

Human Gait Analysis and Recognition

Jianyi Liu, Ph.D., Assistant Prof.

Institute of Artificial Intelligence and Robotics,
Xi'an Jiaotong University,
Xi'an City, China



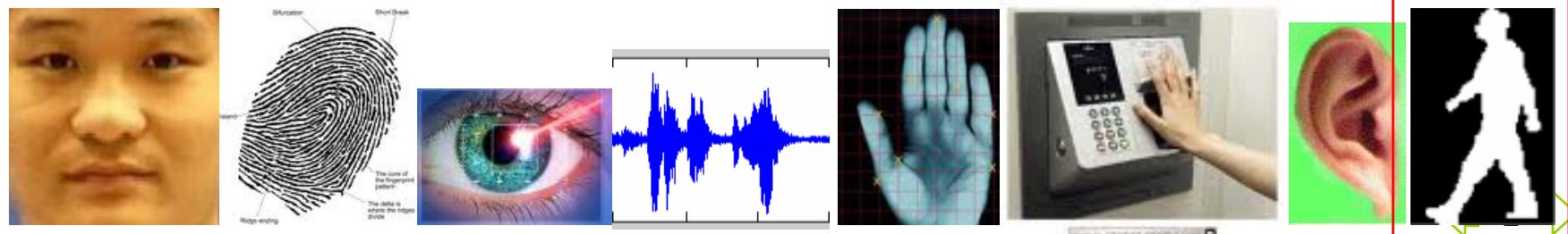
Biometrics

◆ What is it?

- Human identification through the natural biological features of humans, rather than any carried certificates.

◆ Categories:

- Intrinsic / static features: face, iris, finger-print, palm-print, vein-print, ear, etc.;
- Behavior / dynamic features: voice, signature, gait, etc.



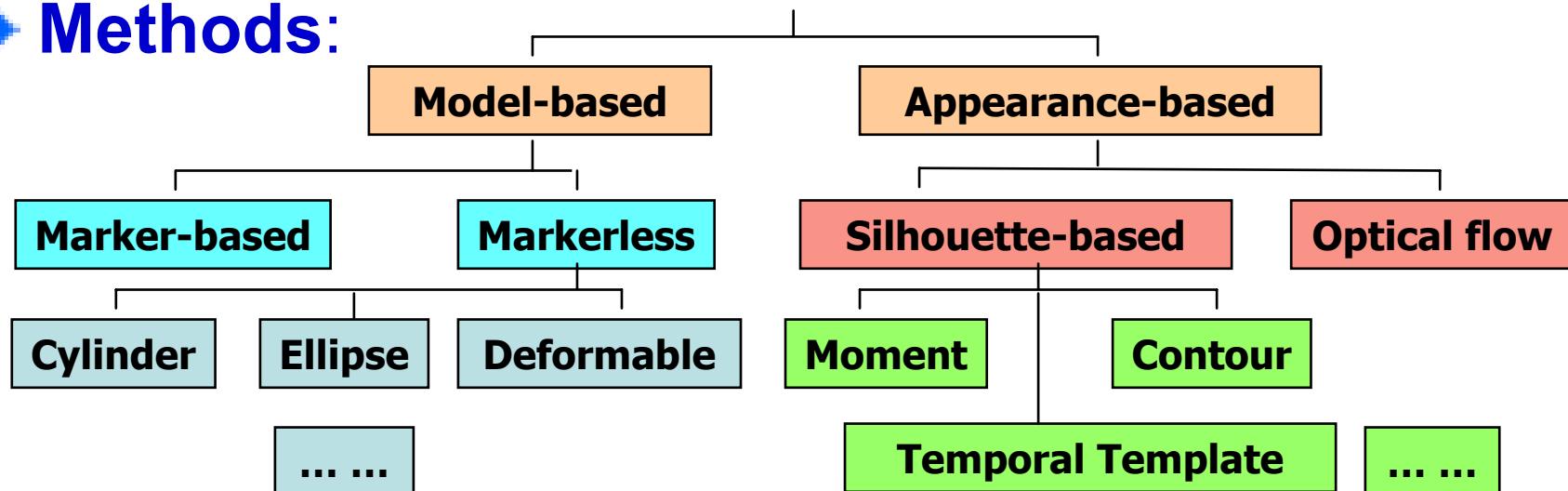
Gait Recognition——A Glance

—A young biometric with potential

- ◆ **Destination:** Automatic human identification and authentication by observation of their walking styles.
- ◆ **Rationality:** Human's ability to recognise people by their gait——heavy; humble; weary; gentle...
(Shakespeare)
- ◆ **Advantage:** data acquisition from distance; non-invasive; hard to conceal, comparing to traditional biometrics.

—A challenging work

- ◆ **Subtle** discriminating features of gait are hiding behind similar motions.
- ◆ **Vulnerable** to variations in clothing, illumination, outdoor background, silhouette noise.
- ◆ **Methods:**



Groups with sound

- ◆ Mark Nixon, Soton@UK
- ◆ S. Sakar and Z. Liu, USF@US
- ◆ T.N. Tan, CASIA@CN
- ◆ D. Xu, NTU@SG
- ◆ R. Challapa, UMD@US
- ◆

General Technique Framework of Gait Analysis & Recognition

Framework of Computer Vision by D. Marr

- ◆ **Basic elements:**

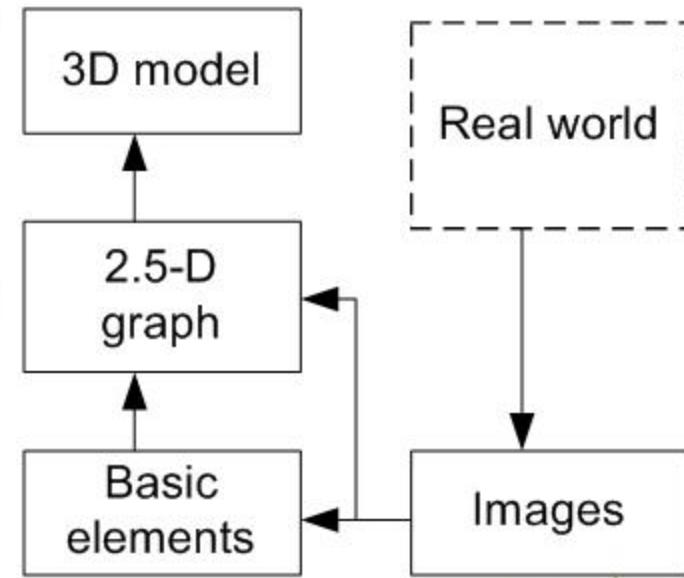
- Edge, corner, texture;

- ◆ **2.5-D elements graph:**

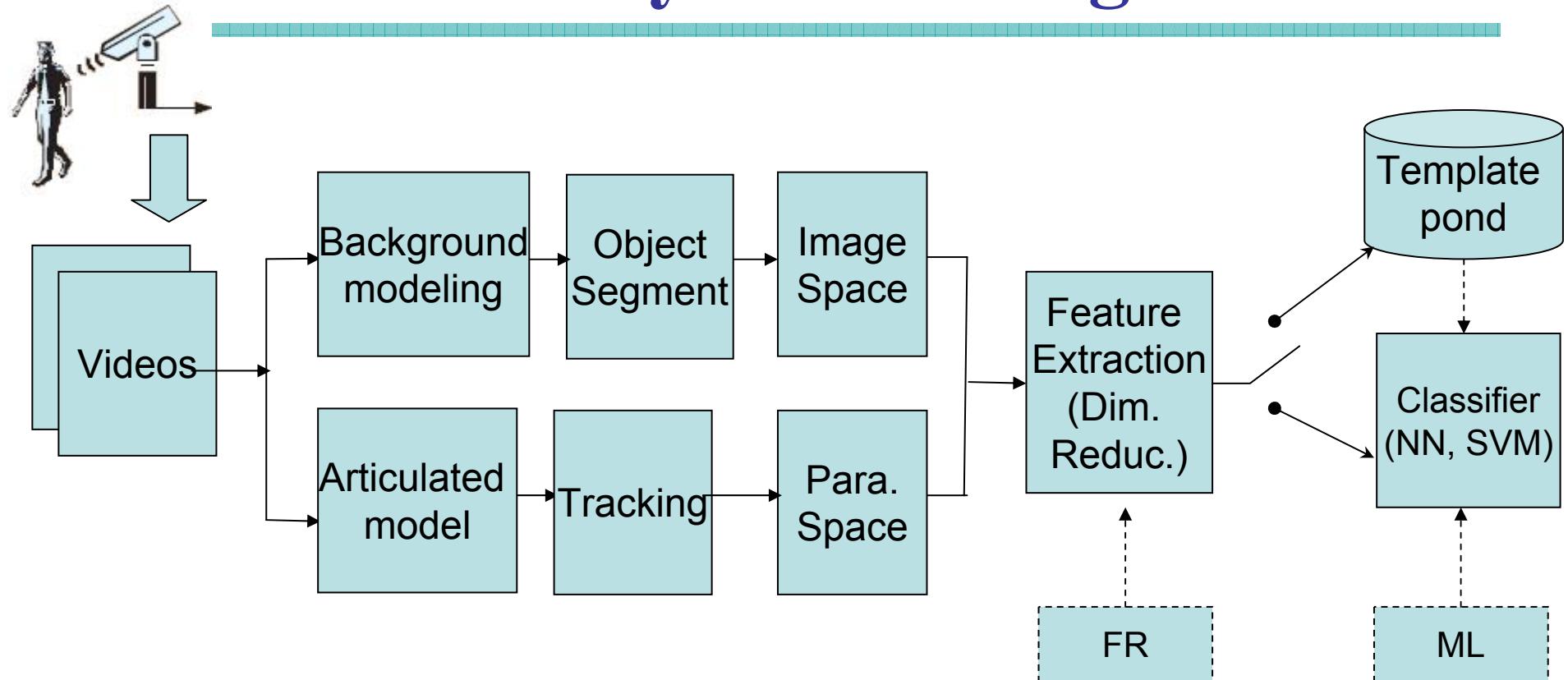
- From viewpoint of observer's coordinates, the normal, depth (stereo vision), discontinuities for each surfaces;

- ◆ **3D model description :**

- 3D scenario understanding and reconstruction.

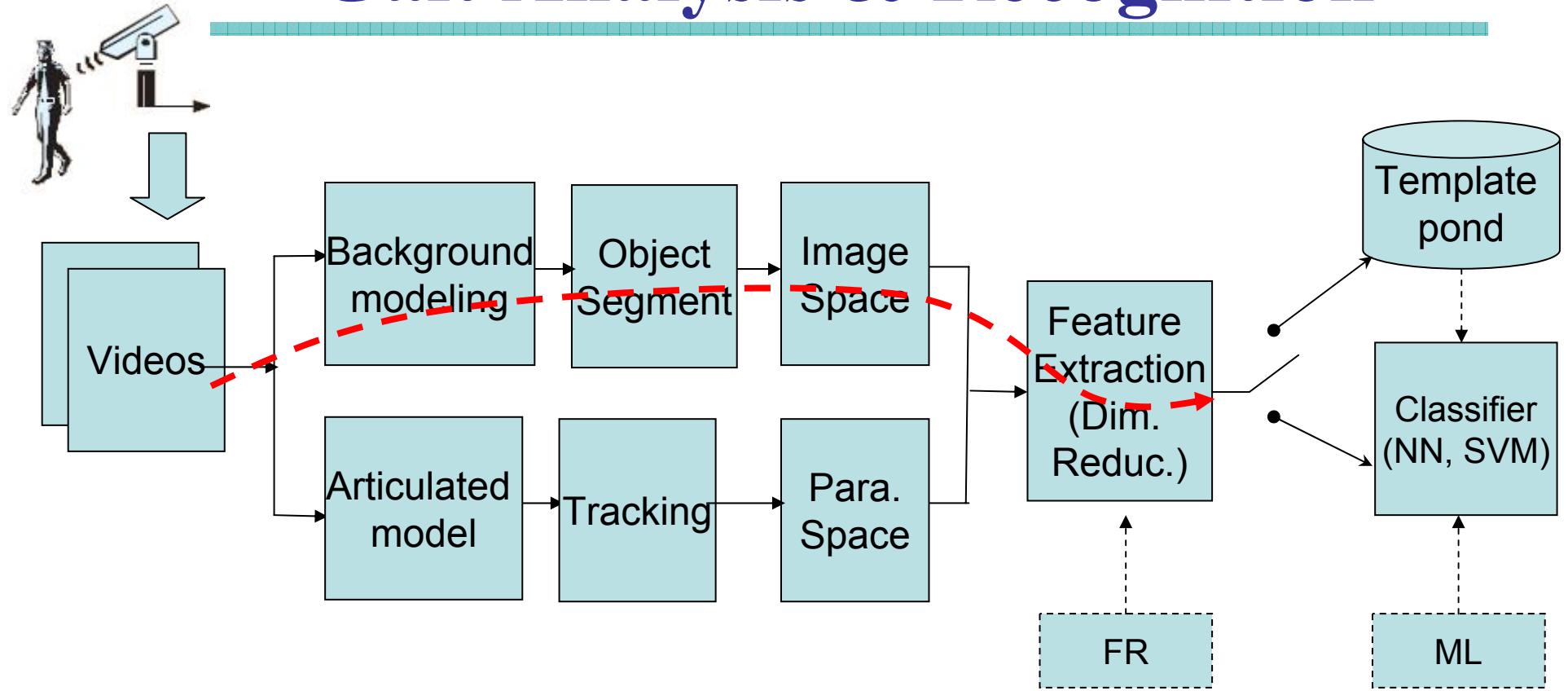


General Technique Framework of Gait Analysis & Recognition



- ◆ Two mainstream routes:
 - Model free: silhouette analysis
 - Model based: Articulated model

General Technique Framework of Gait Analysis & Recognition

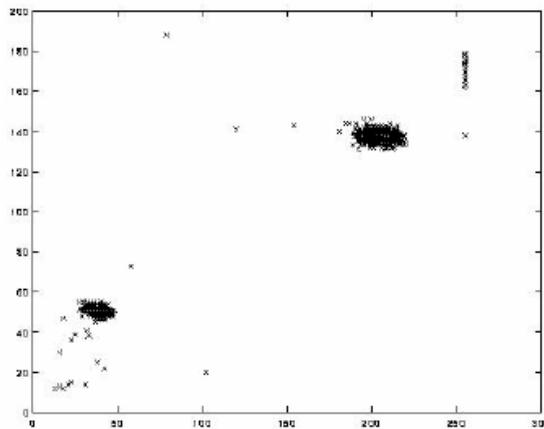


- ◆ Two mainstream routes:
 - **Model free: Silhouette analysis**
 - Model based: Articulated model

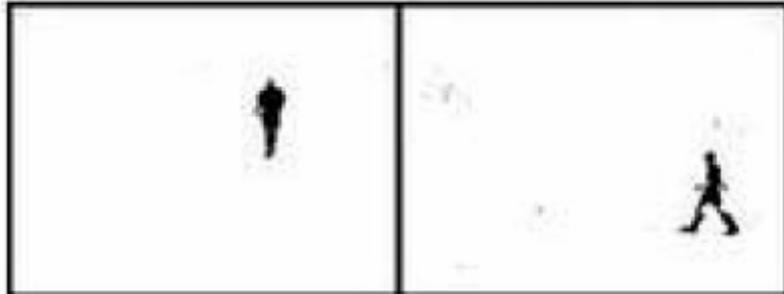
Classical method for background modeling — (GMM)

- ◆ For some complicated background, i.e. lake wave、leaf swing、drizzle, Uni-Gaussian model is no longer competent.

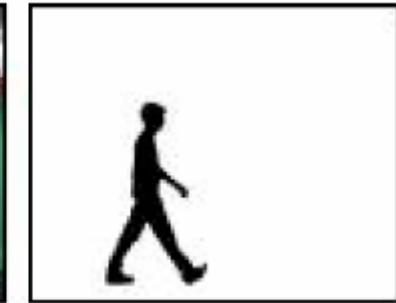
$$P(X_t) = \sum_{i=1}^K \omega_{i,t} * \eta(X_t, \mu_{i,t}, \Sigma_{i,t})$$



Silhouette extraction—— classical segmentation problem



Outdoor



Indoor

- ◆ Typical method: GMM+EM
- ◆ a two-class problem: {Foreground=w1, Background=w2}

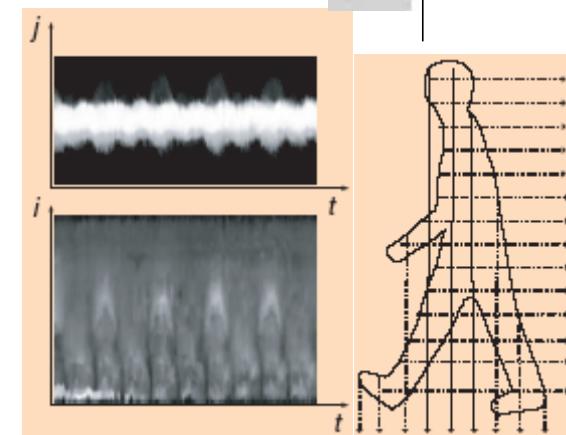
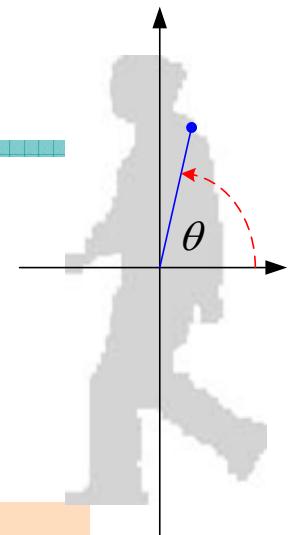
$$P(d_k) = \sum_{i=1}^2 P(\omega_i) p(d_k | \omega_i, \mu_i, \sigma_i)$$

$$p(d_k | \omega_i, \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{(d_k - \mu_i)^2}{2\sigma_i^2}}$$

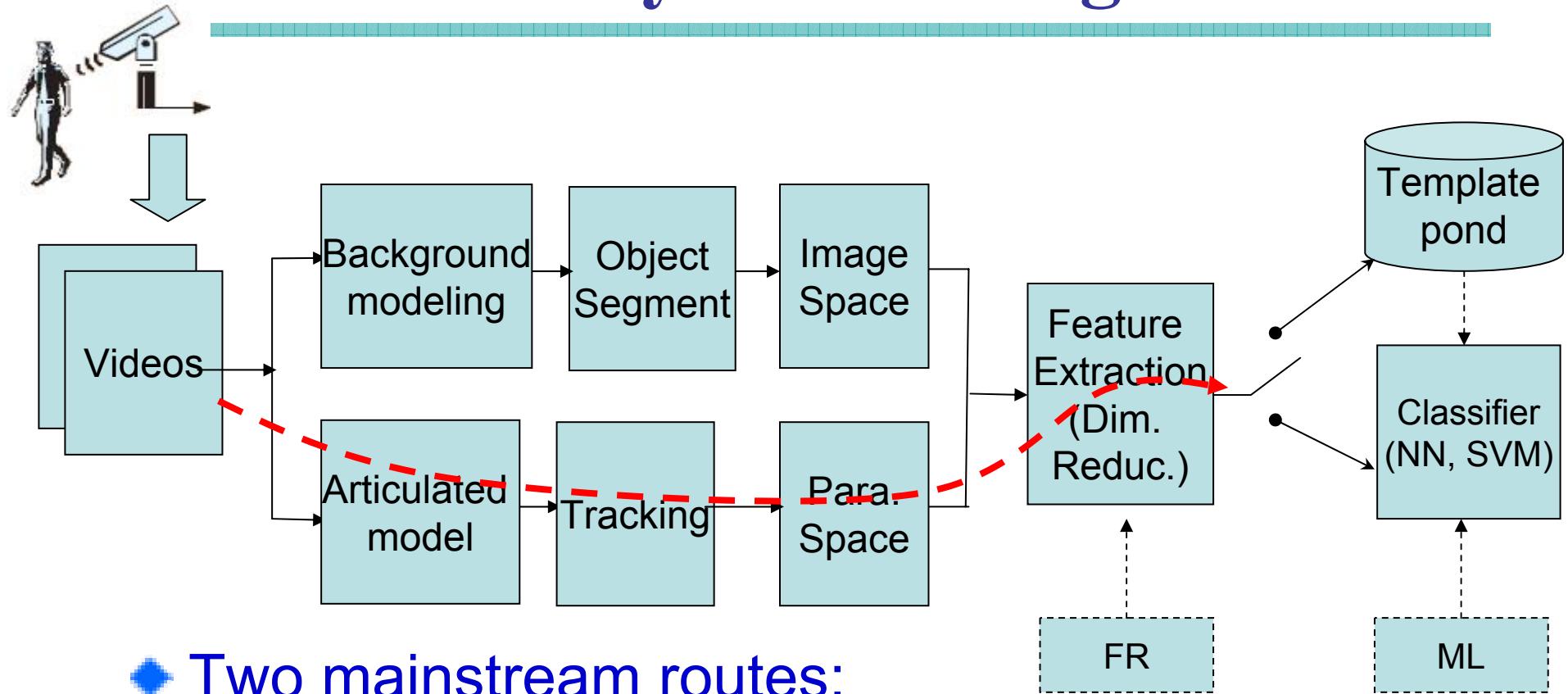


Typical algorithms in model-free gait recognition

- ◆ Gait energy image (GEI) :
represent sequence into image
by overlapping;
- ◆ Tensor Discriminant Analysis:
 $S(x,y,t)$, 3D data representation;
- ◆ Contour measurement:
- ◆ Vertical / horizontal projection.



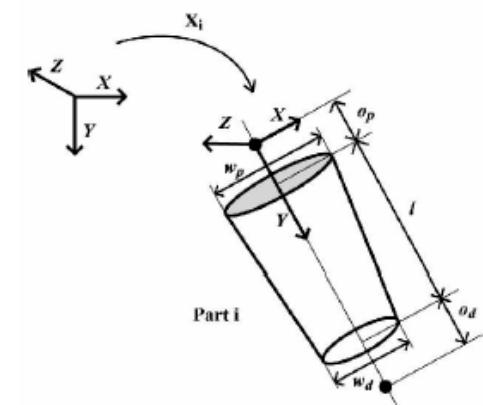
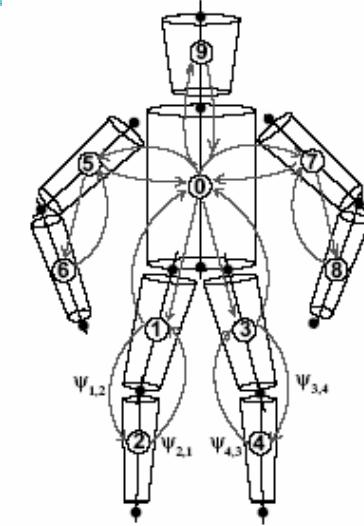
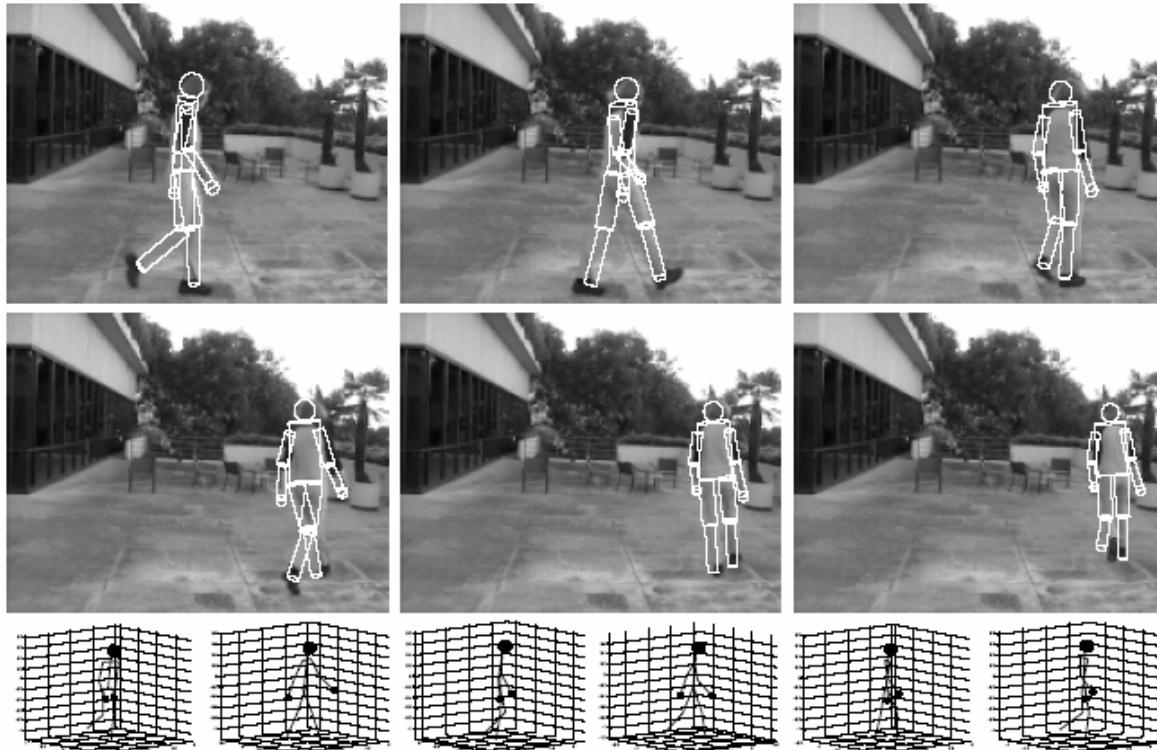
General Technique Framework of Gait Analysis & Recognition



- ◆ Two mainstream routes:
 - Model free: silhouette analysis
 - **Model based: Articulated model**

Articulated body motion tracking

- ◆ 30+ DoF
- ◆ Cylinder model



Kalman filtering based tracking

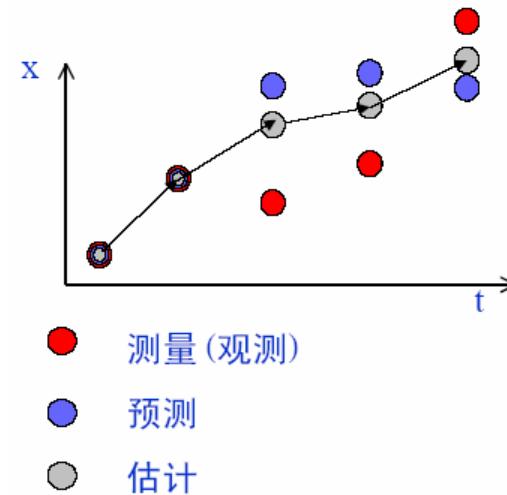
- ◆ Status equation:
- ◆ Measurement equation:
- ◆ Status updating equation:
- ◆ Limitation:
only applicable to linear and Gaussian model.

$$x_k = Ax_{k-1} + u$$

$$y_k = Cx_k + v$$

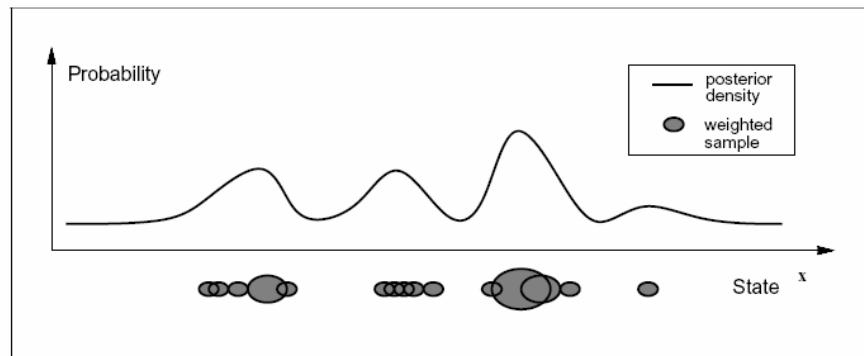
$$\hat{x}_k = \hat{A}\hat{x}_{k-1} + H_k(y_k - \hat{y}_k)$$

1. 工作方式: 预测 + 校正



Particle Filtering (PF)

Importance Sampling:



Bayesian framework of PF:

$$p_t(\mathbf{x}_t | \mathcal{Z}_t) = \frac{p_t(\mathbf{z}_t | \mathbf{x}_t)p_{t-1}(\mathbf{x}_t | \mathcal{Z}_{t-1})}{p_t(\mathbf{z}_t)},$$

$$p_t(\mathbf{x}_t | \mathcal{Z}_t) = \frac{p_t(\mathbf{z}_t | \mathbf{x}_t) \int_{\mathbf{x}_{t-1}} p_t(\mathbf{x}_t | \mathbf{x}_{t-1})p_{t-1}(\mathbf{x}_{t-1} | \mathcal{Z}_{t-1}) d\mathbf{x}_{t-1}}{p_t(\mathbf{z}_t)}.$$

$p_{t-1}(\mathbf{x}_{t-1} | \mathcal{Z}_{t-1})$

\mapsto

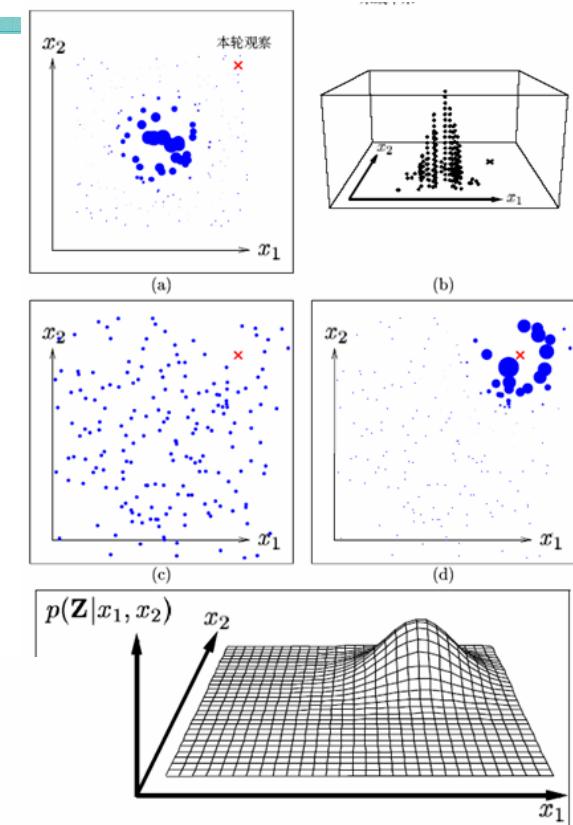
$p_{t-1}(\mathbf{x}_t | \mathcal{Z}_{t-1})$

\mapsto

$p_t(\mathbf{x}_t | \mathcal{Z}_t)$

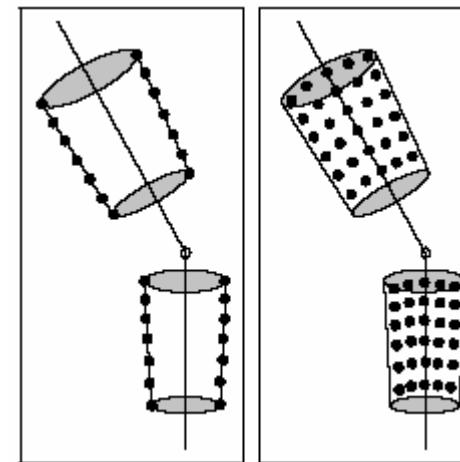
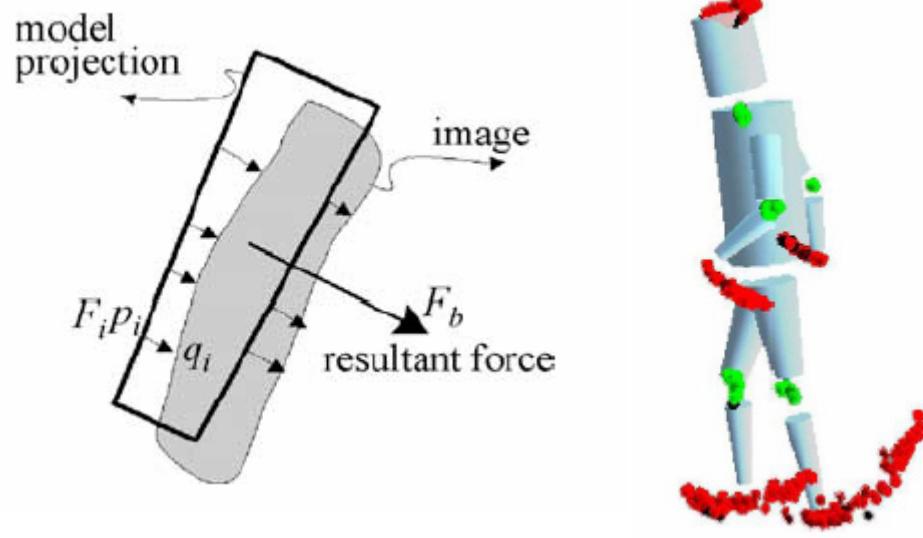
convolve with
dynamics $p(\mathbf{x}' | \mathbf{x})$

multiply by
observation
density $p(\mathbf{z} | \mathbf{x}')$



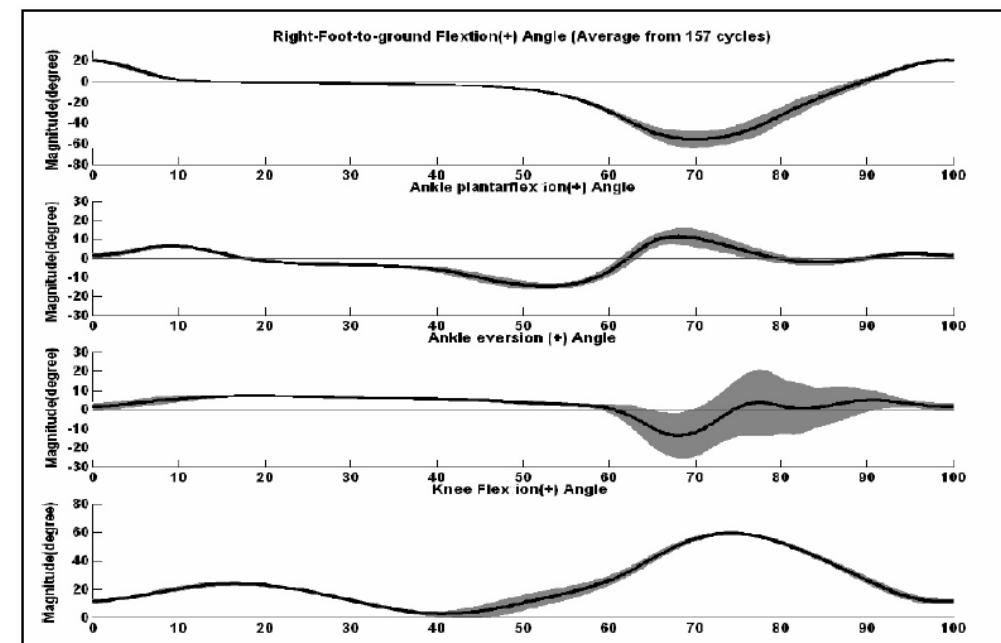
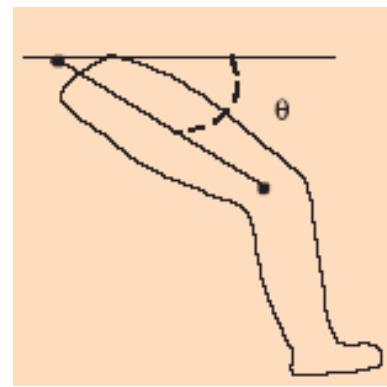
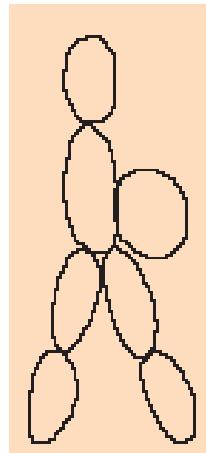
Tracking

- ◆ Status equation —— description of kinematics characteristics;
- ◆ Measurement vector —— low level visual cues: edge detection 、 foreground segmentation、 centroid、 color.....



Typical algorithms in model-based gait recognition

- ◆ Hip rotation model
- ◆ Ellipse fitting
- ◆ Two-joint pendulum model

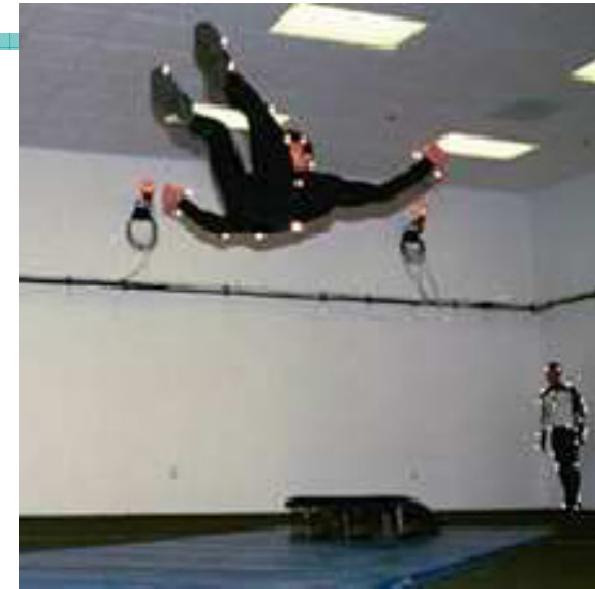


Trajectory analysis of rotation angles

**Other solutions for gait?
— extend our mind!**

Marker-based motion capture

- ◆ Marker's type:
 - LED, infra-red, radio
- ◆ Application
 - Movie production
 - Animation
 - Athlete training aid
 - Human gait analysis



(a)

(b)



(c)

(d)

Multiple-Circle Tracking

- ◆ Single tracking:

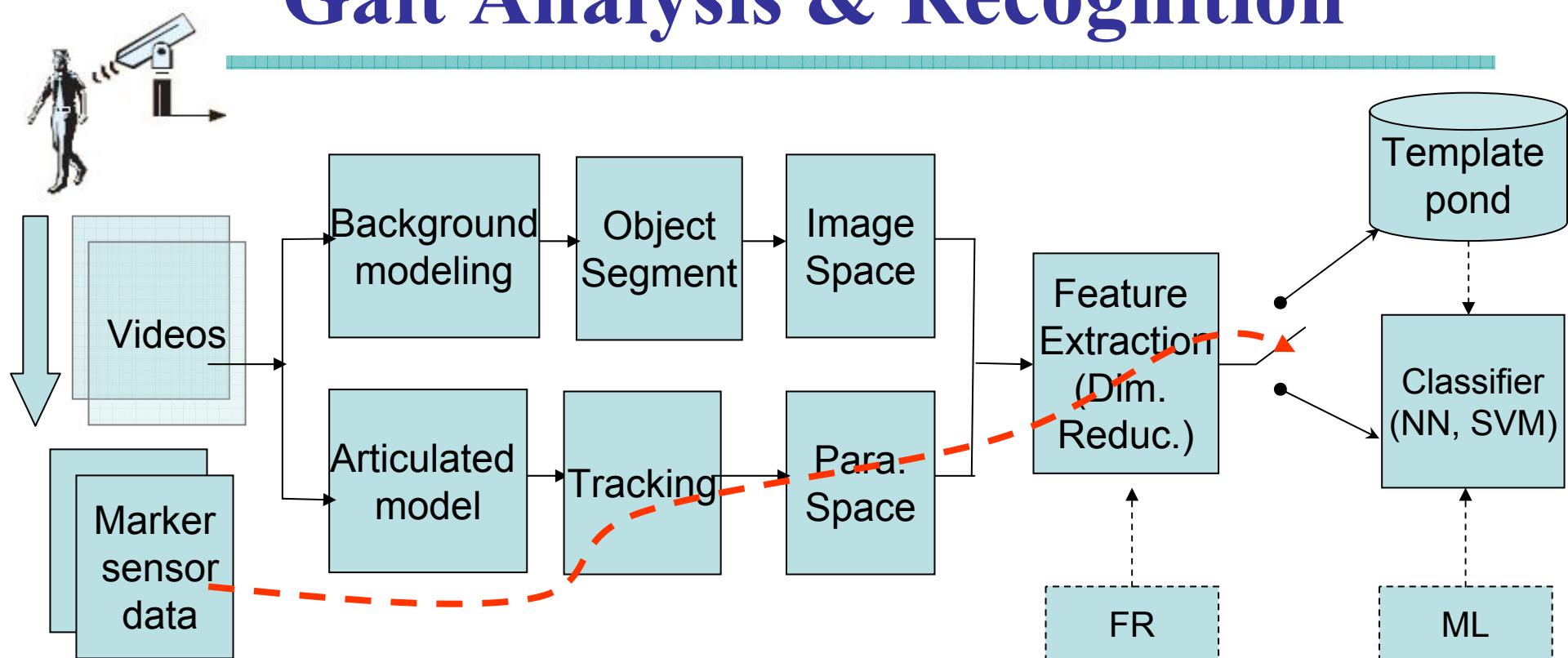


- Multiple Tracking:



- ◆ Difficulties: Overlapping, Agile-movement, Real-time, ID-confusing ...

General Technique Framework of Gait Analysis & Recognition

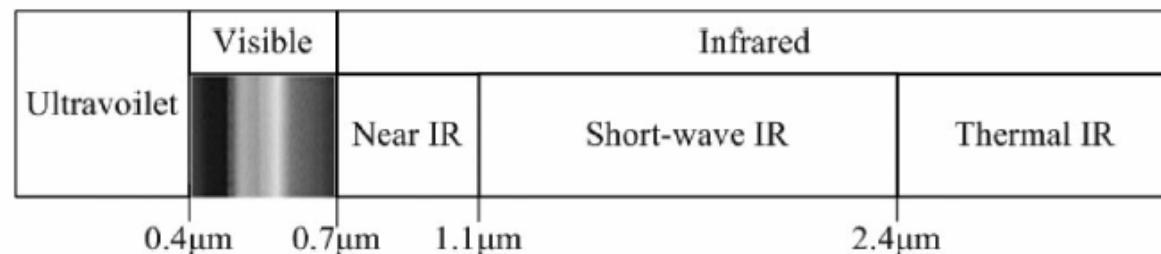


- ◆ **Model free:** silhouette analysis
- ◆ **Model based**
 - Markerless: Articulated model
 - **Marker-based analysis**

Look at Another Case: Face Recognition by NIR

◆ Why NIR (Near Infra-Red) ?

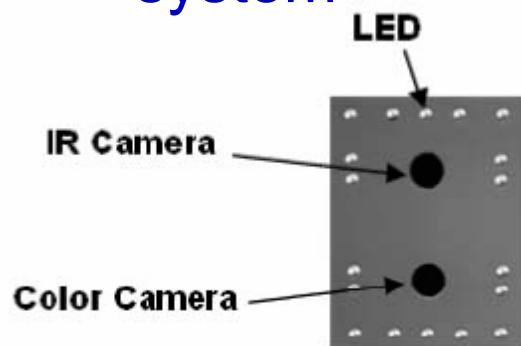
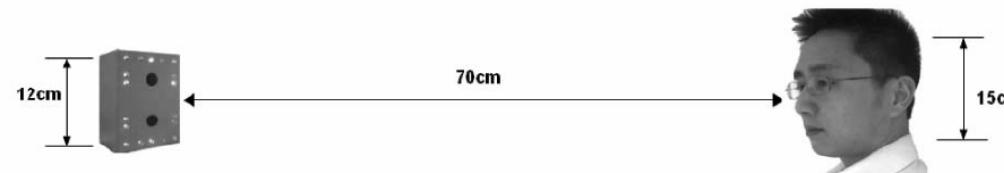
- Radiation Spectrum Ranges

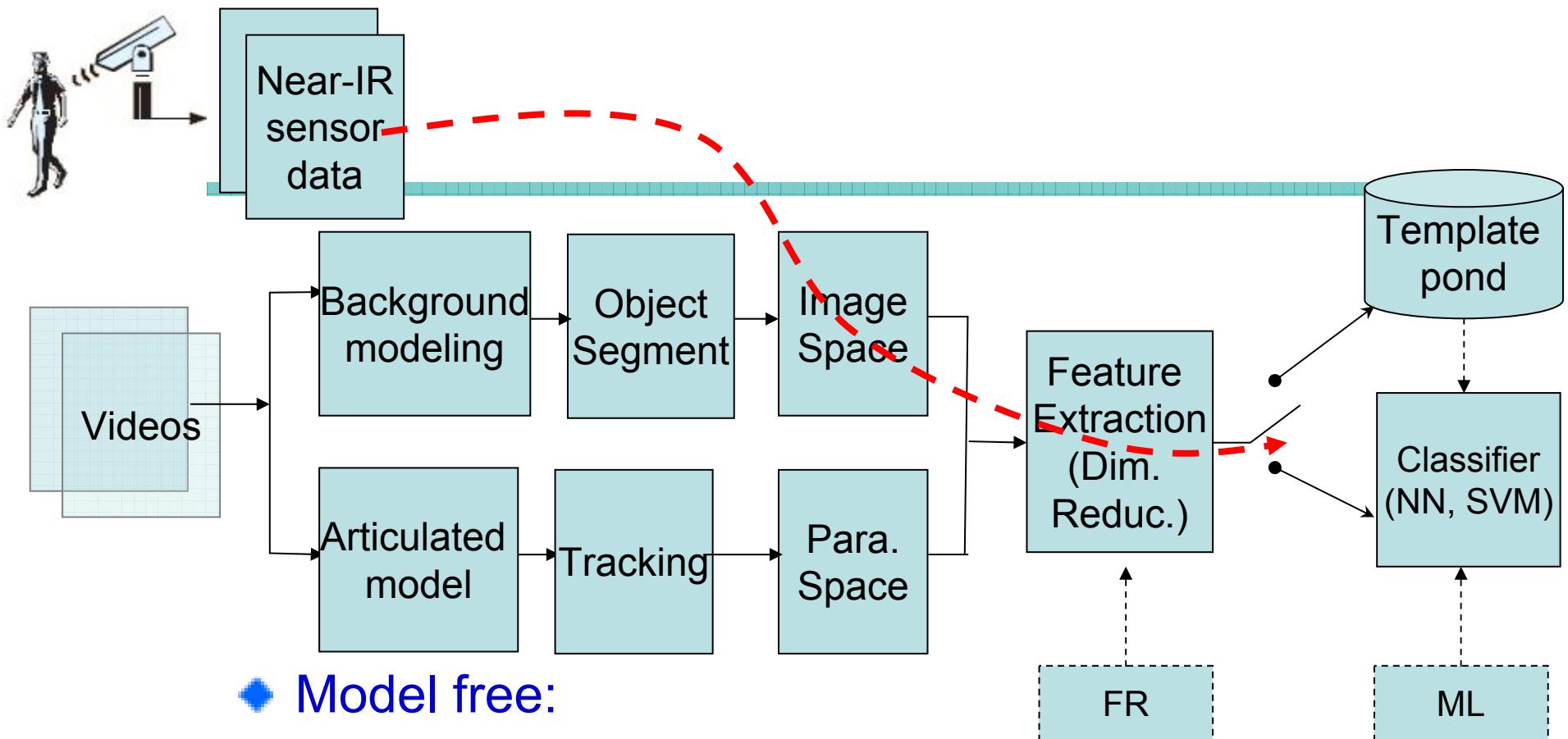


- Robust to illumination variant

- Non-invasive

◆ Active NIR imaging system





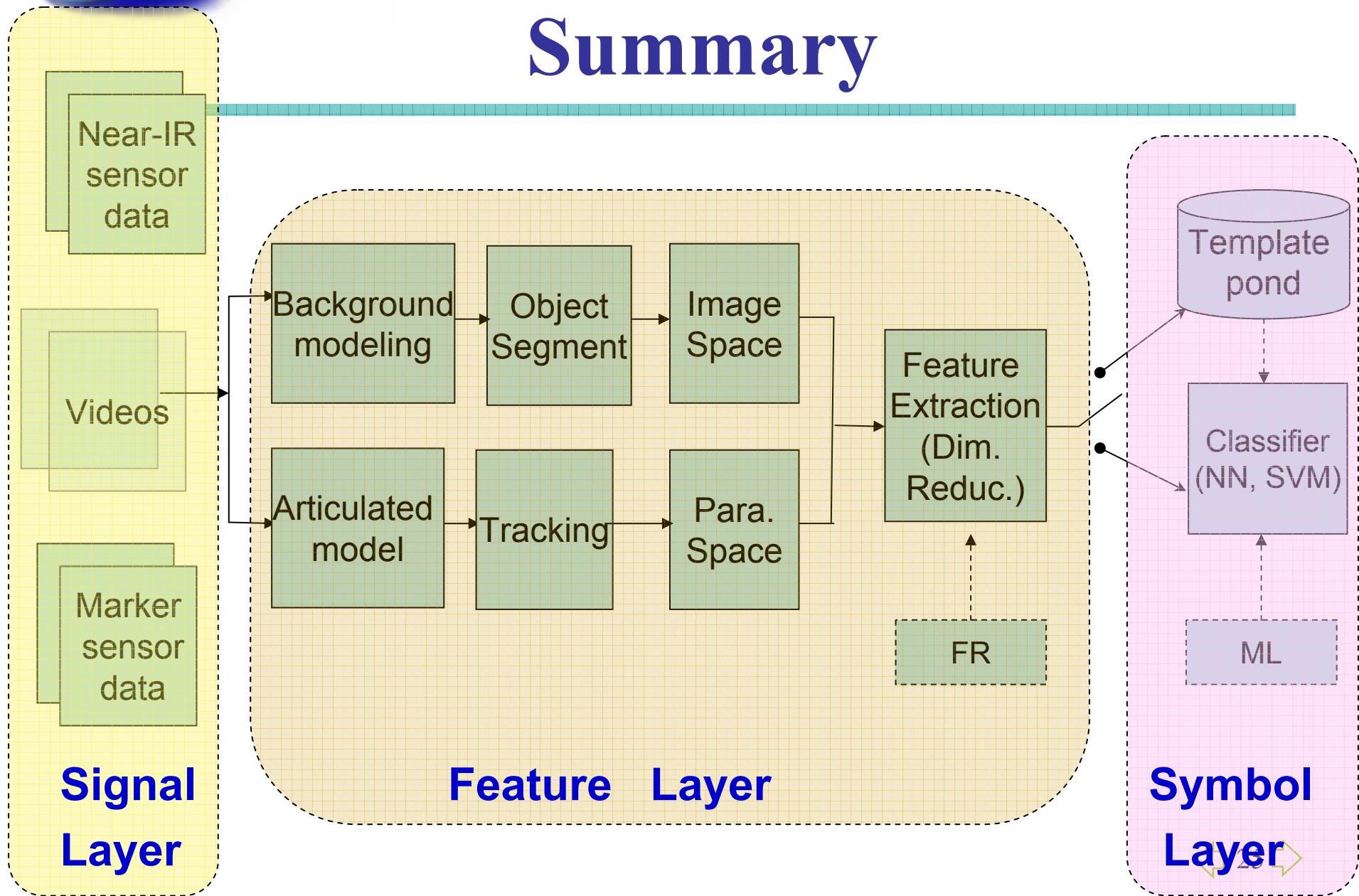
- ◆ Model free:

- Silhouette analysis
- **Near Infra-red image: Non-invasive**

- ◆ Model based

- Markerless: Articulated model
- Marker-based analysis: **Invasive**

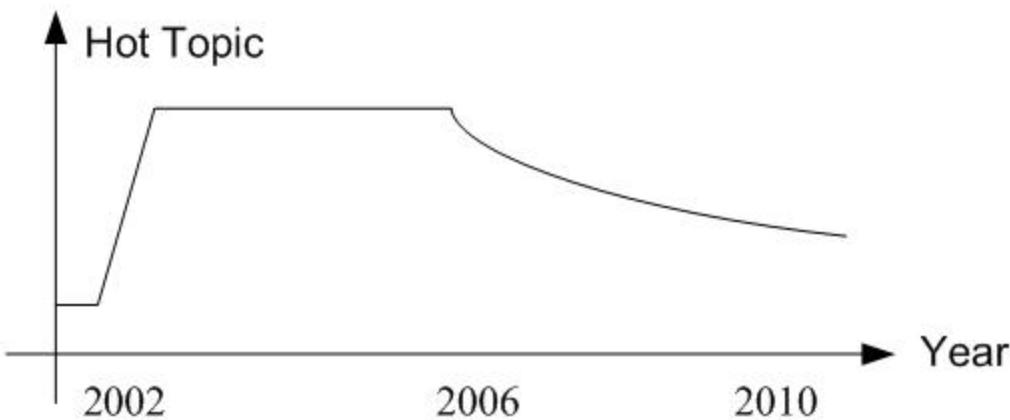
Summary



From Gait to body motion analysis

— possible future trends

- ◆ Tensor based approaches
- ◆ Abnormal behavior detection
- ◆ Body motion capture & driven
- ◆



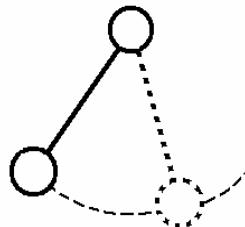
Selected our work on gait recognition

- Gait history image (GHI)
- Silhouette Quality Quantification (SQQ)

Temporal Template

- ◆ **Definition:** In template image, each pixel value is defined as a function of time (frame number) along whole silhouette sequence.
- ◆ **Purpose:** binary image sequence can be represented as a compact image with temporal information reserved.

Temporal Template: Some examples



A scenario of pendulum's motion

- ◆ Motion Energy Image (MEI):

$$E_{\text{MEI}}(x, y) = \bigcup_{t=1}^{\tau} D(x, y, t)$$



- ◆ Motion History Image (MHI):

$$E_{\text{MHI}}(x, y, t) = \begin{cases} \tau & \text{if } D(x, y, t) = 1 \\ \max(0, E_{\text{MHI}}(x, y, t-1) - 1) & \text{otherwise} \end{cases}$$

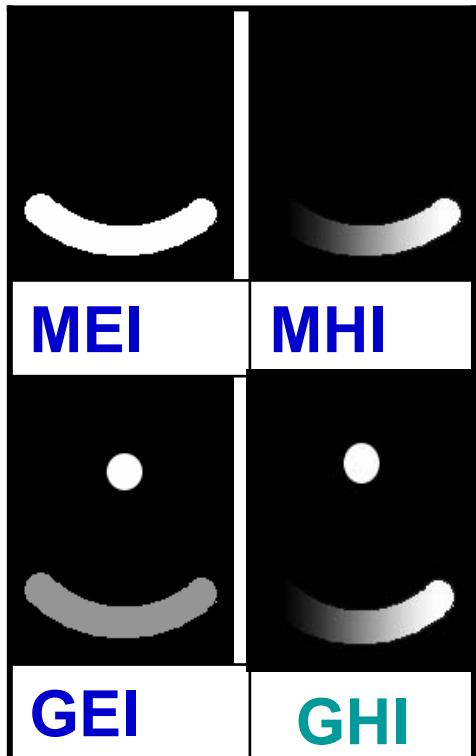


- ◆ Gait Energy Image (GEI):

$$E_{\text{GEI}}(x, y) = \frac{1}{\tau} \sum_{t=1}^{\tau} I(x, y, t)$$



Comparison of GHI with other templates



	MEI	MHI	GEI	GHI
Static Parts	✗	✗	✓	✓
Dynamic Parts	✓	✓	✓	✓
Temporal Info	✗	✓	✗	✓

Gait History Image

◆ Aim:

A novel temporal template should have finer representing ability for gait motion.

◆ Definition:

$$E_{\text{GHI}}(x, y) = \begin{cases} \tau & \text{if } S(x, y) = 1 \\ \sum_{t=1}^{\tau} D(x, y, t) \cdot (t - 1) & \text{otherwise} \end{cases}$$

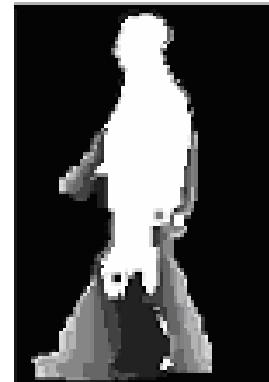
Where $S(x, y) = \begin{cases} 1 & E_{\text{GEI}}(x, y) \geq th \\ 0 & \text{otherwise} \end{cases}$ $th = \max_{(x,y)}(E_{\text{GHI}}) \times 80\%$

◆ Merit:

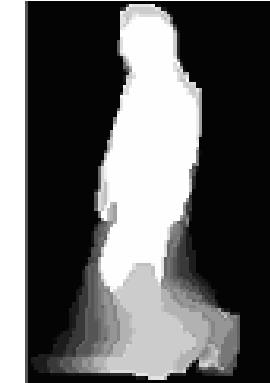
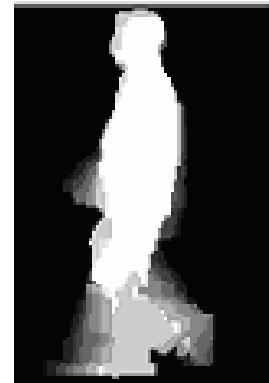
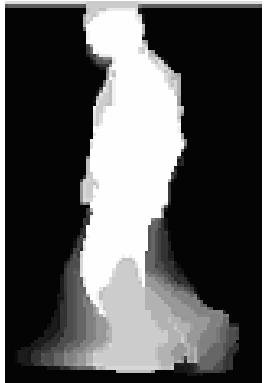
- Static and dynamic characteristics can be represented;
- spatial and temporal variations can be represented.

Some examples of GHI

E_{GHI}^O



E_{GHI}^C



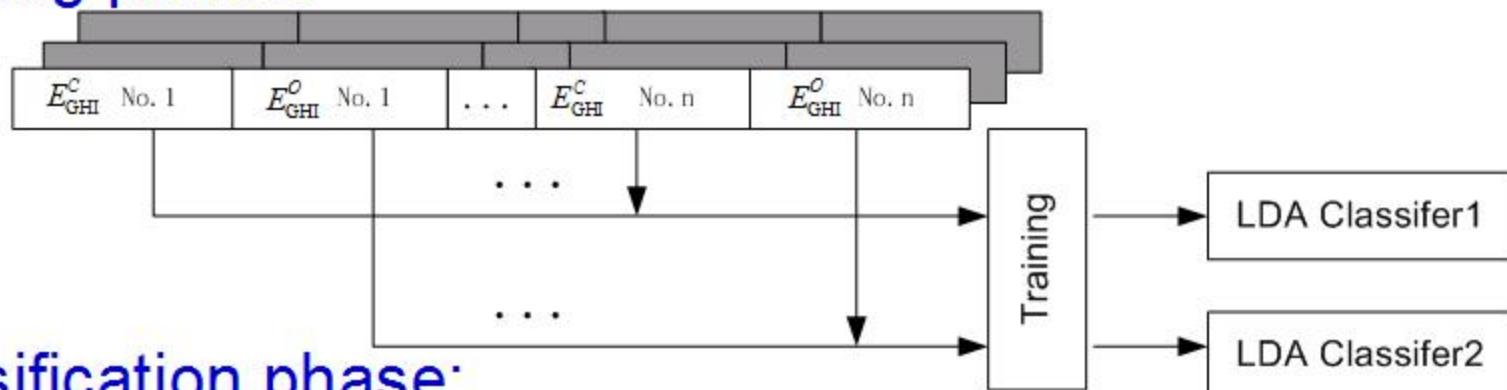
*Subject
1*

*Subject
2*

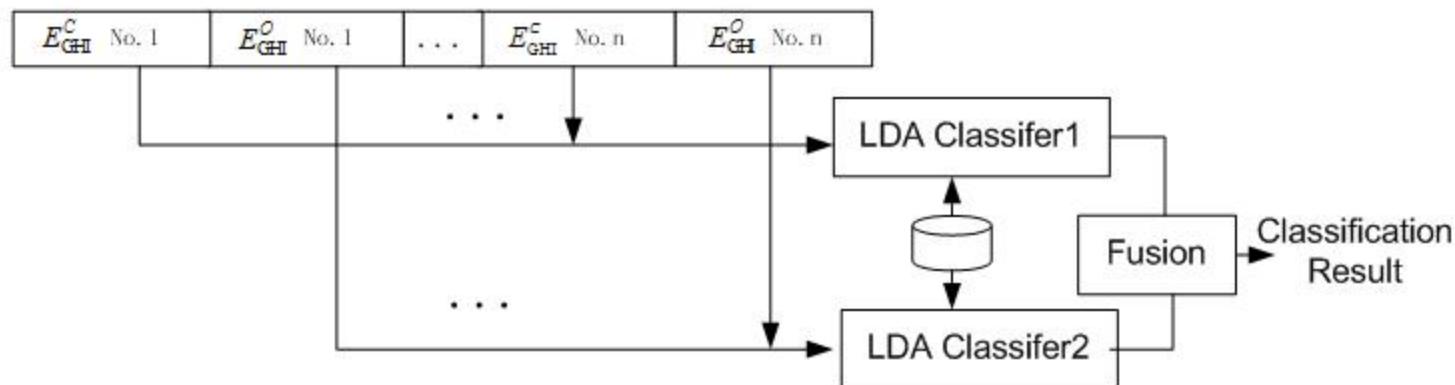
*Subject
3*

Gait Recognition using GHI

◆ Training phase:



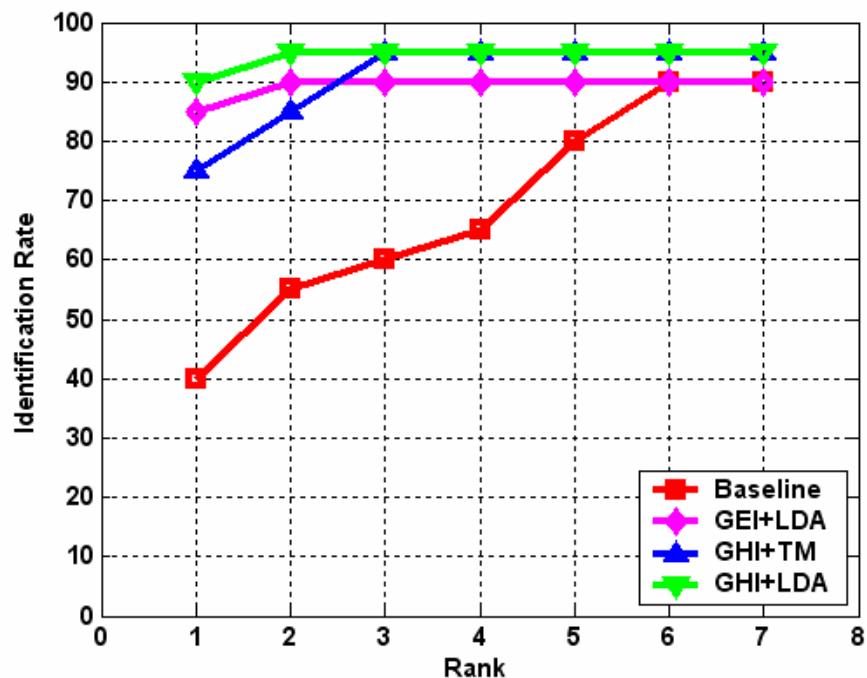
◆ Classification phase:



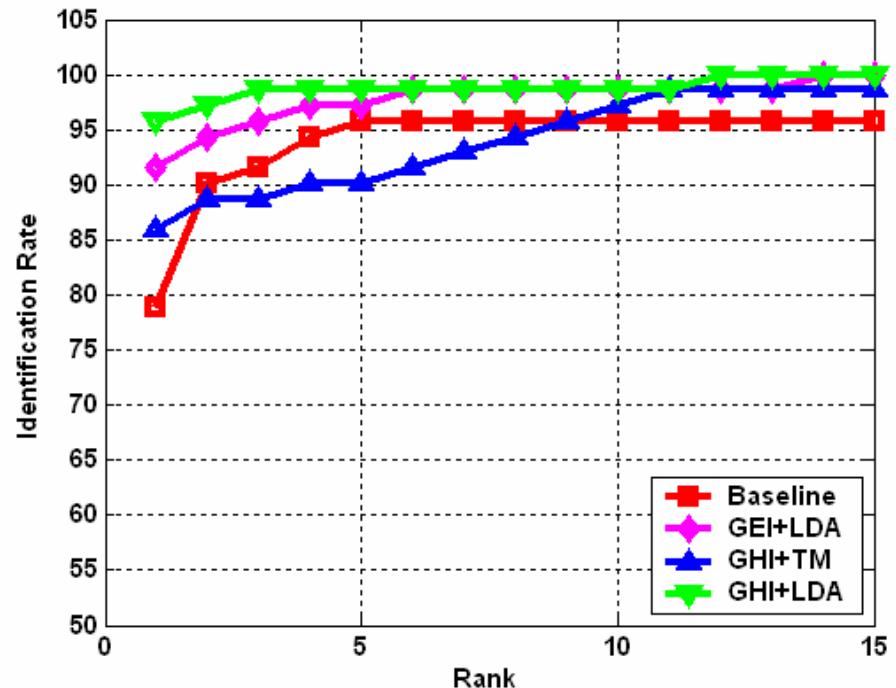
➤ Nearest Center of Class (NCC) criterion is used here:

$$\chi_p = \arg \min_{1 \leq i \leq C} [D(\tilde{\mathbf{G}}^o, \mathbf{G}_i^o) + D(\tilde{\mathbf{G}}^c, \mathbf{G}_i^c)]$$

Experimental results



Cumulative Matching Score (CMS)
results on CASIA dataset



CMS scores on USF dataset

Selected our work on gait recognition

- Gait history image (GHI)
- Silhouette Quality Quantification (SQQ)

Motivation

- ◆ Most gait recognition approaches are designed based on binary images (silhouettes).
 - Simpler compared to articulated model.
 - clothing color / texture information contribute nothing to identification;
 - So, many gait datasets opened public provide silhouette versions.
- ◆ However, In reality, silhouette noise occurs inevitably after *Background Subtraction*.

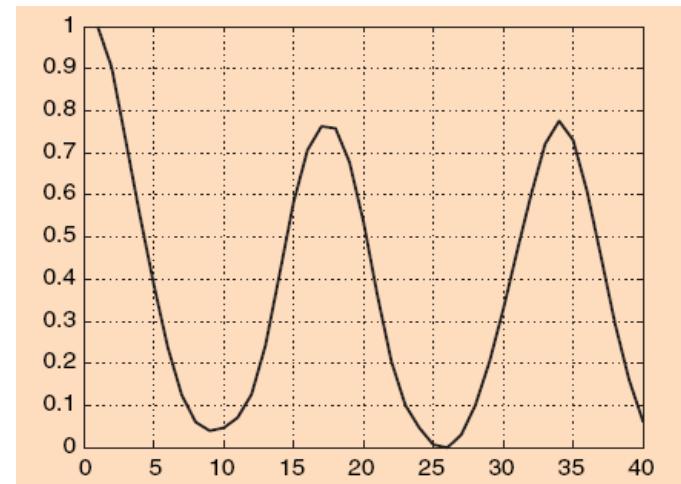
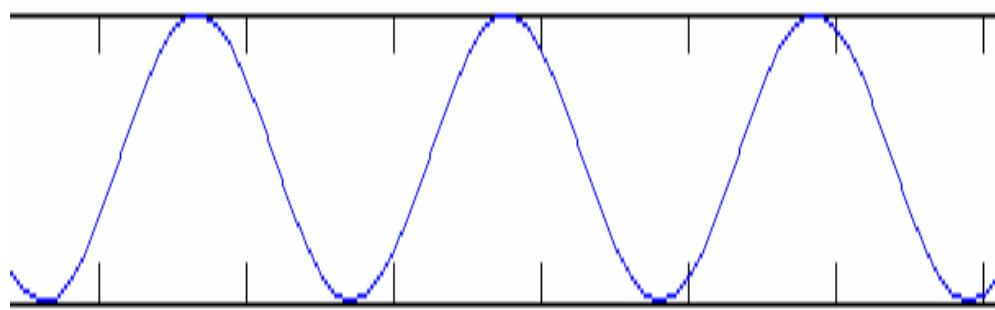


Periodicity and Cycles in gait sequence

- ◆ Time duration of a full walking cycle:



- ◆ Foreground sum signal & its Autocorrelation signal:



Observation

- ◆ **What is FS signal?**

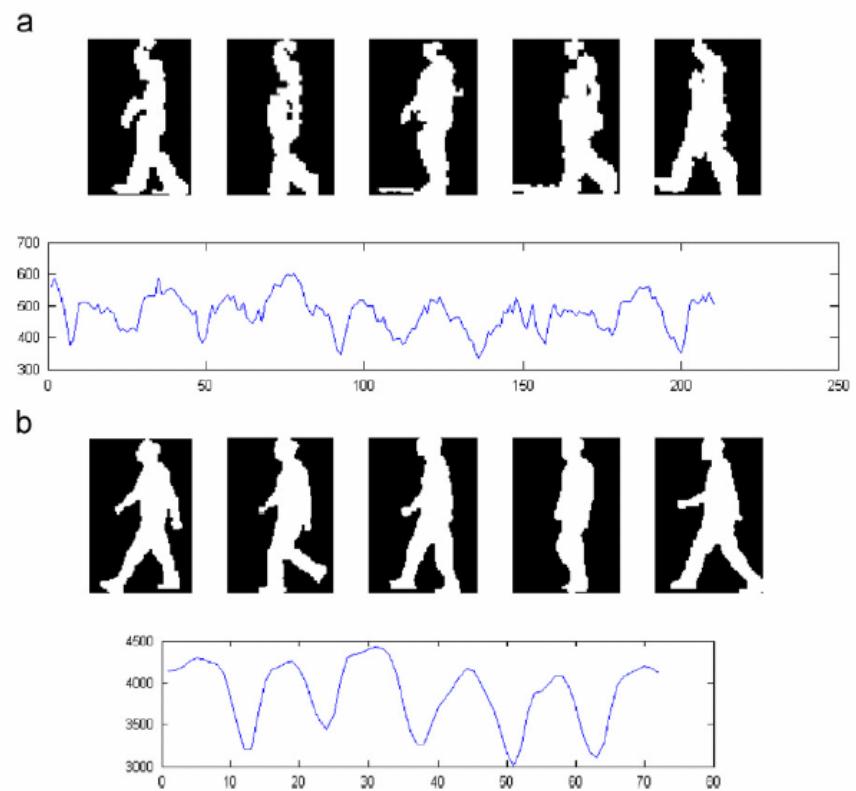
- **Definition:**

$$x(t) = \sum_u \sum_v s(u, v, t)$$

foreground-sum signal

- ◆ **Observation**

**The noise in FS signal
is correlated to noise in
silhouettes.**



Silhouette Quality Quantification (SQQ)

- ◆ Idea: Using FS signal to measure the quality of silhouette sequence.
- ◆ Modeling the FS signal:

$$x(t) = a_0(t) + a_1(t) \cos \omega t + a_2(t) \cos 2\omega t + z(t)$$

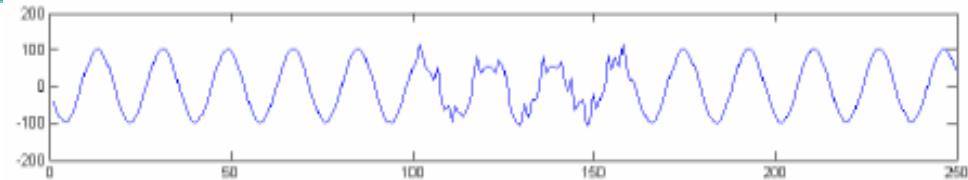
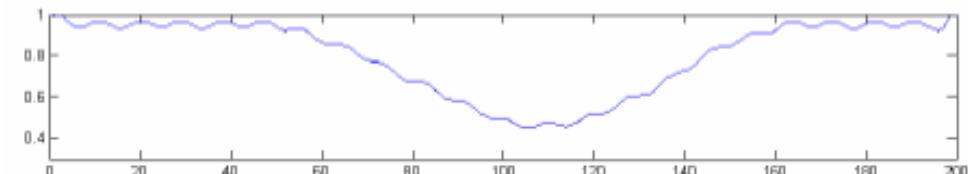
- ◆ Proposed a silhouette quality evaluation function:

$$Q(i) = \sigma_s^2 - \sigma_z^2, \text{ over } f_i(t), \text{ for all } f_i \subset f$$

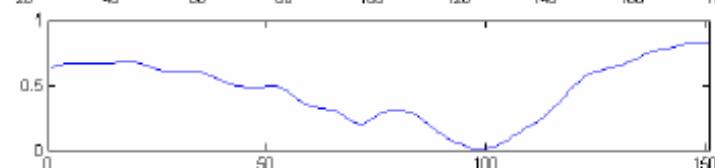
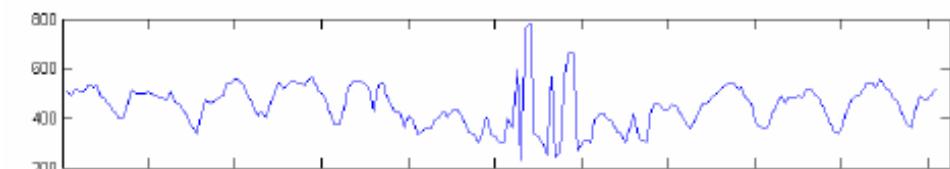
by using the autocorrelation matrix eigen-analysis approach.

Visualization of the evaluation

- ◆ SQQ curve upon simulated data:

(a) $f(t)$ (b) $\mathcal{Q}(i)$ 

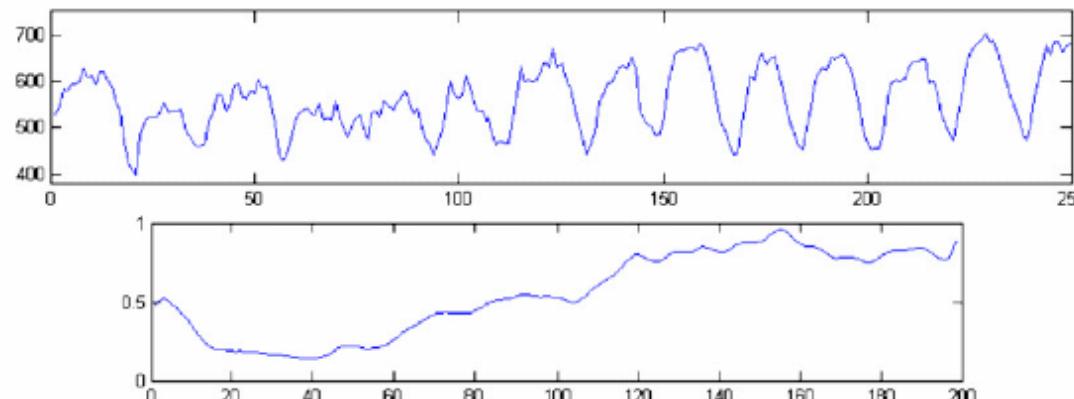
- ◆ SQQ curve upon real silhouette data:



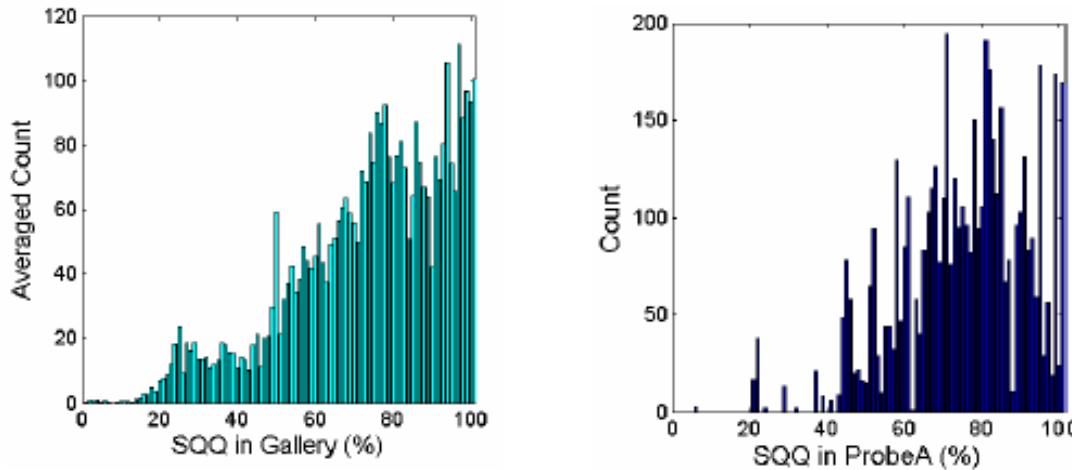
Silhouette Quality Weighted (SQW) Gait Recognition

- ◆ Extending the application of SQQ for gait recognition.
- ◆ Proposed the Silhouette quality weighted (SQW) gait recognition algorithm:

$$k = \arg \min_i \left(\text{Sim}_{(\chi)} (\mathbf{S}_P, \mathbf{S}_i) \right), \text{ with } \mathbf{S}_i \in \{\mathbf{S}_G\}$$
$$\text{Sim}'_{(\chi)} (\langle \mathbf{S}_P, Q_{\mathbf{S}_P} \rangle, \langle \mathbf{S}_G, Q_{\mathbf{S}_G} \rangle)$$



Experimental results



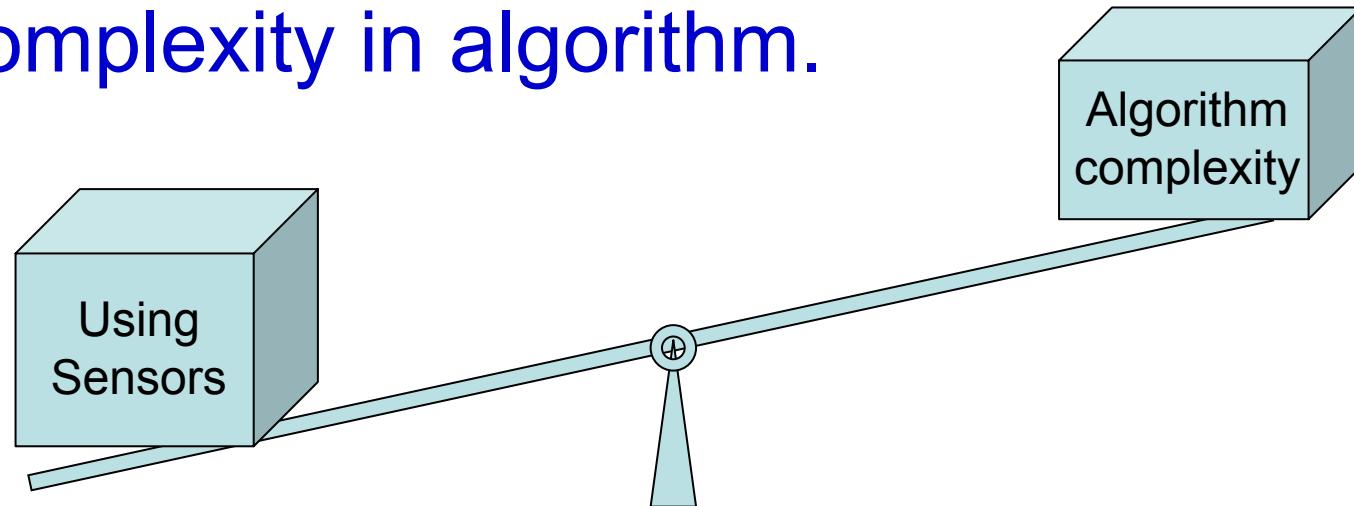
(a) Histogram of SQQ scores for the Baseline algorithm

Exp.	$P_f(\%)$ at rank = 1, 5							
	Method		SQW _{rectangle} + TM		SQW _{hamming} + TM		SQW _{hamming} + FLD	
	Rank	1	5	1	5	1	5	1
A	95.77	97.18	97.18	100	97.18	100	98.59	100
B	80.49	92.68	85.37	95.12	82.93	95.12	87.80	92.68
C	68.29	92.68	70.73	95.12	68.29	97.56	85.37	90.24
D	30.30	50.00	33.33	57.58	33.33	57.58	39.39	66.67
E	28.57	40.48	33.33	54.76	35.71	54.76	45.24	69.05
F	22.73	37.88	25.76	50.00	24.24	48.48	36.36	62.12
G	26.19	42.86	30.95	45.24	30.95	50.00	30.95	59.52
Mean	50.33	64.82	53.81	71.12	53.23	71.93	60.53	77.18

(b) Identification performances on the USF ver1.7 dataset. ↶ 42 ↷

My Advises on GR system building

- ◆ Frontal view is more discriminative,
- ◆ Never discard static feature —— cascade
- ◆ Room is harder than corridor,
- ◆ The more sensor uses, the less complexity in algorithm.



Thank You!