Tutorial Outline

- Introduction
- PART I: Face-based Human Recognition
- PART II: Gait-based Human Recognition
  - **Introduction**
  - Gait-based human identification using appearance matching
  - Statistical framework for gait-based human identification
  - View invariant gait recognition
  - Combining multiple evidences for gait recognition
  - Future research directions
- Discussions

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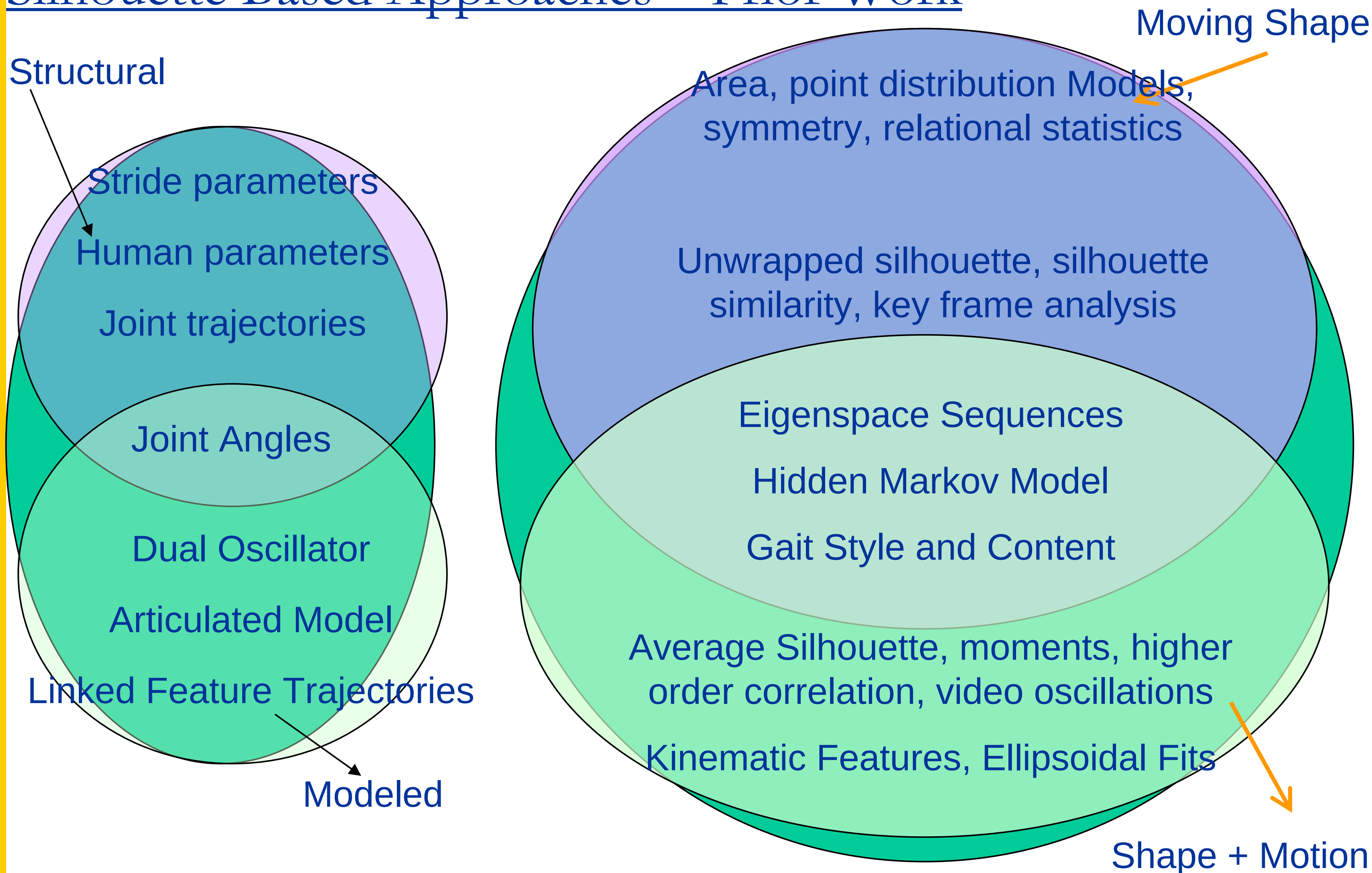
Silhouette Based Approaches – Prior Work

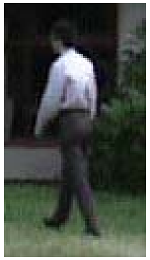


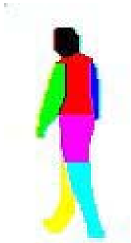
Model Based Methods

Model Free Analysis

Gait Data Bases

- HumanID data base (USF/NIST) (1870 sequences from 122 subjects)
  - For each subject, two views, two surface types and two types of shoes. Some carried brief cases; some were imaged after 6 months.
- UMD (Two data sets: 25 subjects and 55 subjects)
- University of Southampton (Soton) (116 subjects)

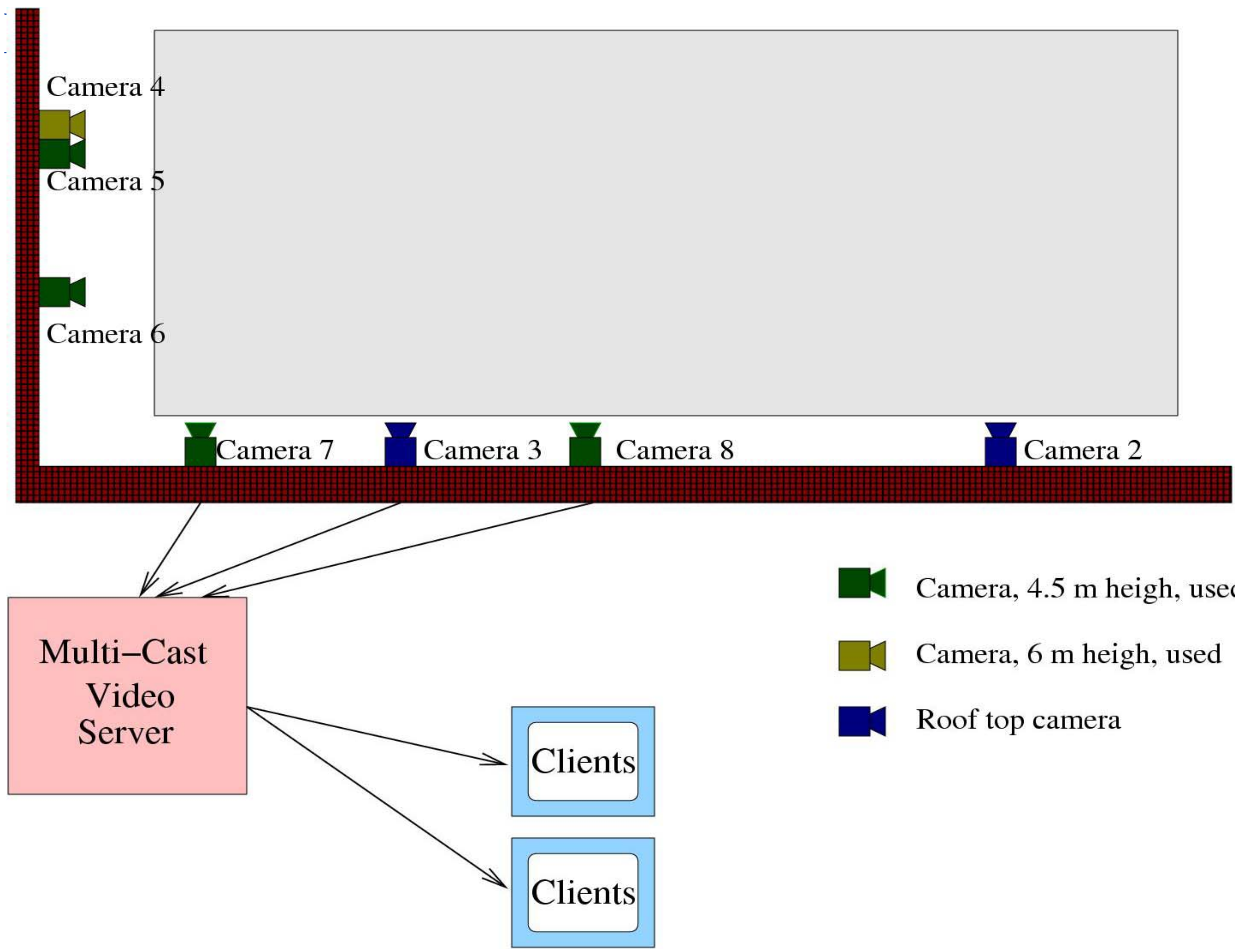




USF Dataset

Experiment	Probe	Difference
A	G,A,L	View
B	G,B,R	Shoe
C	G,B,L	Shoe, View
D	C,A,R	Surface
E	C,B,R	Surface,Shoe
F	C,A,L	Surface,View
G	C,B,L	Surface,Shoe,View
H	G,A,R,BF	Briefcase
I	G,B,R,BF	Shoe,Briefcase
J	G,A,L,BF	View, Briefcase
K	G,A,R,t2	Time
L	C,A,R,t2	Surface, Time

UMD Infrastructure



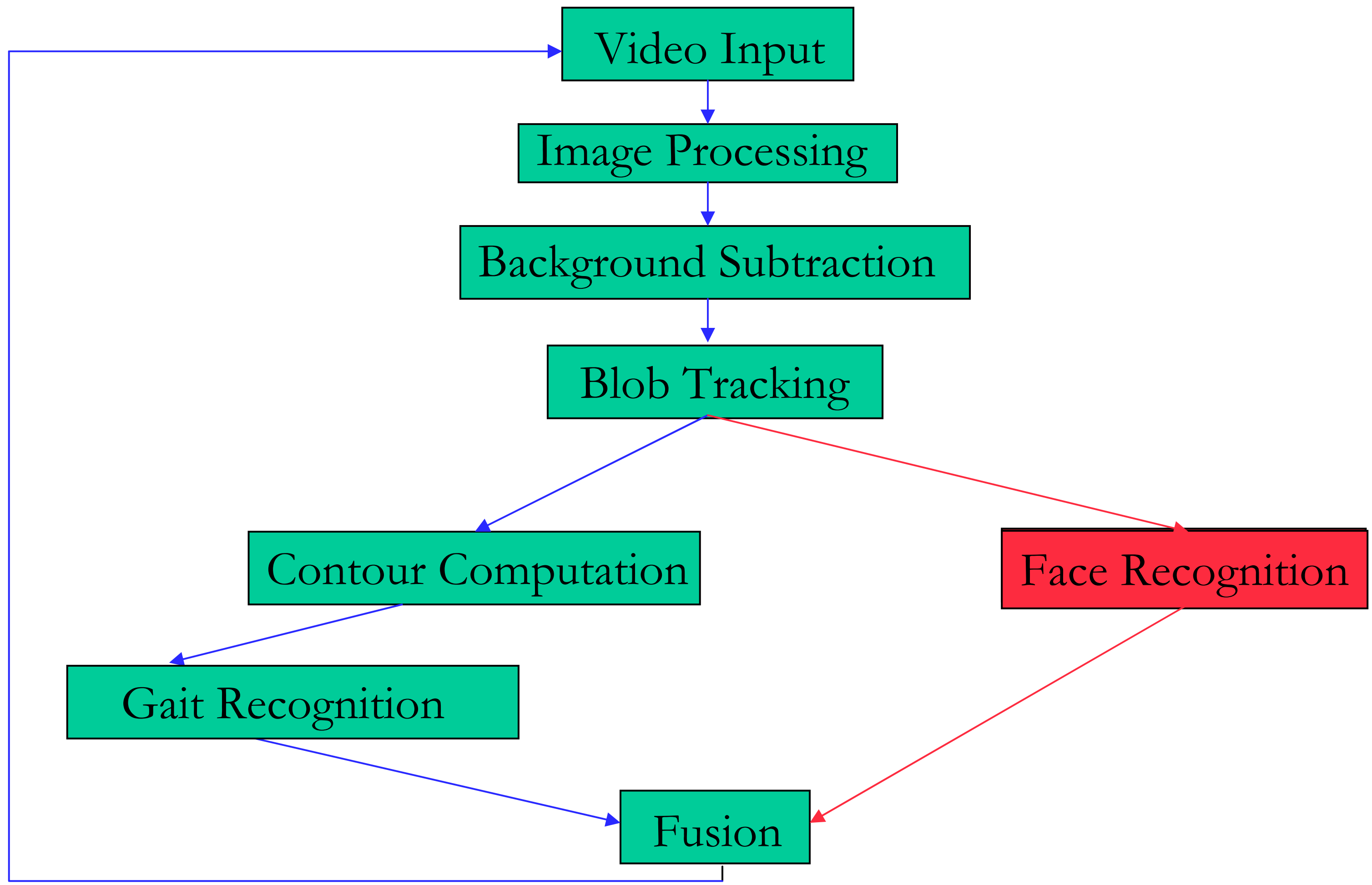
4 Cameras, 4.5m
1 Camera, 6m
1 Camera, roof

1 Video server
N clients

UMD Dataset Acquisition



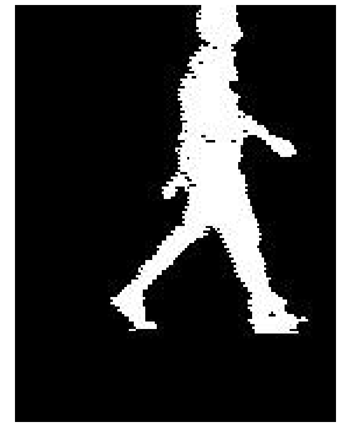

UMD Integrated Software System



Preprocessing

background subtraction

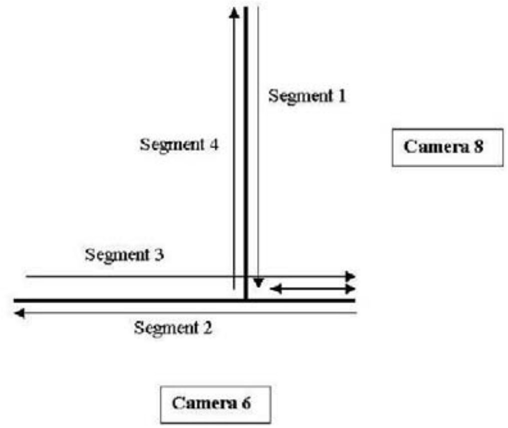
Binarized silhouette



- Independence from Clothing, Illumination

UMD Background Subtraction Results

(a)



(b)

Stances along segment 1

Stances along segment 2

Stances along segment 3

Stances along segment 4

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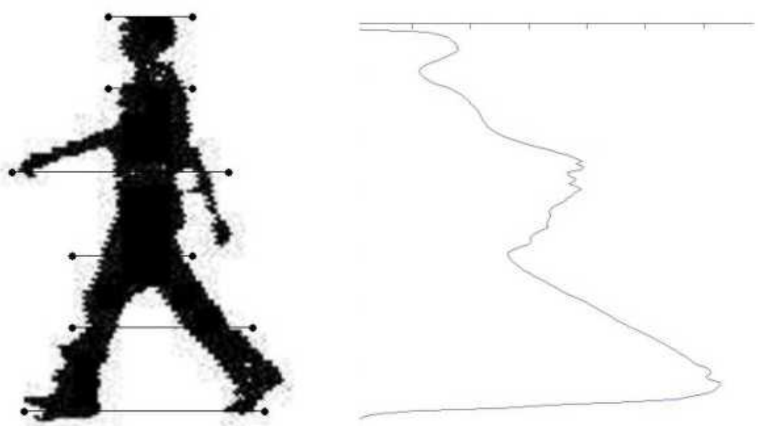
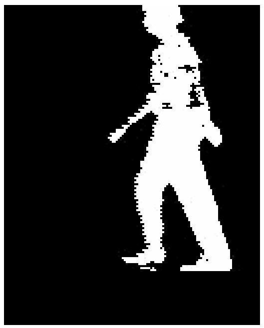
Appearance Matching Approach

- Motivation
  - Similarity with text-based speaker identification
  - Availability of limited training data
- Feature : Width of outer contour of silhouette



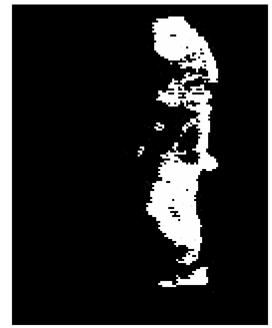
Width Feature

Person 1

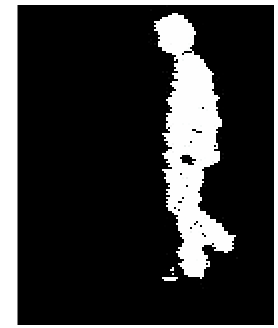


Person 2

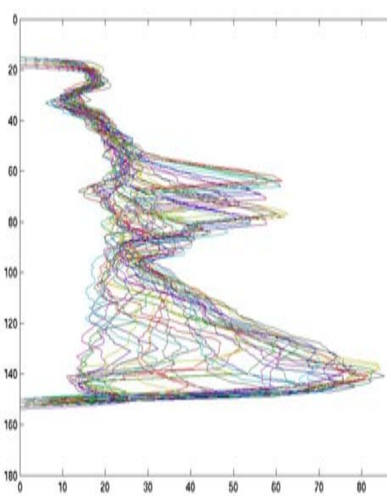
Person 3

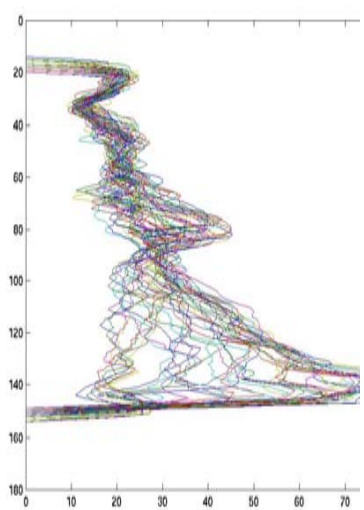


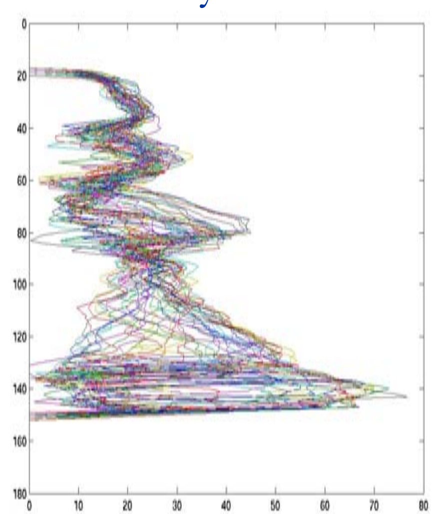
Person 4

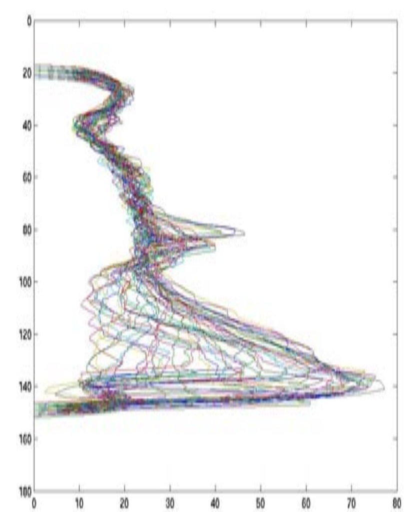


Width Vectors Overlay



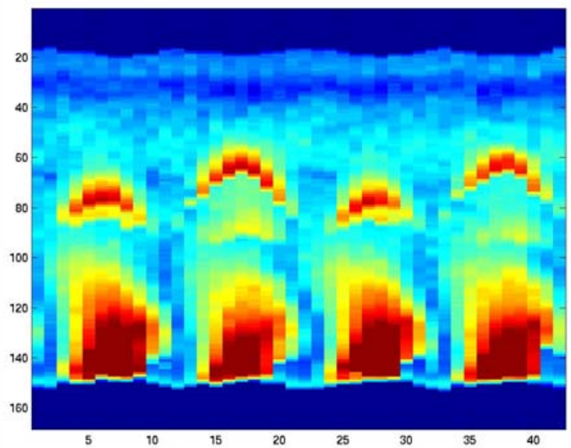




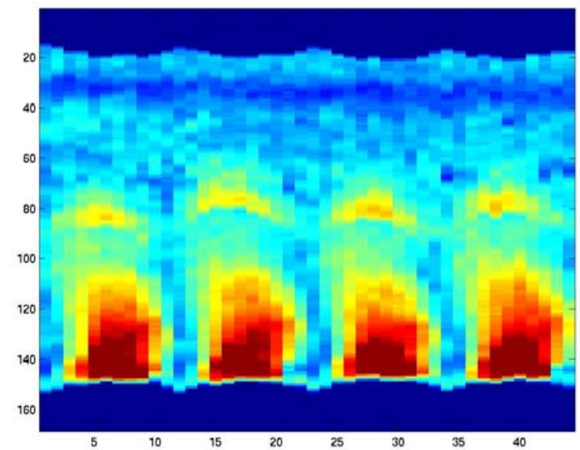


Temporal Plots of Width

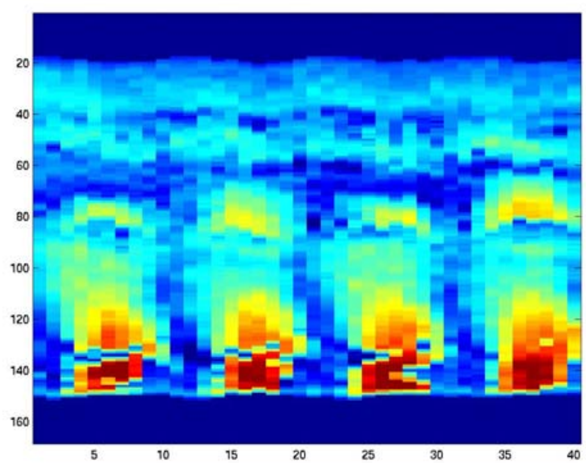
Person 1



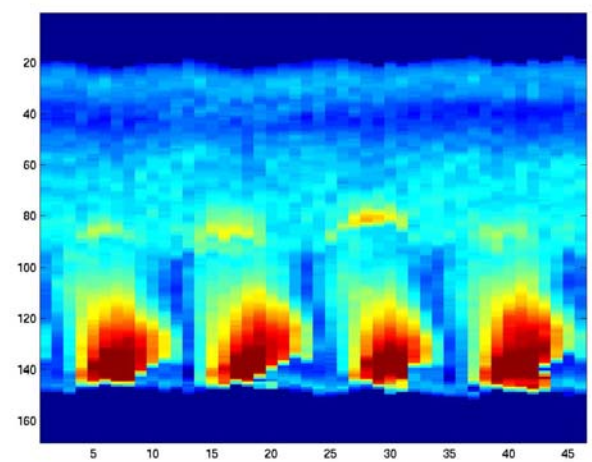
Person 2



Person 3



Person 4



Spatio-temporal Smoothing of Width

$$\{W(1),\ldots\ldots,W(N)\}, W(i) \in \mathrm{R}^{M}$$

Eigen decomposition

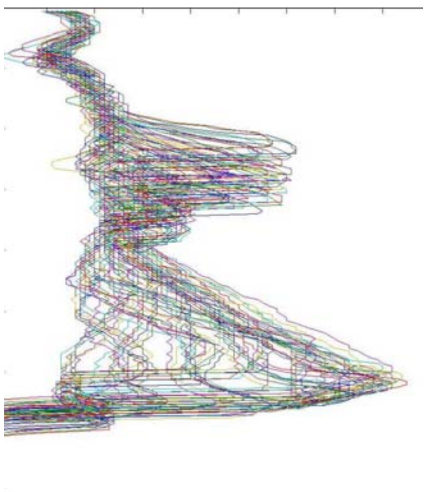
$$\{V(1),\ldots\ldots,V(M)\}$$

$$W_r(i) = \left(\sum_{j=1}^{m} w_j V(j)\right) + \overline{W}$$

$$w_j(i) = \langle W(i), V(j) \rangle, \overline{W} = \frac{W(1) + \ldots\ldots + W(N)}{N}$$

Width Vectors Overlays after Smoothing

Before smoothing



After smoothing

Other features

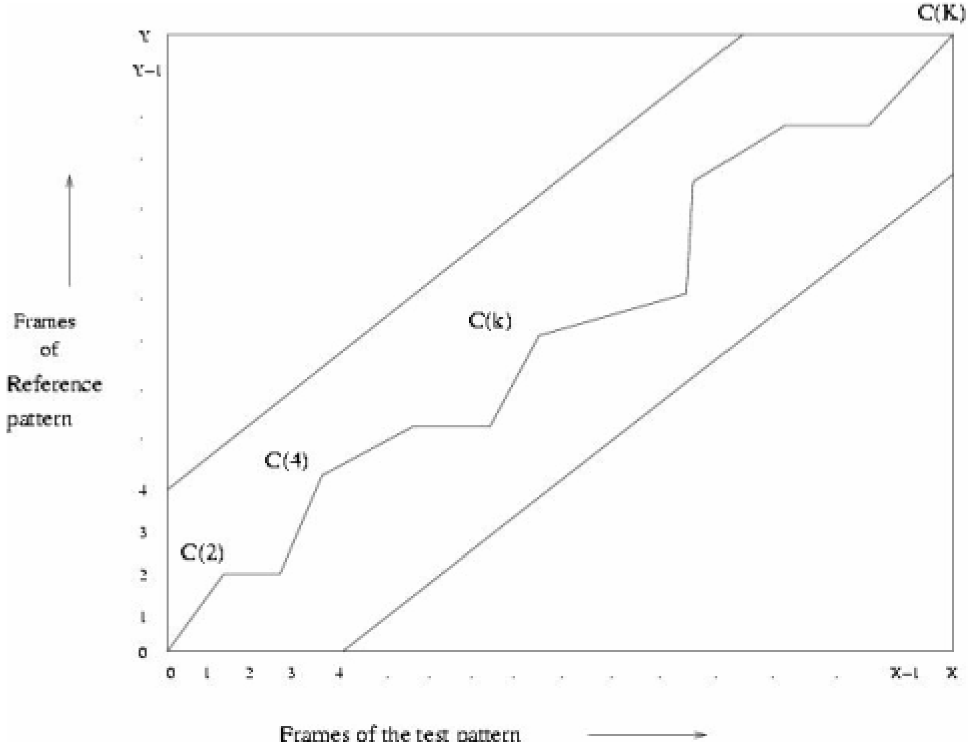
- Direct Smoothed Width Vectors
- Dynamics

Matching Gait Sequences

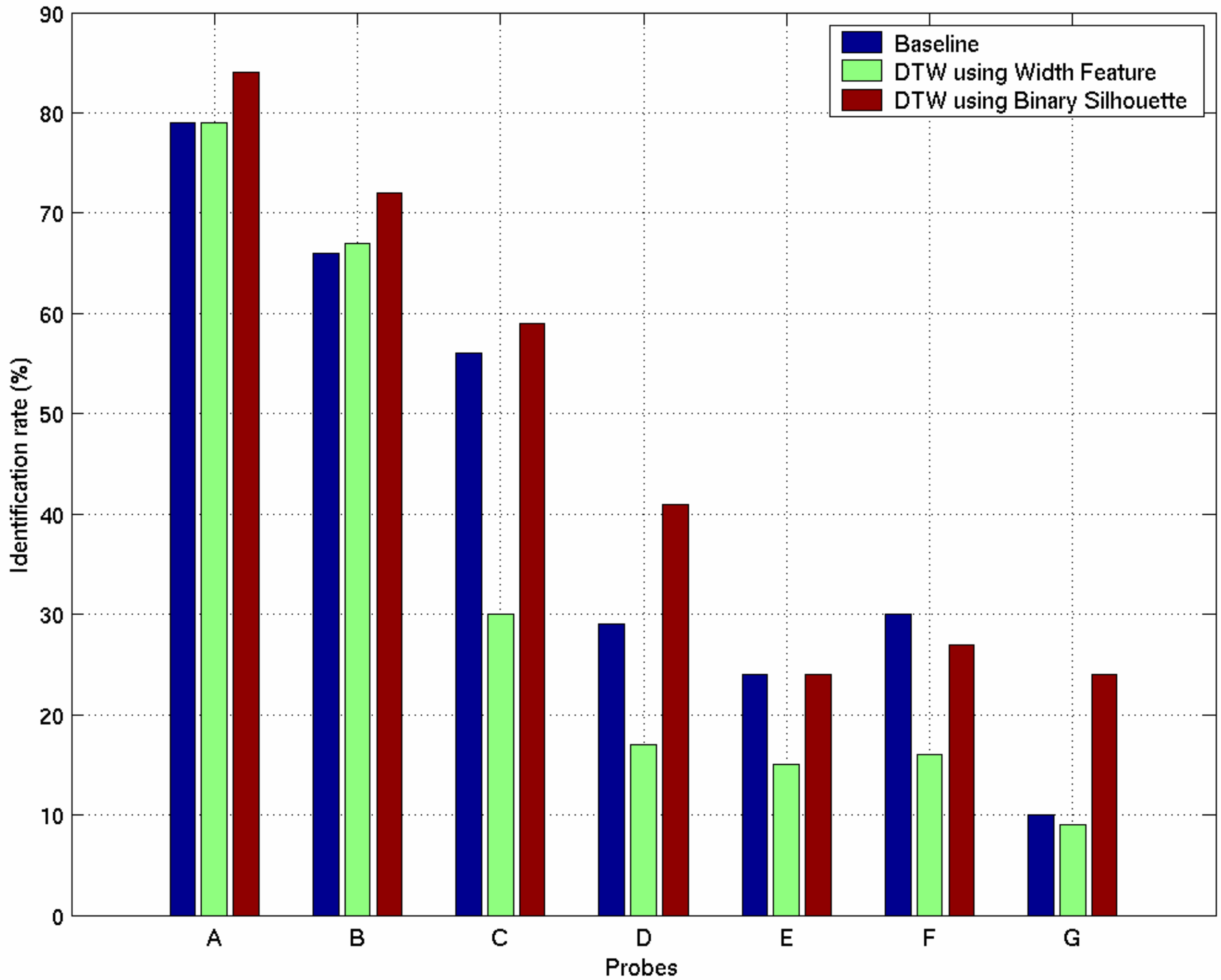
- Template Matching Using DTW
  - Dynamic programming
  - Non-linear time normalization for matching
  - Constraints
    - Monotonicity $X_{k-1} \leq X_k$, $Y_{k-1} \leq Y_k$
    - Local continuity $X_k - X_{k-1} = 1$, $Y_k - Y_{k-1} \leq 2$
    - Global path
    - End point $X_T = Y_R$

Dynamic Time Warping (DTW) Algorithm

- Local distance computation $L(k,l) = ||Y_k - X_l||$
- Cumulative distance computation
  $D(X_k, Y_k) = L(X_k, Y_k) +$
  $min\{ D(X_{k-1}, Y_k), D(X_{k-1}, Y_{k-1}), D(X_{k-1}, Y_{k-2}) \}$
- Backtracking



Results on the USF database



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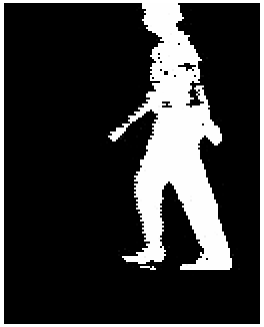
Statistical Framework for Gait-based Human Identification

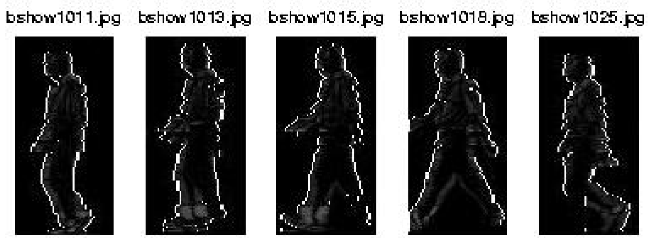
- Components of gait : Structure and dynamics

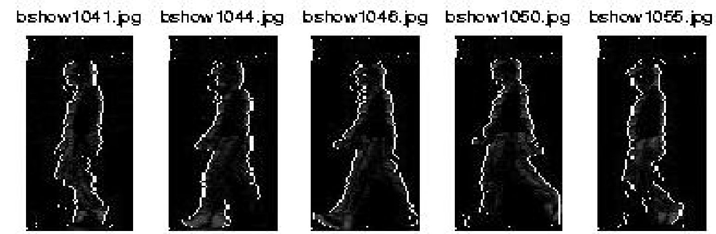


- Features
  - Width of the outer contour of the silhouette (UMD,CMU,USF)
  - Entire binary silhouette (USF)

Exemplars: Structure

- Distinct Stances occur during a walk cycle

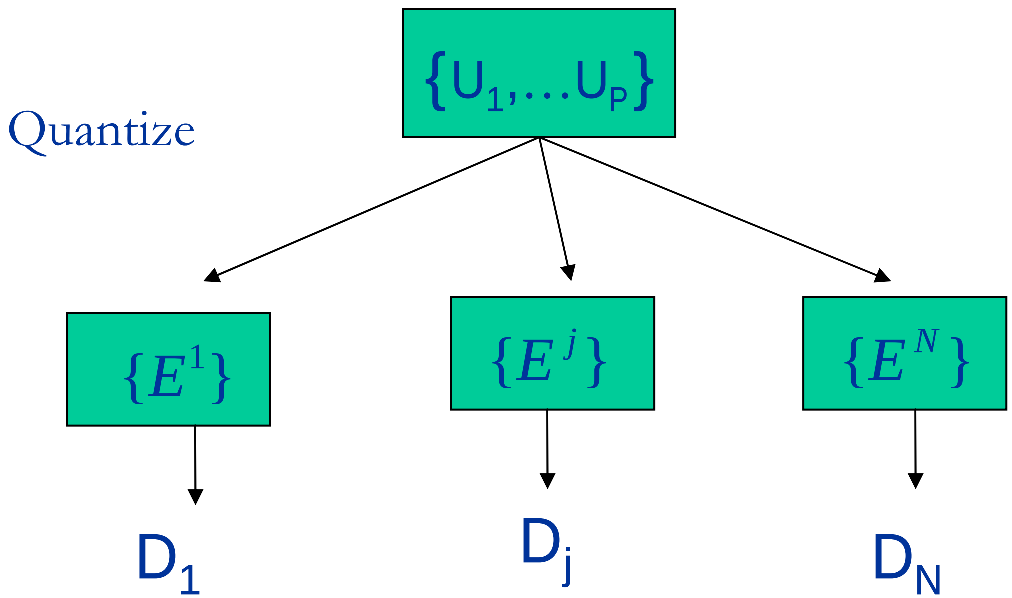




- Divide gait cycles into N segments
- Pool features from the j^{th} segment
- Pick e_j such that $D_j = \sum_{i=1}^{M} \min_{j \in \{1,\ldots,N\}} \mathrm{d}(x_i, e_j)$ is minimized
- Optimum Exemplar set $\{e_1, \ldots, e_N\}$
- Choice of N

Dynamics

- Difficulties with the simple classification criterion



- Use dynamics of transition across exemplars

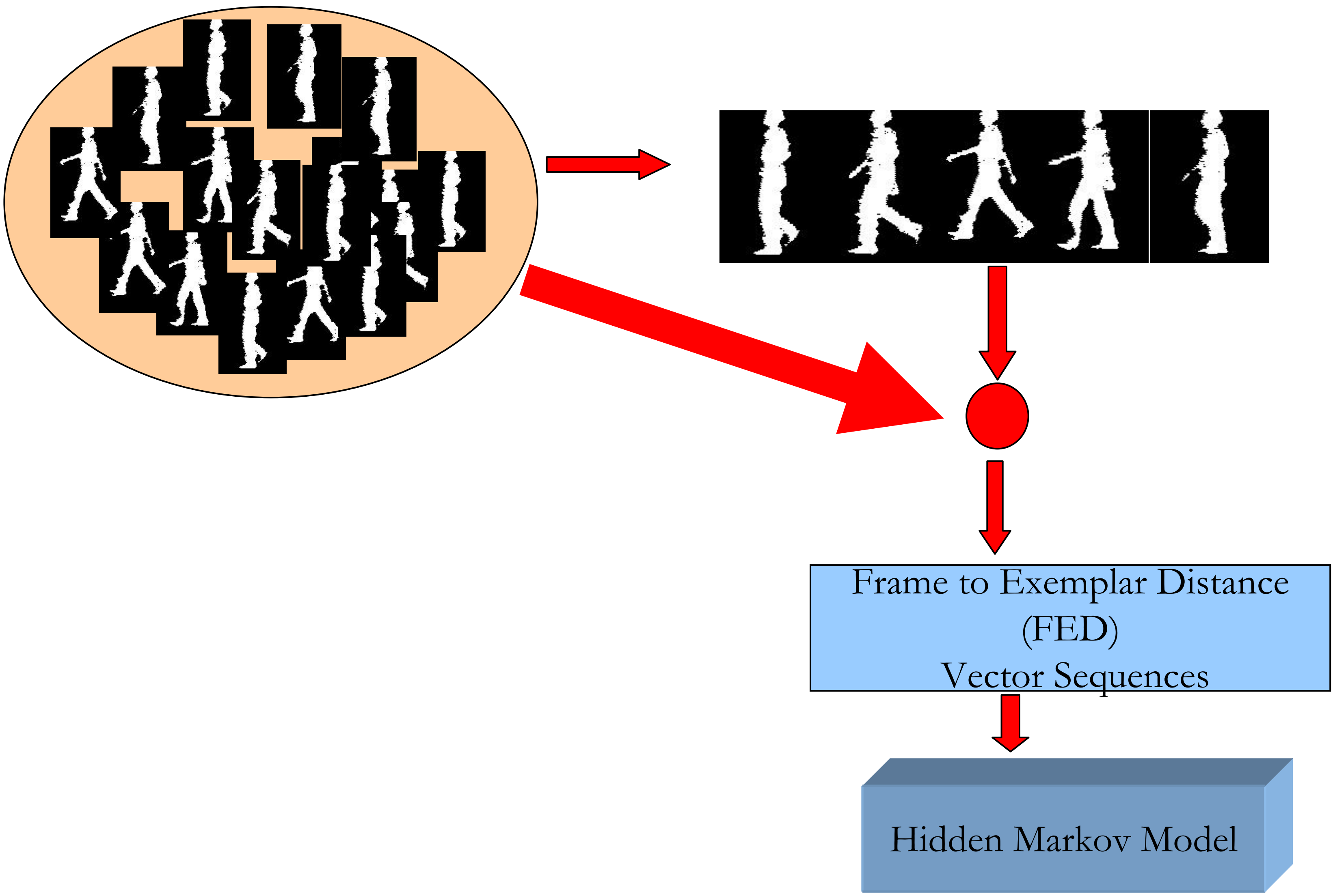
$$A = [\, p(e_i(t) \mid p(e_j(t))]$$

Hidden Markov Model (HMM)

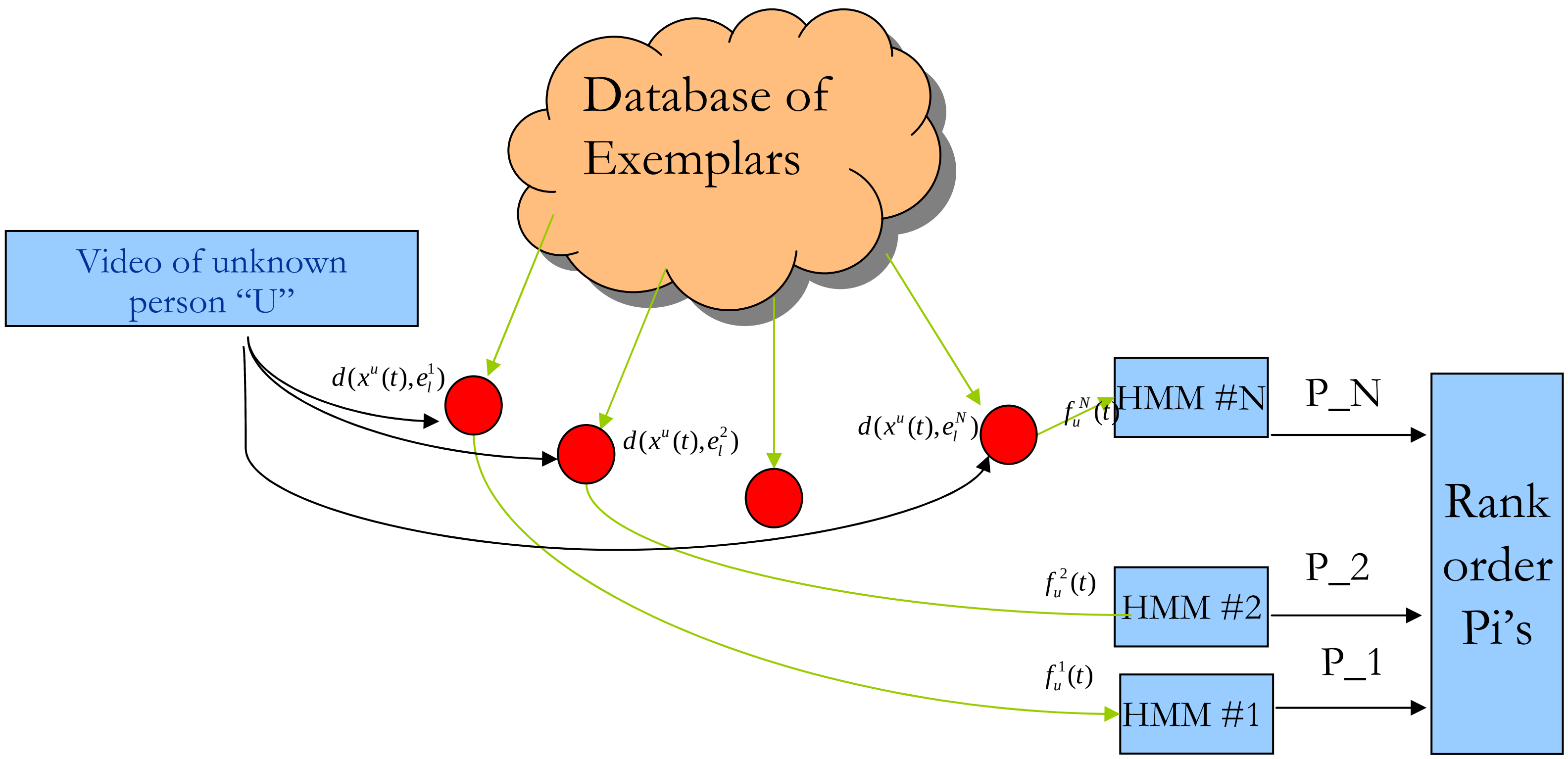
- Problem: Dimensionality vs Training data available
- Solution : Indirect Approach:

- FED vectors $f_j(t) = d(x^j(t), e_l)$ where t=1,…,T, l=1,…,5
  - Encodes structure ($D_u^u < D_j^u$) and dynamics of individual
  - FED vector sequence as the observed process corresponding to the Markov matrix: HMM $\lambda = (A, B, \Pi)$
  - Generality of FED vector for different Representations

Training


Frame to Exemplar Distance
(FED)
Vector Sequences
Hidden Markov Model

Evaluations



Direct Approach

– Usual Approach for HMMs : Mixture of Gaussians for modeling B.
– Redefine B in terms of Exemplars

$$b_n(x(t)) = P(x(t) \mid e_n) = \beta e^{-\alpha D(x(t), e_n)}$$

Training

- We start with a predefined value for A, a uniform distribution for π, and the initial estimate of the exemplars.
- The Expectation-Maximization algorithm is used to refine the estimates of the exemplars and A.
- The model parameters usually converge in a few iterations.

Updating Exemplars

$$E_j^{(i+1)} = \arg_E \max \prod_{t \in \{j^{th} group\}} P(O_t \mid E) \Rightarrow E_j^{(i+1)} = \arg_E \min \sum_{t \in \{j^{th} group\}} D(O_t, E)$$

Updating Transition Matrix, A

$$A^{(i+1)} = \arg_A \max P(O \mid (A^{(i)}, B^{(i)}, \pi)) \ \ (\text{Baum} - \text{Welch Algorithm})$$

Testing

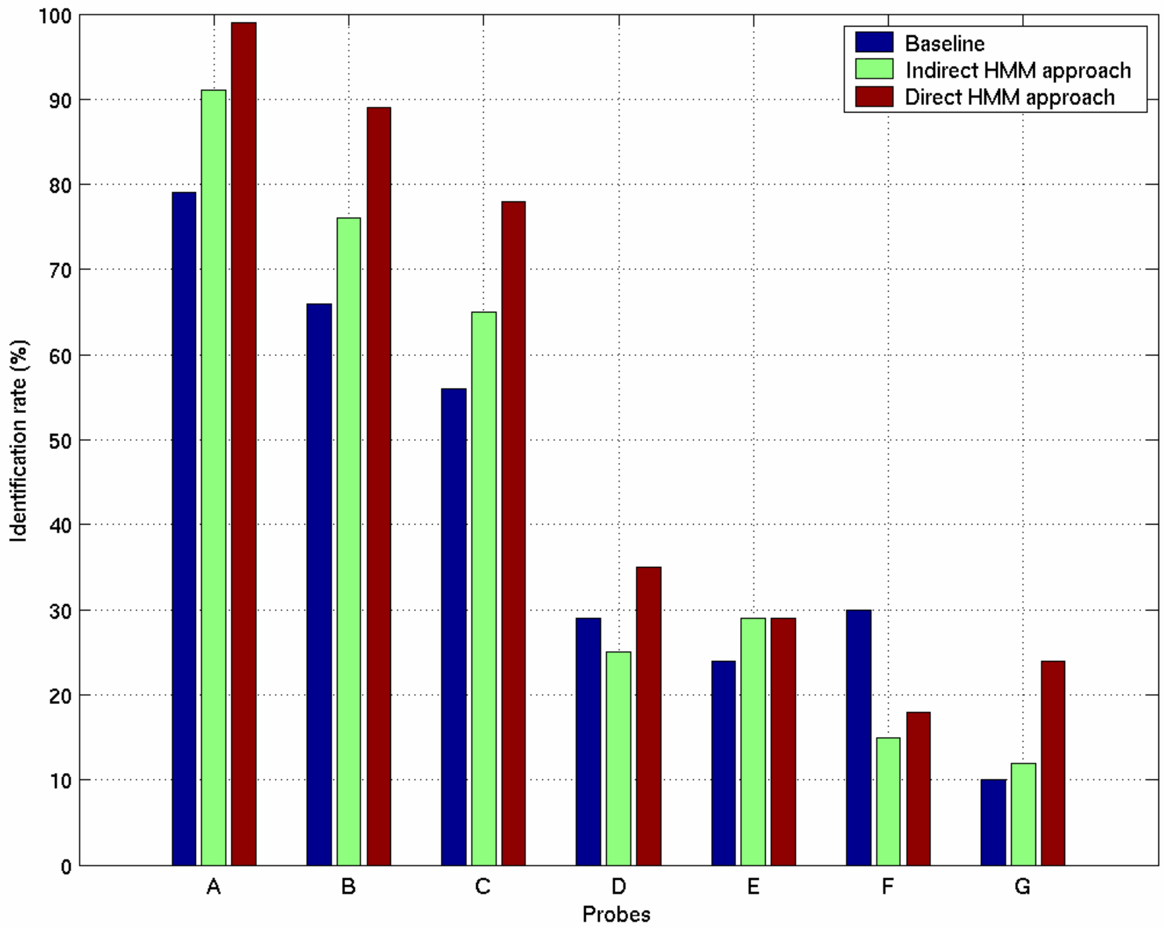
- A sequence X can be identified by finding the HMM parameters (λp) from the gallery that maximizes the probability of the observation sequence given λp.

- We use the Viterbi algorithm to compute the probability of a sequence given the model.

$$ID = \arg_p \max P(X \mid \lambda_p),$$

$$\text{where } \lambda_p \text{ is the HMM for } p^{th} \text{ person.}$$

Results on the USF Database



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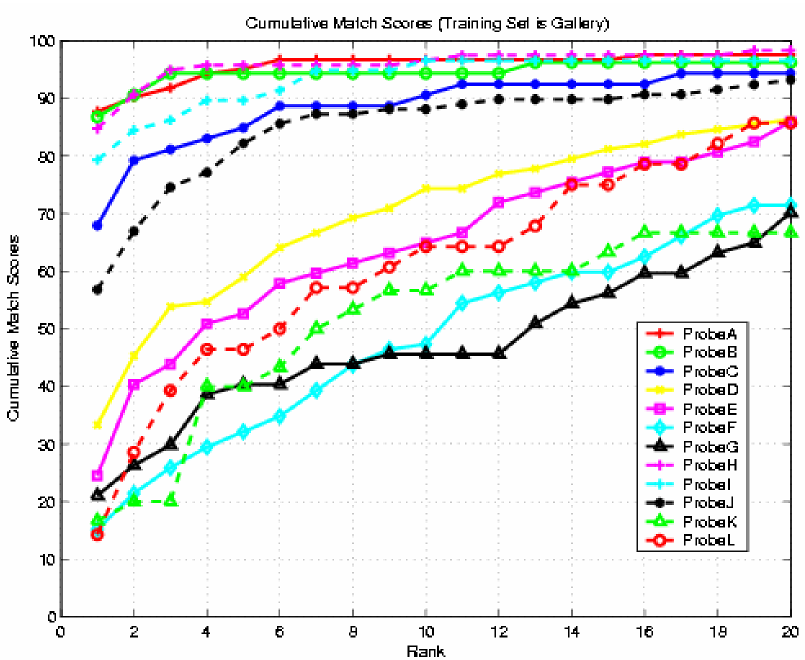
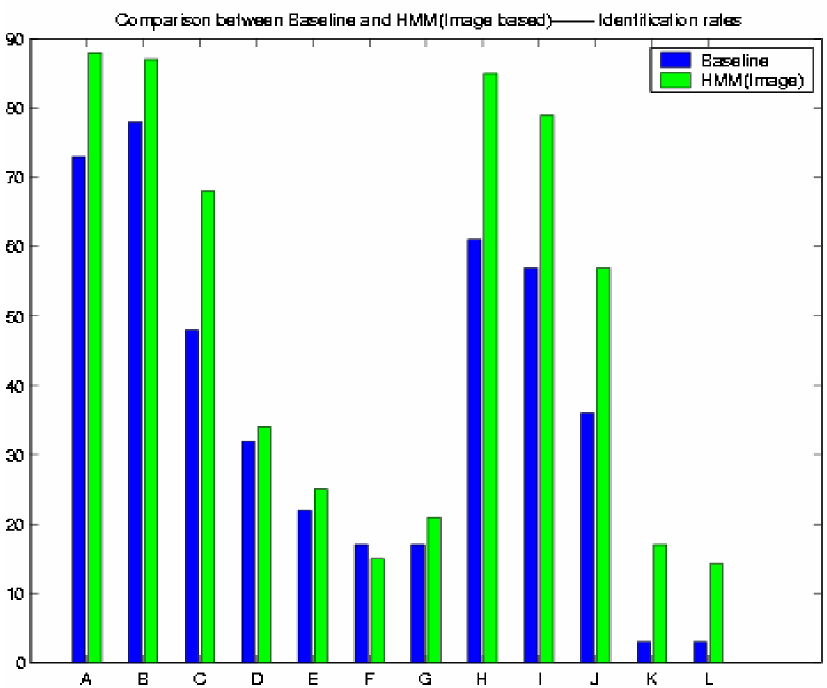




Statistical Feature Fusion

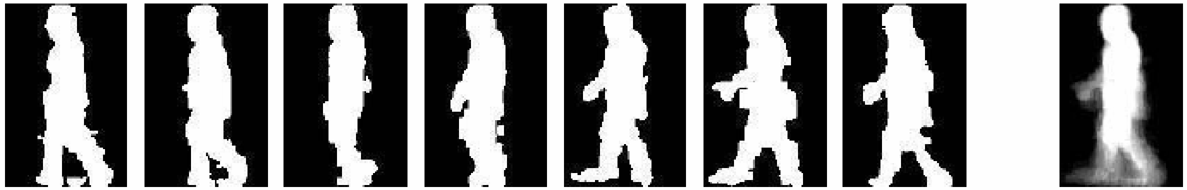


Figure 2. Sample silhouette images in a gait cycle and the corresponding GEI (the right most image).

- Gait Energy Image (GEI) is used as a feature to tackle silhouette errors.
- Use real Silhouettes with a distortion model to generate synthetic templates; Synthetic Templates account for gait in varying conditions.
- PCA and MDA features are fused to obtain recognition results.
- J. Han and B. Bhanu, "Statistical feature fusion for gait-based human recognition," Proc. IEEE Conference on Computer Vision and Pattern Recognition, pp. 842-847, 2004.

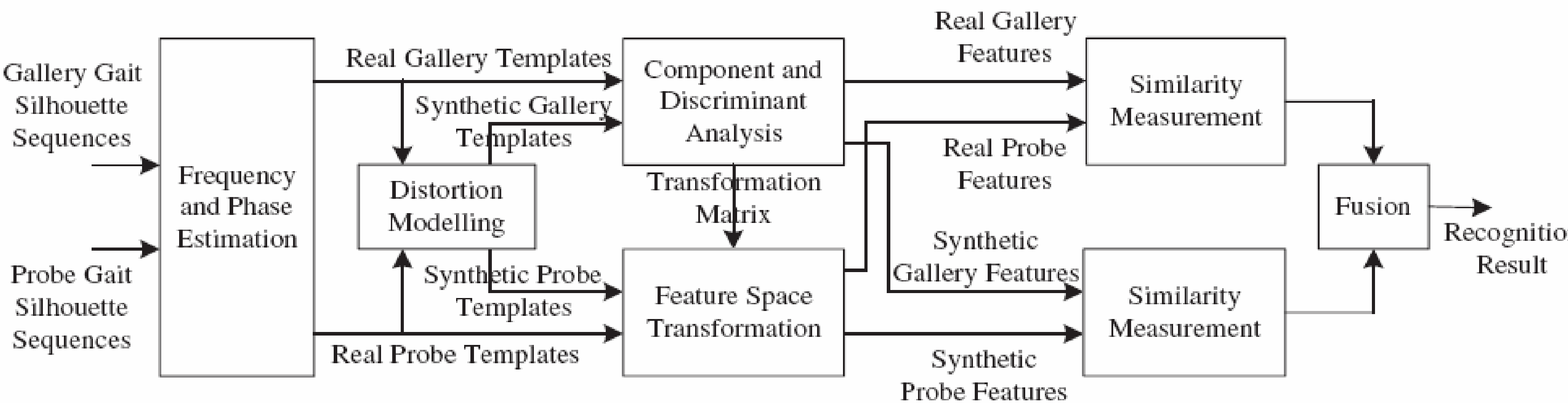
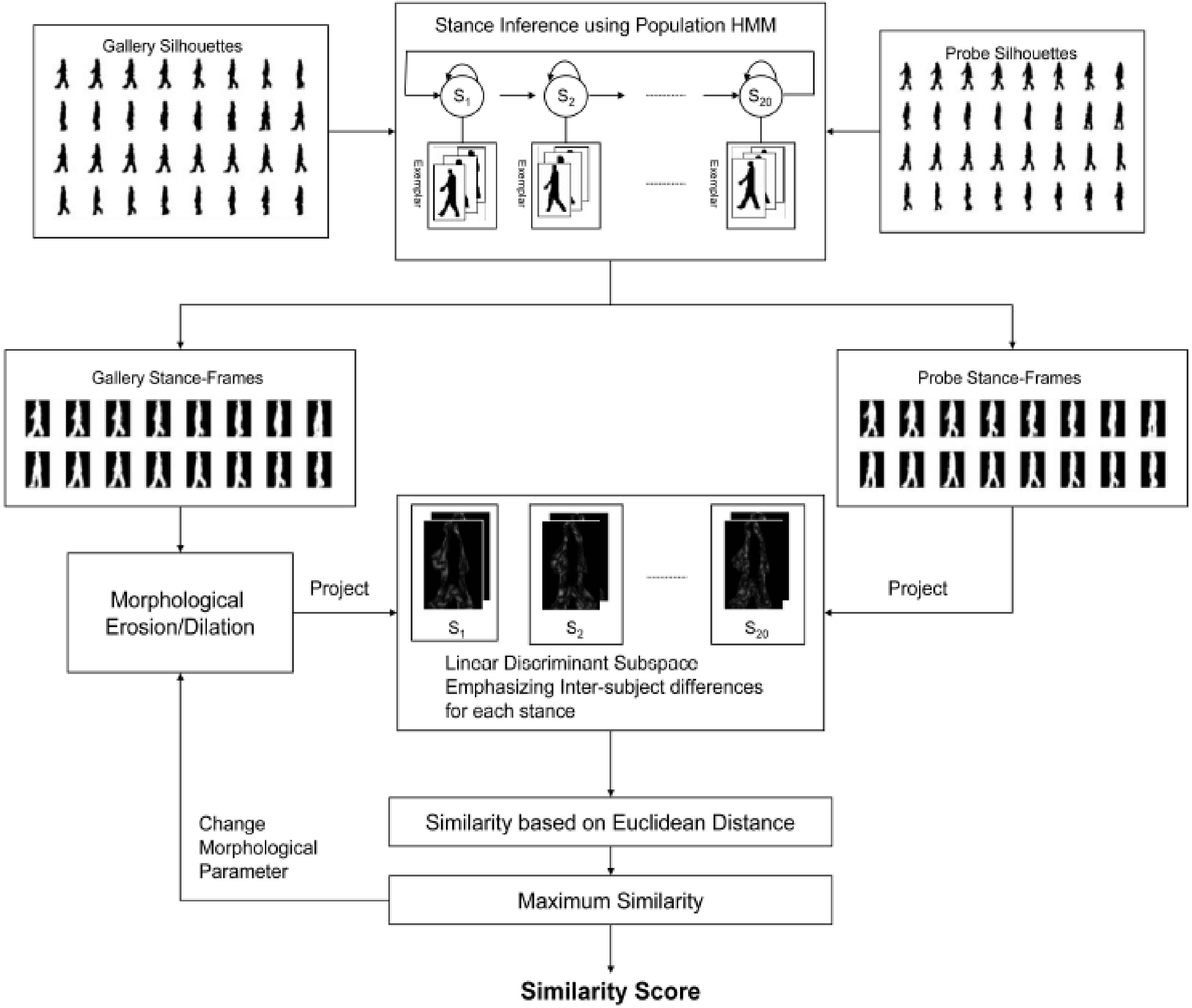


Figure 1. System diagram of human recognition using proposed statistical feature fusion approach.

Gait Dynamics Normalization

- The dynamics of the observed probe sequences are normalized using the pHMM model.
- Population Hidden Markov Model is used as a Generic Model for walking.
- Viterbi Decoding for Recognition.
- Z. Liu and S. Sarkar, IEEE TPAMI, vol. 28, June 2006.



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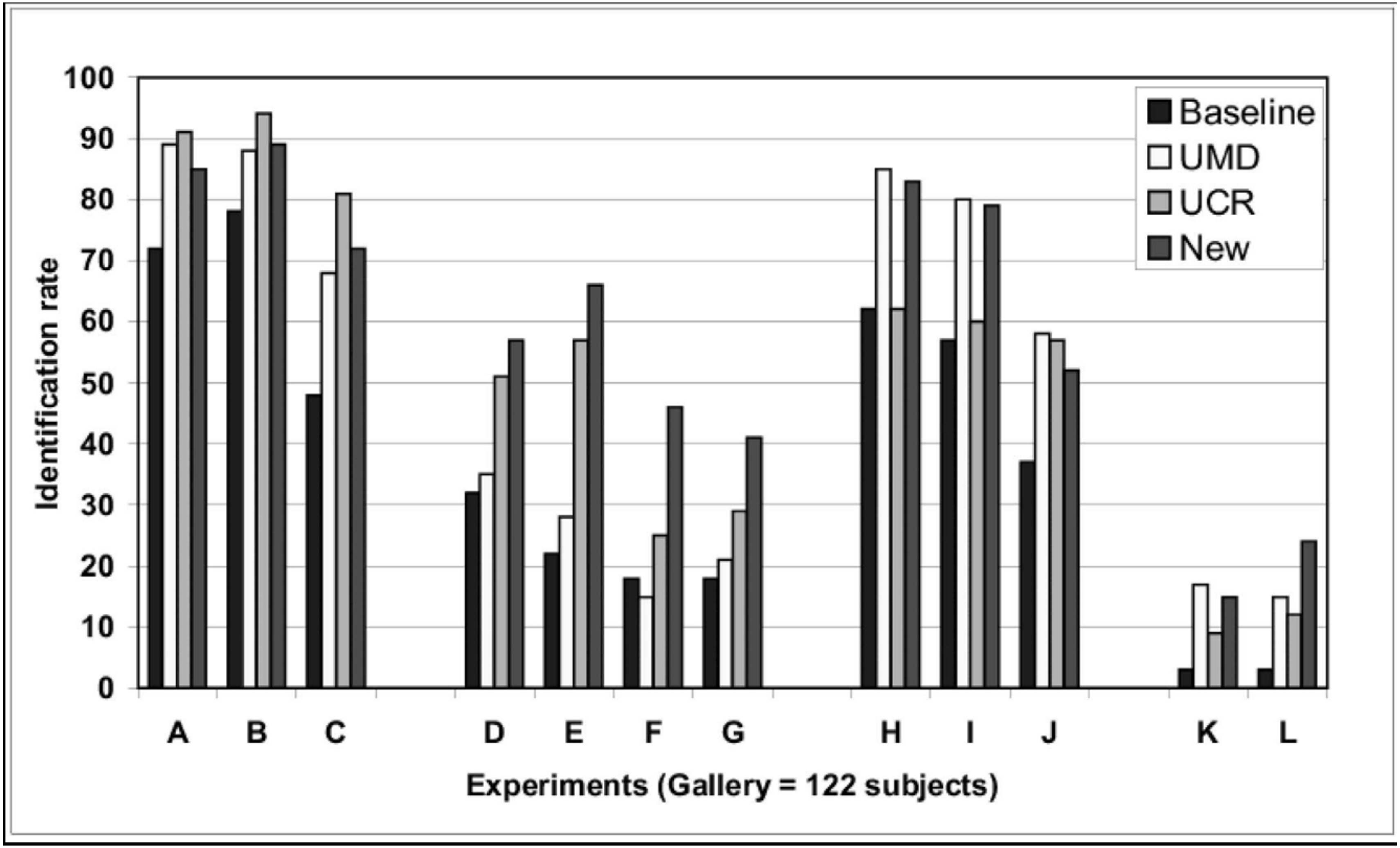
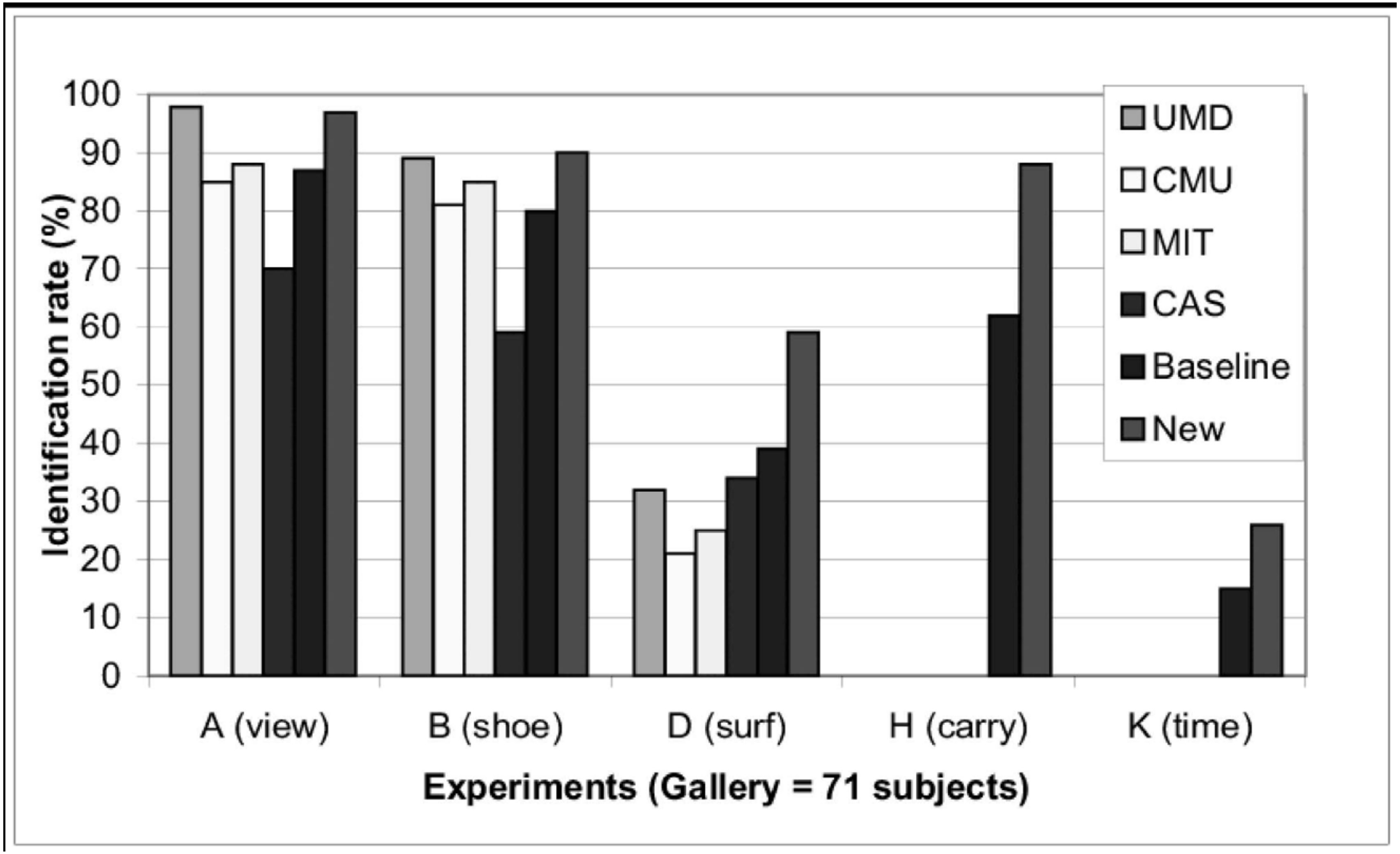
Some New Results from USF



From IEEE TPAMI, June 2006, Liu and Sarkar

Summary of the Top Rank Recognition for Experiments



From IEEE TPAMI, June 2006, Liu and Sarkar

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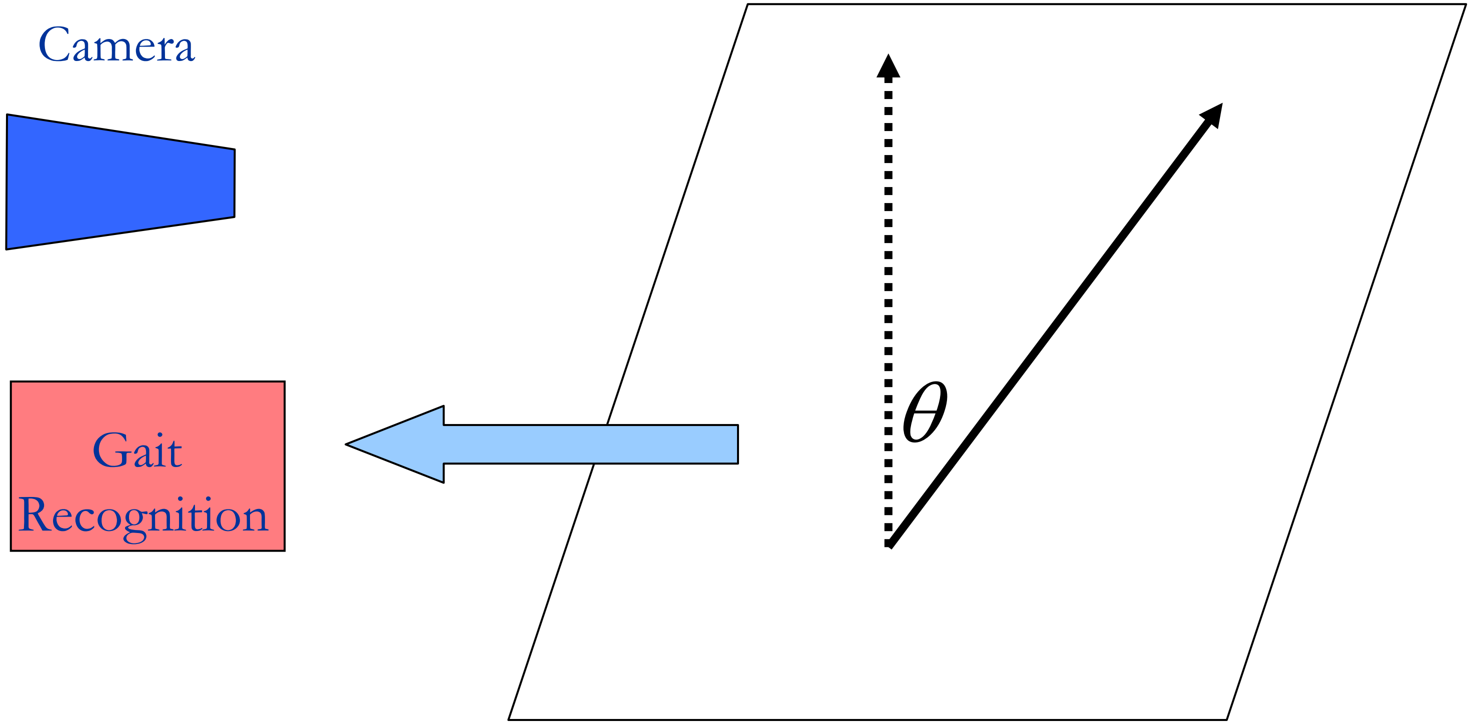
View Invariant Gait Recognition

- Limitations of present gait recognition algorithms
  - Require exact side-view of the walking person
  - Solution : 3D models (Hard!)
  - Alternative: Visual hull
    - Needs at least 4 cameras
    - Computation of the order of O(kmn)

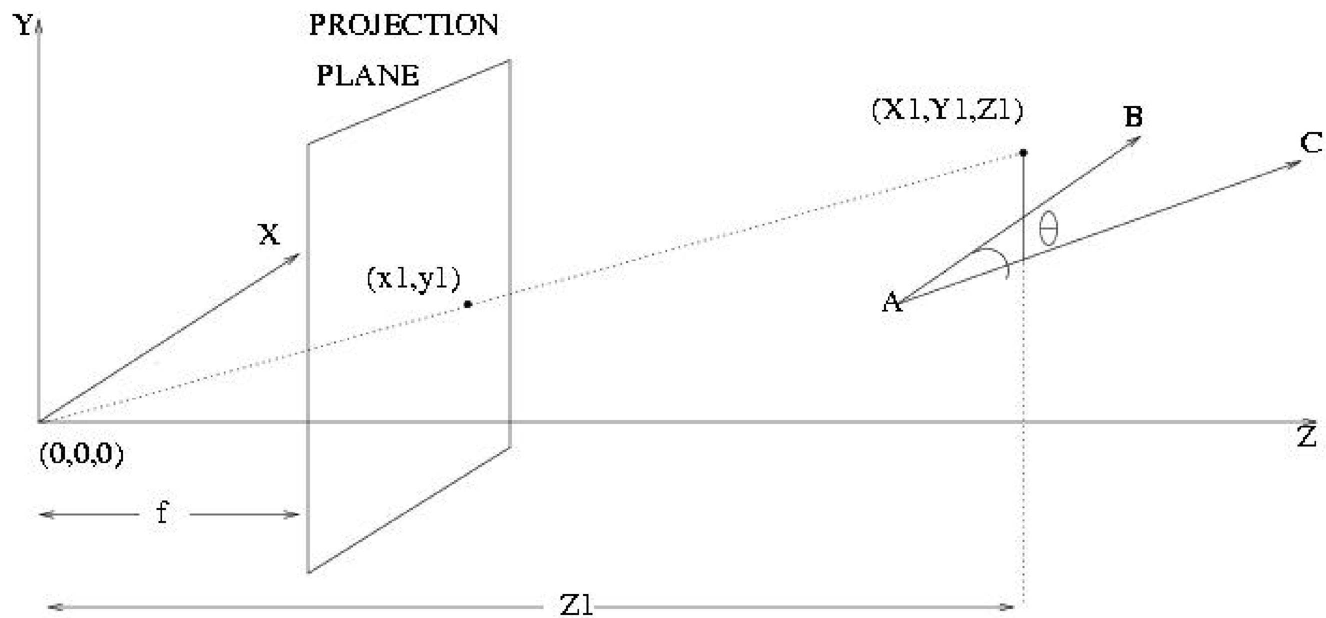
- Idea: Person walking far from the camera can be approximated as a planar object

Overview of Our Method



Done entirely in video domain, no explicit 3D computation

Imaging Geometry



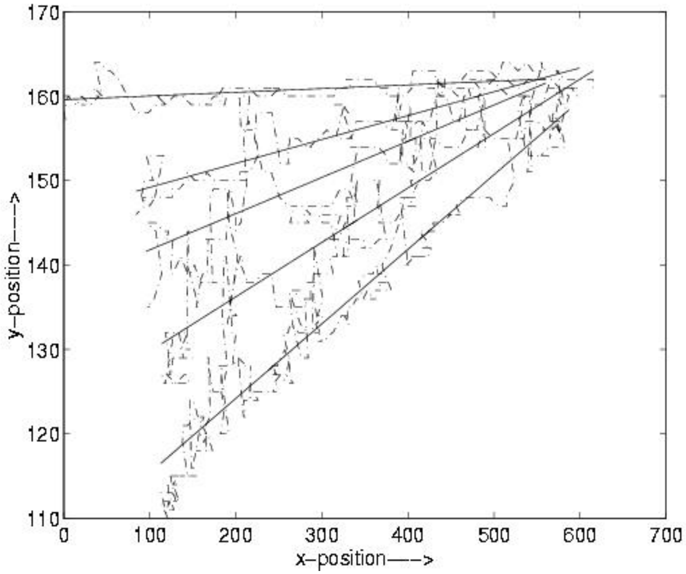
Z1>>f

Translational velocity $[v_{X,} 0, v_Z]$

Framework for Novel View Synthesis

- Tracking
  - Assume initial position of a fixed point on the object (x_{ref}, y_{ref})

Tracks of (x,y) positions of the head for different θ

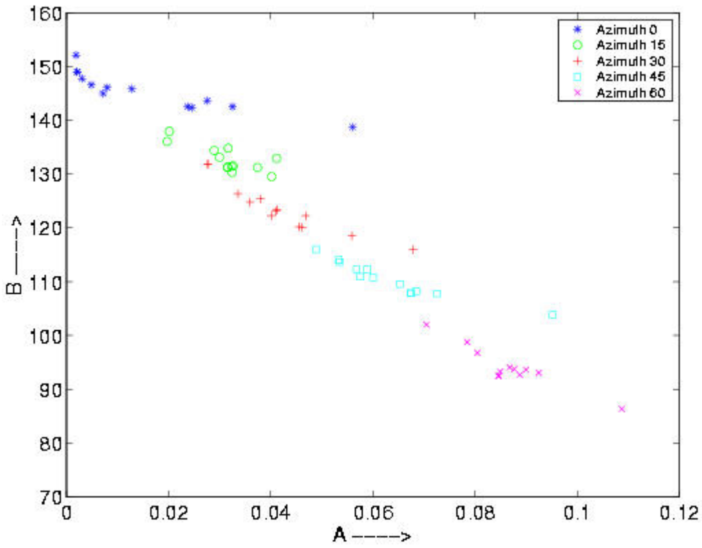


Slope of the lines = Tan (α)

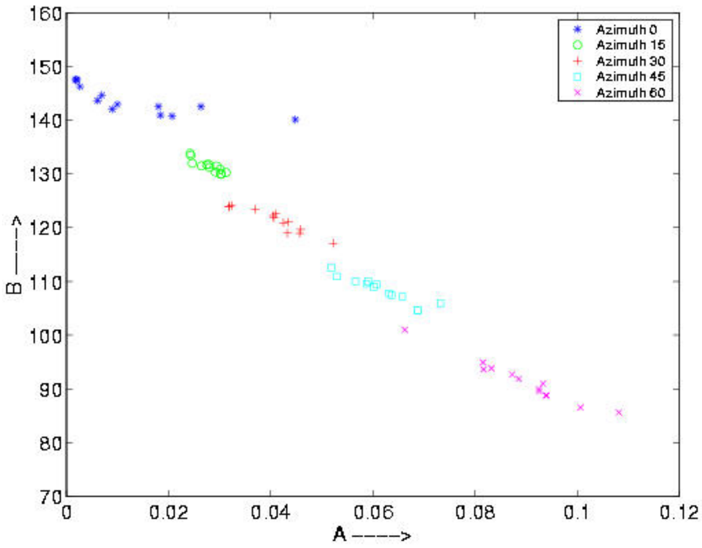
Framework for Novel View Synthesis

- Robust Estimation of α

LS estimate



LMEDS estimate



Framework for Novel View Synthesis

- Estimation of θ (for constant velocity models)

$$\cot(\alpha) = \frac{x_{ref} - f\cot(\theta)}{y_{ref}}$$

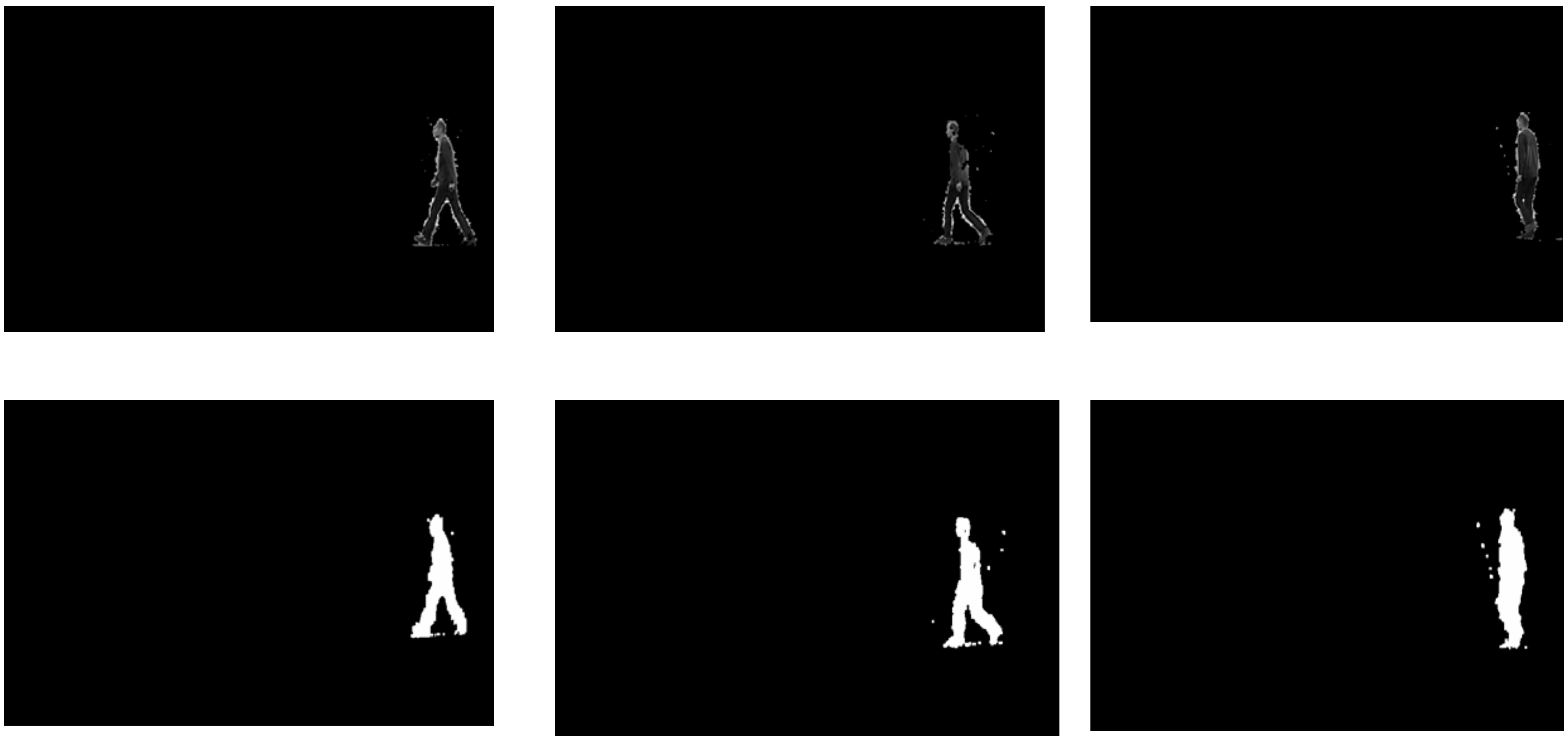
- Synthesis

$$x_0 = f\frac{x_\theta \cos(\theta) + x_{ref}(1 - \cos(\theta))}{-\sin(\theta)(x_\theta + x_{ref}) + f}$$

$$y_0 = f\frac{y_\theta}{-\sin(\theta)(x_\theta + x_{ref}) + f}$$

Synthesis Examples

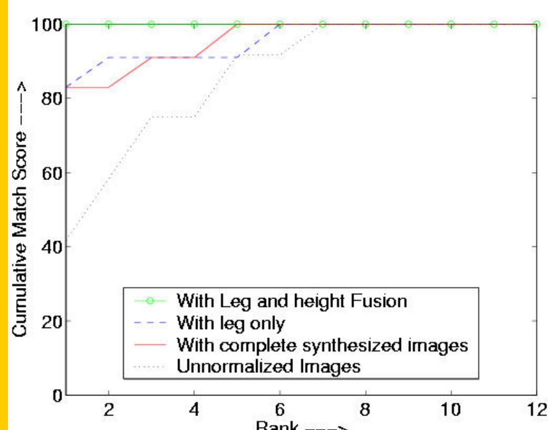
15 degrees | 30 degrees | 45 degrees



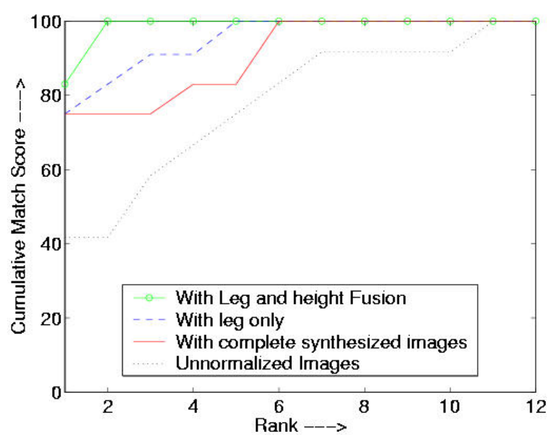
Gait Recognition Results

- Feature : Binarized silhouette
- Classifier : DTW with binary correlation as local distance

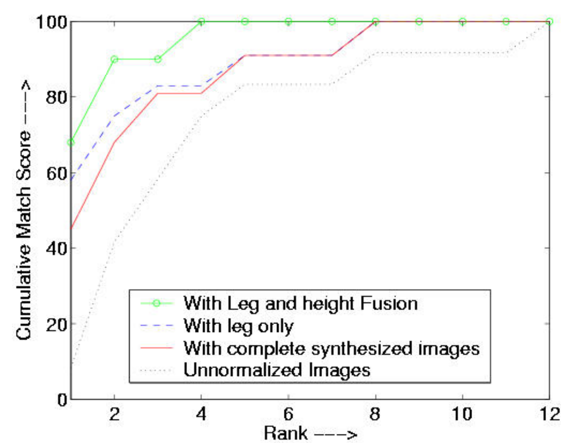
$\theta = 15$



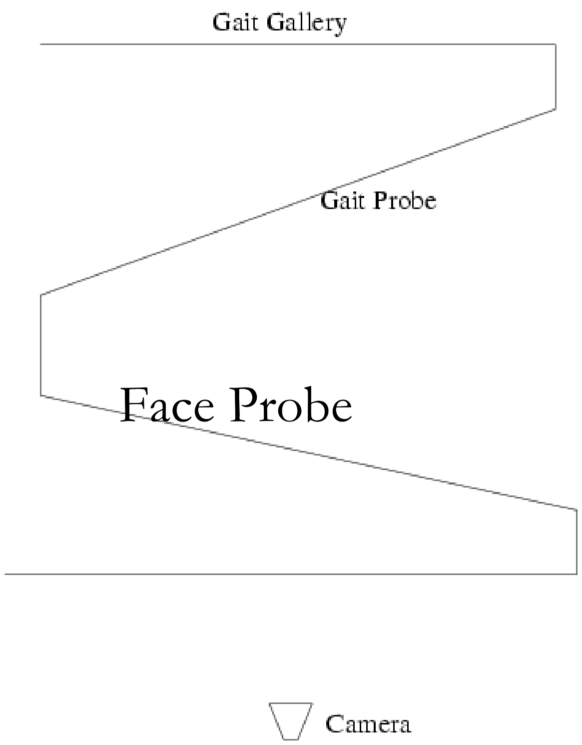
$\theta = 30$



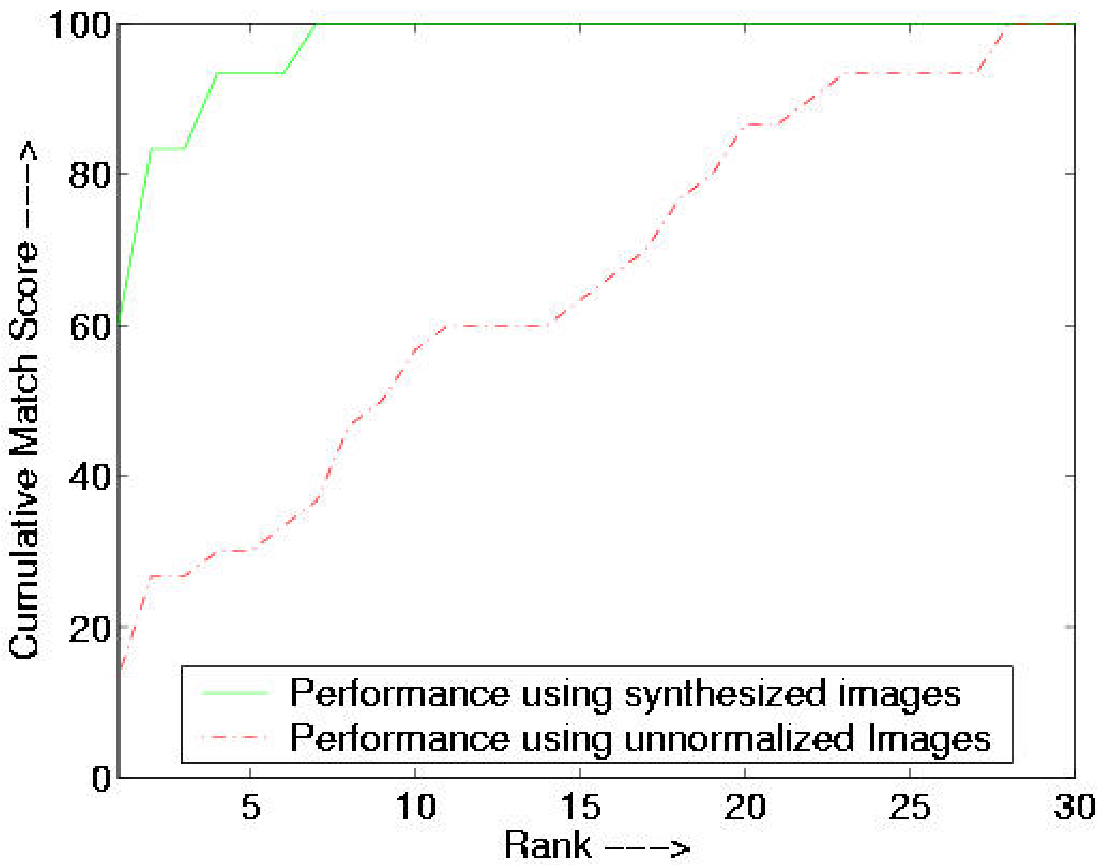
$\theta = 45$



NIST Database & Walking Pattern



Gait Recognition (NIST Database)



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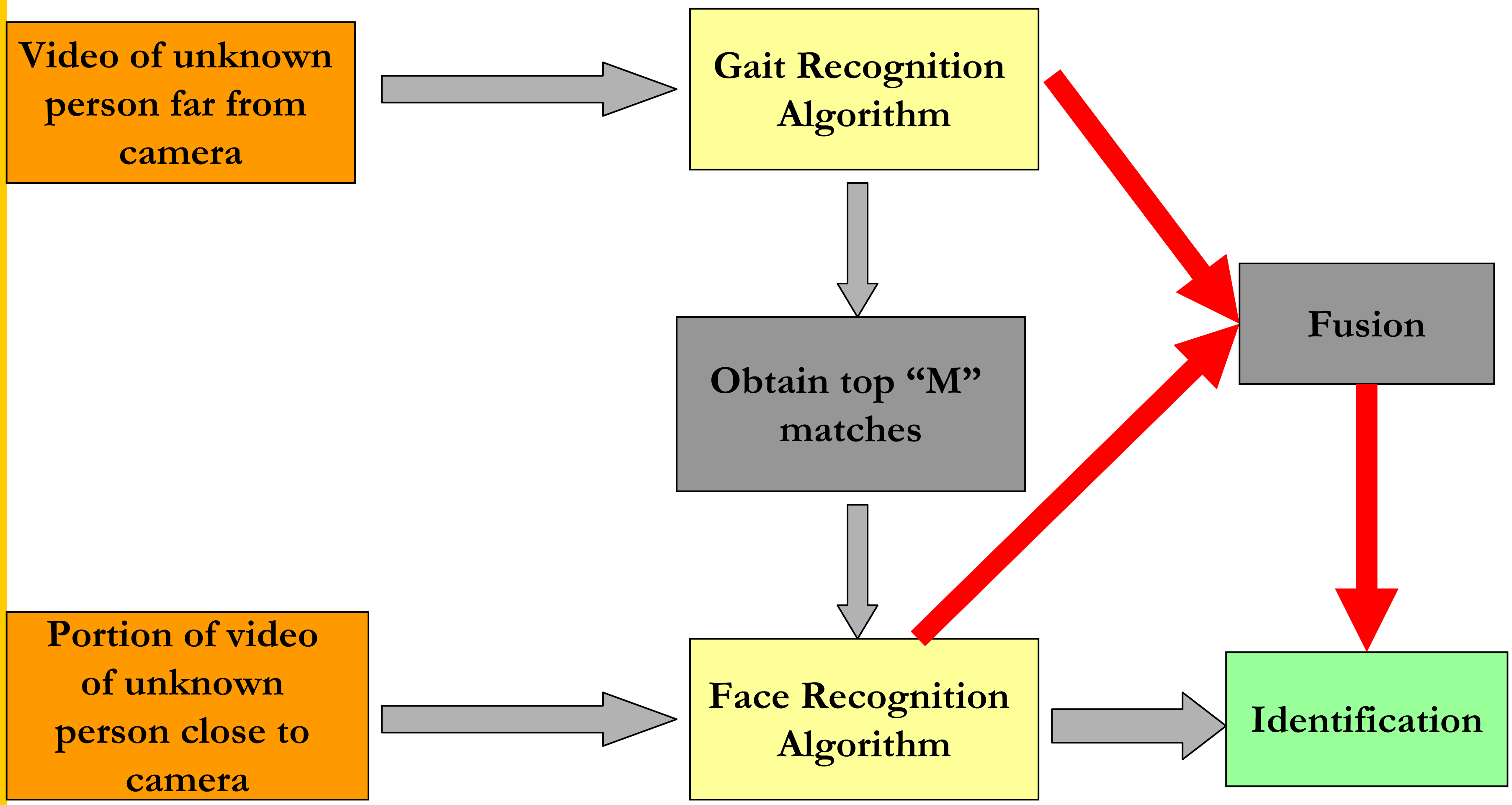
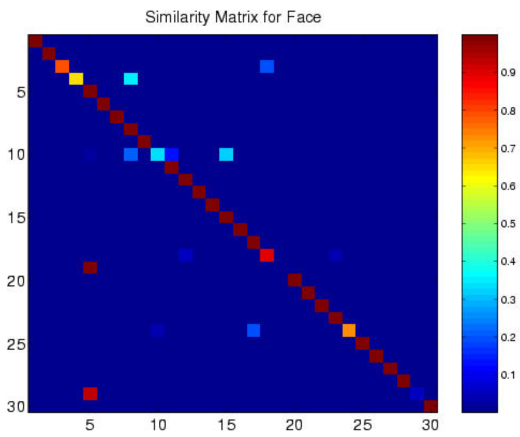
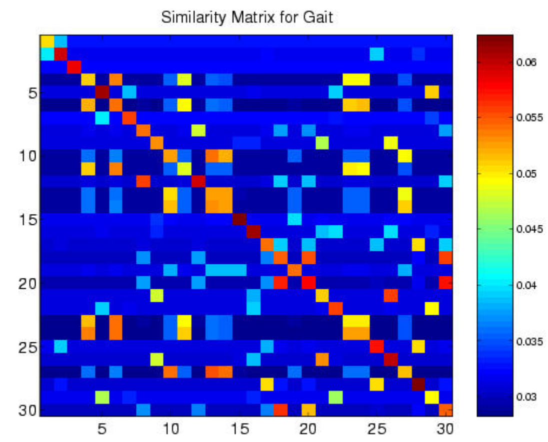
Application: Multimodal Biometrics

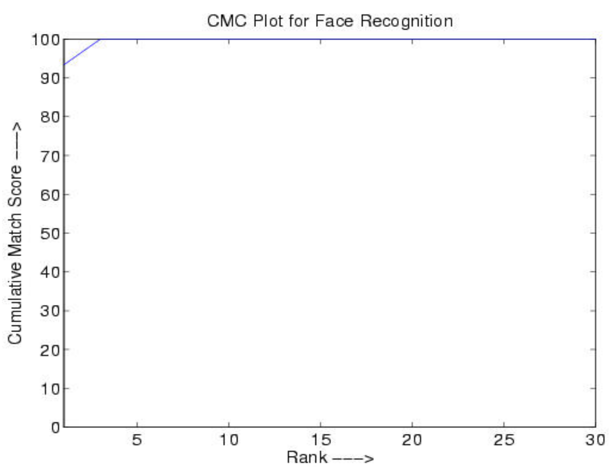


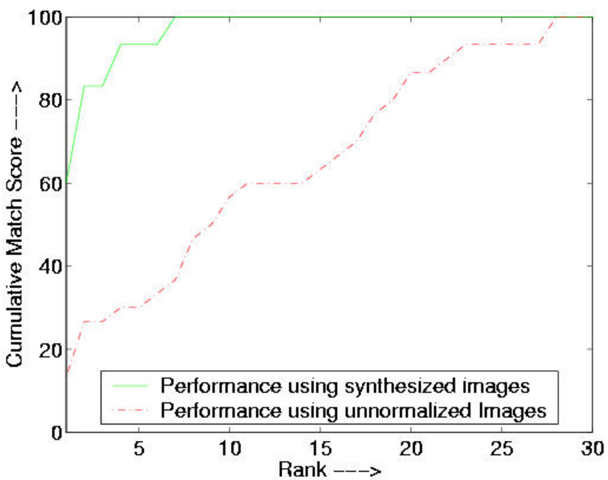
Fusion of Face and Gait

FACE NIST Database **GAIT**



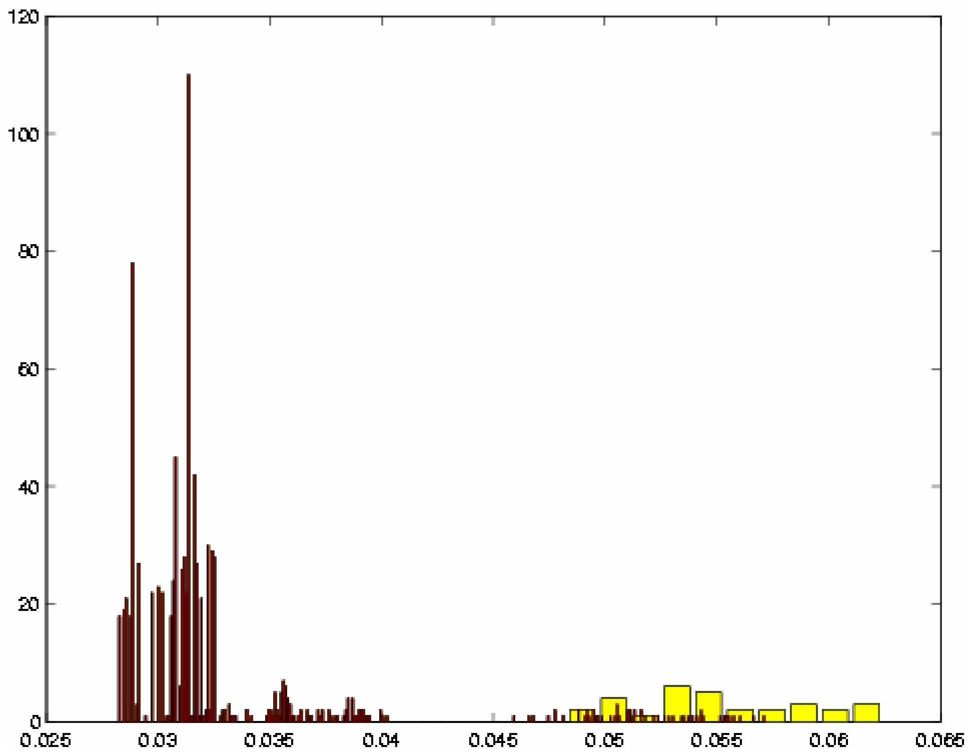






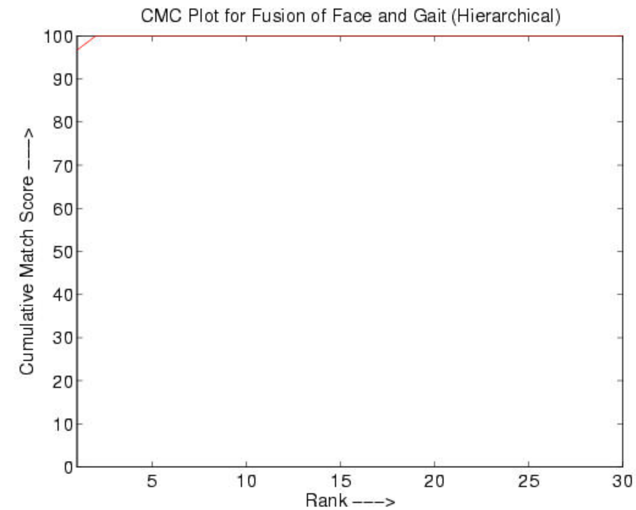
Fusion of Face and Gait

Histogram of True Matches and False Matches

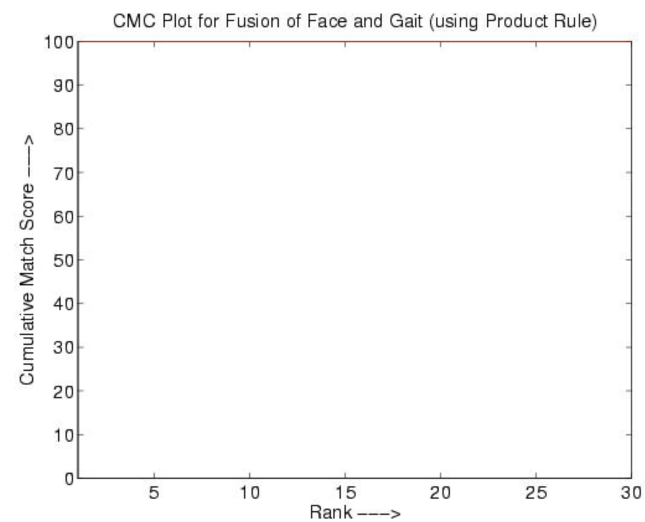


Fusion of Face and Gait

A. Hierarchical Fusion: Gait -> Face
 - top matches above a threshold
 - 1/5 th time for face recognition.



B. Product rule on similarity scores
 - 100 % recognition.



Shape or Dynamics (or Is It Both?)

- Human perception
- Most gait recognition algorithms are shape based !
- Relative importance of shape and dynamics
- Definition of shape
  - "Shape is all the geometric information that remains when location, scale and rotational effects are filtered out from the object".
  - Kendall's Statistical Shape Theory used for the characterization of shape.
  - Pre-shape accounts for location and scale invariance alone.

Pre-Shape

- k landmark points (complex vector)
- Translational invariance: Subtract mean
- Scale invariance : Normalize the scale

$$Z_c = \frac{CX}{\| CX \|}, \quad where \quad C = I_k - \frac{1}{k} 1_k 1_k^T$$

Feature Extraction

Silhoutte

↓

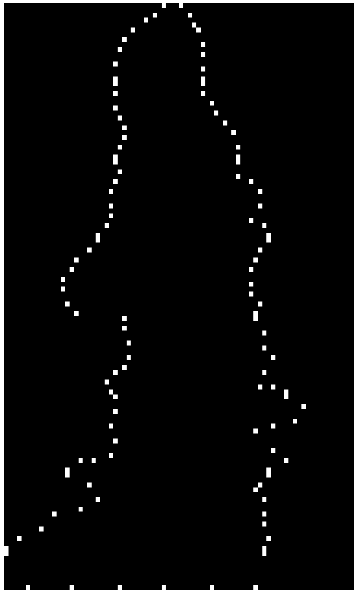
Landmarks

↓

Centered Landmarks

↓

Pre-shape vector



Distance Between Shapes

- Shape lies on a spherical manifold.
- Shape distance must incorporate the non-Euclidean nature of the shape space.
- 1)Full Procrustes distance.

  2)Partial Procrustes distance.

  3)Procrustes distance.

Full Procrustes Distance

- Procrustes Fit

$$d(Y, X) = \left\| \beta - \alpha s e^{j\theta} - (a + jb) 1_k \right\| .$$

- Full Procrustes distance=Minimum Procrustes fit.

$$d_F(Y, X) = \inf_{s,\theta,a,b} d(Y, X).$$

Other Shape Distances

- Partial procrustes distance

$$d_P(X,Y) = \inf_{\Gamma \varepsilon SO(m)} \left\| \beta - \alpha \Gamma \right\|.$$

- Procrustes distance (ρ): distance on the Great circle.

$$d_F(X,Y) = \sin \rho ,$$

$$d_P(X,Y) = 2 \sin(\frac{\rho}{2}) .$$

Tangent Space

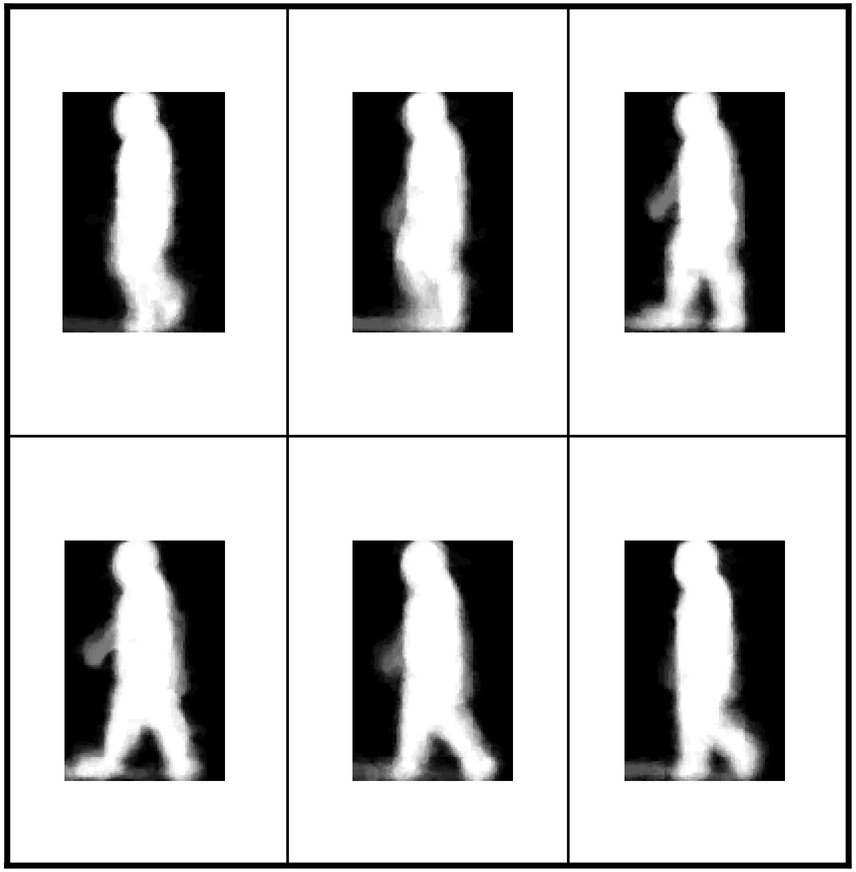
- Linearization of spherical shape space around a particular pole.
- The Procrustes mean shape is usually chosen as the pole.
- If the shapes in the data are very close to each other then Euclidean distance in tangent space approximates shape distances.

Three Shape Based Methods for Recognition

- Stance Correlation.
- Dynamic time warping in shape space.
- Hidden Markov Model in shape space.

Stance Correlation

- Exemplars for 6 stances for each individual.
- The correlation between exemplars is used as the matching criterion.
- Performance comparable to Baseline.



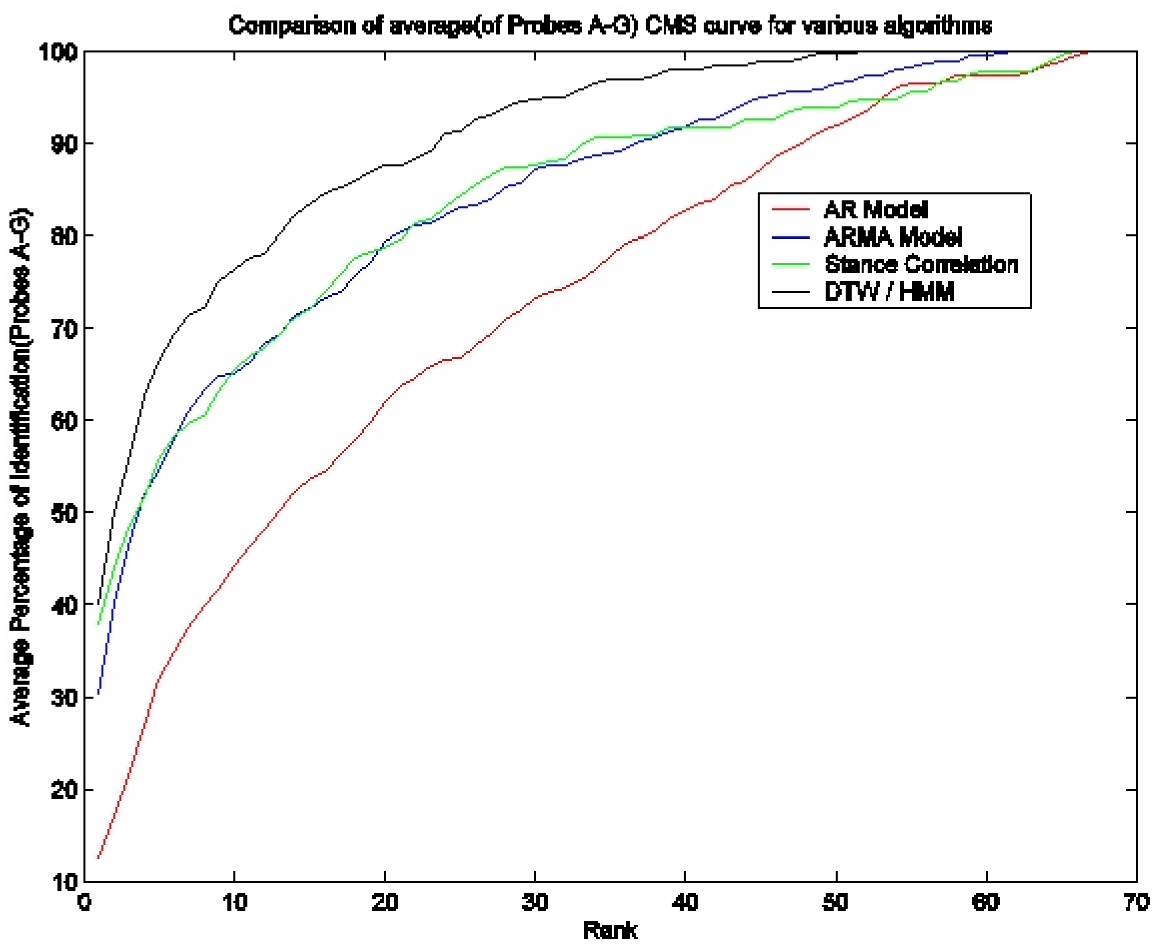
Dynamic Time Warping in Shape Space .

- Enforce end-point constraint.
- Obtain best warping path.
- Cumulative error is computed using the shape distances described.
- Performance is better than baseline.

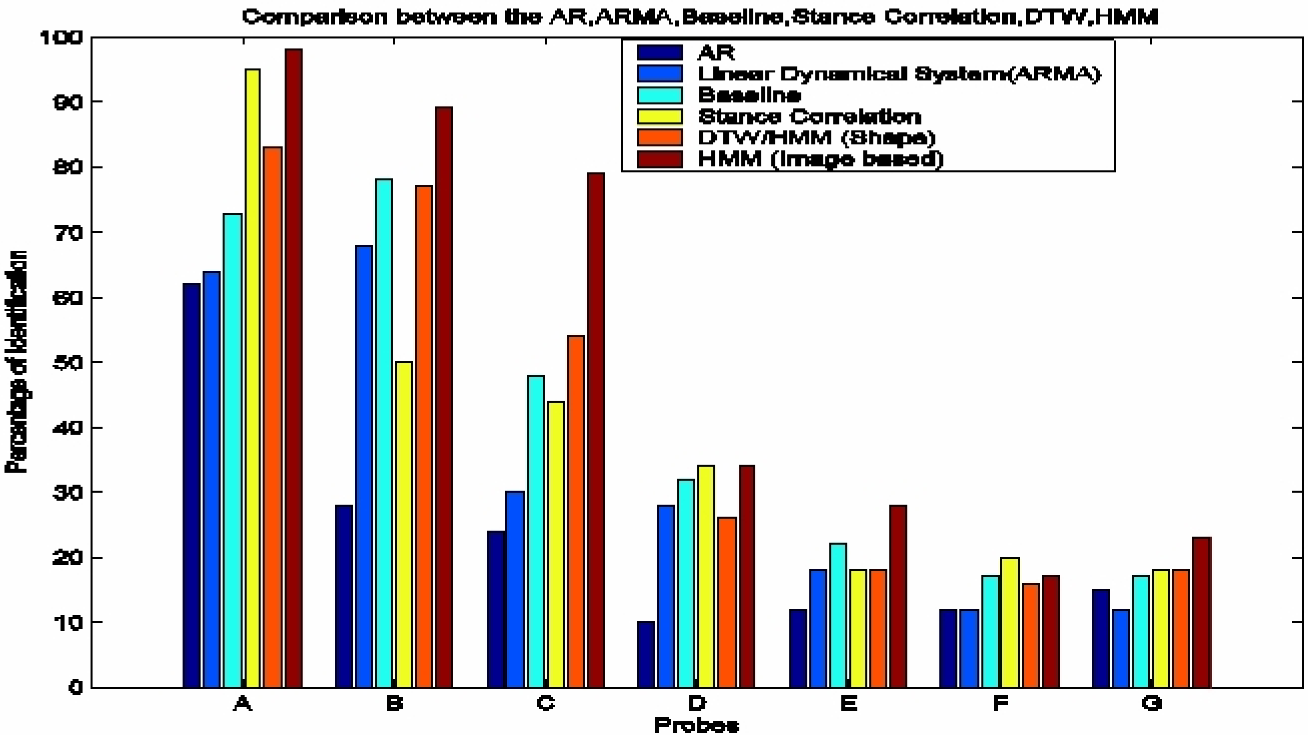
Hidden Markov Model in Shape Space

- Exemplars are regarded as states.
- HMM built for each person in the gallery.
- Identity established by maximizing the probability that the observation came from the model in the gallery.
- Performance is better than baseline and comparable to DTW.

Comparison of Various Methods on the USF Database



Comparison of Various Methods on the USF Database



• Shape is more important for recognition than dynamics. Shape also provides for speed change invariance.

• Dynamics can help to improve performance of shape based methods.

Tutorial Outline

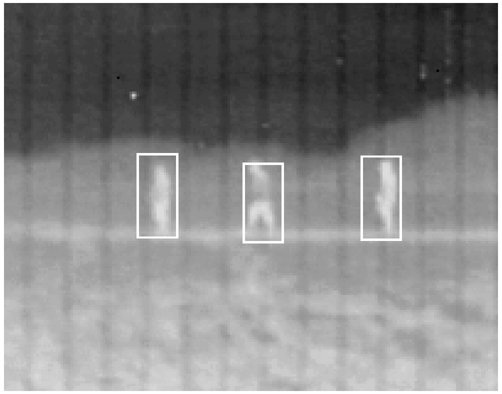
- Introduction
- PART I: Face-based Human Recognition
- PART II: Gait-based Human Recognition
  - Introduction
  - Gait-based human identification using appearance matching
  - Statistical framework for gait-based human identification
  - View invariant gait recognition
  - Combining multiple evidences for gait recognition
  - **Future research directions**
- Discussions

Applications and Future Work

- Short-time Verification problems.
- Using "generalized" gait eigen vectors for subspace based activity recognition.
- Extensions of the view invariant approach using 2 cameras.
- 3D parameterized models for gait vs. 2D approaches.
- Applications in video indexing and retrieval.
- Using 3-D models of objects for synthesis of non-planar object.
  - Novel view synthesis and recognition of face images..

Applications and Future Work

- Is gait effective?
  - Maybe for a small data set (< 100 persons) viewed from fronto-parallel direction.
  - Can be fooled by changing the shoe type, intentional disguises etc.
  - Starbucks 8:00 a.m. gait versus going home gait!
- Gait analysis is useful for detecting abnormal walking patterns



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- Numerous journal and conference papers from UMD, U. of Southampton, MIT, CMU, USF….

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- Discussions