

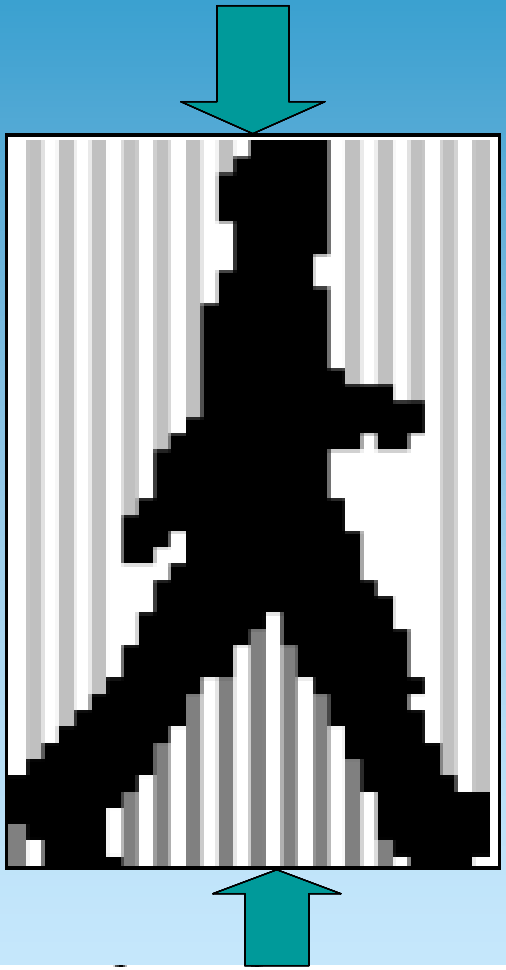


bs : binary silhouette,

$\overline{bs}$: complement of bs

Top & Bottom Projections

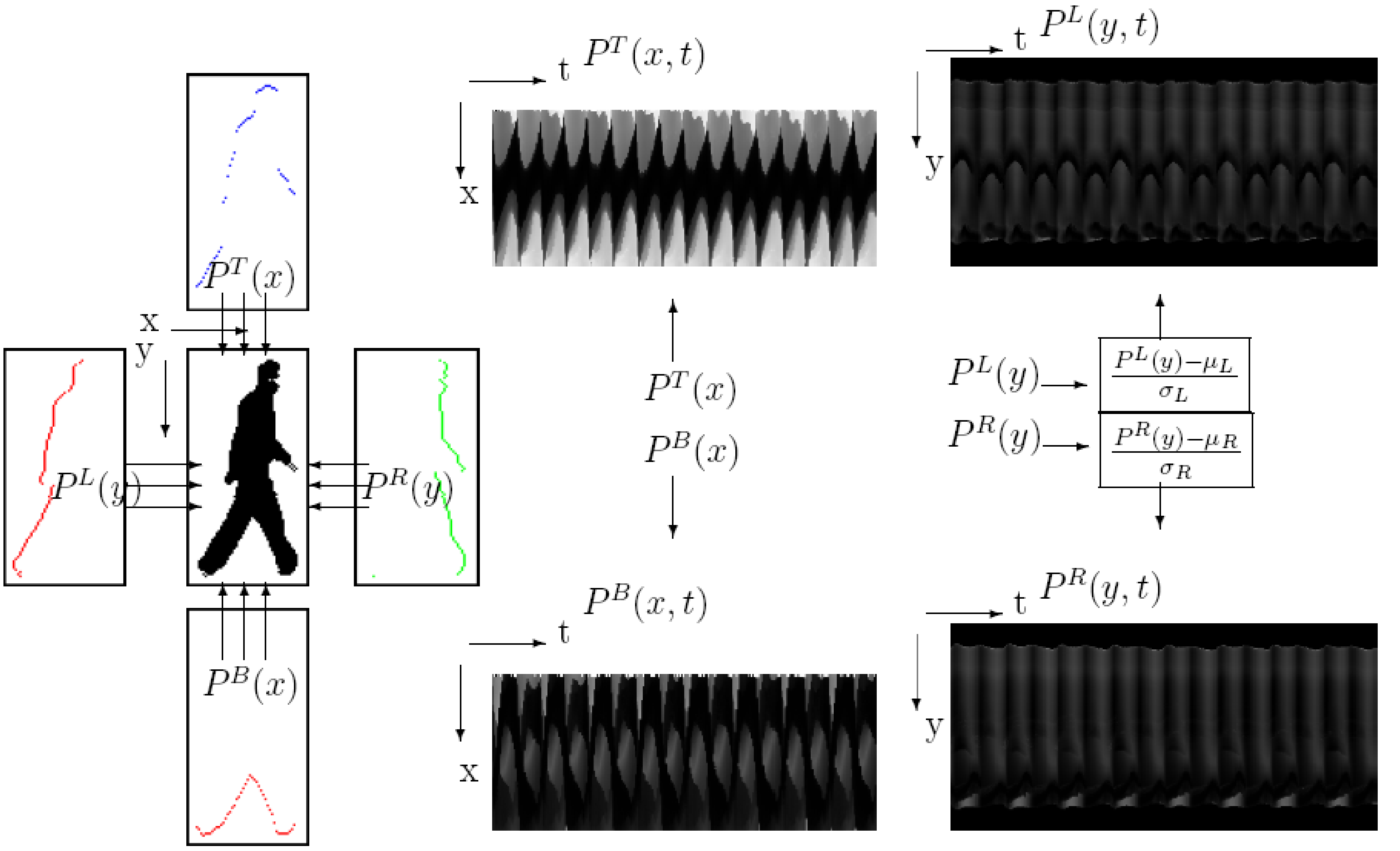
$$F_T(x,t) = \sum_y \overline{bs}(x,y,t)$$



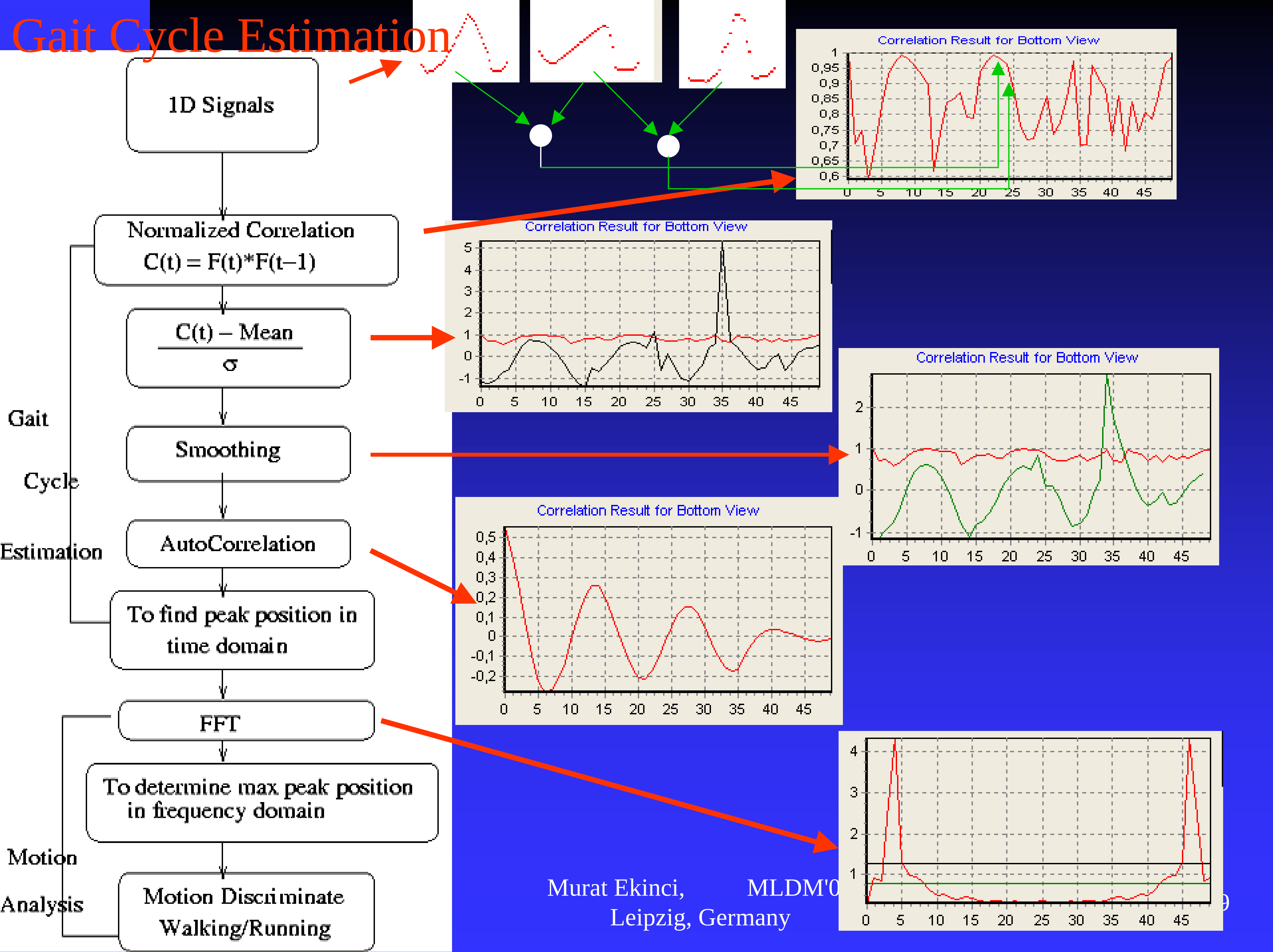
$$F_B(x,t) = \sum_{-y} \overline{bs}(x,y,t)$$

- Top projection is also 1D signal. The size of the signal is equal the width of the bounding box. The values in the signals are equal to the row-distances between the top of the box and top-most boundary pixels of silhouette at each column.
- Bottom projection is also produced from bottom of the box to silhouette.

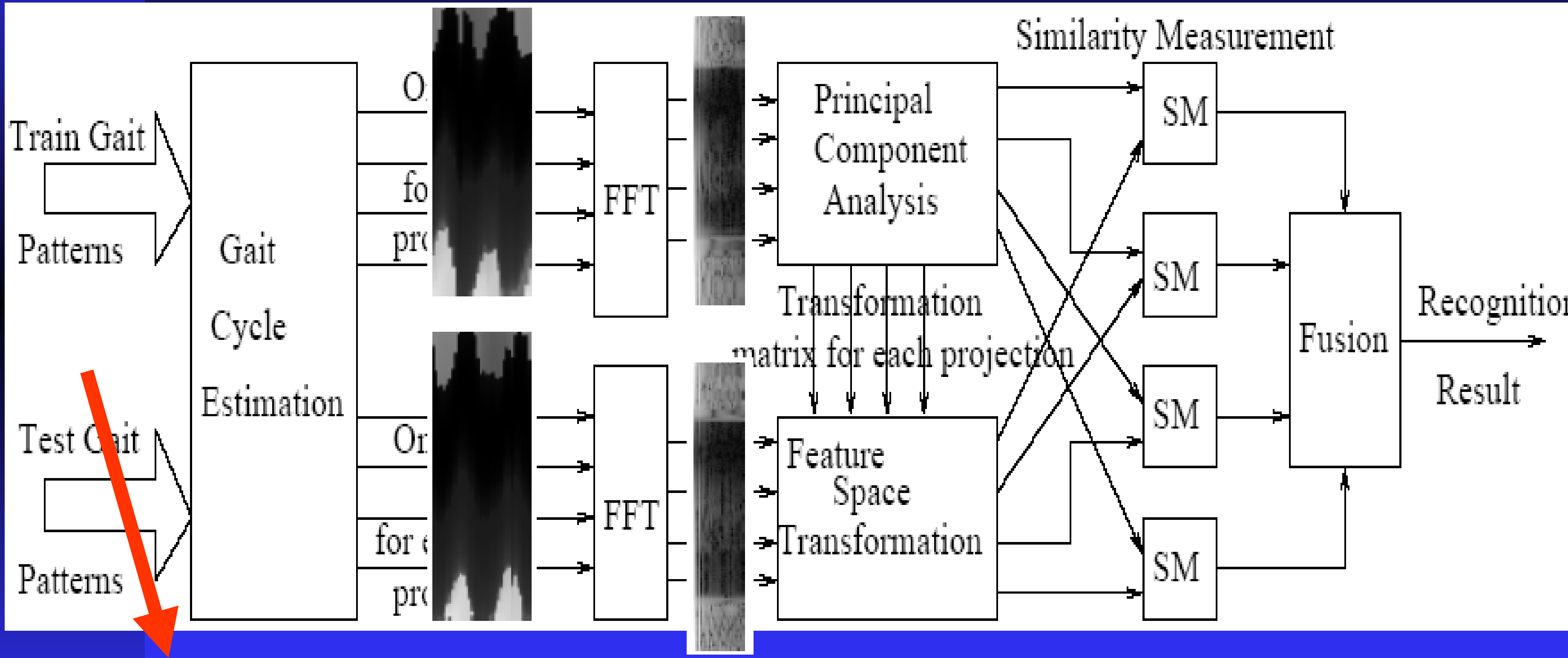
Multiple Projection Based Silhouette Respresentation

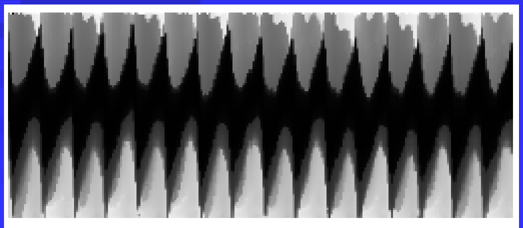


Gait Cycle Estimation

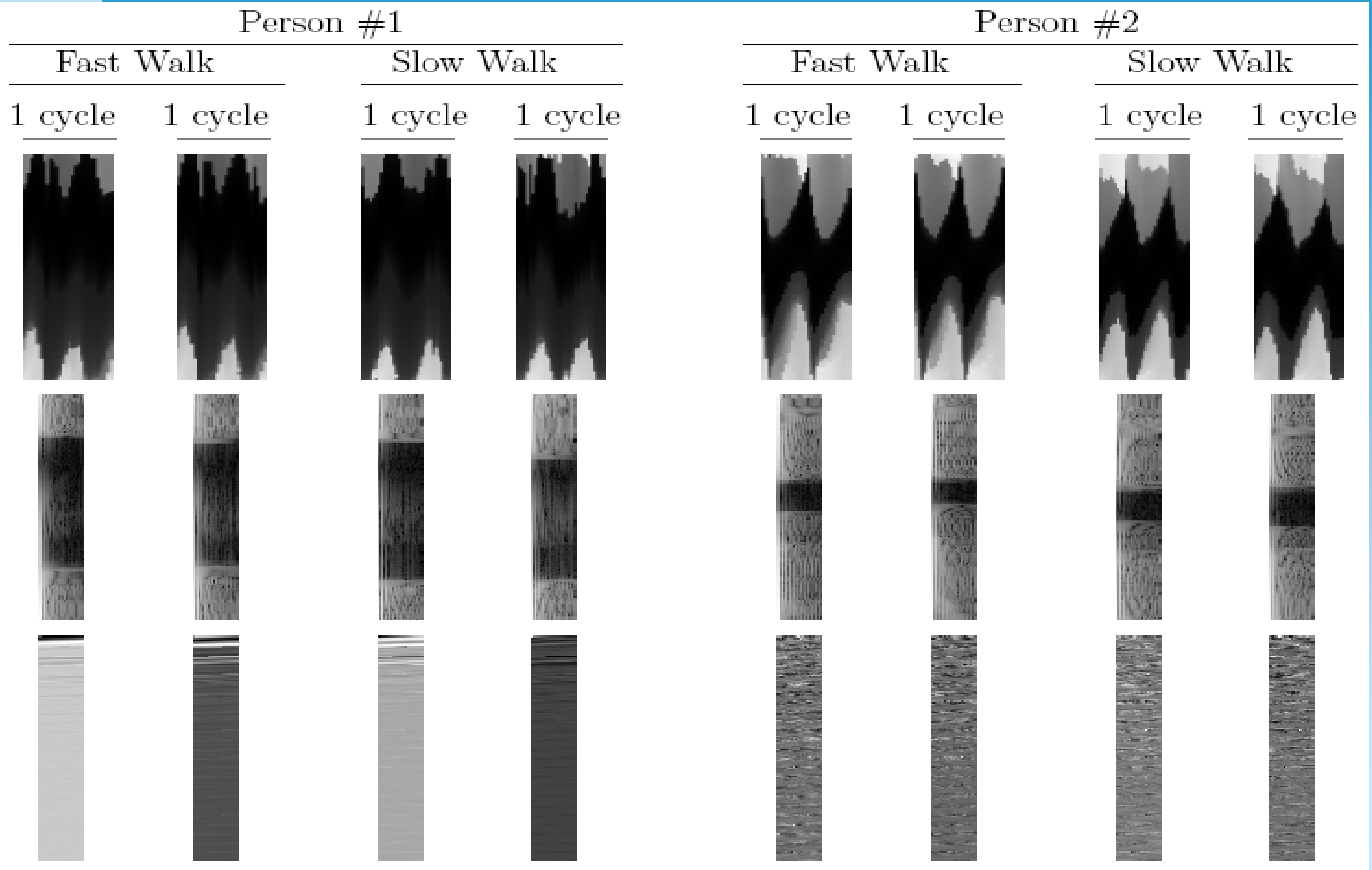


The Proposed Approach



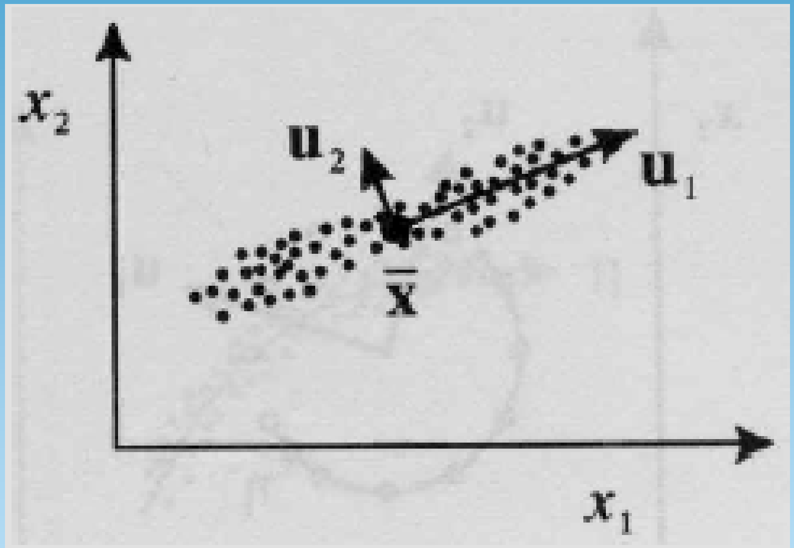


FFT to achieve transition invariant



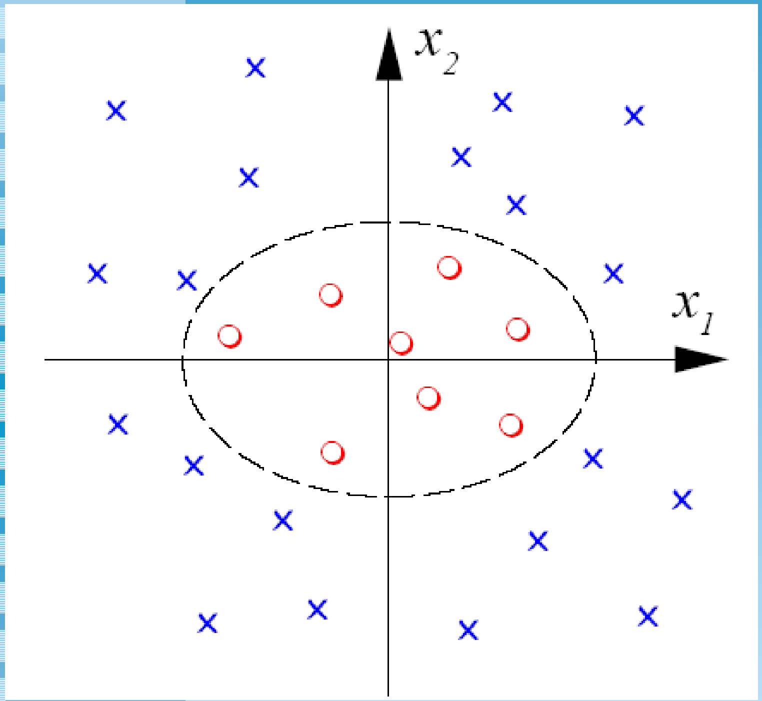
Principal Component Analysis (PCA)

- Commonly used as a cluster analysis tool,
- Captures the variance of a dataset in terms of (orthogonal principal components),



- The goal of PCA is to reduce the dimensionality of the data while **retaining as much as possible of the variation present in the dataset**

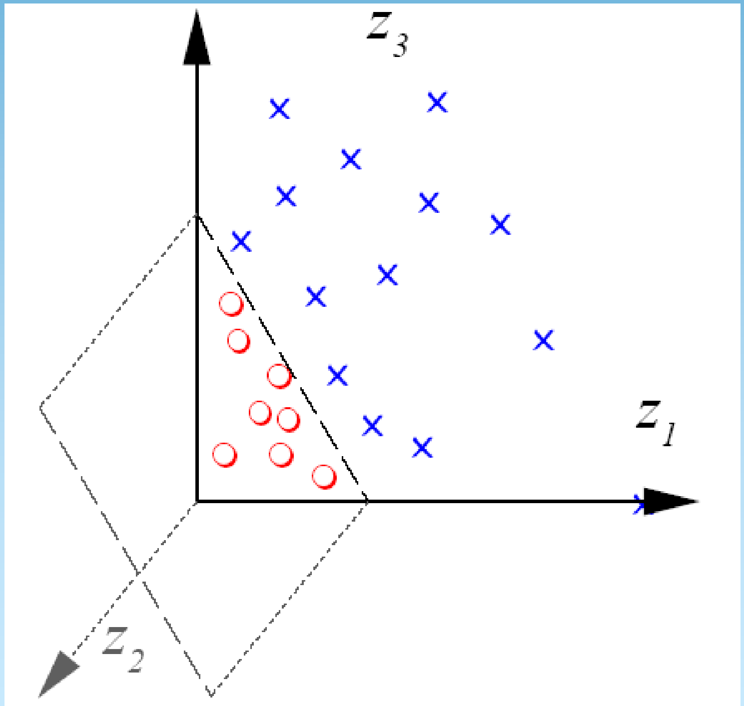
Kernel PCA



Apply simple mapping from

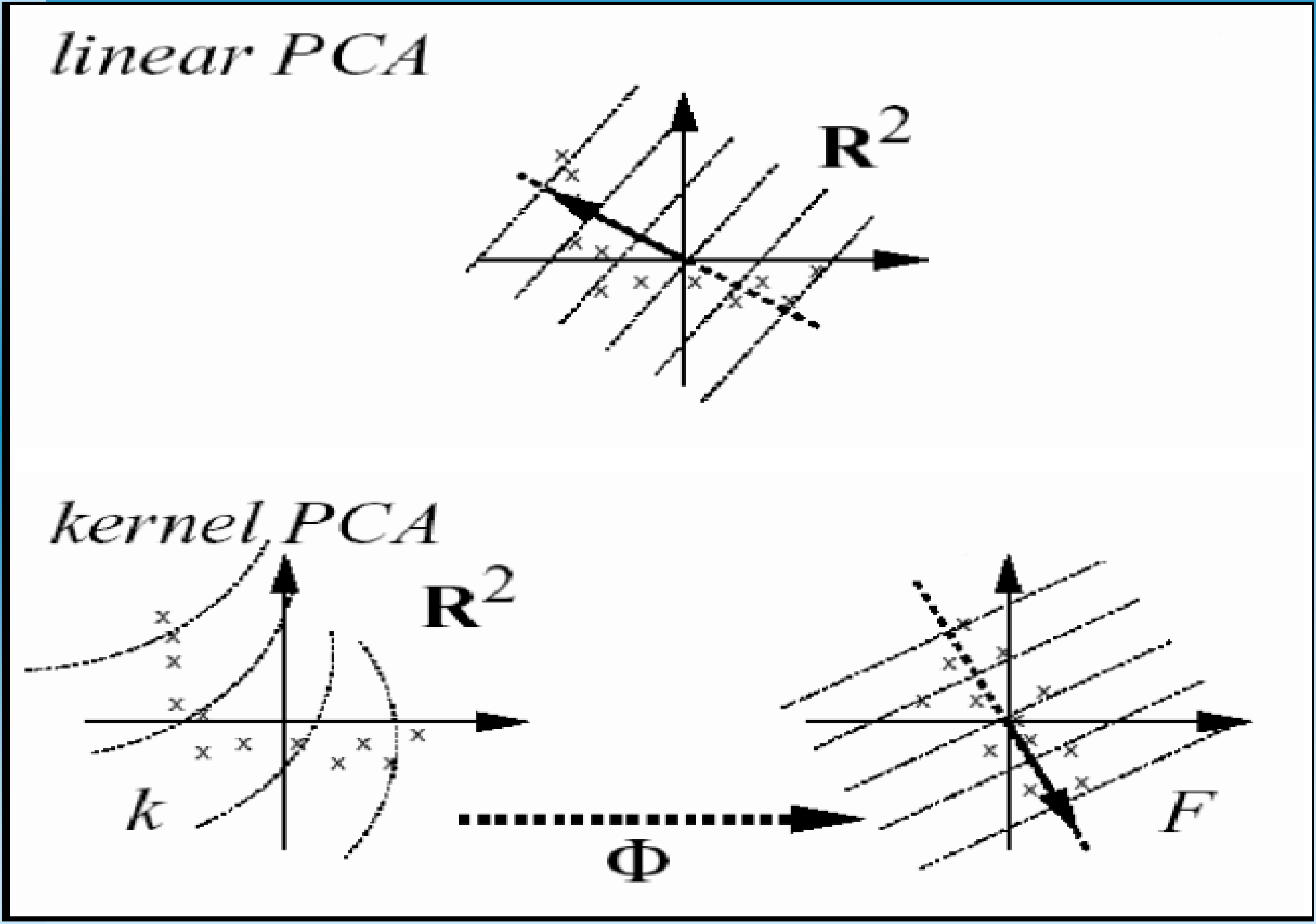
$$\Phi : \mathbb{R}^2 \rightarrow \mathbb{R}^3$$
$$(x_1, x_2) \mapsto (z_1, z_2, z_3) := (x_1^2, \sqrt{2}\, x_1 x_2, x_2^2)$$

Classes can now be separated by a plane

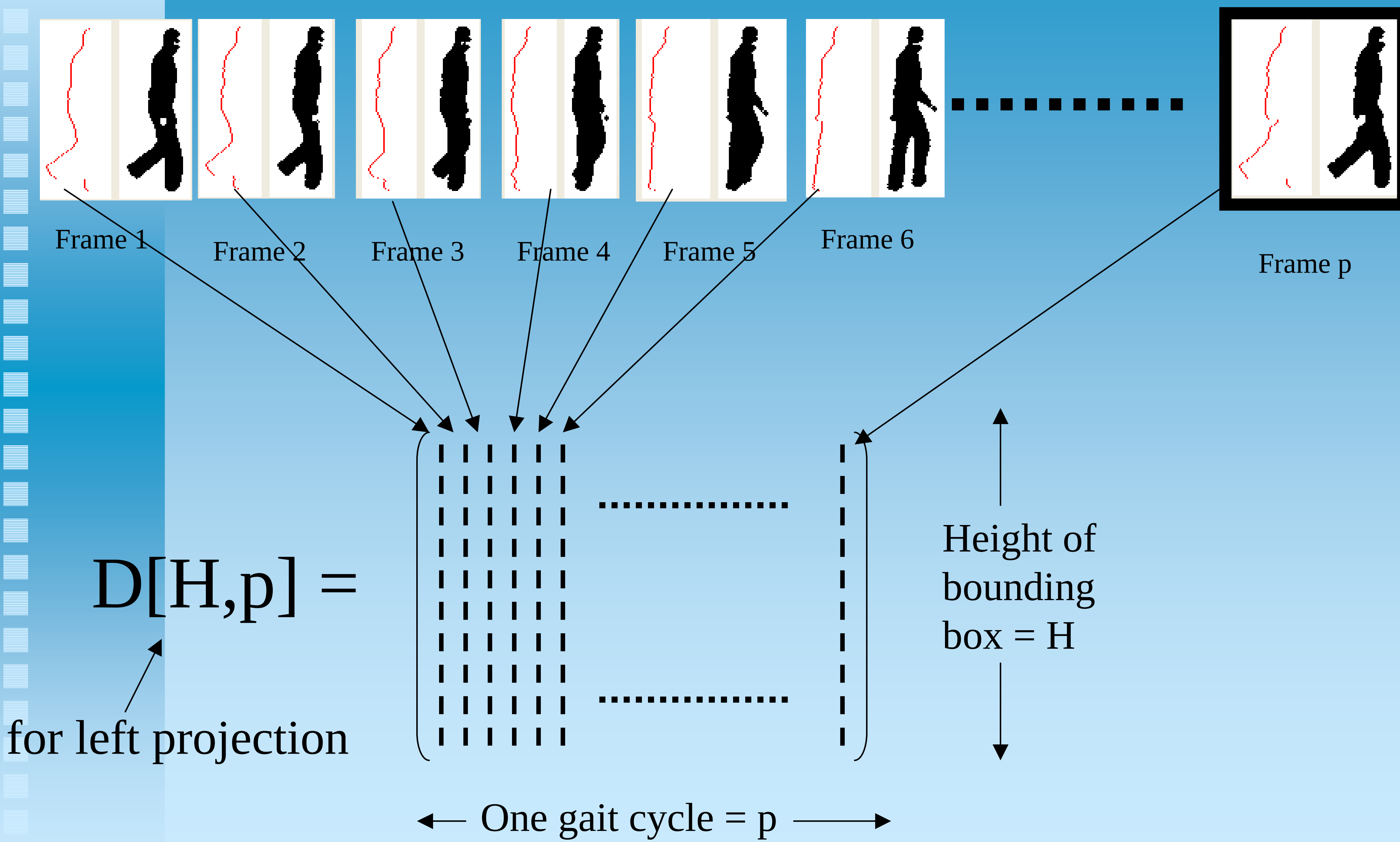


Classes are linearly inseparable in input space,

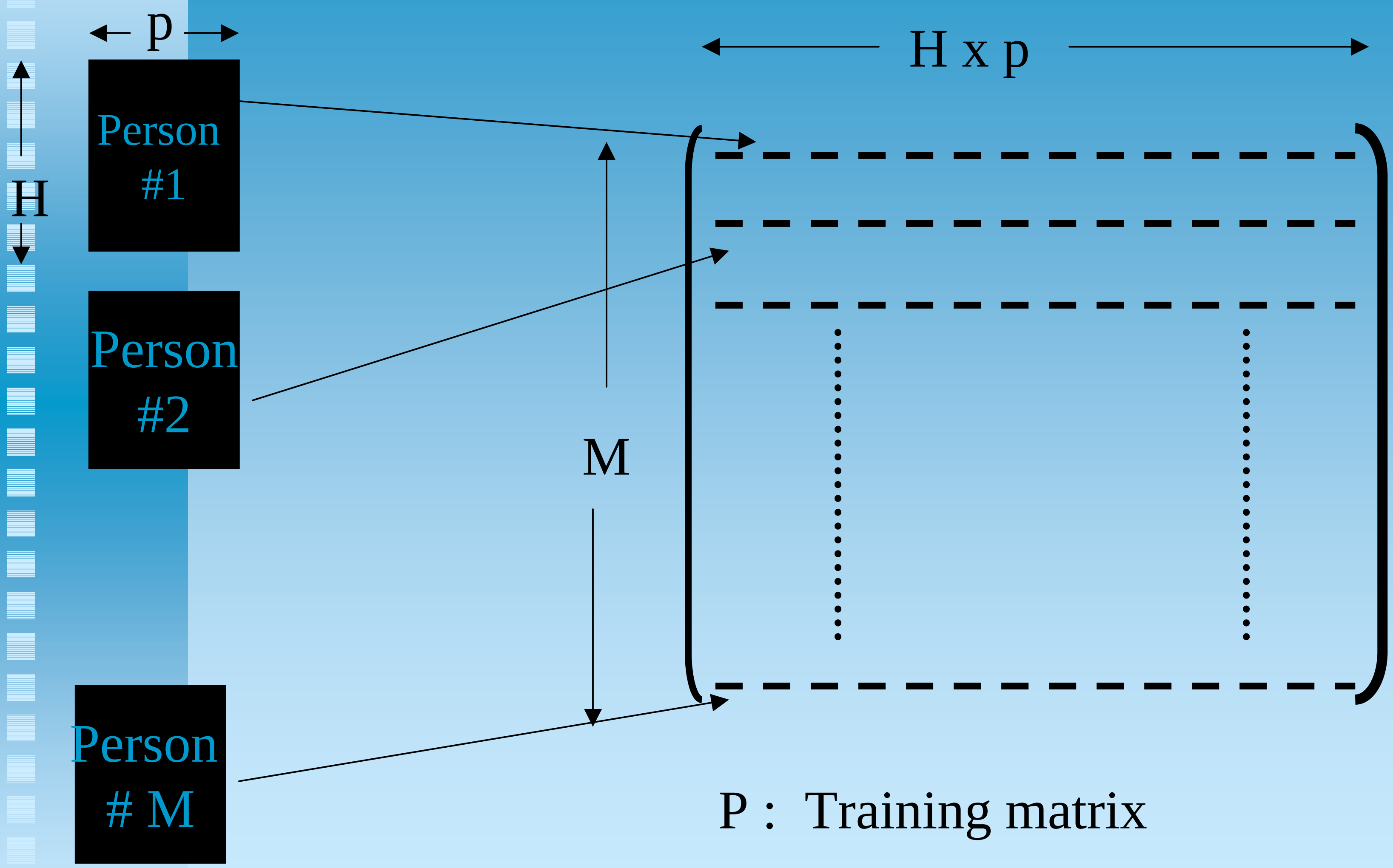
Kernel PCA vs (Linear) PCA



Obtain *Each* class for training



Producing training matrix



P : Training matrix

PCA in dot-product form

- PCA finds the principal axes by diagonalizing the covariance matrix C with singular value decomposition

$$\lambda \upsilon = C \upsilon \qquad (1)$$

Eigen value

Covariance matrix

Eigen vector

$$C = \frac{1}{m} \sum_{j=1}^{m} x_j x_j^T \qquad (2)$$

PCA in dot-product

$$\boxed{(C - \lambda I)\upsilon = 0 \rightarrow C - \lambda I = 0}$$

If the rank of the matric C is N, then N nonzero eigenvalues

Eigenvalues $\rightarrow$ $\lambda = [\lambda_1, \lambda_2, ..\lambda_N]^T$

Corresponding eigenvectors $\rightarrow$

$$\lambda_1 \rightarrow \upsilon_1 = [\upsilon_{1,1}, \upsilon_{1,2}, \ldots\ldots, \upsilon_{1,N}]$$

$$\lambda_2 \rightarrow \upsilon_2 = [\upsilon_{2,1}, \upsilon_{2,2}, \ldots\ldots, \upsilon_{2,N}]$$

....

$$\lambda_N \rightarrow \upsilon_N = [\upsilon_{N,1}, \upsilon_{N,2}, \ldots\ldots, \upsilon_{N,N}]$$

Projection into the Feature Space

Eigen transformation matrix, E

$$E = \begin{bmatrix} \upsilon_{1,1}, \upsilon_{1,2}, \ldots\ldots, & \upsilon_{1,N} \\ \upsilon_{2,1}, \upsilon_{2,2}, \ldots\ldots, & \upsilon_{2,N} \\ \ldots\ldots\ldots\ldots & \ldots. \\ \upsilon_{N,1}, \upsilon_{N,2}, \ldots\ldots, & \upsilon_{N,N} \end{bmatrix}$$

Projection to eigenspace

$$f_{i,j} = E^{T} * P_{i,j}$$

Kernel PCA algorithm

- Produce kernel (covariance) matrix, $K_{i,j} = K(\chi_i, \chi_j) = (\Phi(\chi_i)\Phi(\chi_j))$

Gaussian kernel function was used $k(\chi_i, \chi_j) = exp\left(-\frac{\|\chi_i - \chi_j\|^2}{2\sigma^2}\right)$

We can write the expression as the eigenvalue problem, $K\alpha = \lambda\alpha$

Kernel matrix

Eigenvalues are then normalized by $\alpha_j = \alpha_j / \sqrt{\lambda_j}$

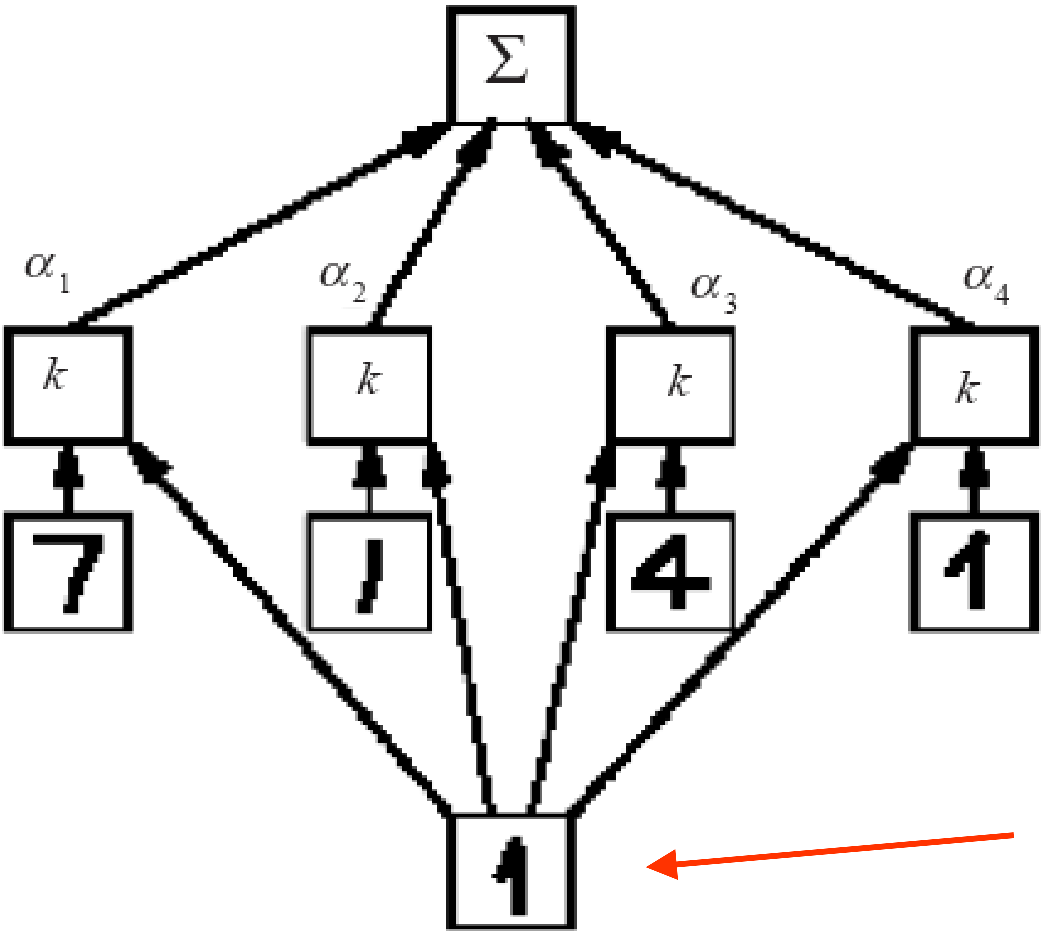
Project to the feature space →

$$\tilde{q}_k^T \Phi(\chi_i) = \sum_{j=1}^{N} \alpha_{kj} K(\chi_j \chi_i)$$

For test sample,

$$\tilde{q}_k^T \Phi(\chi) = \sum_{j=1}^{N} \alpha_{kj} K(\chi_j \chi)$$

Transform to feature space by kernel PCA



feature value

$(V\Phi(x)) = \Sigma\alpha_i k(x_i, x)$

weights (eigenvector coefficients)

comparison: $k(x_i, x)$

sample $x_1, x_2, x_3, \ldots$

input vector x

Similarity Measuring

- Weighted Euclidean distance (WED)

$$WED: d_k = \sum_{i=1}^{N} \frac{(f(i) - f_k(i))^2}{(s_k)^2}$$

- f: feature vector of the unknown gait pattern,
- f_k : the *k*th feature vector
- s_k: its standard deviation,
- N: the feature length

Fusion Task

- Includes two strategies: **Strategy 1:**
- Each projection is separately treated. Then the strategy 1 is combining the distances of each projections at the end by assigning equal weight.
- If D_i higher or equal to 0.5 for i*th* person, it assumed as correctly recognized,

$$D_i = \sum_{j=1}^{4} \alpha_j * d_{ji}$$

d_j,i : j*th* projection distance similarity for i*th* person,

α_ j : weight coefficients are being 0.25 for each projection.

Strategy 2: Dominant feature;

Depending on human motion direction in the image sequence, some projections chosen as dominant feature can give more robust results than others,

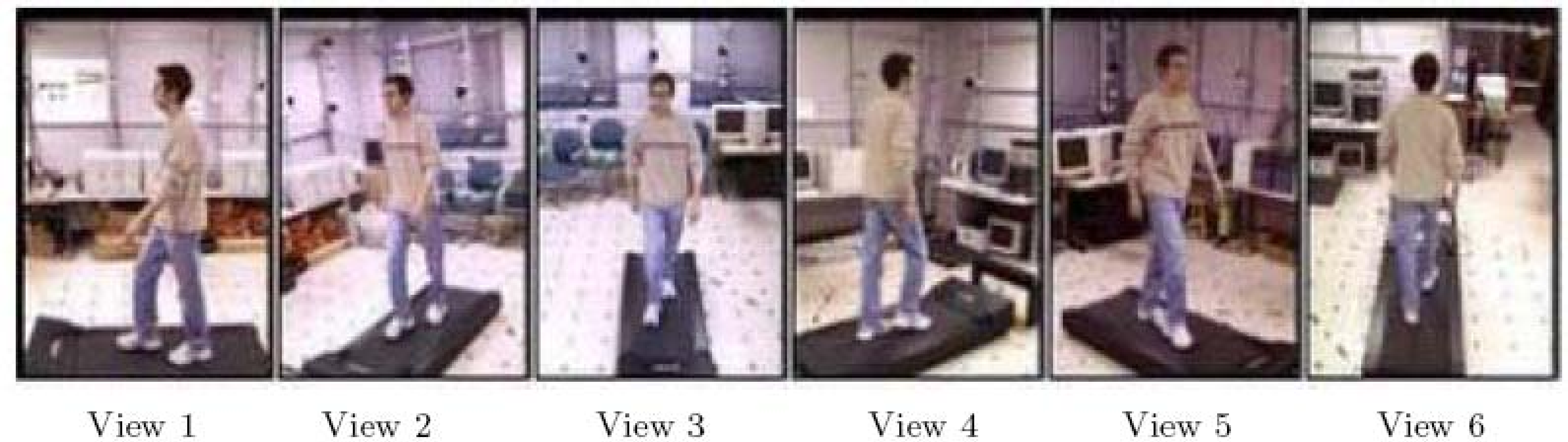
If (Dominant_Feature → Positive, || any two of other projections → Positive for i*th* person)

Then, it is assumed as correctly recognized

Experiments:

Four gait database: CMU, USF, SOTON, NLPR

- CMU Gait Database:



25 subjects, 8 gait cycle, each cycle includes 30-45 frames, different types of walking: Slow-Fast Walking.

Experiments on the CMU database:

- Two type experiments: Types I and II,
- I: All subjects in train set and test set walk with same walking style.
- I.1: Train on fast walk, test on fast walk
- I.2: Train on slow walk, test on slow walk
- II: All subjects walk different walking styles
- II.1: Train on slow walk, test on fast walk,
- II.2: Train on fast walk, test on slow walk

Exp. Type I:

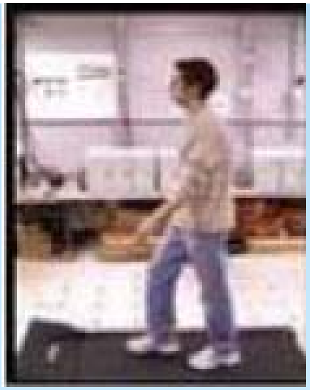
			CMU database View points				
Test/Train	Train	Test	View 1	View 3	View 4	View 5	View 6
Fast/Fast	1	7	97.7	99.4	98.8	100	98.8
	2	6	100	100	100	99.3	98.6
	3	5	99.2	99.2	100	100	99.2
	4	4	99	100	100	100	99
	5	3	100	100	100	100	98.6
	6	2	100	100	100	100	100
	7	1	100	100	100	100	100
Slow/Slow	1	7	97.7	90.8	97.1	100	98.2
	2	6	98	93.3	98	100	98
	3	5	97.6	94.4	98.4	100	99.2
	4	4	97	97	100	100	99
	5	3	97.3	98.6	100	100	98.6
	6	2	100	100	100	100	100
	7	1	100	100	100	100	100

Experiment: Type II

Train		View 1		View 3		View 4		View 5		View 6	
Test	Method	Rank: 1	5	Rank: 1	5	Rank: 1	5	Rank: 1	5	Rank: 1	5
Slow	KPCA	40	78.5	68	81.5	34.5	73.5	38.5	54.5	37.5	58.5
Fast	FFT+KPCA	84.5	98	91	98	87.5	99	92.5	98.5	77.5	92
Fast	KPCA	48.5	72	66.5	82	33.5	77.5	29	62.5	37.5	60.5
Slow	FFT+KPCA	86.5	99.5	92.5	98.5	78.5	96	82.5	94	73	86

Comparison

Train	Slow		Fast		Slow		Fast	
Test	Slow		Fast		Fast		Slow	
Viewpoint	View 1	View 3	View 1	View 3	View 1	View 3	View 1	View 3
Proposed method	100	100	100	100	84.5	91	86.5	92.5
BenAbdelkader *et.al.*[3]	100	96	100	100	54	43	32	33
UMD [9][10][11]	72	-	70	-	32	-	58	-
UMD [13]	72	-	76	-	12	-	12	-
CMU [14]	100	-	-	-	76	-	-	-
Baseline [8]	92	-	-	-	72	-	-	-
MIT[19]	100	-	-	-	64	-	-	-


View 1

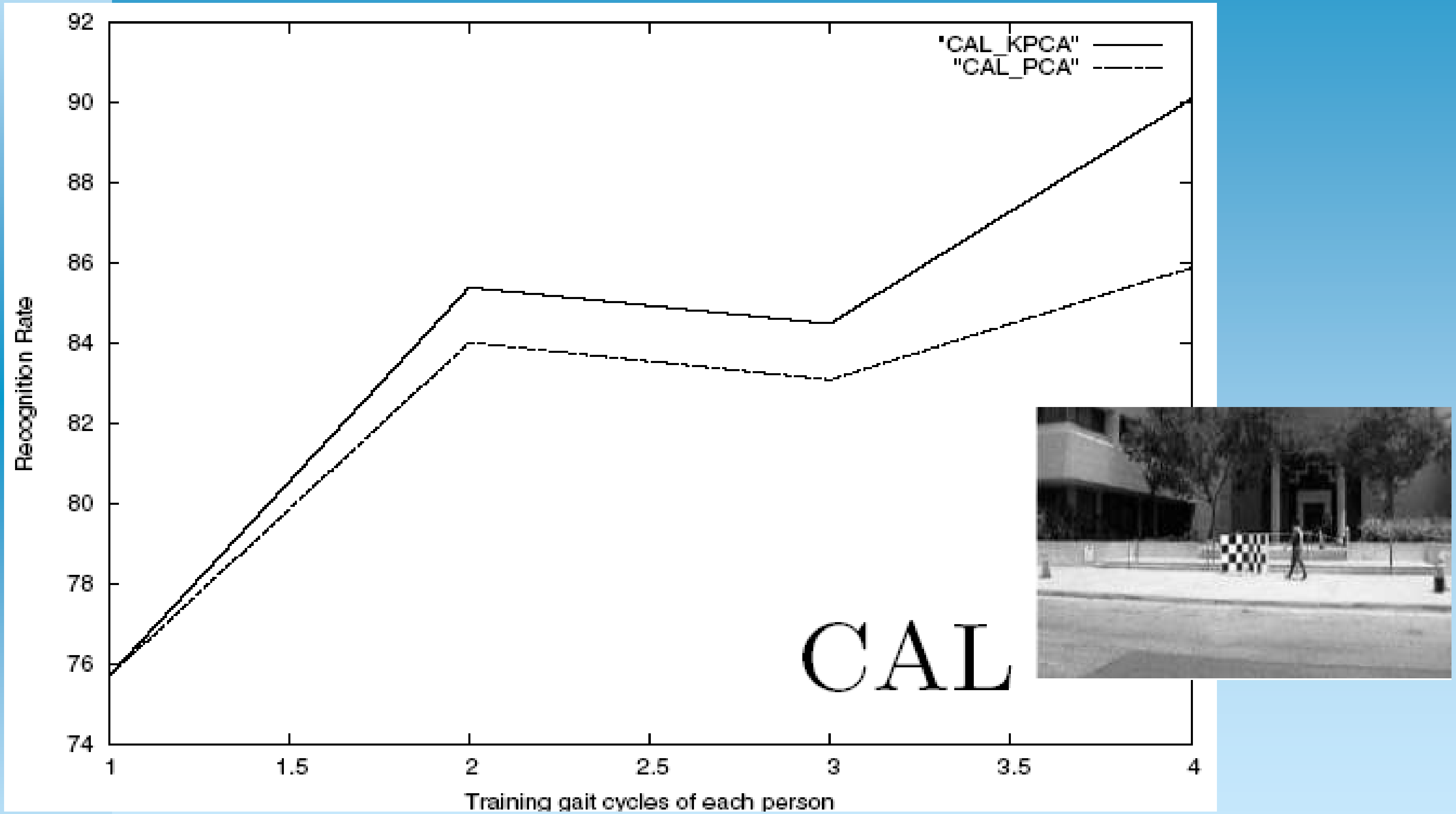

View 3

Experiments on the USF Gait Database:

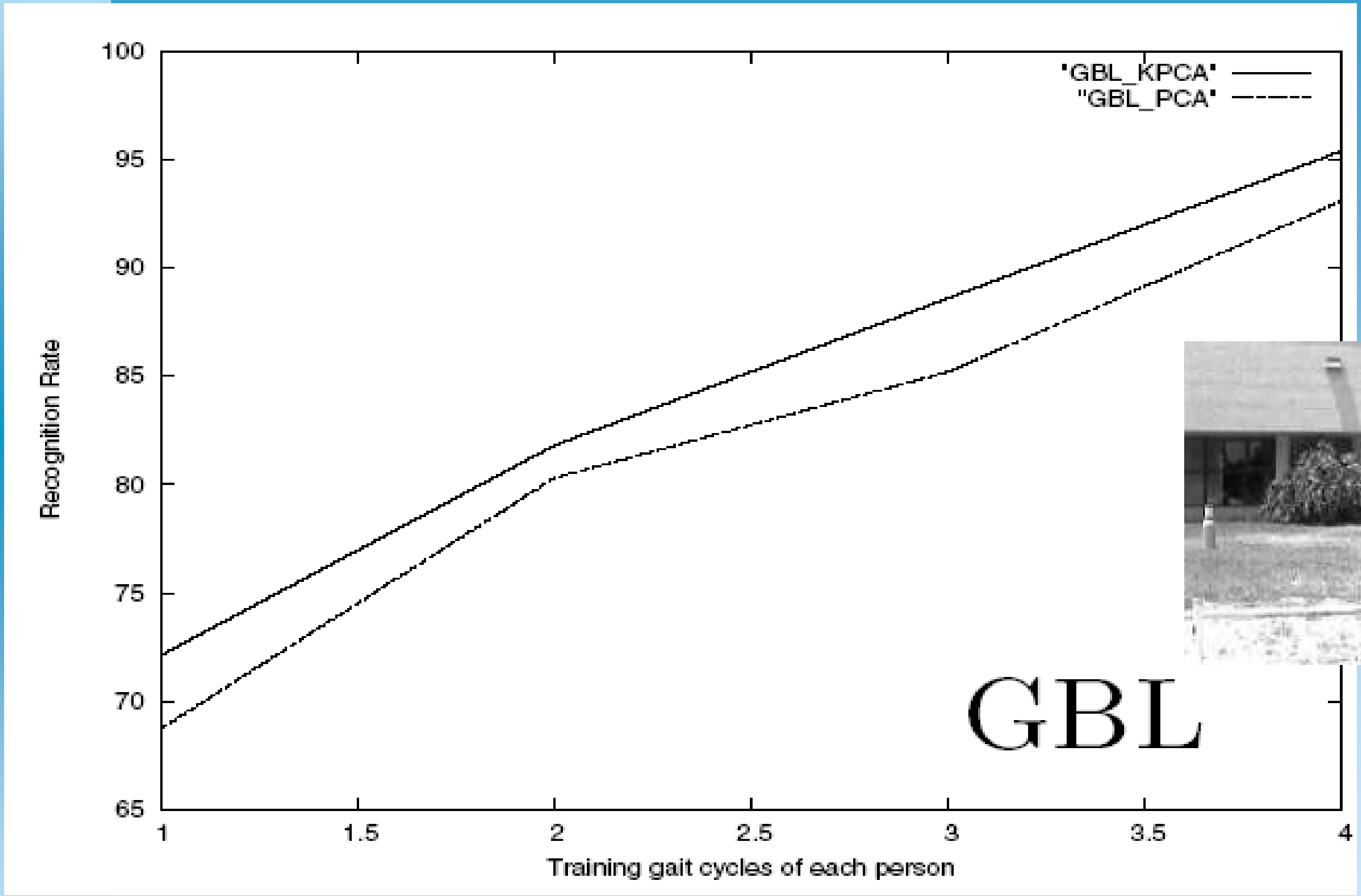
	PCA		KPCA	
Experiment	Fusion 1	Fusion 2	Fusion 1	Fusion 2
CAL[71]	78.8	85.9	84.5	90.1
CAR[71]	85.9	88.7	85.9	87.3
CBL[43]	74.4	86.04	81.3	90.6
CBR[43]	83.7	93.02	79.06	88.3
GAL[68]	86.7	92.6	88.2	92.6
GAR[68]	79.4	82.3	80.8	85.2
GBL[44]	90.9	93.1	93.1	95.4
GBR[44]	77.2	86.3	86.3	90.9

G, C: Grass and concrete surface; A, B : shoe types; L,R: left &right cameras

Experiments on the USF database



Experiments on the USF database



SOTON Gait Database:

It includes 115 persons walked constantly and passed in front of camera in both directions.

Kernel PCA

Train – Test samples	Walking Towards to Right		Walking Towards to Left	
	Rank 1	Rank 5	Rank 1	Rank 5
1 cycle – 4 cycles	74.56	86.31	66.31	84.34
2 cycles – 3 cycles	90.14	96.23	82.31	93.04
3 cycles – 2 cycles	93.04	97.39	86.08	94.34
4 cycles – 1 cycle	95.65	99.13	91.304	96.52

PCA

Training sample	Walking Towards to Right		Walking Towards to Left	
	WED	SVM	WED	SVM
1 gait cycle	62.39	63.91	71.3	72.39
2 gait cycles	76.81	82.89	85.79	91.3
3 gait cycles	83.91	88.26	89.13	95.65
4 gait cycles	86.95	94.78	92.17	98.26

Comparison:

The proposed method	In [13]	In [14]	In [29]	In [28]	In [23]	In [27]
98.26	84	96.67	97.3	84	92.7	94

NLPR Gait Database

It includes 20 subjects and four sequences for each viewing angle per subject. All subjects walk along a straight-line path.

Experiments on NLPR Gait Database

Walking Towards to Right		Walking Towards to Left	
Rank 1	Rank 5	Rank 1	Rank 5
90	100	90	95

Comparison:

Proposed	BenAbdelkader [3]	Collins [14]	Lee [19]	Phillips [22]	Wang [2]
90	72.50	71.25	87.50	78.75	75

Conclusions

- A new silhouette representation for gait recognition and gait cycle estimation,
- Multi-features of silhouette are extracted,
- FFT was used to achieve transition invariant,
- Kernel PCA based feature extraction approach
- Experimental results are demonstrated on four public gait databases.

Thank you

Questions ?