# Activity Recognition: Gait Analysis and Recognition

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# Outline

- *What is activity recognition?*
- *Some indicative examples*
- *Activity recognition for authentication*
- *Gait as a biometrics*
- *Gait recognition – Potential*
- *State-of-the-art approaches*
- *Gait recognition in realistic applications*
- *Improvement of Gait recognition using soft biometrics*
- *Conclusions*

## Activity recognition

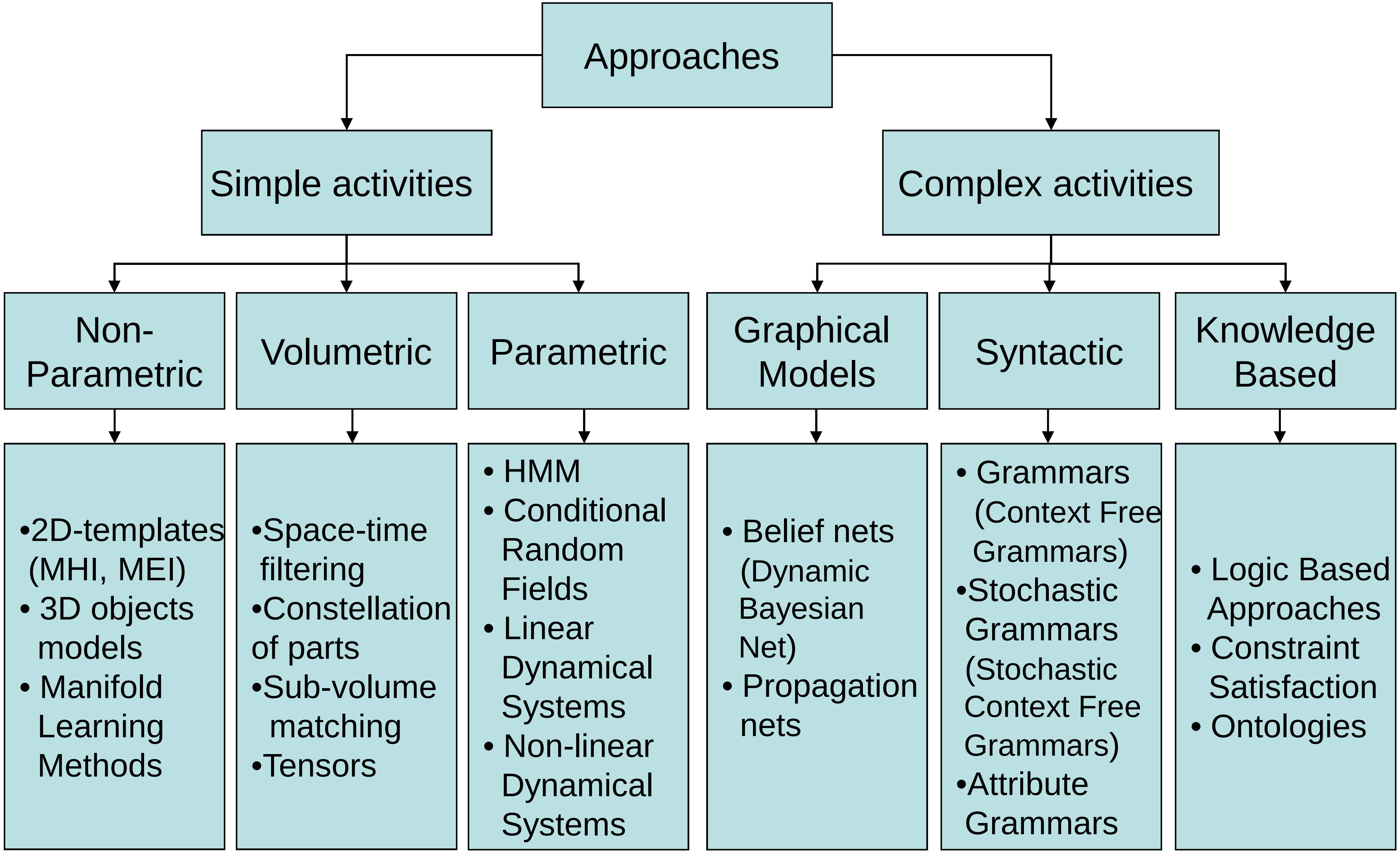
Aims to recognize the actions and goals of one or more agents from a series of observations on the agents' actions and the environmental conditions.

## Activity recognition approaches:

In real life activity recognition, systems typically follow a hierarchical approach:

- **Lower levels**: Background-foreground segmentation, tracking and object detection
- **Mid-level:** Action recognition modules
- **High-level:** Reasoning engines, which encode the activity semantics based on the lower level action-primitives.

# Mid-level, Modelling and recognising activities




*(Adapted from Turaga et al., 2008)*

# Mid-level, Modelling and recognising activities:

- **Non parametric approaches**: Extract a set of features from each frame of the video. The features are then matched to a stored template.
- **Volumetric approaches:** Do not extract features on a frame by frame basis. A video is considered as a 3D volume of pixel intensities and extend standard image features to the 3D case.
- **Parametric approaches:** Impose a model on the temporal dynamics of the motion. The particular parameters for a class of actions is then estimated from training data.

*(Turaga et al., 2008)*

# Mid-level, Modelling and recognising activities:

- **Graphical models:** Probabilistic model for which a graph denotes the conditional independence structure between random variables.
- **Syntactic approaches:** Syntactic approaches such as Grammars express the structure of a process using a set of production rules.
- **Knowledge and Logic-based approaches:** Rely on formal logical rules to describe common-sense domain knowledge to describe activities. Logical rules are useful to:
  a) express domain knowledge as input by a user or
  b) present the results of high-level reasoning in an intuitive and human-readable format.

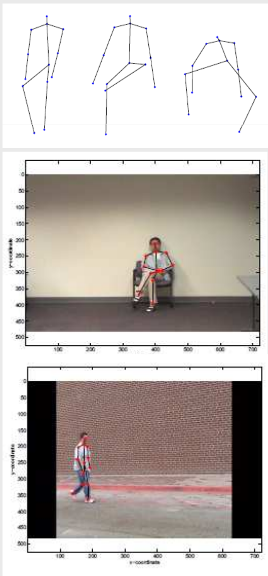
*(Turaga et al., 2008)*

**Two main approaches**:

- methods based on various sensors placed on the subject to extract meaningful features
- methods based on video analysis to detect human activity (*one of the most promising and challenging applications of computer vision*)

# Approaches of Video based action recognition

## Model based

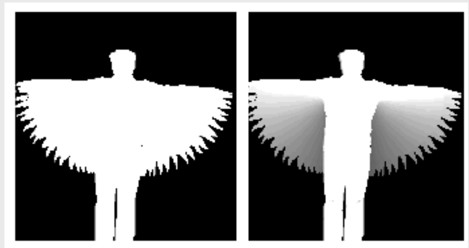


*(From Sheikh et al, 2005)*

e.g.
- Joint angles
- Joint positions

## Direct mapping of image cues

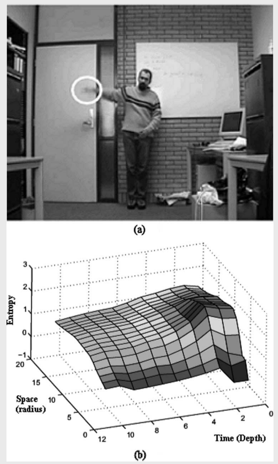
### Global/holistic



*(From Bobick & Davis, 2001)*

e.g.
- Silhouettes
- Edge images
- Optical flow

### Patch-based




e.g.
- Spatio-temporal silent points

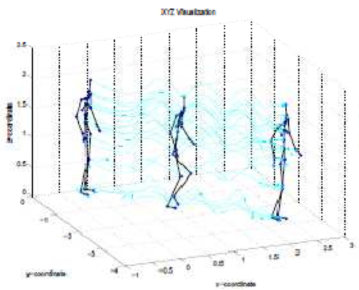
*(Oikonomou et al,. 2006)*

# Model-based approach

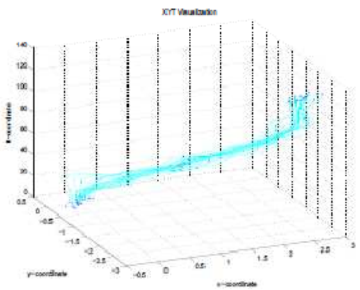
**Activities:** (a) walking, (b) sitting, (c) standing, (d) running

**Modeling the action** → **Matching algorithm** → **Classify activity**

## Representation of an action in 4-space



**Action in XYZ space**



**Action in XYT space**

(*Sheikh et al., 2005*)

**For each action $A_i$, $i \in 1,2,\ldots N$ do**

1. **Normalisation.** Compute a similarity transform, transforming the mean of the point to the origin and making the average distance of the points from the origin equal to $\sqrt{2}$ (Separately for each action instance)
2. **Compute Subspace Angle between $W$ and $W_t$:**
   - **Compute Orthogonal Bases:** Uses SVD to reliably compute orthonormal bases of $W'$ and $W_t$, $\tilde{W}'$ and $\tilde{W}_t$
   - **Compute Projection:** Using the iterative procedure described in Bjork and Golup (1973) for $j \in 1, \ldots p$

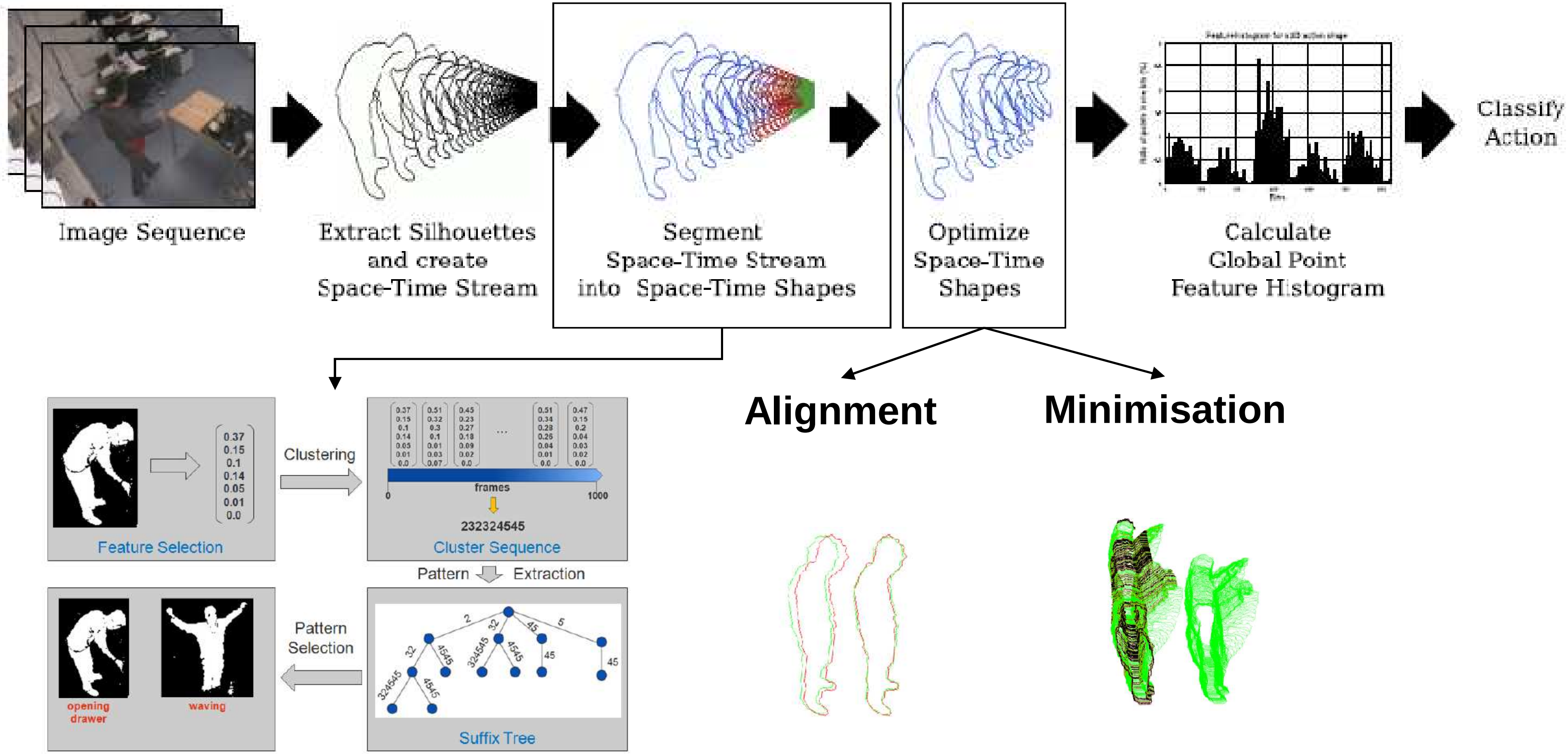
$$\mathbf{W}'_{i+1} = \mathbf{W}'_i - \mathcal{W}\mathcal{W}^{\mathsf{T}}\mathbf{W}'_i$$

   - **Find Angle:** Compute $\theta = \arcsin \ \min(1, \|\mathbf{W}'_p\|_2)$

Select $i^* = \arg\max_{i \in \{1,\cdots,N\}} \cos(\theta_1)$.

Where *W´ corresponds to the projection* of an action instance, and matrices W1, W2, … $W_N$ each modeling the N different actions.

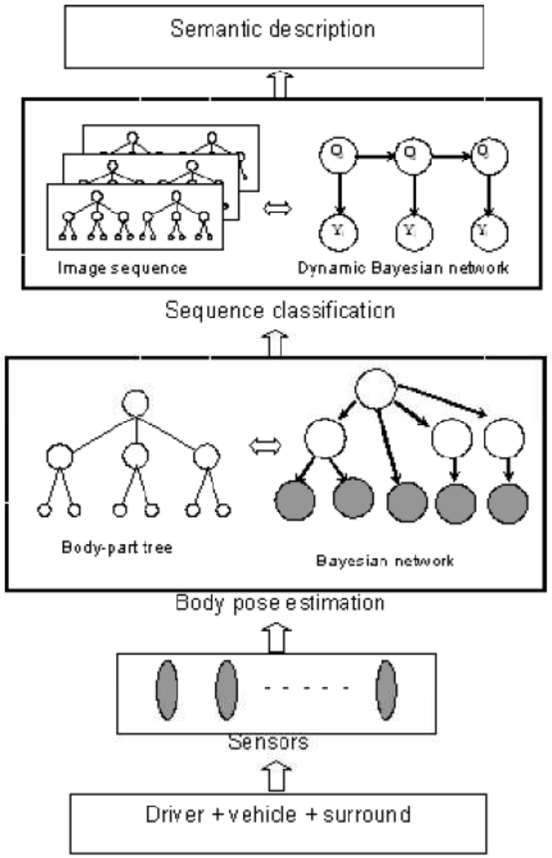
# Global/holistic approach: Activity recognition in office

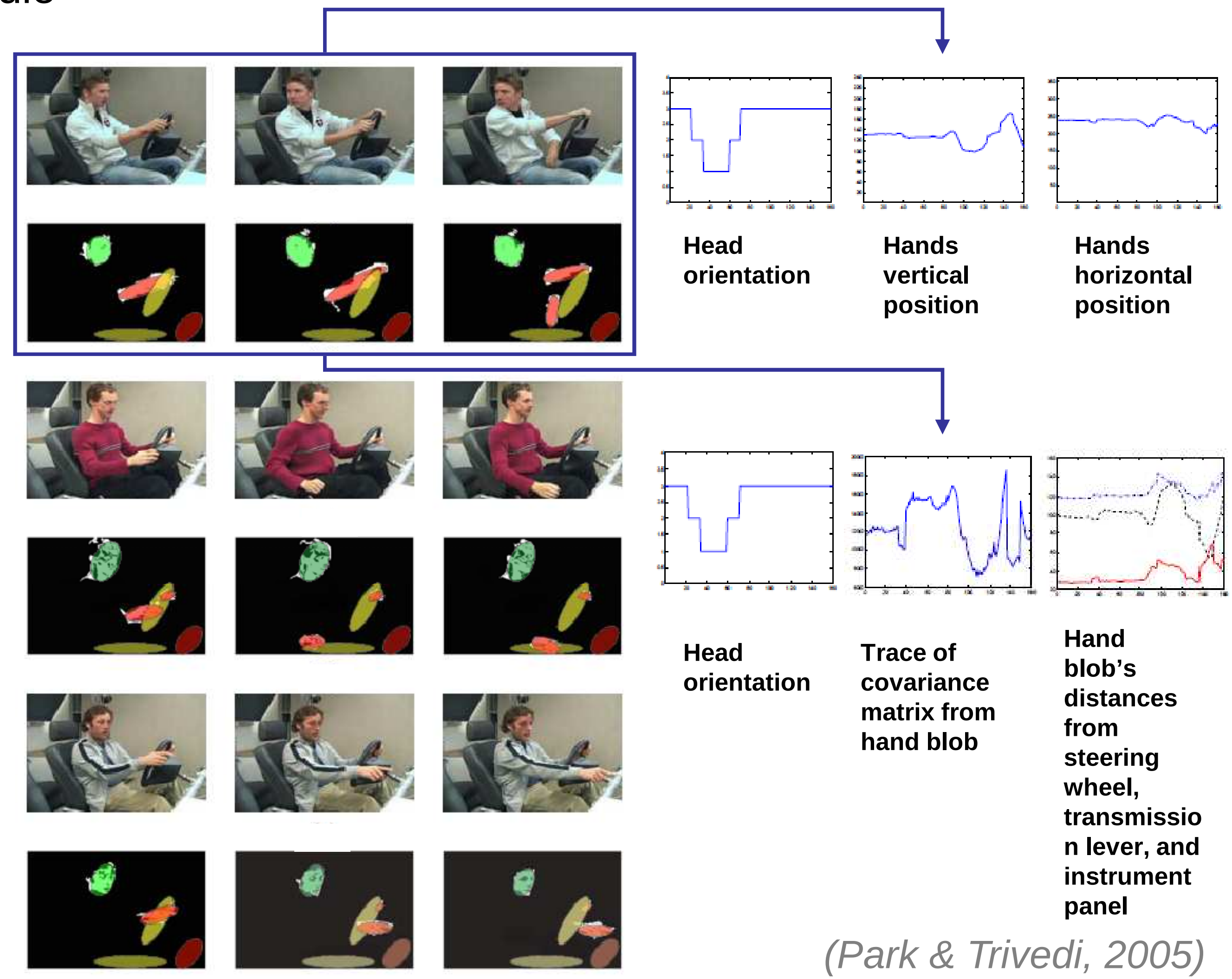



*(Rusu et al., 2009)*

# Activity recognition in a vehicle

**Activities:** (a) drive-forward, (b) backup, (c) shift-gear, (d) turn-left, (e) turn-right (f) touch-radio

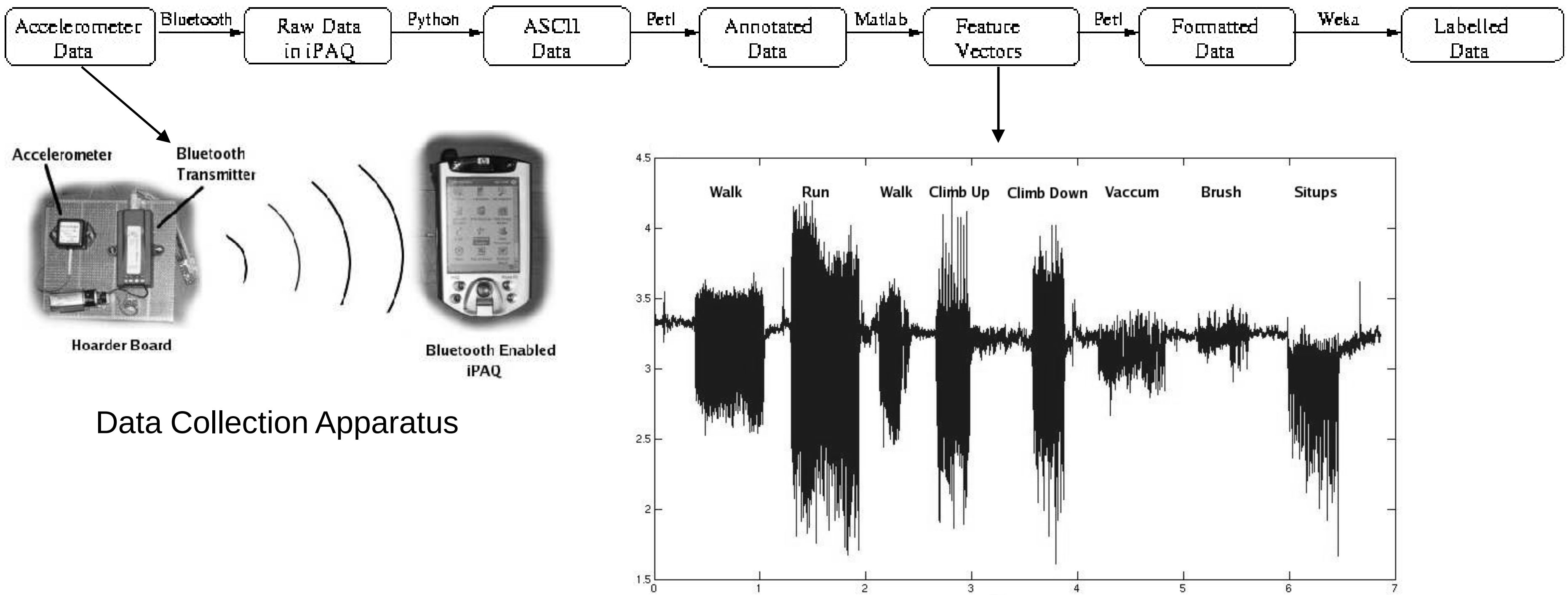



*(Park & Trivedi, 2005)*

# Activity Recognition from Accelerometer Data

**Activities:** (a) Standing, (b) Walking, (c) Running, (d) Climbing up stairs, (e) Climbing down stairs, (f) Sit-ups, (g) Vacuuming, (h) Brushing teeth.




Data Collection Apparatus

*(Ravi et al., 2005)*

# Applications of activity recognition (1/4):

- **Content Based Video Analysis:** With video sharing websites experiencing relentless growth, it has become necessary to develop efficient indexing and storage schemes to improve user experience. Most commercially viable application: summarization and retrieval of consumer content (i.e. sports videos) *(Chang, 2002)*.
- **Animation and Synthesis:** The gaming and animation industry rely on synthesizing realistic humans and human motion.

# Applications of activity recognition (2/4):

- **<u>Interactive Applications and Environments:</u>** Essential for designing human-machine interfaces with vital applications:
  a) Context aware computing to support cognitively impaired people
  b) Health monitoring and fitness
  c) Seamless services provisioning based on the location and activity of people.
  d) Smart rooms that can react to a users gestures (i.e. at community-dwelling for older people).

# Applications of activity recognition (3/4):

- **Security and Surveillance:** Automatic recognition of abnormalities in a camera's field of view.
  - Abnormal activities: Activities that occur rarely and have not been expected in advance
  - Example:
    - In working Environment:
      - Raising hands
      - Lying down
    - In community-dwelling
      - Falling down (backwards/forwards)
      - Lying down
      - No movement
      - Raising hands

*(Hu et al., 2009)*

# Applications of activity recognition (4/4):

- **Behavioural biometrics:** Biometrics involves study of approaches and algorithms for uniquely recognising humans based on physical or behavioural cues. Regarding **activity related biometrics**, although **gait** has been excessively studied, to our knowledge **no other body motions have been reported to be utilised as biometric for authentication purposes**.

# CERTH/ITI Activity recognition system

## ❖ Biometric purposes - Activity Related Authentication

Extracting an activity-related signature that characterises the individual by the way he/she responses to a stimulus (e.g. during working in an office).

Examined Activities:

- Talking to panel
- Answering to a phone call

## ❖ Security purposes

Detecting abnormal activities that denote danger (e.g. in the working environment/office)

Examined Activities:

- Raising hands

# Approaches

- **Activity recognition Approaches**
  - Motion Energy/History Images
  - Feature Extraction (RIT/CIT)
- **Activity-related authentication**
  - Tracking three points of interest (head, hands)
  - Authentication based on HMMs

# Motion Images

- **Motion Energy Image (MEI)**
  - Describes the motion energy for a given view of action.
  - Binary image.

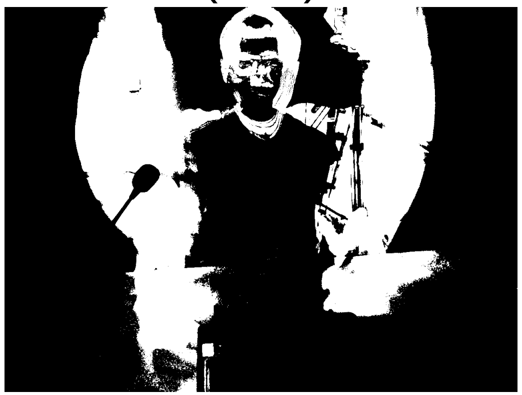
$$E_T(x,y,t) = \bigcup_{i=0}^{\tau-1} D(x,y,t-i)$$

- **Motion History Image (MHI)**
  - Intensity image.

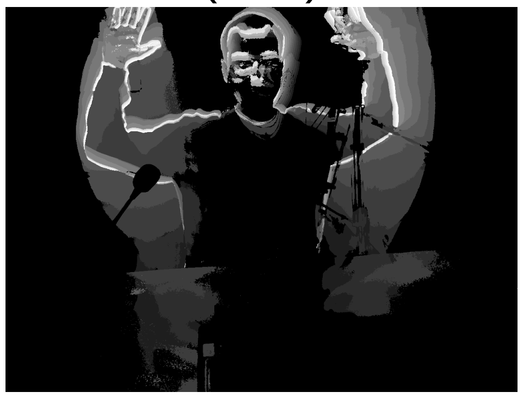
$$H_T(x,y,t) = \begin{cases} \tau & ,if\ D(x,y,t)=1 \\ \max(0, H(x,y,t-1)-1) & ,otherwise \end{cases}$$

# Motion Images – Activity Recognition

Motion Energy Image (MEI)

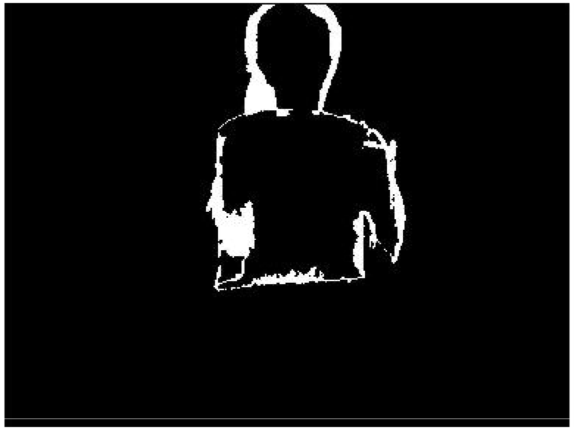


Motion History Image (MHI)



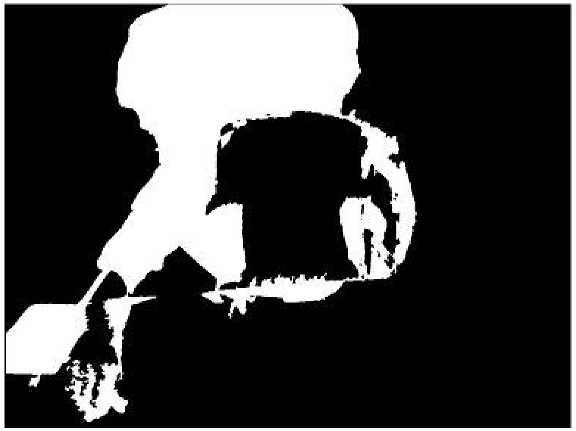
# MEI Templates of Six Micro-Activities

Pick up or put back



Phone Conversation

Activate Alarm

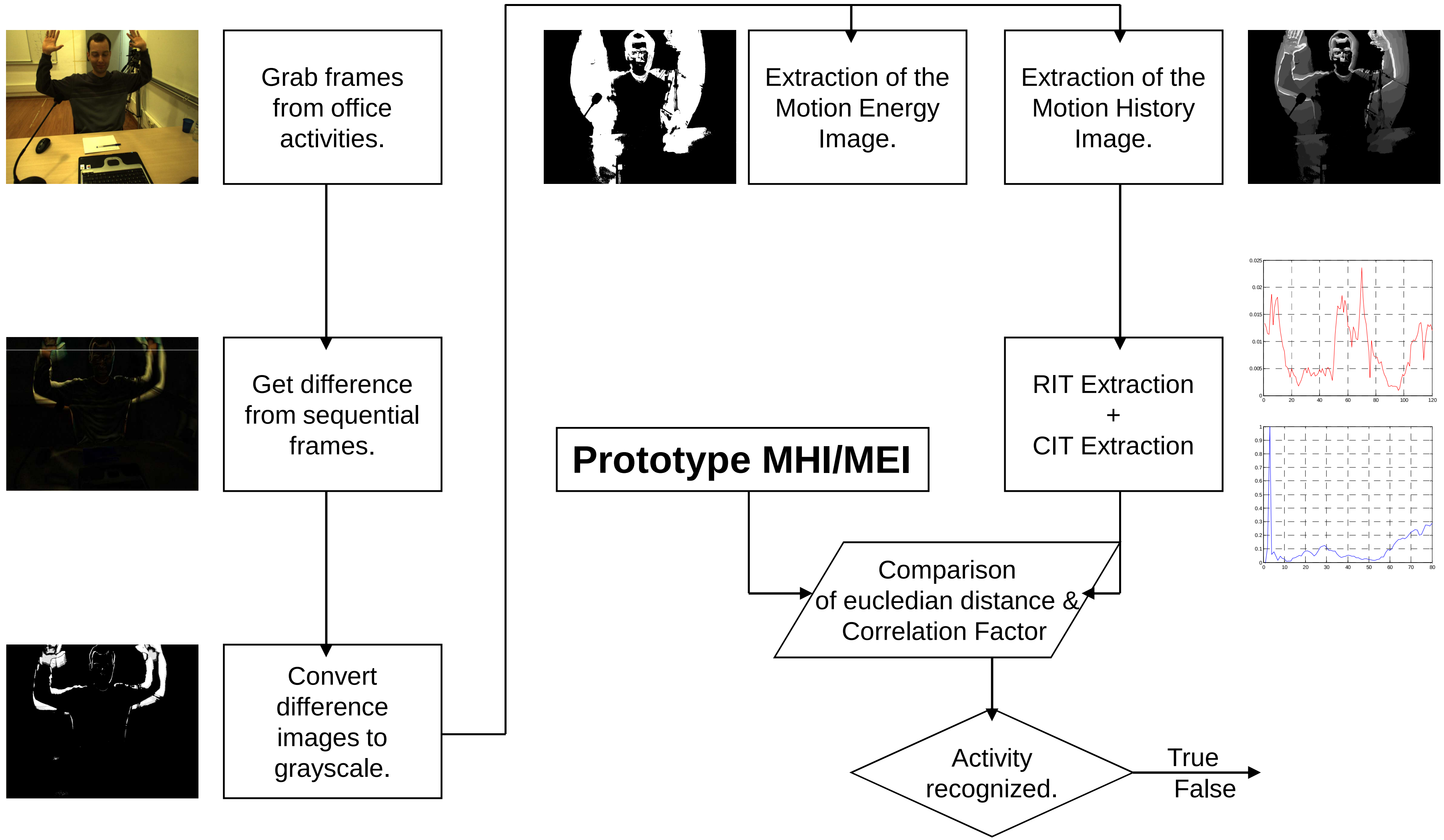


Talking to the microphone

Raising Hands

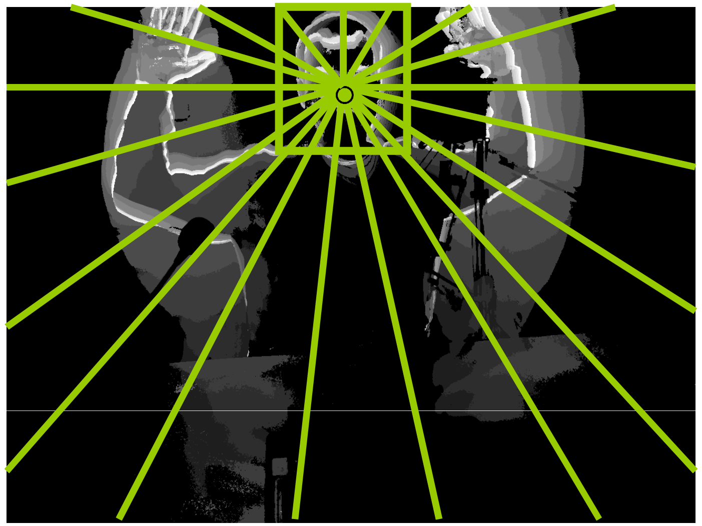
Drink from Glass

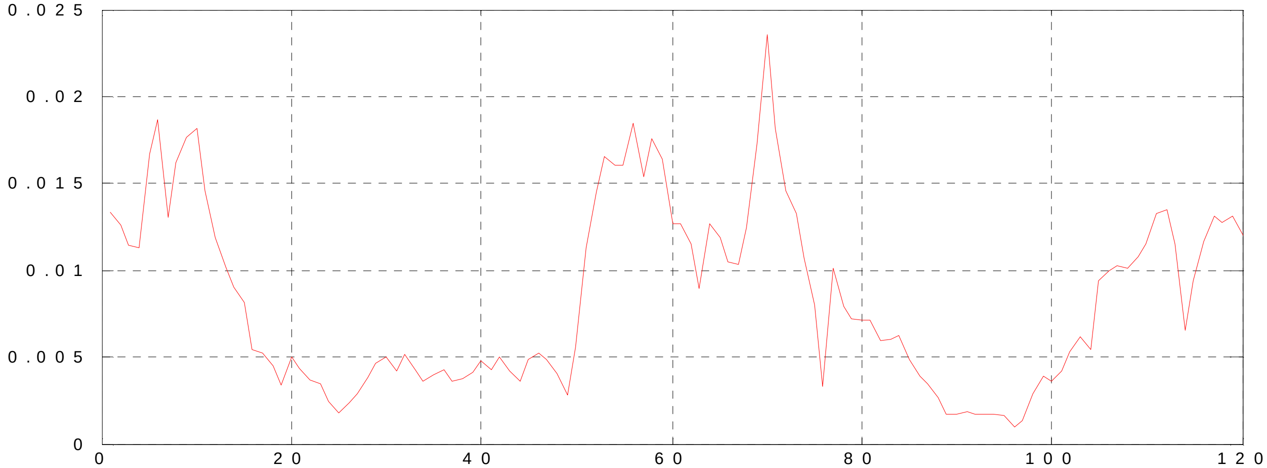
# Flow Chart


Grab frames from office activities.
Get difference from sequential frames.
Convert difference images to grayscale.
Extraction of the Motion Energy Image.
Extraction of the Motion History Image.
RIT Extraction
+
CIT Extraction
Prototype MHI/MEI
Comparison of eucledian distance & Correlation Factor
Activity recognized.
True
False

# RIT Extraction

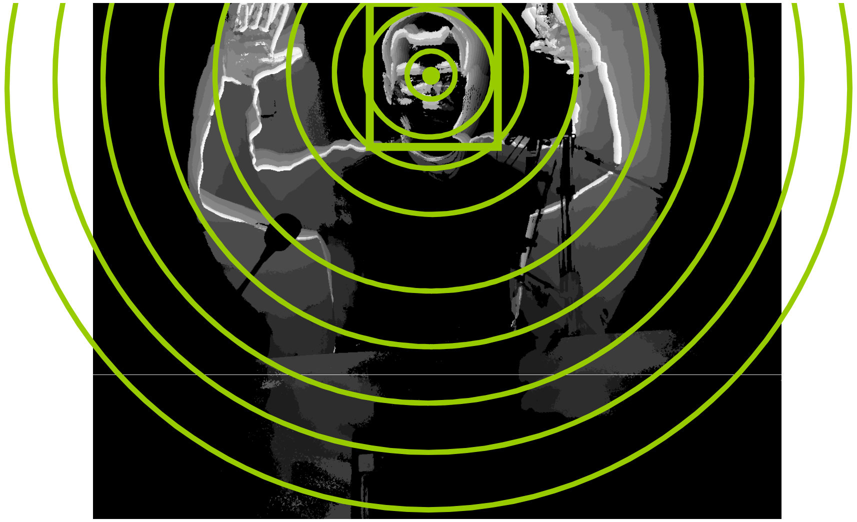
1. Face detection
2. Centre of Face
3. RIT Extraction

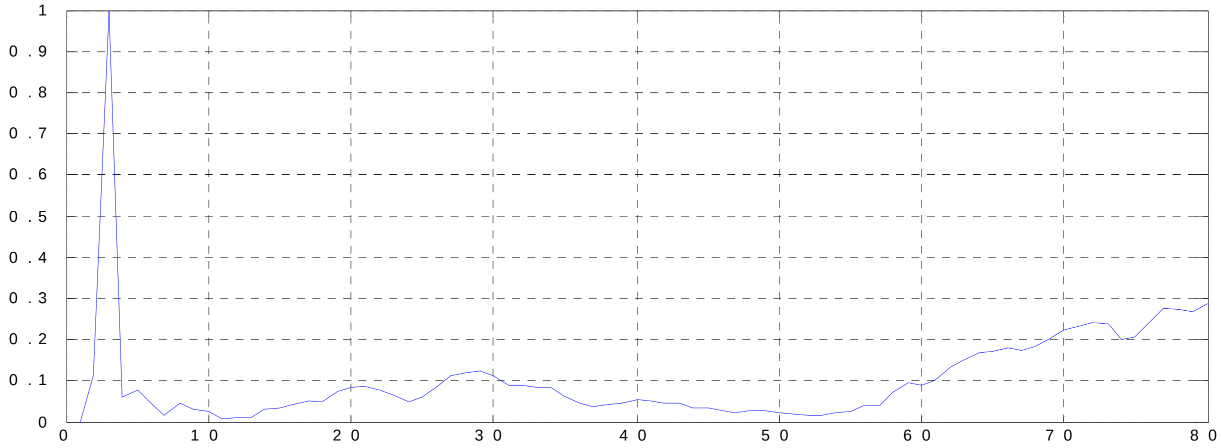




# CIT Extraction

1. Face detection
2. Centre of Face
3. CIT Extraction





# Metrics

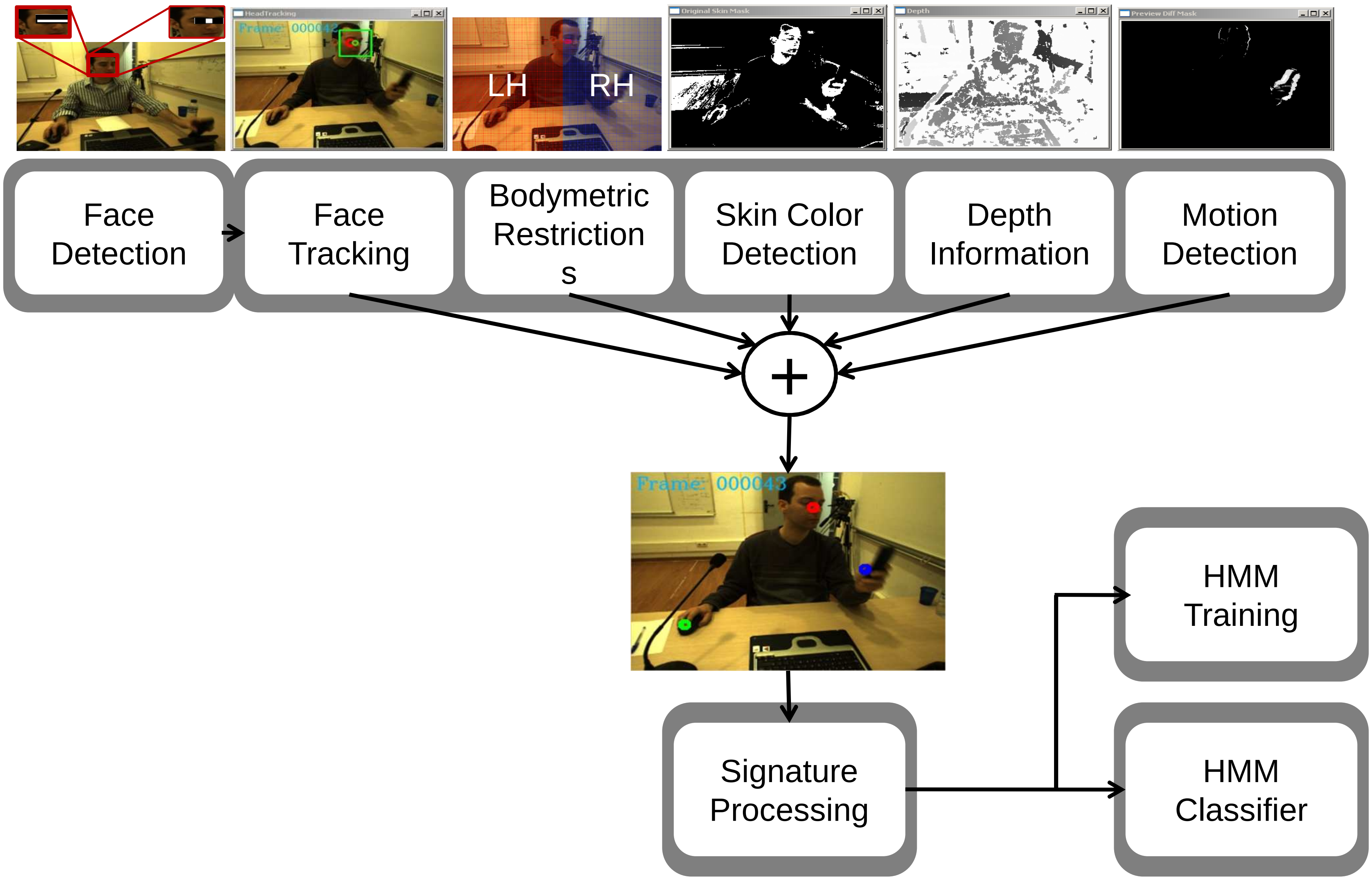
- **Euclidian Distance**

$$D_E = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \ldots + (x_n - y_n)^2} = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

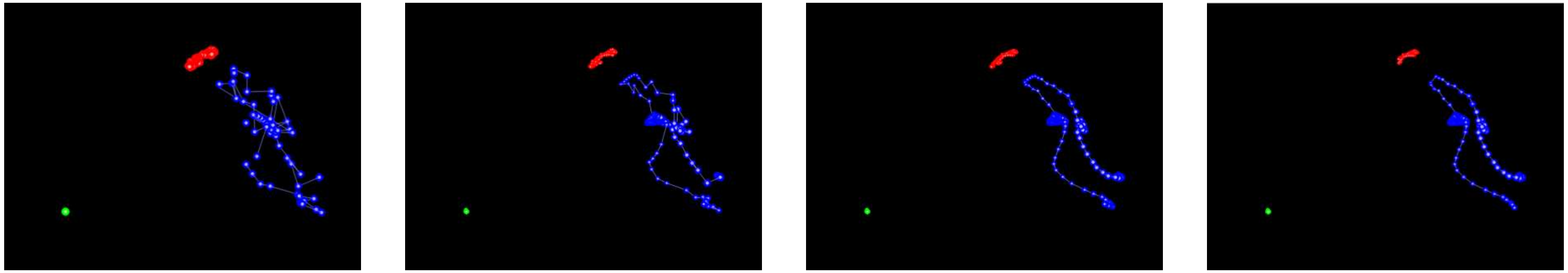
- Correlation Factor - Coefficients

$$corr(x, y) = \rho_{x,y} = \frac{\mathrm{cov}(x, y)}{\sigma_x \sigma_y} = \frac{\mathrm{E}((x - \mu_x)(y - \mu_y))}{\sigma_x \sigma_y}$$

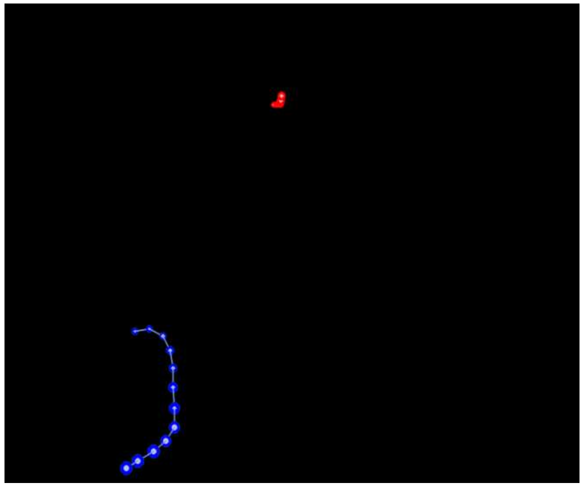
# Authentication System Overview



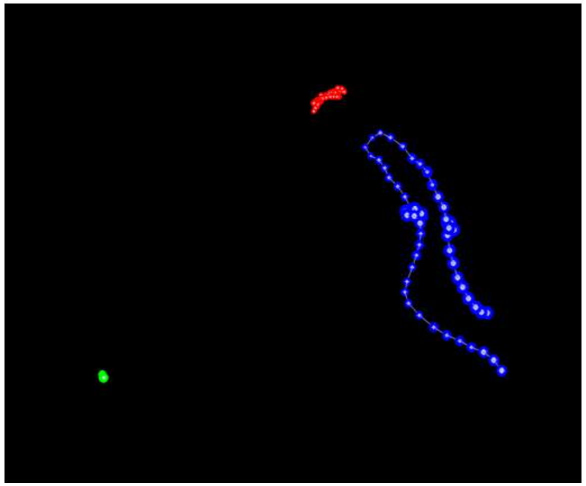
# Signature Extraction



pre-Interpolation → Smoothing → Trimming → Kalman Filtering → uniform Interpolation



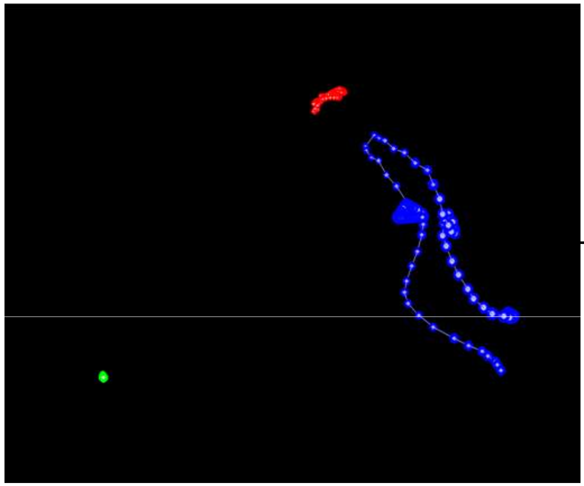
Activity: **Office Panel**



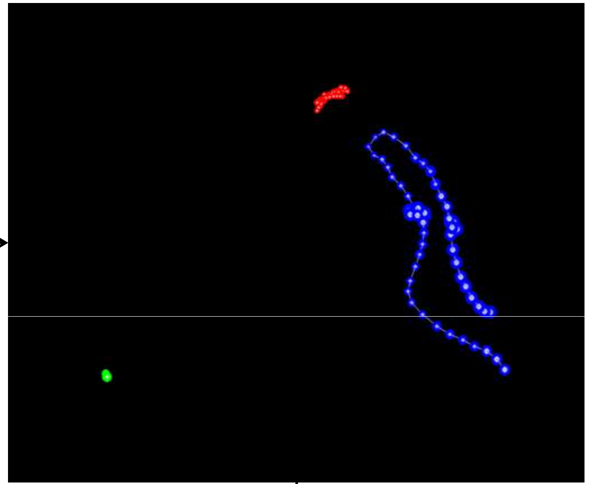
Activity: **Phone Conversation**

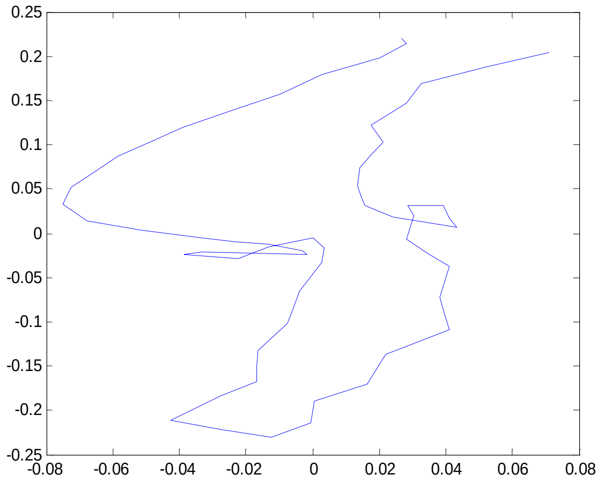
# Trajectory’s Features for authentication

Trajectory Features Extraction (curvature, torsion)



Uniform Interpolation (losing speed information)





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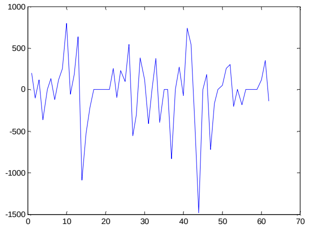
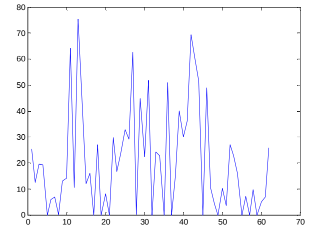
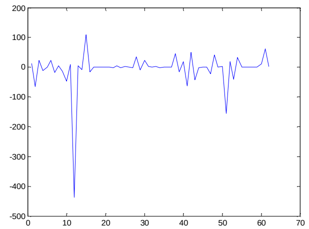
Trajectory Features Extraction (curvature, torsion)



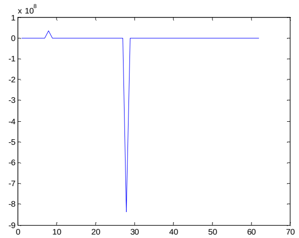
$$\kappa^*(P_i) = 4\frac{\sqrt{\hat{s}(\hat{s}-a)(\hat{s}-b)(\hat{s}-c)}}{abc}$$



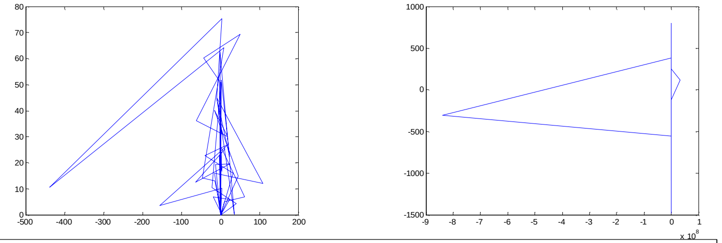
$$\kappa_s^*(P_i) = 3\frac{\kappa^*(P_{i+1}) - \kappa^*(P_{i-1})}{2a+2b+d+g}$$



$$\tau^*(P_i) = \frac{1}{2}\left(6\frac{H^+}{def \cdot \kappa^*(P_i)} + 6\frac{H^-}{gmm \cdot \kappa^*(P_i)}\right)$$



$$\tau_s^*(P_i) = 4\frac{\tau^*(P_{i+1}) - \tau^*(P_{i-1}) + r(\tau^*(P_i)\kappa_s^*(P_i)/6\kappa^*(P_i))}{2a+2b+2d+h+g}$$



Motion symmetry perception:
a) Curvature sub-signature b) Torsion sub-signature

,whereas

$$\frac{1}{3!}\begin{vmatrix} x_i & y_i & z_i & 1 \\ x_{i-1} & y_{i-1} & z_{i-1} & 1 \\ x_{i+1} & y_{i+1} & z_{i+1} & 1 \\ x_{i+2} & y_{i+2} & z_{i+2} & 1 \end{vmatrix} = V_{abcdef} = \frac{\Delta_{abc} \cdot H^+}{3}$$

$$r = 2a + 2b - 2d - 3h + g$$

$$\hat{s} = (a+b+c)/2$$

# Hidden Markov Model

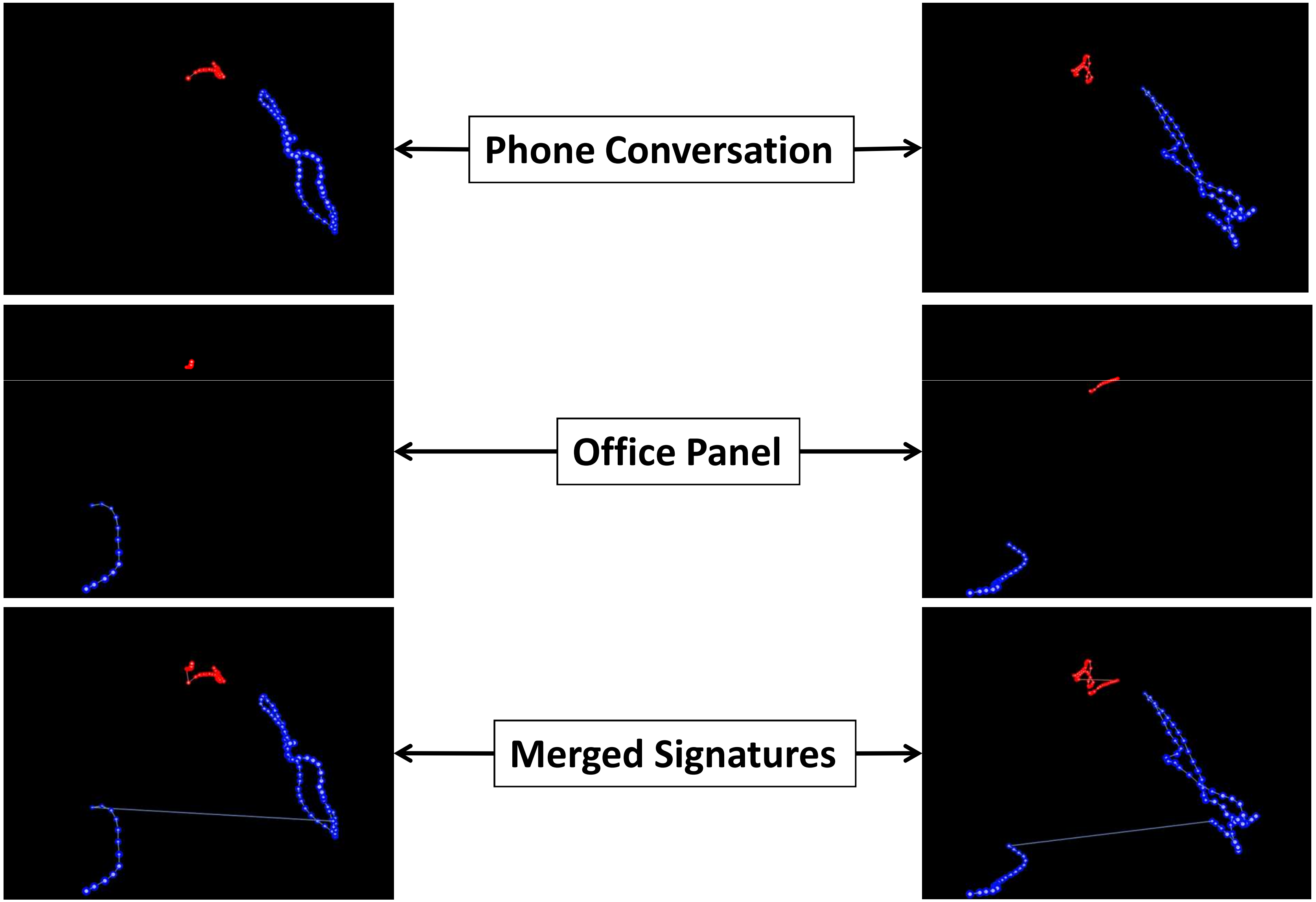
- HMM is characterized by:
  1. N, the number of states in the model
  2. M, the number of distinct observation symbols per state
  3. The state probability distribution $A=\{a_{ij}\}$
  4. The observation symbol probability distribution
  5. The initial state distribution

- Three basic Problems:
  1. *Evaluation Problem* – how to compute the probability that the observed sequence was produced by the HMM.
  2. *Determination of a best sequence of model states* – since no correct state, find the optimal solution.
  3. *Training problem* – optimization of model parameters so to best account for the observed signal

# HMM Classification

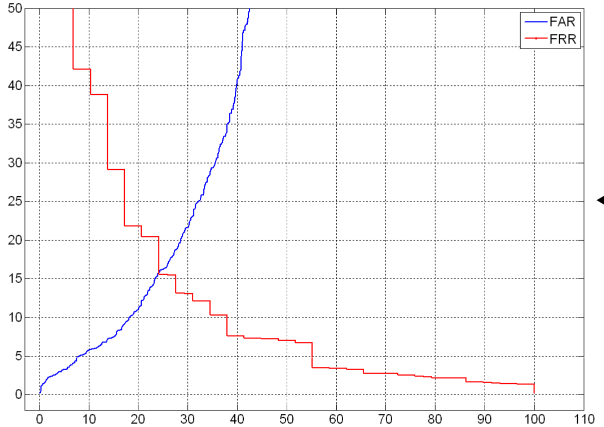
- Activity – related signature of a person for a specific action is the set of stored Hidden Markov Model parameters, trained with action sample(s) of the particular user
- Enrolment: HMM Signatures are created by training an HMM using a limited training set (3 or more samples of an action) for a given person.
- Selected experimentally: No of states=5, No of distinct observation symbols (3D position of head and moving head)
- Authentication:
  - Segmented action is fed to the claimed user's stored HMM
  - Action's similarity to the user's behavior is evaluated (log – likelihood calculation) using forward – backward algorithm
  - Acceptance/Rejection is based on thresholding the calculated likelihood

# Client - Impostor

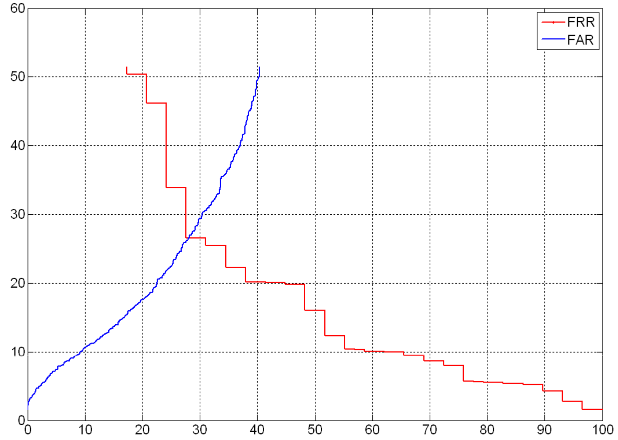


# Results FAR – FRR (1/2)

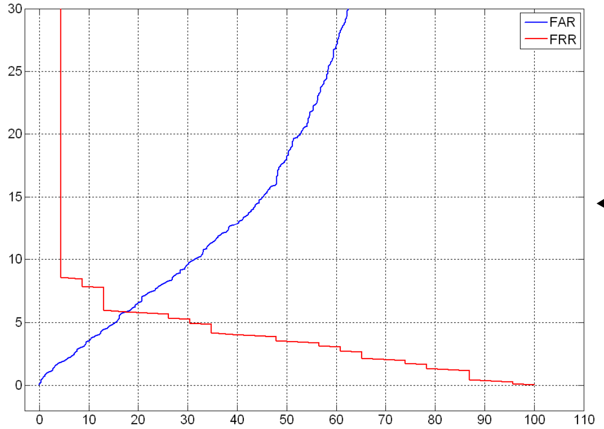
SNR = 28



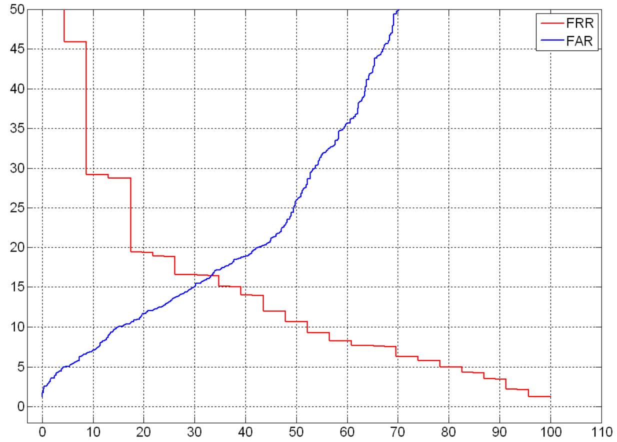

Phone Conversation




SNR = 28

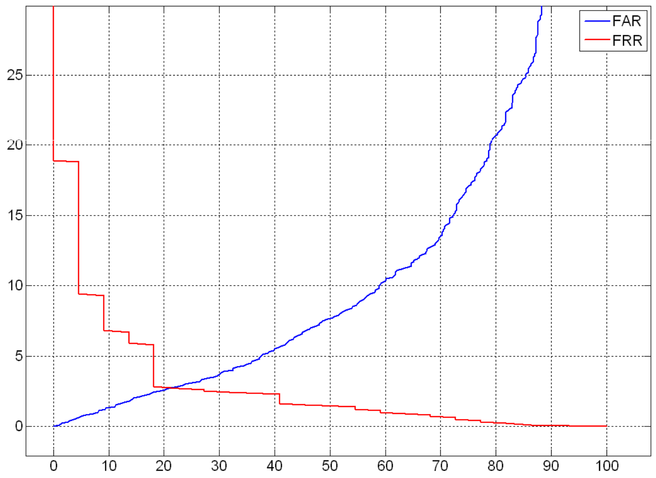



Office Panel

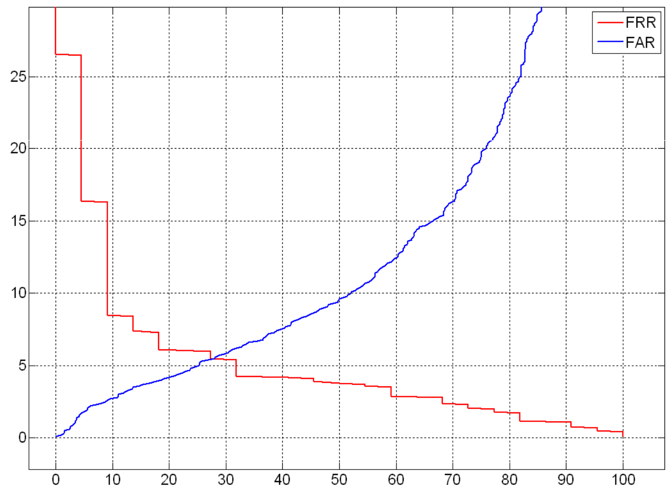


# Results FAR – FRR (2/2)

SNR = 28




Merged Signature

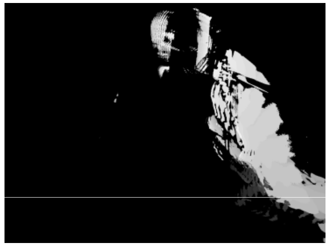


# Summarising…

- Three (3) activities tested up to now with very promising results.

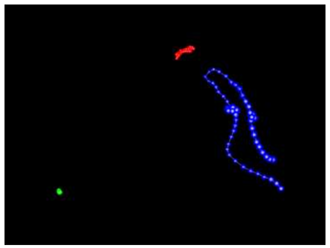
Hands Up

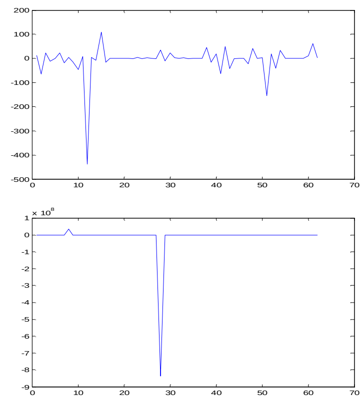
Phone Conversation



Talking to Mic. Panel

- Body Tracking - Signature Extraction – Trajectories – Identification



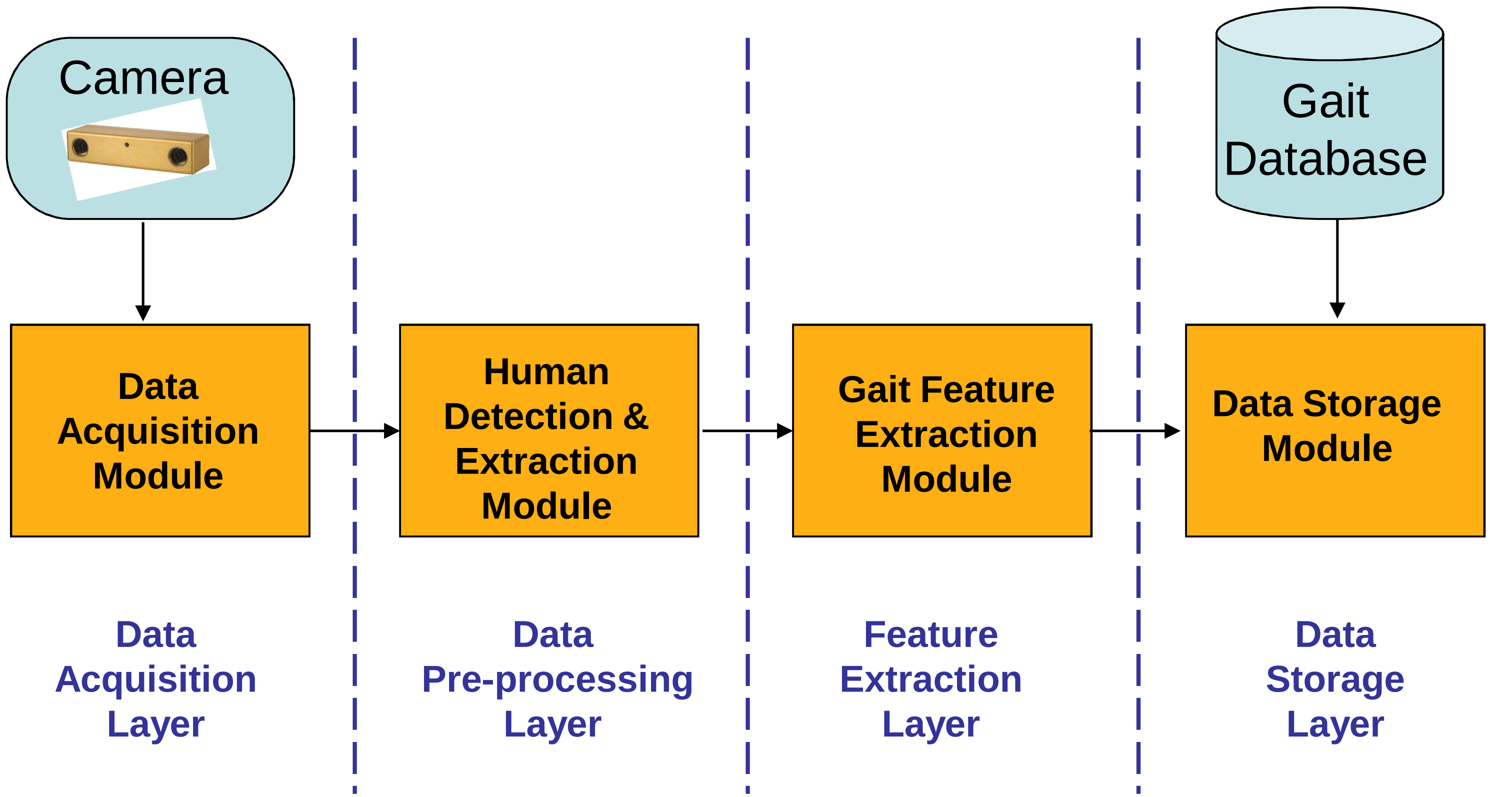
**Activity-related biometric authentication provided very promising results and is expected to maximize the performance of a multimodal biometric system.**

# Gait…

- is the personal, idiosyncratic way in which people walk or move on foot
- has received significant attention as a biometric, in the last 10-15 years
  (Nixon & Carter, 2006; Rahati et al., 2008; Boulgouris et al., 2005)
- has demonstrated high recognition rates
  (Zhang et al., 2007; Bouchrika & Nixon, 2007)

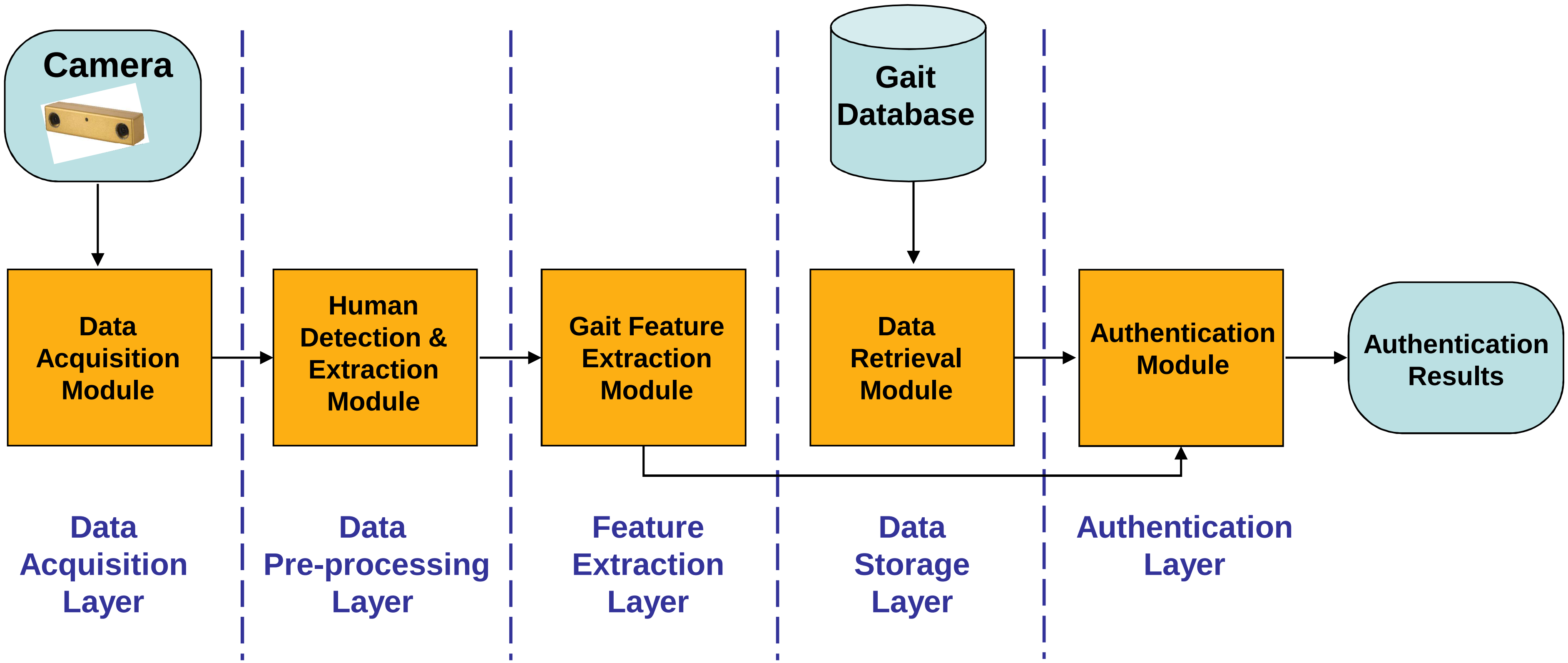
# General Gait Authentication System

– Enrolment procedure



# General Gait Authentication System

## – Authentication procedure



# Approaches to the gait recognition

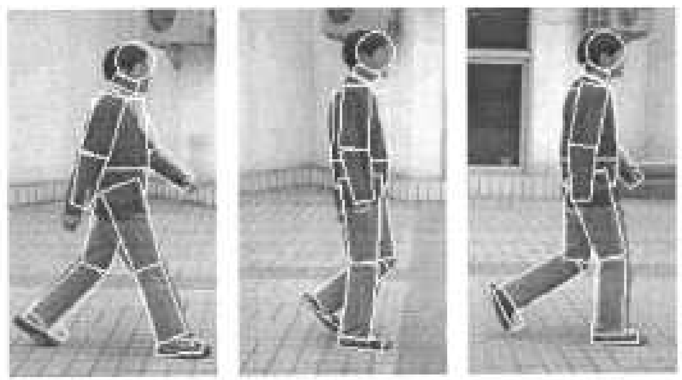
**Featured based (model free):**

Focus on the spatiotemporal information contained in the silhouette images (low level measurements).

(*From Li et al. 2004*)

**Model based:**

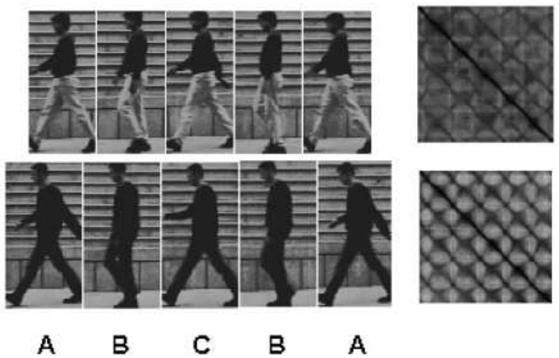
Serve as prior knowledge to predict motion parameters, to interpret human dynamics, or to constrain the estimation of low-level image measurements.



(*From Wang et al. 2004*)

# Features for gait recognition
# Featured-based method (1/2)

- Width of the outer contour of the silhouette *(Kale et al. 2004)*
- Entire binary silhouette *(Kale et al. 2004)*
- Boundary vector variations from the centre of silhouette *(Wang et al. 2003)*
- Statistical moments from body parts ellipses *(Lee et al. 2002)*
- Height, stride length and cadence *(BenAbdaker et al., 2002)*
- Height, distance between head and pelvis, max distance between pelvis and feet, and the distance between feet *(Johnson & Bobick 2001)*
- Self similarity plot *(BenAbdelkader et al., 2001)*




$$S(t_1, t_2) = \sum_{(x,y)\in B_{t_1}} |O_{t_1}(x,y) - O_{t_2}(x,y)|,$$

Where $1 \le t_1, t_2 \le N$, $B_t$ is the bounding box of the person in frame $t_1$, and $O_{t1}$, $O_{t2}$, …, $O_{tN}$ are the scaled image templates of the person.

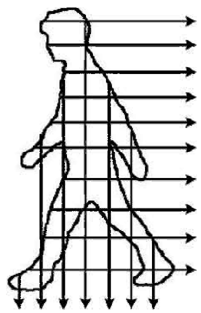
# Features for gait recognition
# Featured-based method (2/2)

- Horizontal and vertical projections

$$P_h(x) = \sum_{y=1}^{N_c} S(x,y), \qquad x = 1,\dots,N_r$$

$$P_v(x) = \sum_{r=1}^{N_r} S(x,y), \qquad y = 1,\dots,N_c$$

$$S(x,y) = \begin{cases} 1, & \text{if } (x,y) \text{ is a foreground pixel} \\ 0, & \text{otherwise} \end{cases}$$

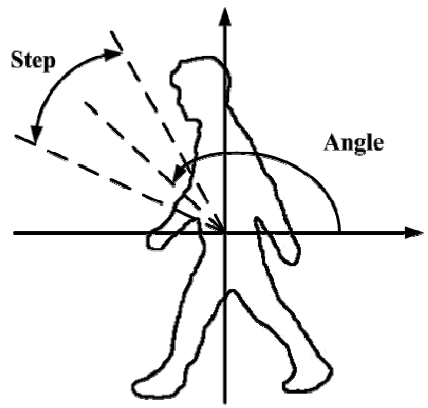


*(Liu et al. 2002)*

- Angular transform

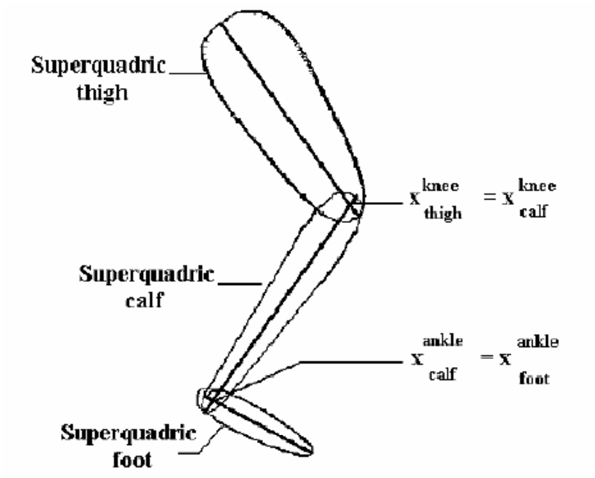
$$\mathrm{A}(\theta) = \frac{1}{N_\theta} \sum_{(x,y)\in\phi_\theta} S(x,y)\sqrt{(x-x_c)^2 + (y-y_c)^2}$$

where $\theta$ is an angle, $\Phi_\theta$ is the set of the pixels in the circular sector $\left(\theta - \frac{\Delta\theta}{2}, \theta + \frac{\Delta\theta}{2}\right)$ and $N_\theta$ is the cardinality of $\Phi_\theta$ *(Boulgouris et al. 2004)*.

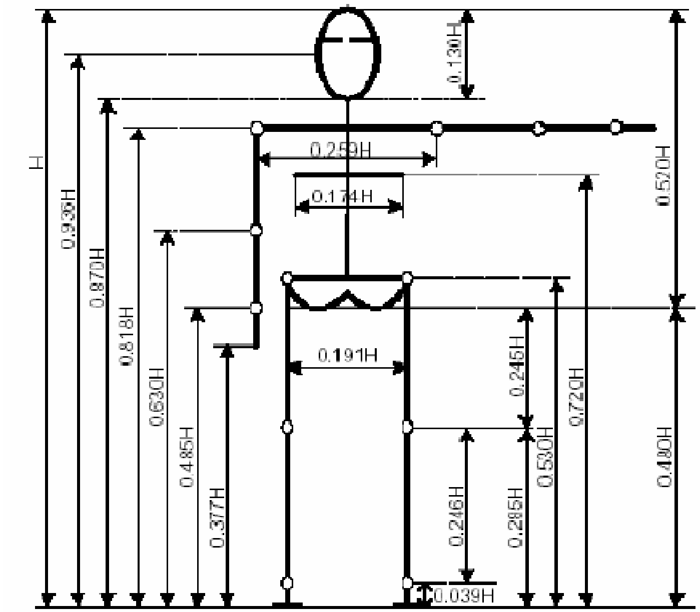


# Features for gait recognition
# Model-based method (1/2)

- Absolute joint positions *(Zhang et al. 2004)*
- Limb angles *(Zhang et al. 2004, Goffredo et al. 2008, Lu et al. 2006)*
- Lengths of various body parts *(Lu et al. 2006)*
- Widths/thickness of body parts *(Lu et al. 2003)*
- Height *(Han et al. 2006)*




*(From Desseree & Legrand, 2005)*




Human parts proportions *(Winter 2004)*

# Features for gait recognition
# Model-based method (2/2)

- Area of a body component
- Vector distance between the gravity centres of a body component and the whole body

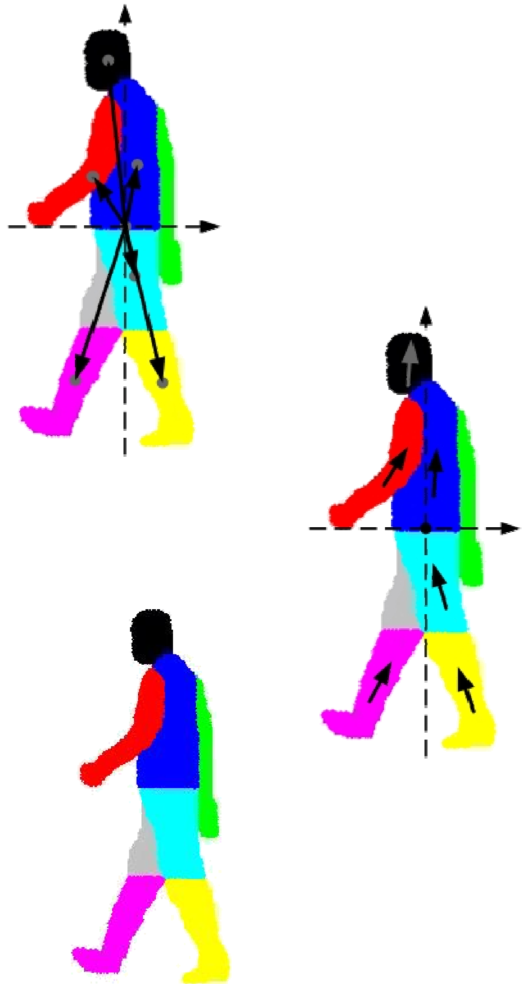
*(Huang & Boulgouris, 2009)*

- Orientation of a body component

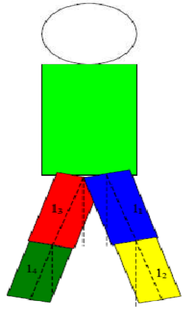
*(Huang & Boulgouris, 2009)*

- Similarity based on body components

*(Boulgouris & Chi, 2007)*



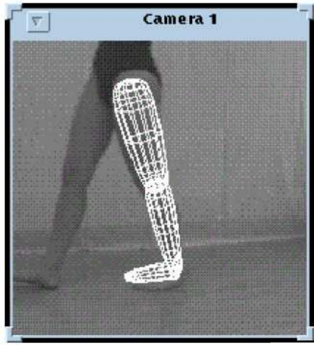
# Creating a human model



## Whole body models

•14 rigid bodies *(Wang et al. 2004)*

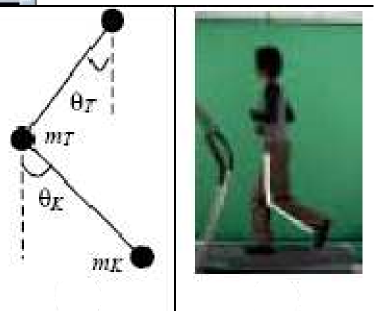
• 5 rigid bodies *(Zhang et al. 2007; Cheng-Chang et al. 2007)*




## Leg model models

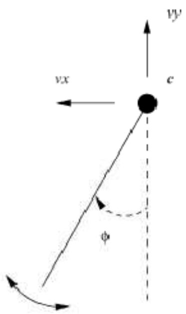
• 3 rigid bodies (thigh, shank, foot)

*(Desseree et al.2005)*




• 2 rigid bodies (thigh and shank)

*(Yam et al. 2002)*



• 1 rigid body (the thigh)

*(Cunado et al. 2003)*

# Creating a human model

Constrains:

- Gait is symmetrical and periodical (healthy population)
  - ➲ adequate to define the model for only one leg
  - ➲ the same model can describe either leg

*(Yam et al. 2004)*

- Dependency of the neighbouring joints:
  - shoulder-elbow, thigh-knee, knee-ankle
  - lower limb is driven by the upper limb

*(Wang et al. 2004)*

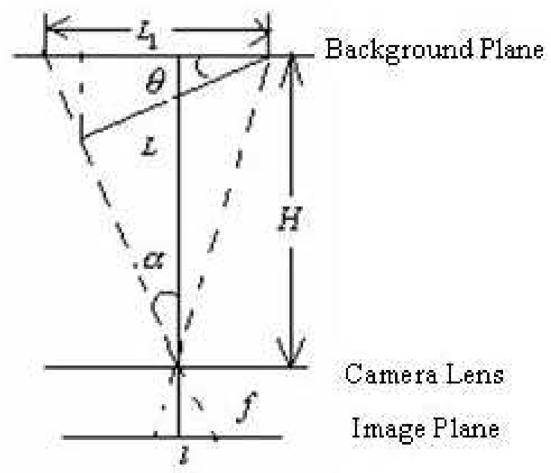
- Minimum and maximum values of the joint angles

# Problems in gait recognition

## Overcoming the dependency to the gait direction

- Based on pinhole imaging model and weak-perspective projection, the gait direction is obtained and thus the projection function:

$$L = \frac{lH}{f(\cos\theta + \sin\theta \tan\alpha)}$$



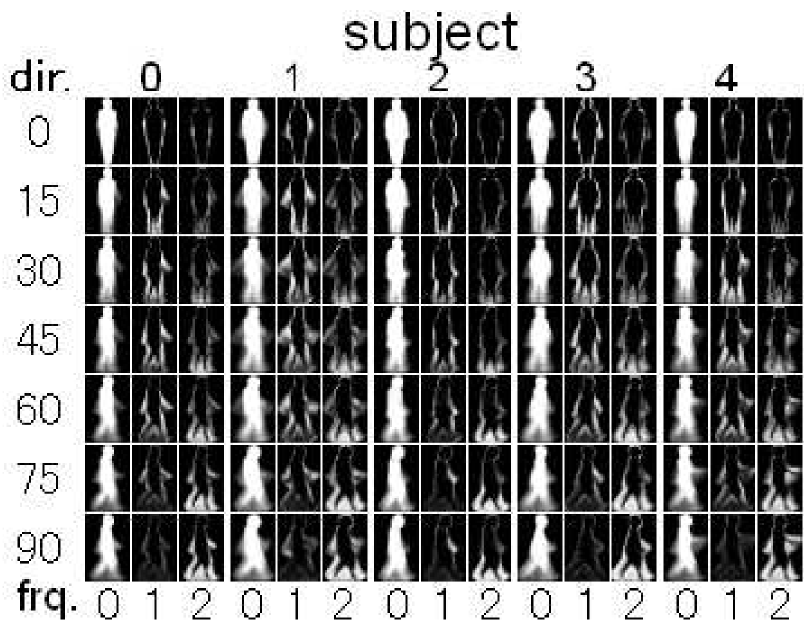

- Recognition rate: 50-70%

*(Han et al. 2006)*

# Problems in gait recognition

## Proven references to be used for gait invariant analysis

- Simple Reference: 45 deg and 135 deg angle views achieve better results
- Two references: Combinations of orthogonal references such as combination of 0 and 90° are effective

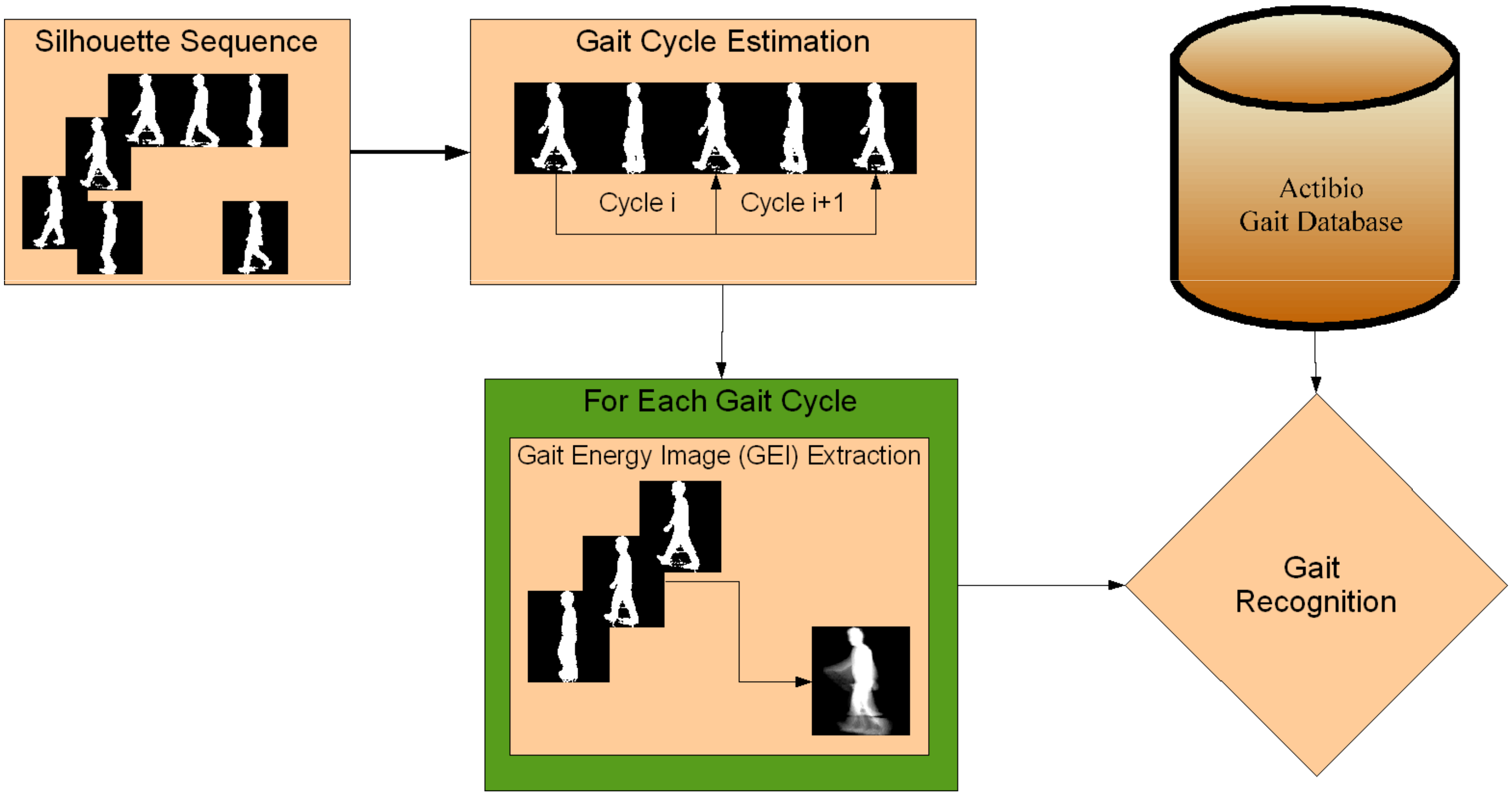



*(Makihara et al 2006)*

## CERTH/ITI Gait Recognition Approach -Functionalities

- Live capturing frames / Reading frames from database
- Human Extraction based on original frames
- Live Enrolment and Authentication based on live capturing and Human Extraction
- Offline Enrolment and Authentication on the database

# Gait Recognition Algorithm Block Diagram

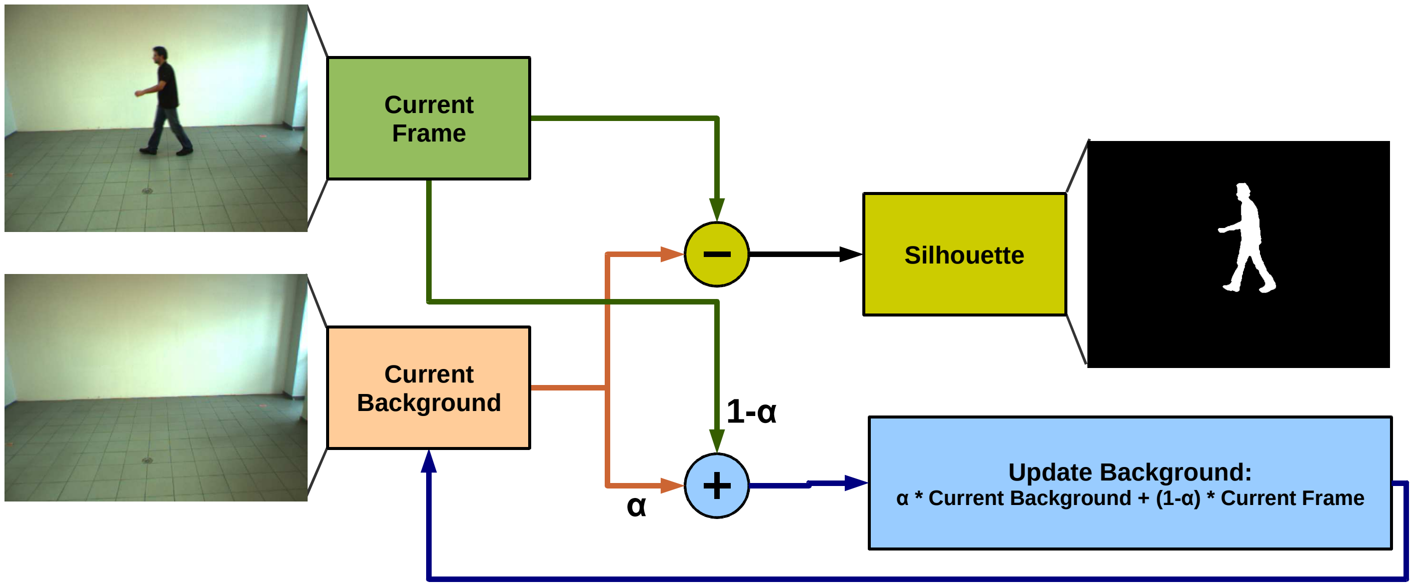


# Dynamic background update and silhouette extraction

- Background image is updated every time a new frame arrives using an interpolation rule:

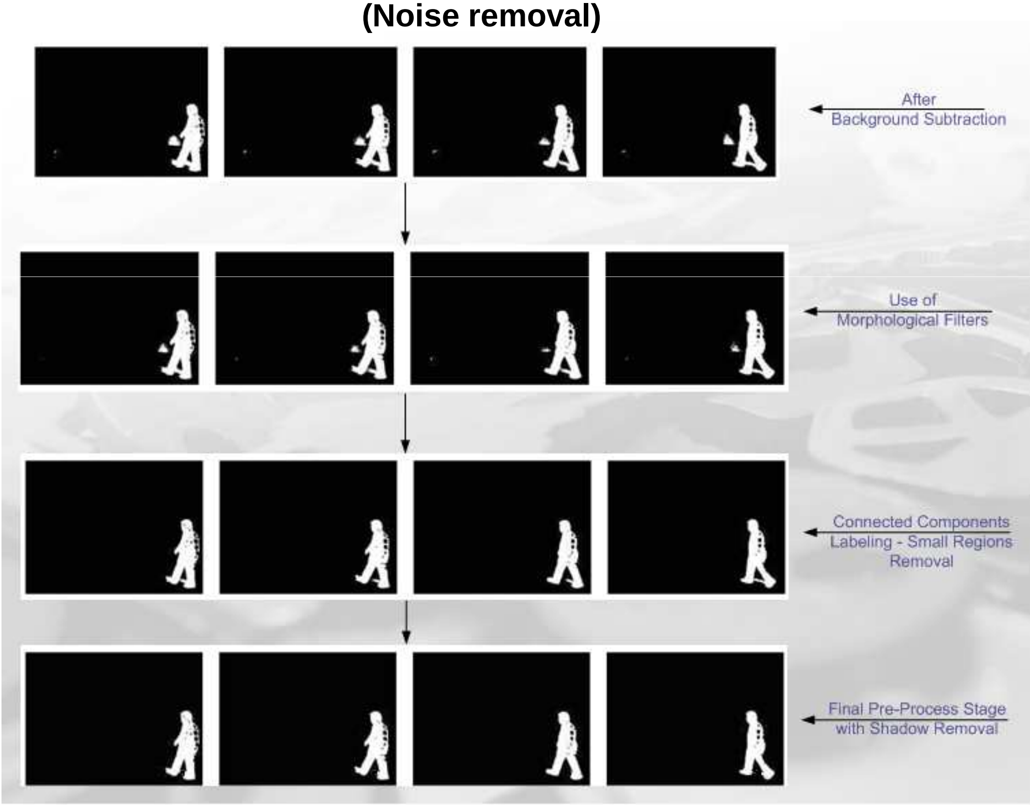
  $\alpha$ * Current Background + (1-$\alpha$) * Current Frame

  where $\alpha$ is an adaptive weight factor that changes in every frame.
- Depending on chosen segmentation algorithm, we could have: the same $\alpha$ for all frame pixels, based in global illumination changes or every pixel in frame could have its own weight factor based on its local illumination changes.



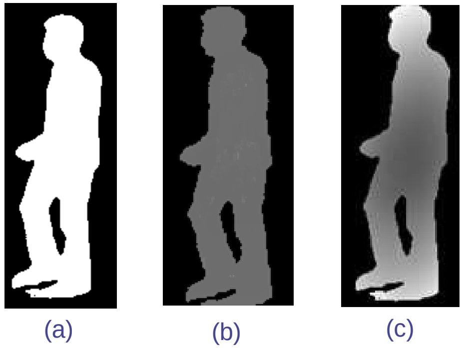
# Pre-Processing Stage

**Pre-processing of foreground silhouettes (Noise removal)**




# Usage of Depth

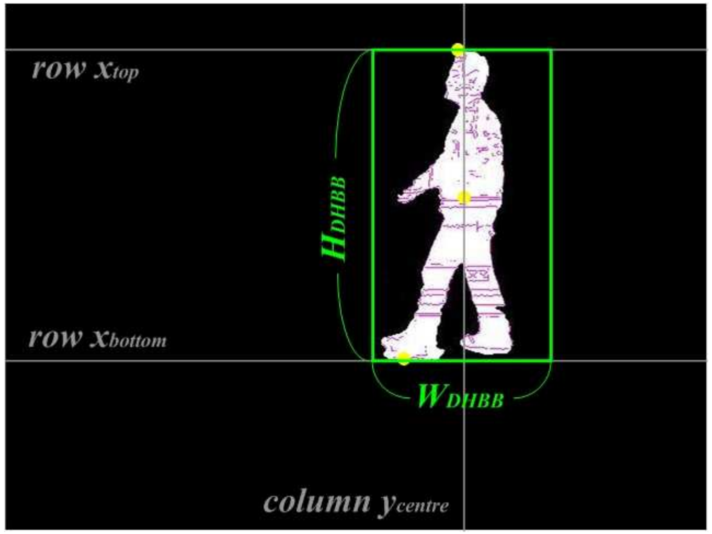
**Silhouette Representation**

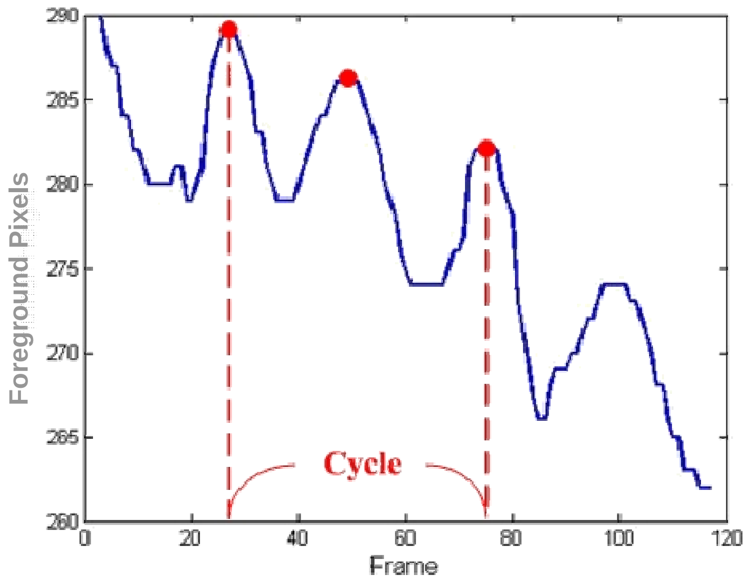



Binary Silhouette (a),
3D Radial Distributed Silhouette (b), and
3D Geodesic Distributed Silhouette (c)

# Gait Cycle Estimation: Algorithm I

- Human Height (calculated in the Human Extraction stage).
- Number of foreground pixels in the lower half of the human silhouettes.

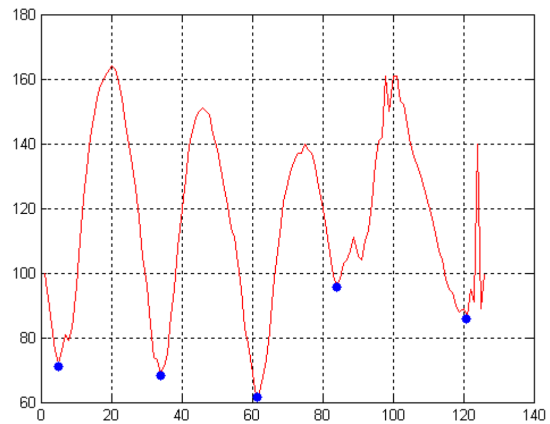



**Period :** Number of frames in one cycle ($NF_C$) is calculated by observing the peaks.

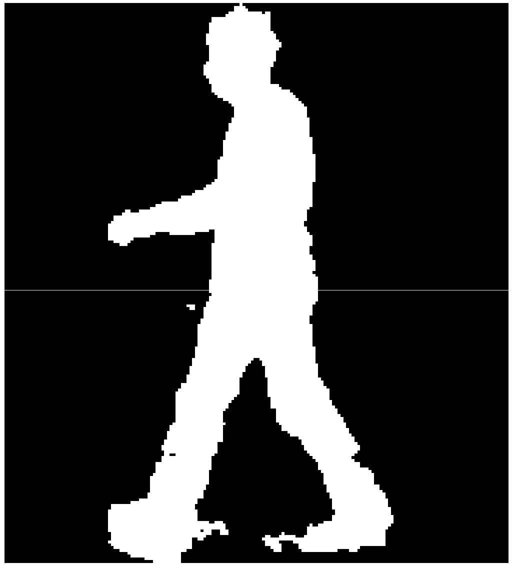
# Gait Cycle Estimation: Algorithm II


- Period is estimated by calculating the bounding box's width in each frame and getting the local minima for the entire sequence
- Local Minima that are too close (<5 Frames) are discarded.

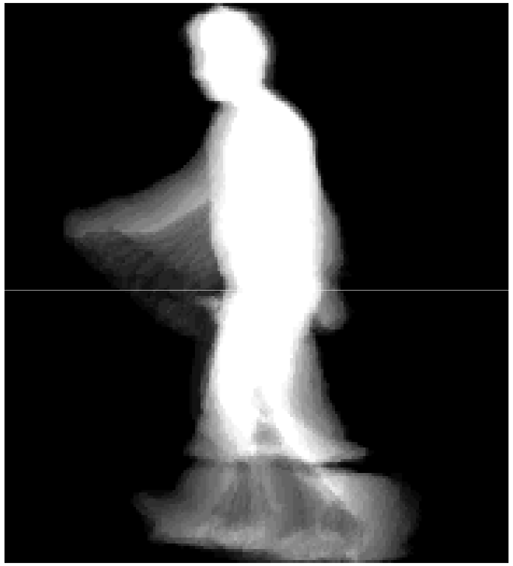



$$C_i = LocalMin(BoundingBoxWidth(n) | n \in 1, numberOfFrames)$$

# Utilization of Gait Energy Images (GEI)



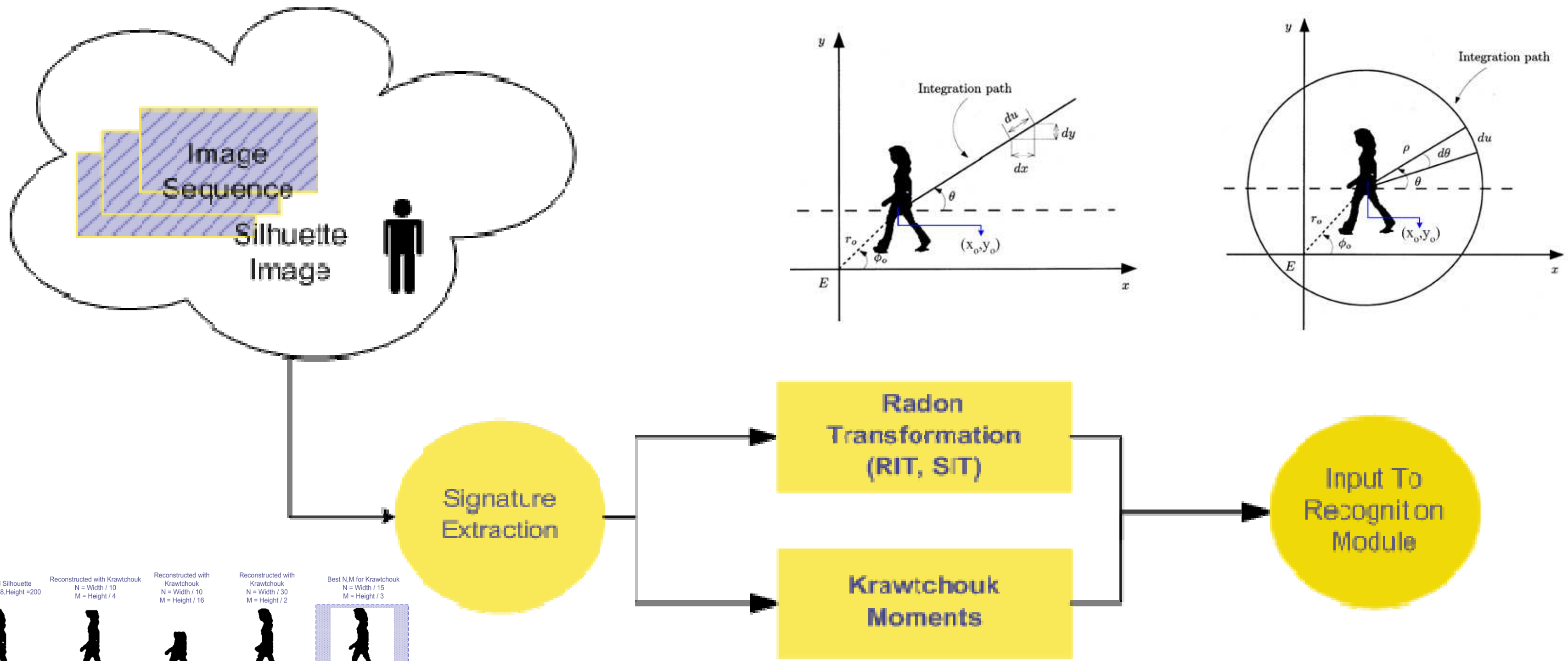
Gait frame

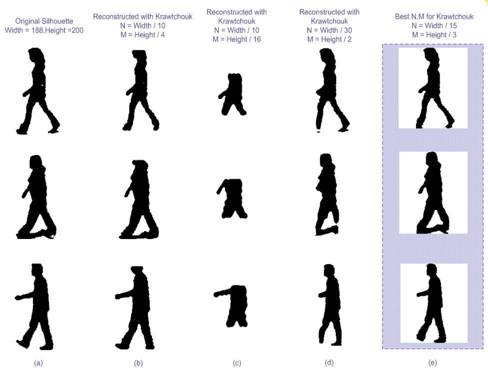


Gait Energy Image

$$GEI = \frac{1}{CycleLenght} \cdot \sum_{i=CycleStart}^{CycleEnd} gaitFrame(i)$$

# Signature Extraction Stage

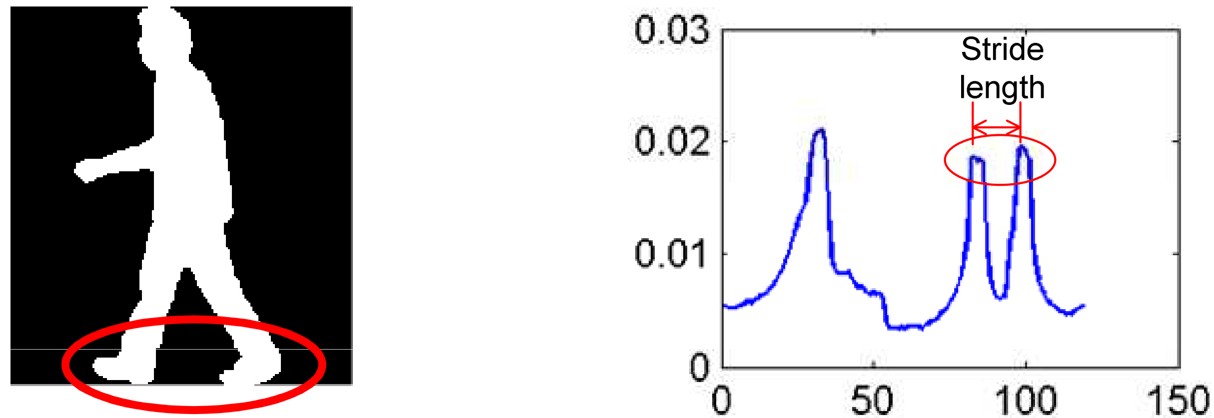


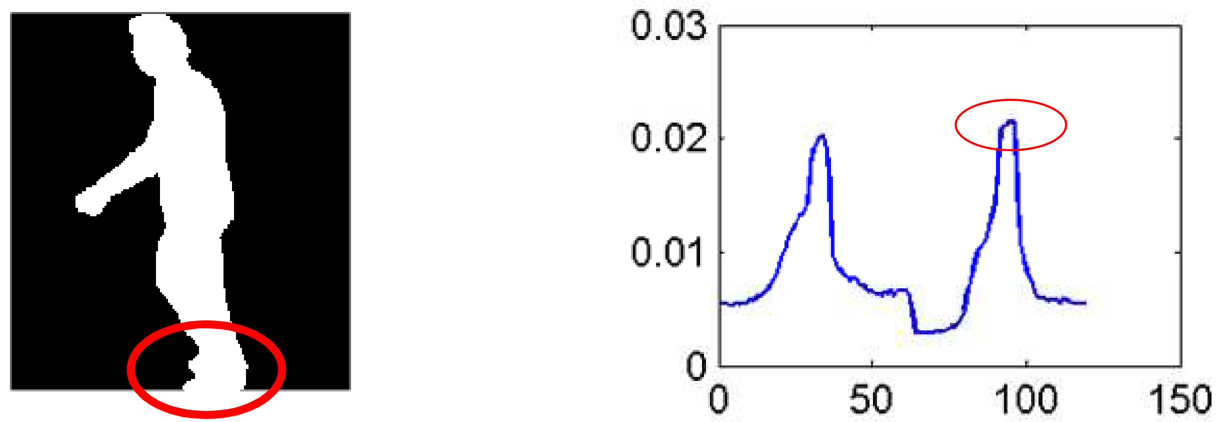
$$Q_{nm} = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \overline{K}_n(x; p_1, N-1) \overline{K}_m(y; p_2, M-1) f(x, y)$$

# Mapping of gait characteristics into gait transforms

Double support position



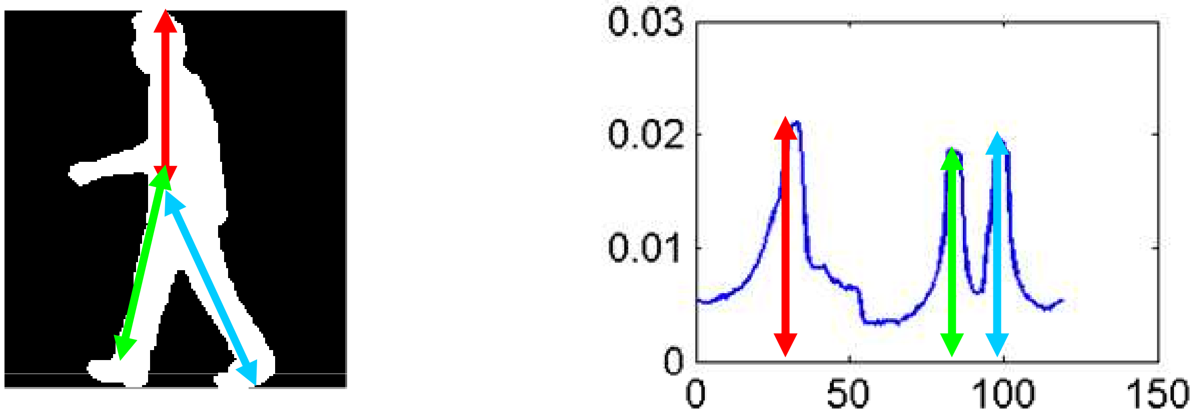

Mid-stance position



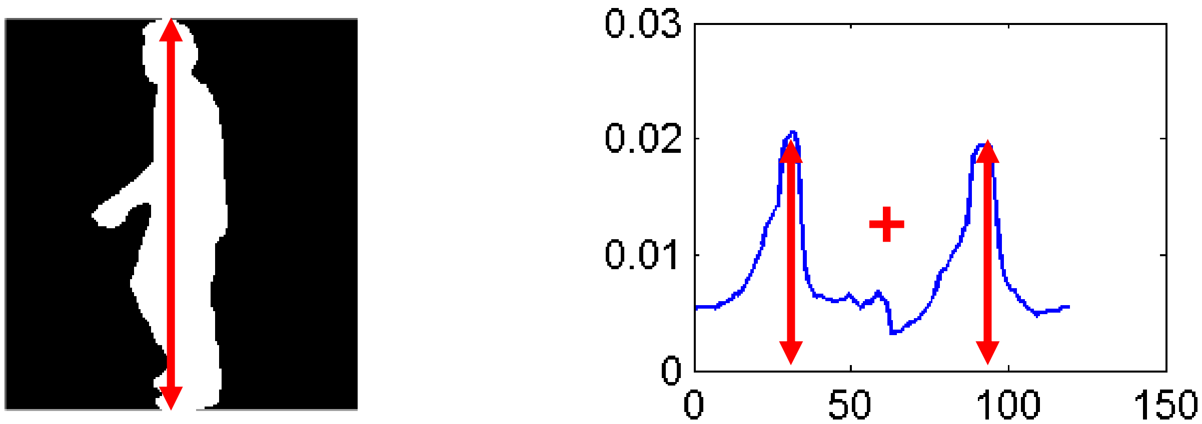

Length of stride mapping in the RIT Transform

# Mapping of gait characteristics into gait transforms

Distance between:
- ➢Pelvis and feet
- ➢Pelvis and head



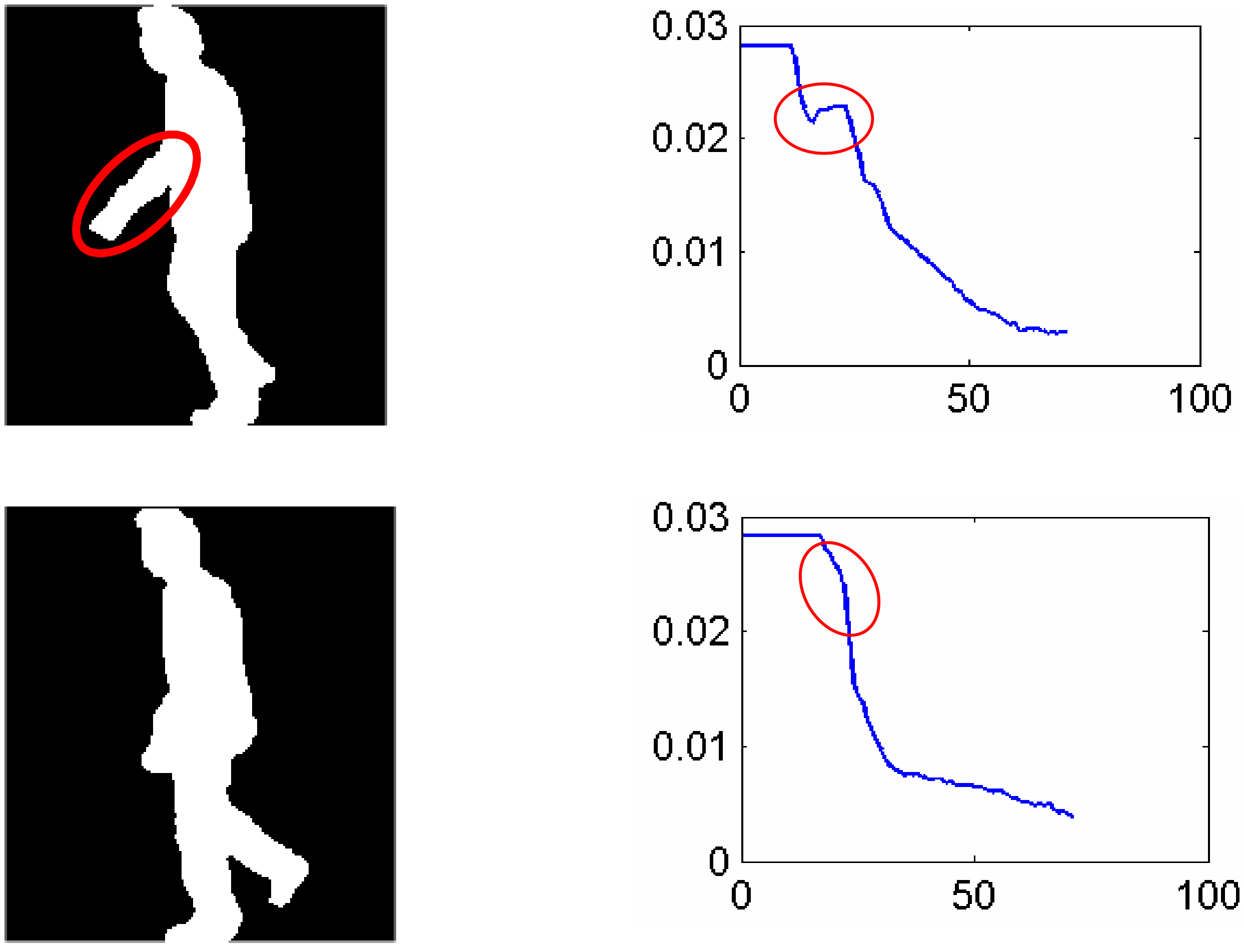

Height estimation




Gait dynamics parameters of the RIT Transform

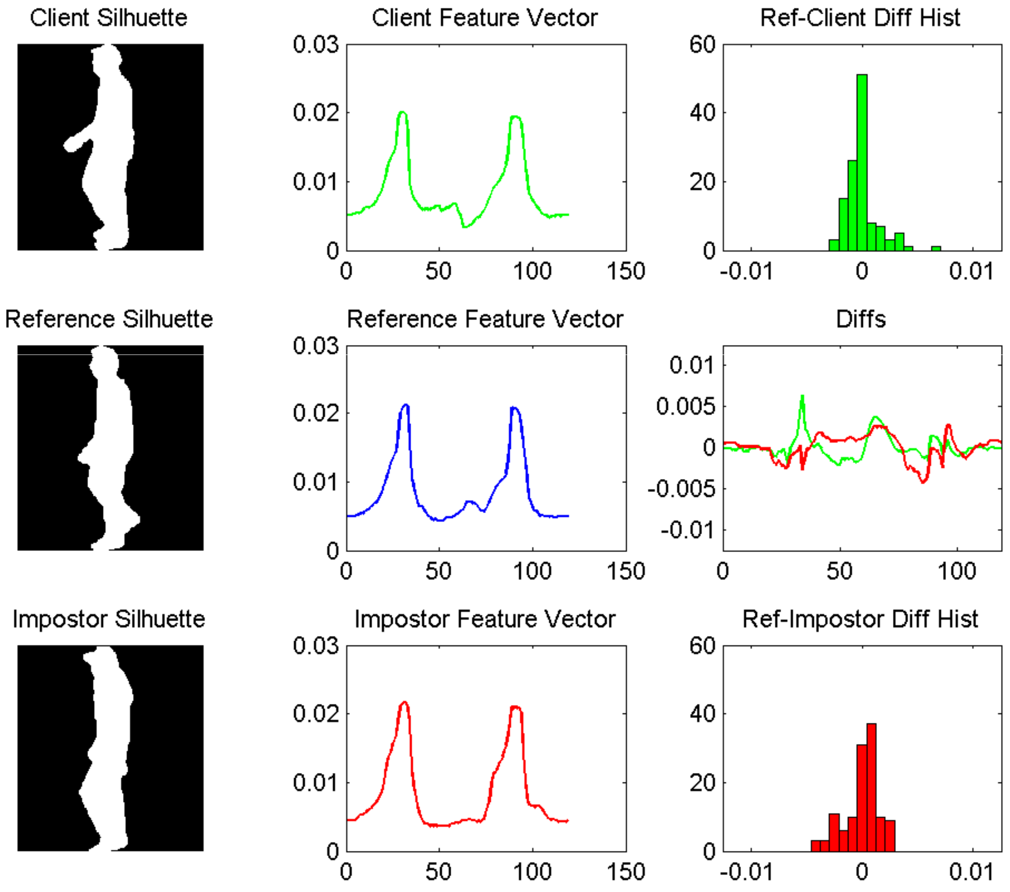
# Mapping of gait characteristics into gait transforms

Hand movement

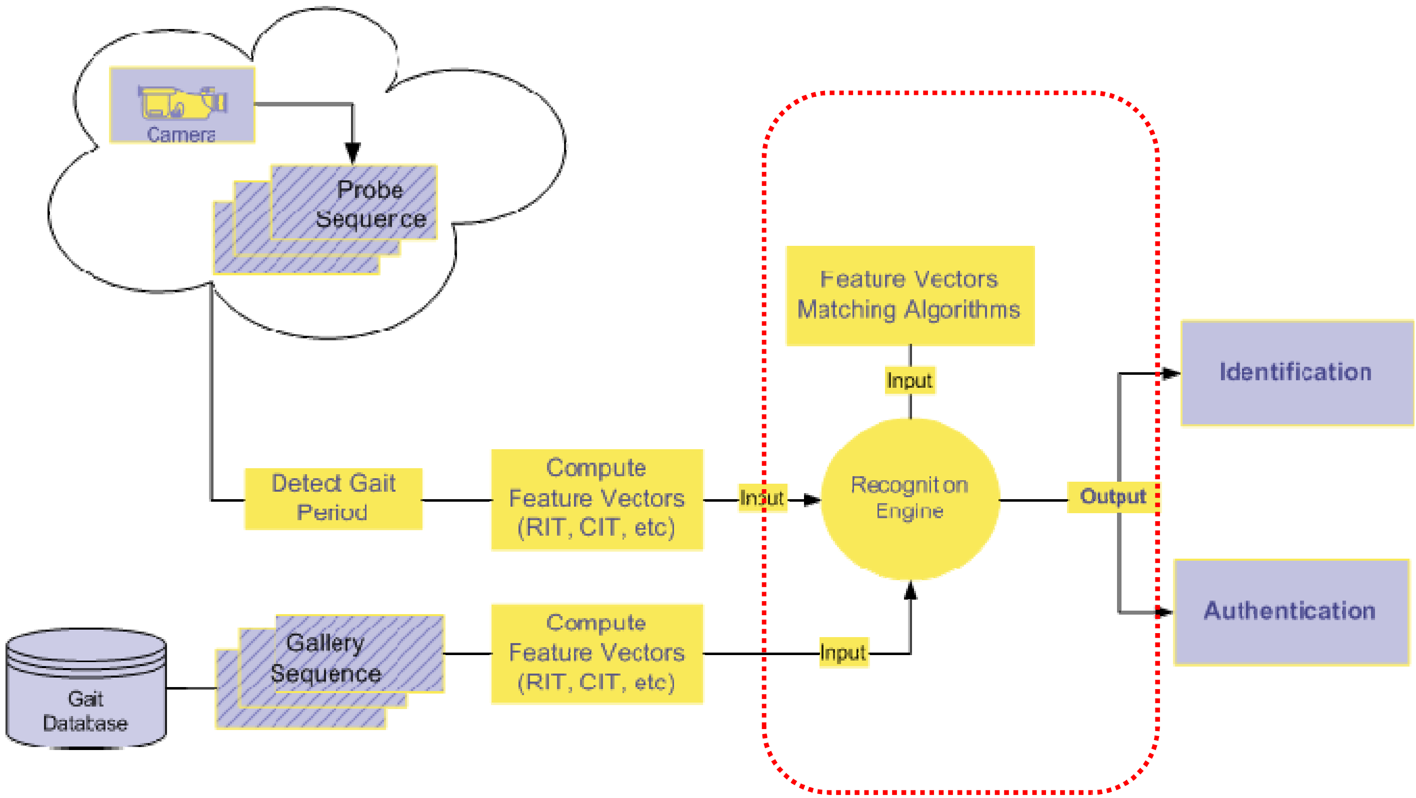



Hand movement detection using the CIT Transform

# Mapping of gait characteristics into gait transforms



# Template Matching using temporal correlation




For each gait cycle compute the distance between the stored (gallery) and the claimed (probe) gait signature

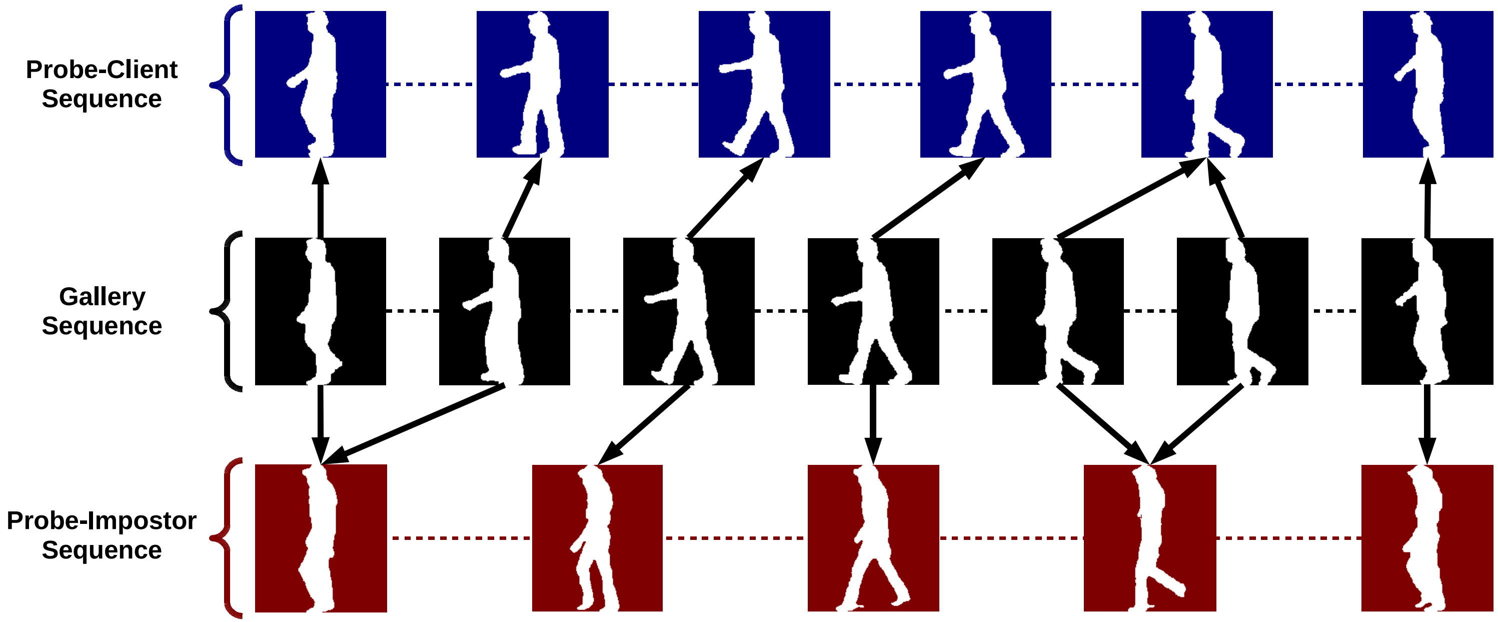
$$D = \min_{l} \sum_{i=1}^{Np} \sqrt{\sum_{n=0}^{FVecSize} (\Pr obFeatVec_i(n) - GalleryFeatVec_{i+l}(n))^2}$$

# Template Matching using time warping (LTN)

- The probe frame is determined by linearly compensating the cycle length differences.
- Each gallery frame (***X***) is compared with a probe frame (***Y***). If gallery cycle has ***G*** feature vectors, Probe cycle has ***P*** feature vectors then:

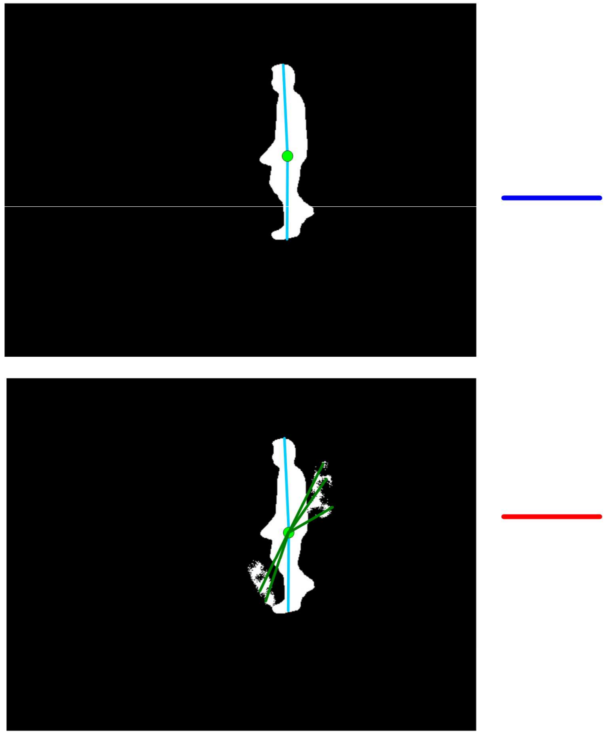
$$Y = X * P / G + w$$

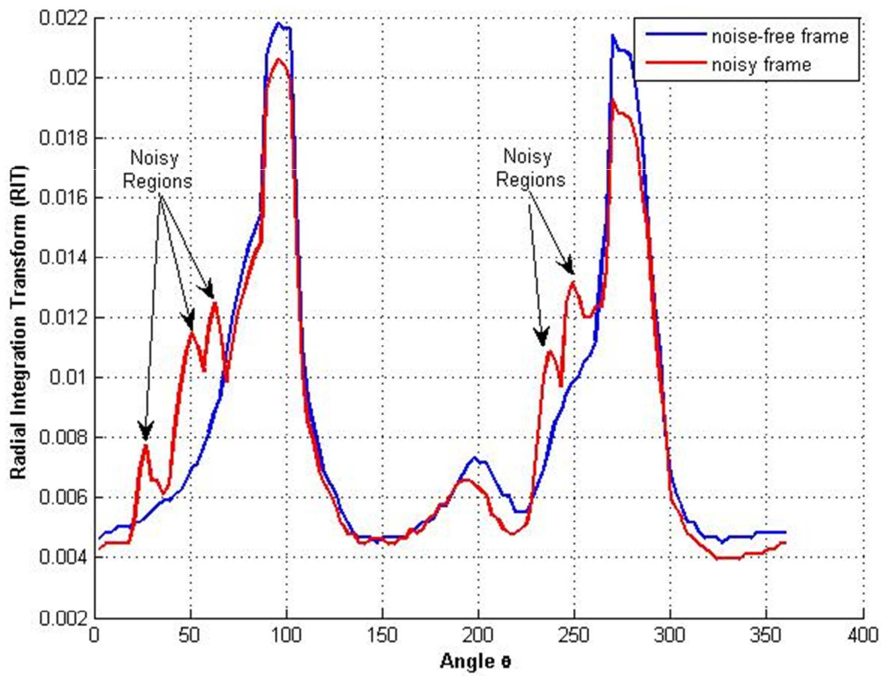
where ***w*** is a *search-for-best-matching* frame window: -***k*** <= ***w*** <= ***k***, where ***k*** is a small positive number, i.e. ***k*** = 2.



# Reliability Factor and Quality measurement of the gait signal

- Quality of the gait signal using $\mathbf{Q_{RIT}}$ metric
  - ✓ Estimates the quality of the gait signal using the coefficient values of the Radial Integration Transform to the interval [0, 360º]






Detection of noisy region(s) using the coefficients of the RIT transform

Although it has been reported that the side view silhouettes contain most discriminative information, the problem of gait direction dependency still remains.

New approach:

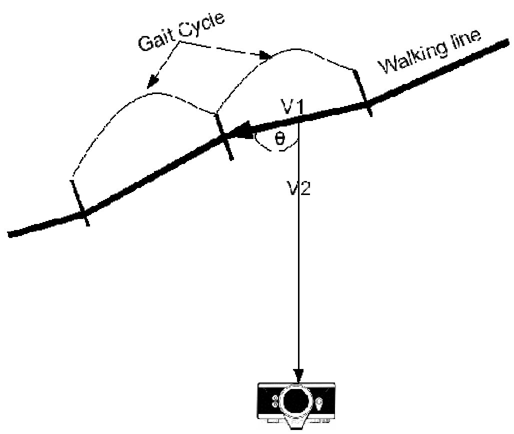
- Rotation of silhouettes in order to synthesize the side view
  - Challenge: some pixels may have to be guessed.

# Walking Angle Determination

Using the 3D data from the stereoscopic camera, the walking direction can be estimated.

- The head position is extracted, and the mean head's 3D point is estimated at the first and the last frame of each gait cycle.
- The walking angle, with respect to the camera, is calculated using the formula.

$$\partial = \cos^{-1}\left(\frac{V_1 \bullet V_2}{|V_1||V_2|}\right)$$



## Silhouette rotation

The 3D coordinates of each silhouette pixel are extracted using the disparity data from the stereoscopic camera. This way a 3D point cloud is generated, which is rotated using the following formula.

$$P_i^{rotated} = P_i \cdot \begin{bmatrix} \cos(\partial) & \sin(\partial) & 0 \\ -\sin(\partial) & \cos(\partial) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

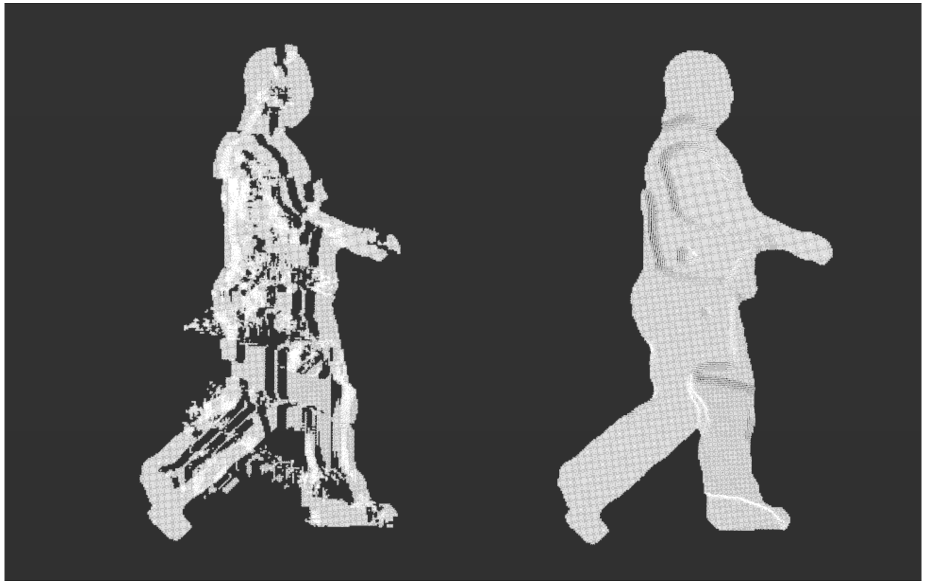
Original Silhouette    Rotated Silhouette    Silhouette with added emerging points

The new point cloud is now reprojected on the camera to create a new silhouette, which is used to extract the gait features

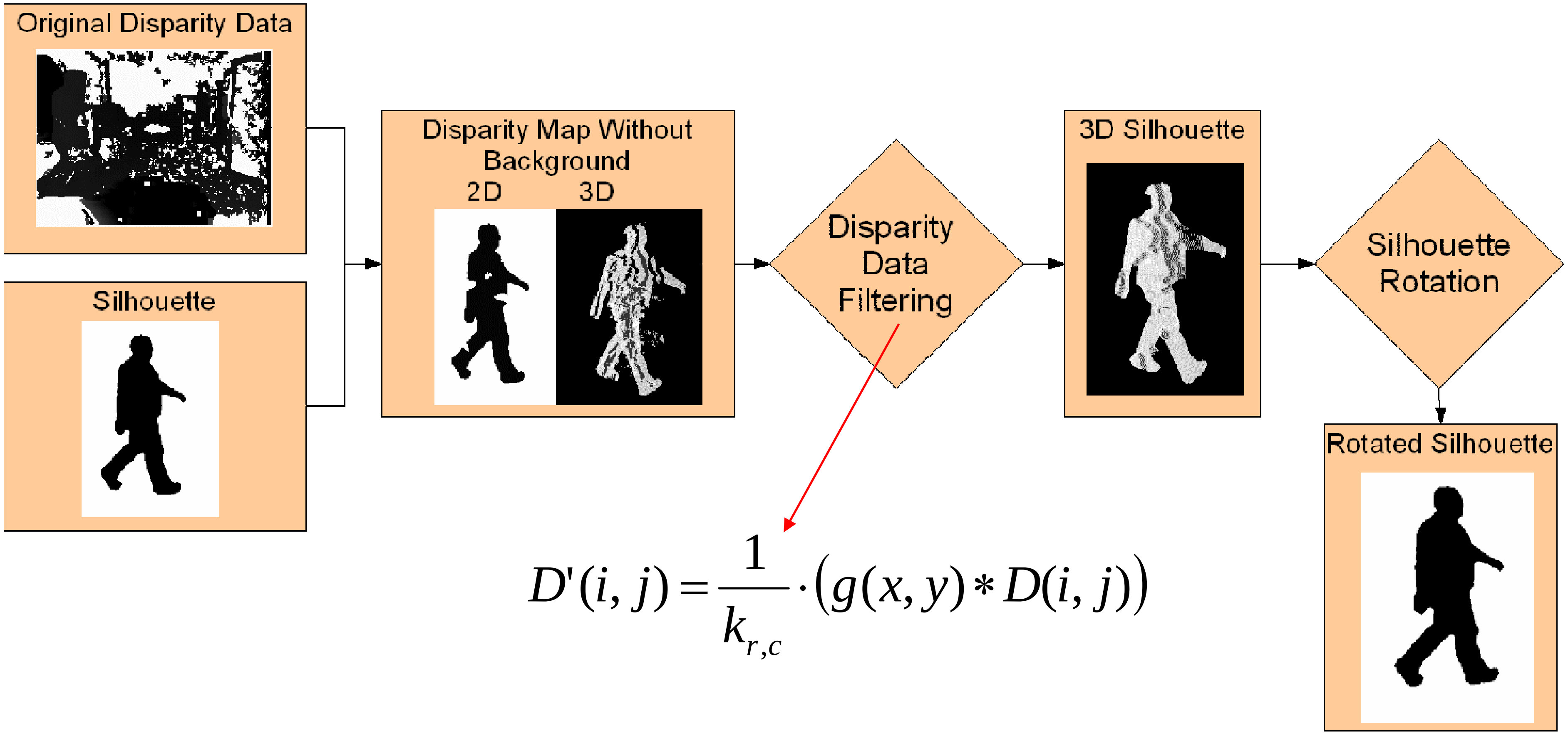
# Further improvement: Disparity Data Smoothing

The disparity data from the stereoscopic camera are, in general, quite noisy.

➲ The data are denoised using a Gaussian filter in order to achieve better results



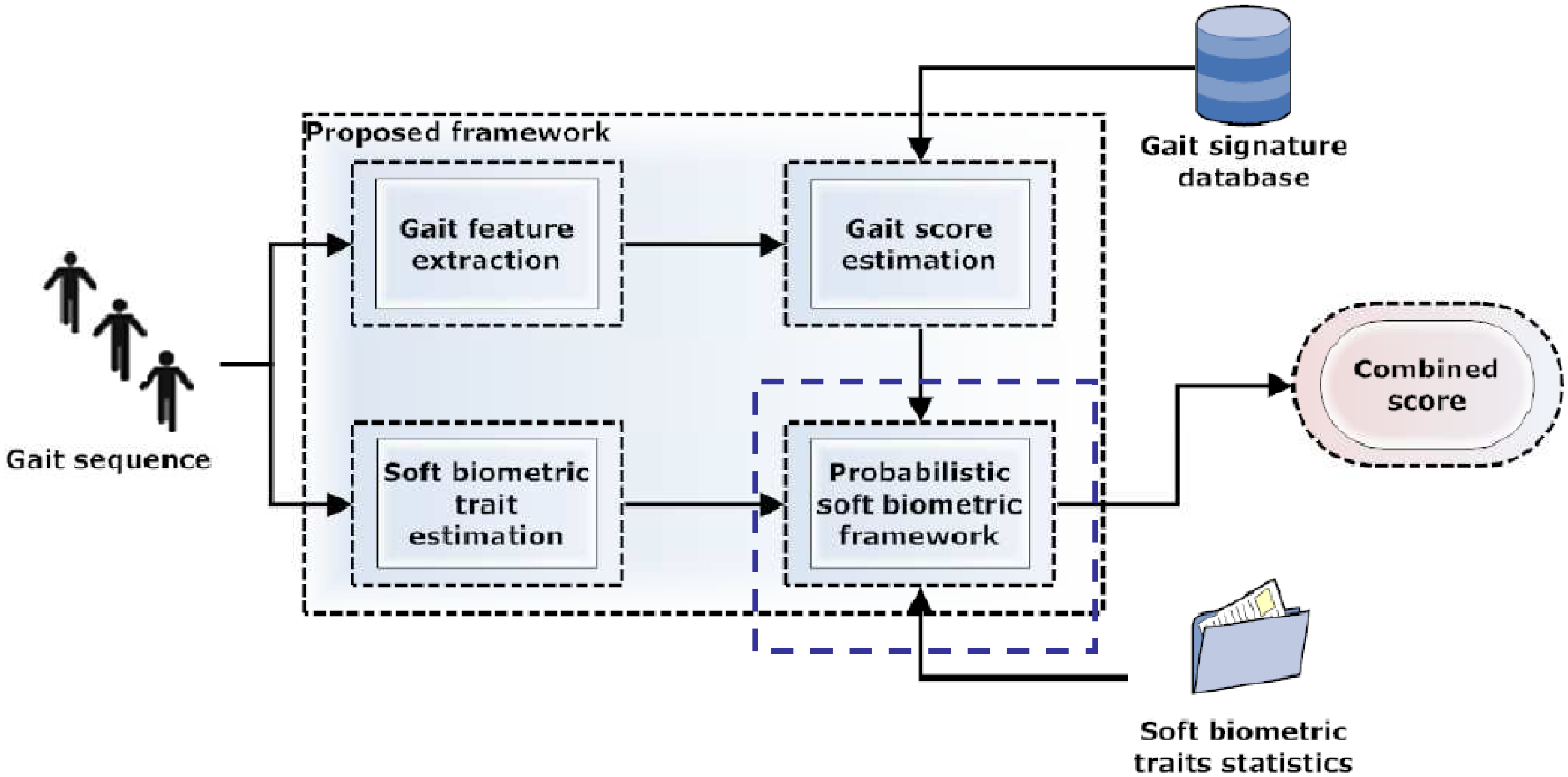
# Gait Recognition Algorithm with Disparity Data Refinement Block Diagram




$$D'(i,j) = \frac{1}{k_{r,c}} \cdot \left( g(x,y) * D(i,j) \right)$$

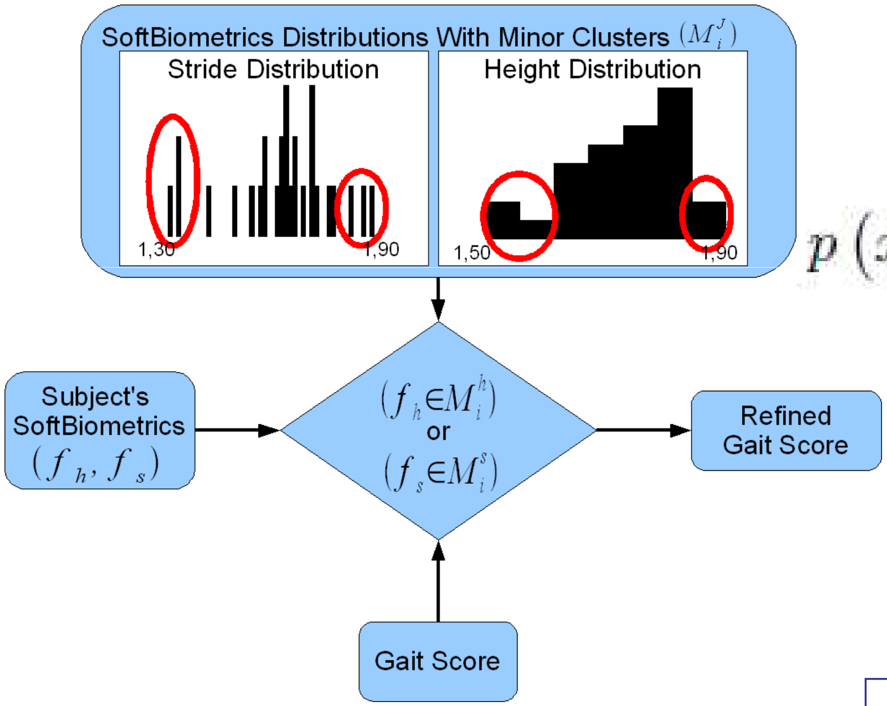
# Further improvement: Use of soft biometrics (1/2)

Height and stride length were utilized to augment the information obtained by the gait recognition system.



# Further improvement: Use of soft biometrics (2/2)

## Probabilistic Soft Biometrics framework




$$p(x|f_g)$$

$$p\left(x|f_g, f_h \in M_i^h, f_s \in M_i^h\right) = \frac{k}{1-p^h+kp^h}\,\frac{l}{1-p^s+lp^s}\,p(x|f_g)$$

Height-coefficient

Stride-coefficient

Calculated similarly to height-coefficient

$$\frac{p\left(x|f_g, f_h \in M_i^h\right)}{p\left(x|f_g, f_h \notin M_i^h\right)} = \frac{p_x^h\left(1-p^h\right)}{\left(1-p_x^h\right)p^h} = k$$

where $p_x^h = p\left(f_h \in M_i^h|, x\right)$ and $p^h = p\left(f_h \in M_i^h\right)$.

# Database HUMABIO

- Database data from **two sessions**
  - ✓ 1st session consists of 75 Persons (3 covariates – hat, briefcase, shoe)
  - ✓ 2nd session consists of 53 Persons, 48 common with the 1st session (3 covariates – hat, briefcase, coat)

- Capture Details
  - ✓ Indoor scenario similar to the airport pilot
  - ✓ Four experiments were defined (Hat-Exp.A, Briefcase-Exp.B, Shoe-Exp.C and Time-Exp.D)

Normal

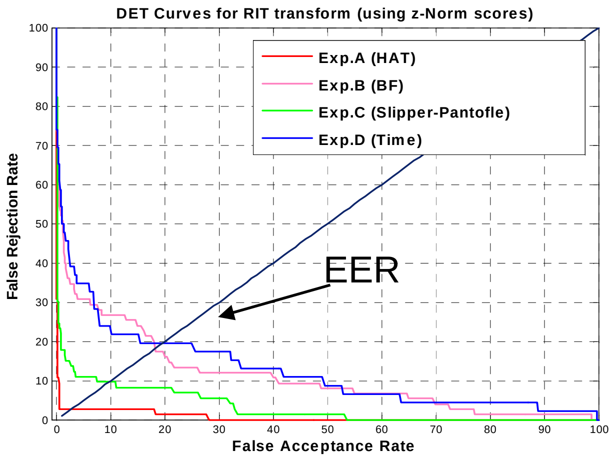
Hat

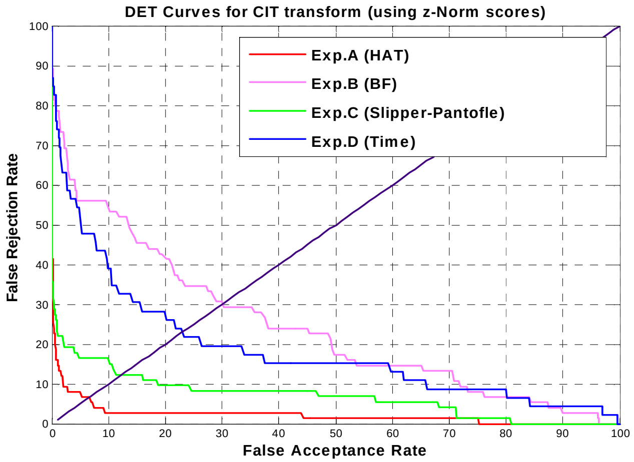
Briefcase

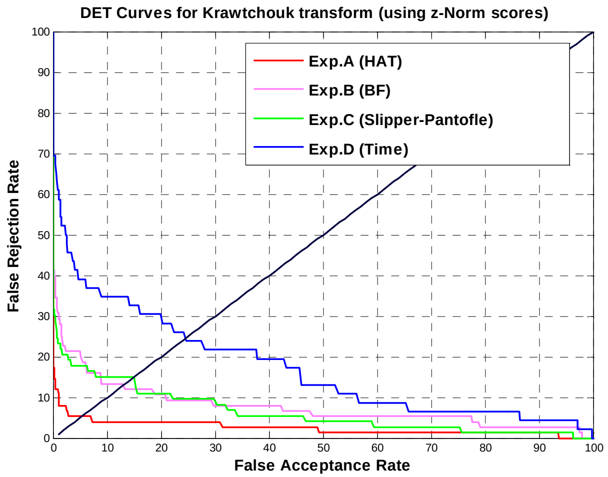
Coat

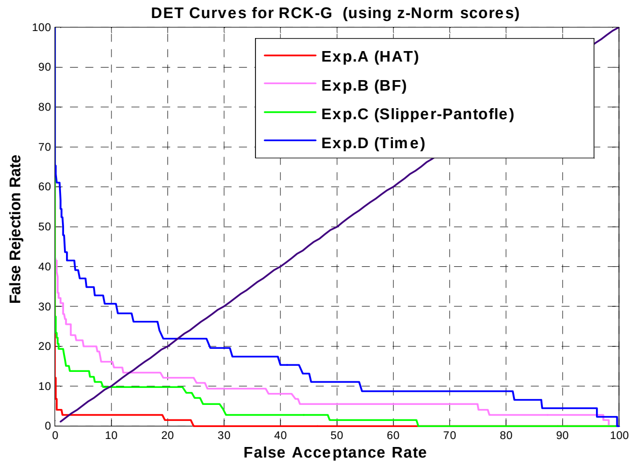
# Verification results on the HUMABIO database

- ✓ Detection Error Trade-off curves (DET) for estimating the Equal Error Rates (using z-Norm scores) for each feature extractor and the weighted algorithm on all experiments



# Recognition results comparison on the USF "Gait Challenge" database

| Probe Set | Rank 1 | | | | | | Rank 1-5 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ITI | BASE (1) | CMU (2) | LTN-A (3) | PAGR (4) | UMD-HMM (5) | ITI | BASE | CMU | LTN-A | PAG R | UMD-HMM |
| A (GAL) [71] | 97 | 79 | 87 | 89 | 86 | 99 | **100** | 96 | 100 | 99 | 100 | 100 |
| B (GBR) [41] | 88 | 66 | 81 | 71 | 68 | 89 | **93** | 81 | 90 | 81 | 83 | 90 |
| C (GBL) [41] | **83** | 56 | 66 | 56 | 59 | 78 | **93** | 76 | 83 | 78 | 81 | 90 |
| D (CAR) [70] | **39** | 29 | 21 | 21 | 27 | 36 | **73** | 61 | 59 | 50 | 52 | 65 |
| E (CBR) [44] | **32** | 24 | 19 | 26 | 29 | 29 | **73** | 55 | 50 | 57 | 57 | 65 |
| F (CAL) [70] | 27 | 30 | 27 | 15 | 14 | 24 | **60** | 46 | 53 | 35 | 35 | 60 |
| G (CBL) [44] | **27** | 10 | 23 | 10 | 14 | 18 | **61** | 33 | 43 | 33 | 38 | 50 |

Best Score

Computational intensive Training (increase enrolment time)

## References


1. Sudeep Sarkar,P.Jonathon Phillips, Zonguy Liu, Isidro Robledo, Patrick Grother, Kevin Bowyer, **The Human Gait Challenge Problem Data Sets, Performance, and Analysis**
2. R. Collins, R. Gross, and J.Shi, **"Silhouette Based Human Identification from Body Shape and Gait**," Proc. Int'l Conf.Automatic Face and Gesture Recognition
3. Nikolaos V. Boulgouris,, Konstantinos N. Plataniotis, Dimitrios Hatzinakos, **"Gait recognition using linear time normalization"**
4. Nikolaos V.Boulgouris, Konstantinos N.Plataniotis, Dimitris Hatzinakos, **An Angular Transform of Gait Sequences for Gait Assisted Recognition**
5. Amit Kale, Aravind Sundaresan, A. N. Rajagopalan, Naresh P. Cuntoor, Amit K. Roy-Chowdhury, Volker Krüger,and Rama Chellappa, **"Identification of Humans Using Gait"**

# Database ACTIBIO

- Database data from **two sessions**
  - ✓ 1st session consists of 28 Persons (5 covariates – coat, briefcase, shoe, stopped during walking, diagonally)
  - ✓ 2nd session consists of the same 28 Persons after one month, (1 covariate – stop during walking)
- Capture Details
  - ✓ Indoor scenario
  - ✓ The subject was not walking in a strictly straight line

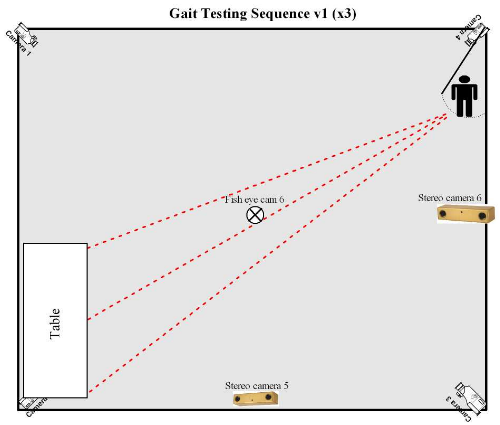
Normal

Briefcase

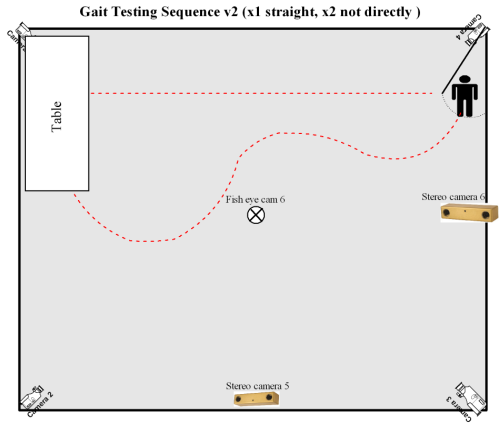
View angle

With stop

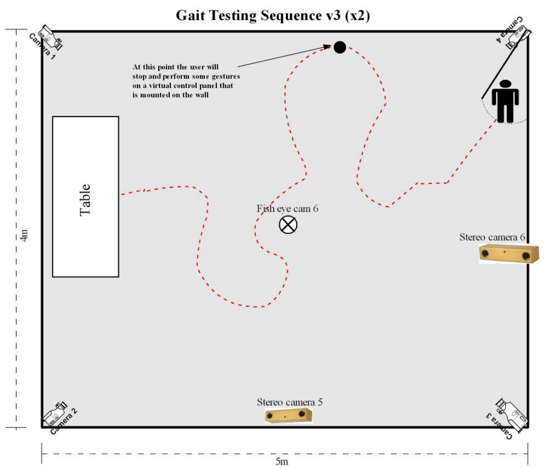
# ACTIBIO Database – Gait recorded paths




**Different Angles**

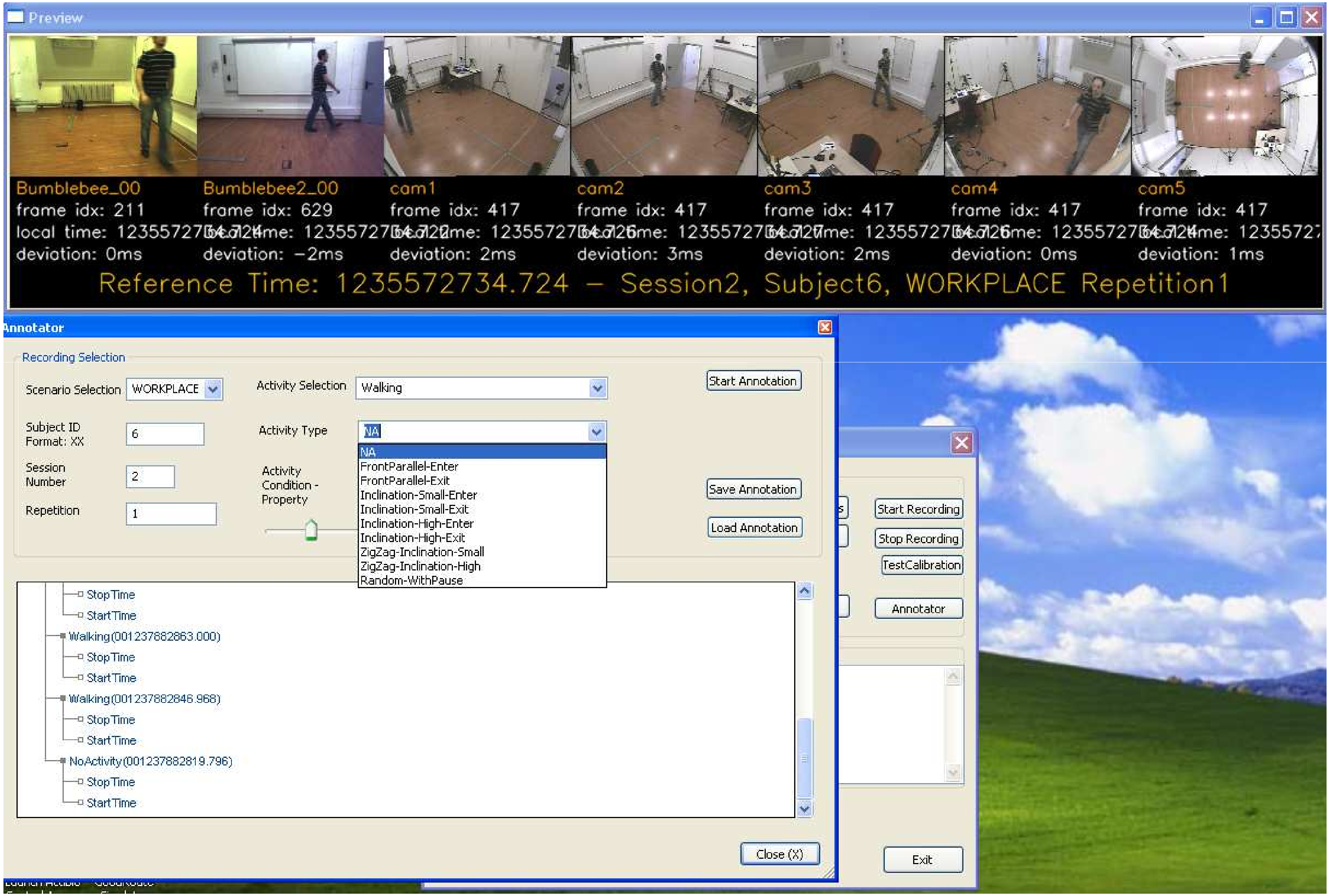



**Straight and random paths**

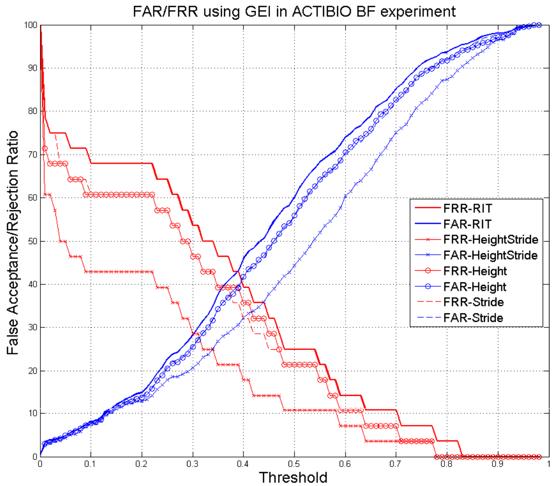



**Random paths with stops and pressing buttons to control panel**

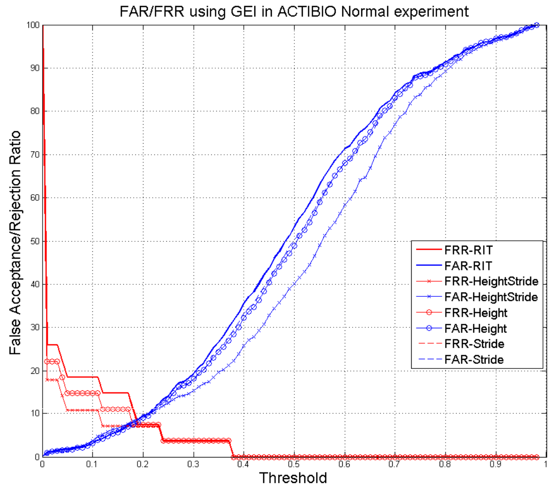
# Database Actibio – Multiple views (High Sync)



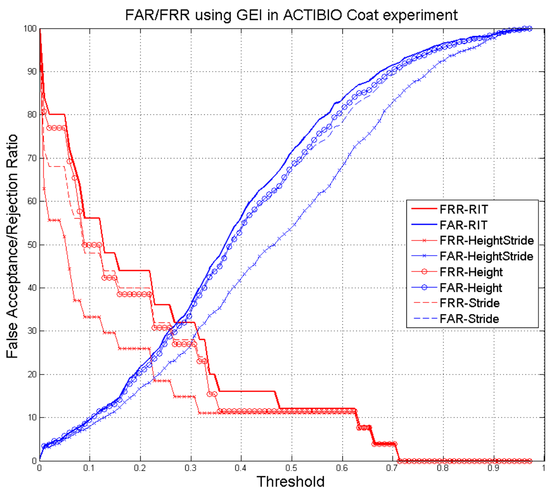
# Results on the ACTIBIO database



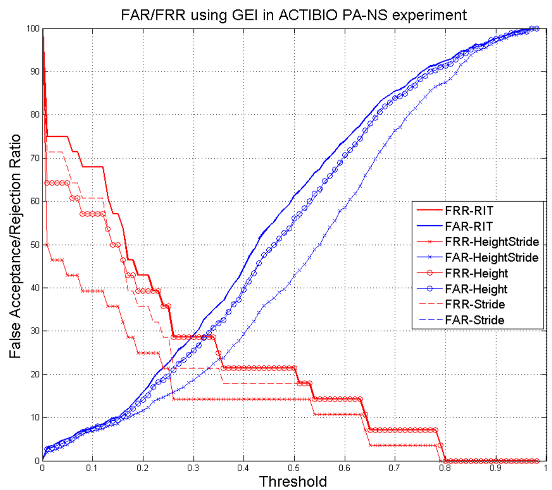

***Briefcase experiment***




***Normal walking experiment***

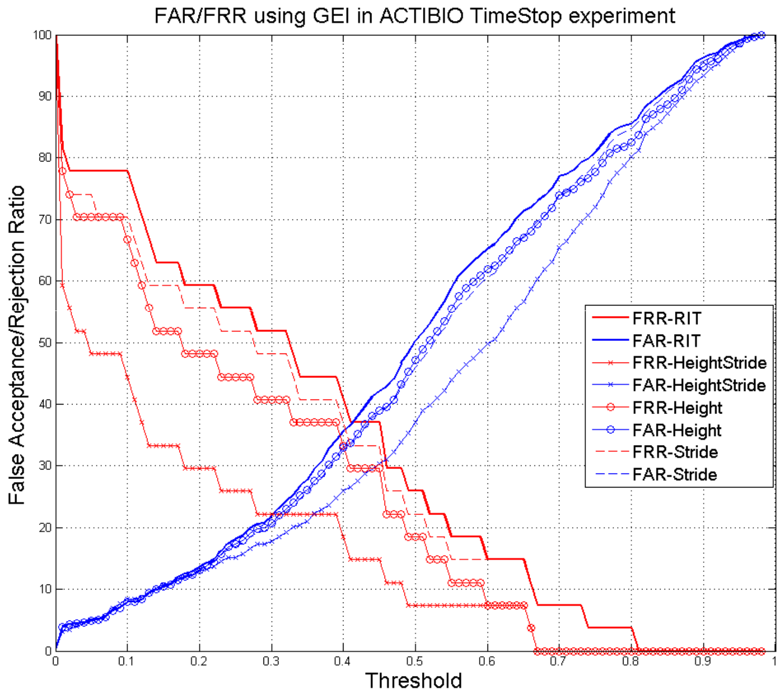



***Coat experiment***

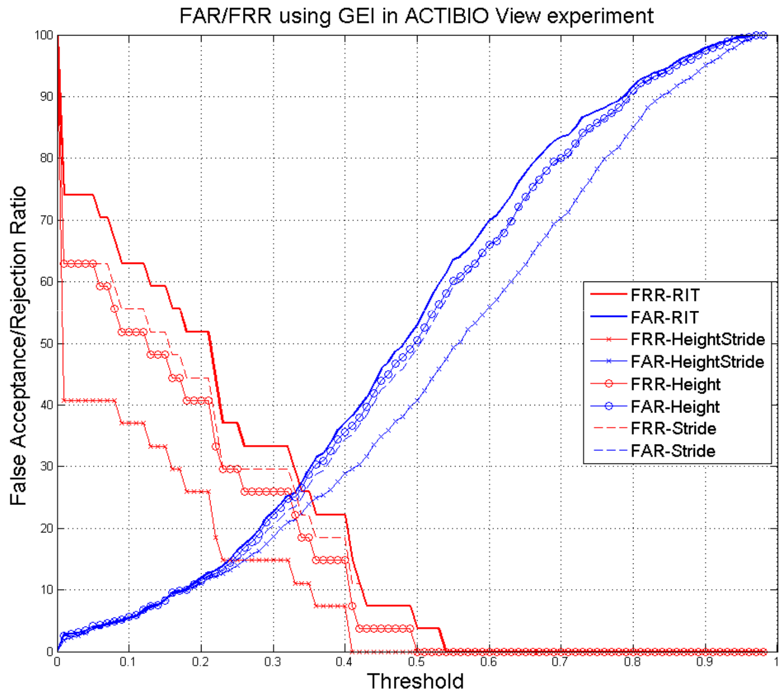



***Wearing slippers or socks experiment***

# Results on the ACTIBIO database

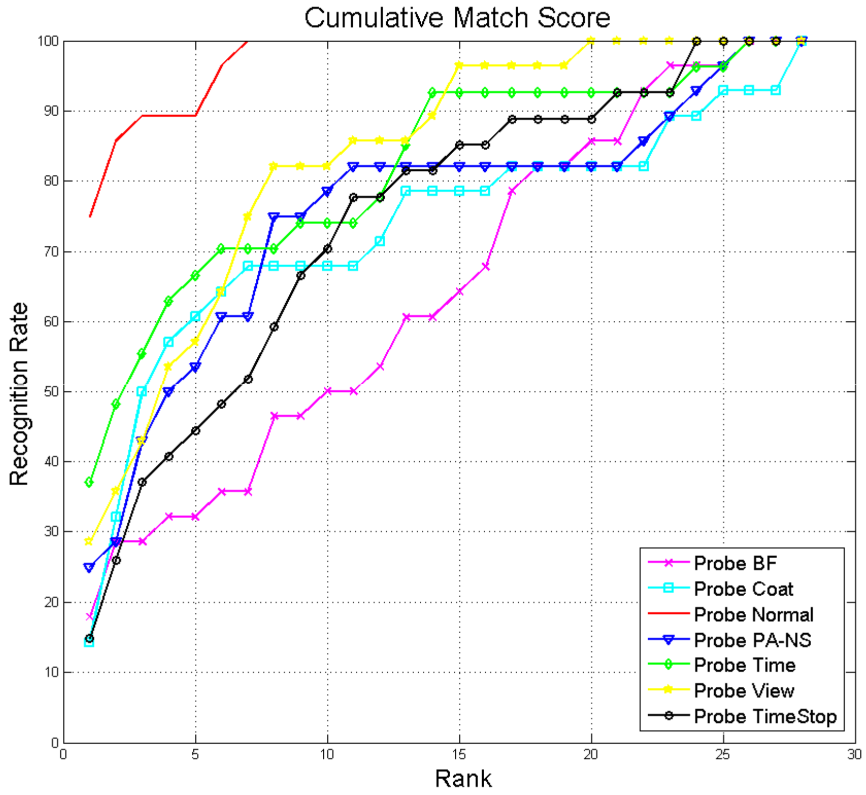



*During walking stopping  experiment*

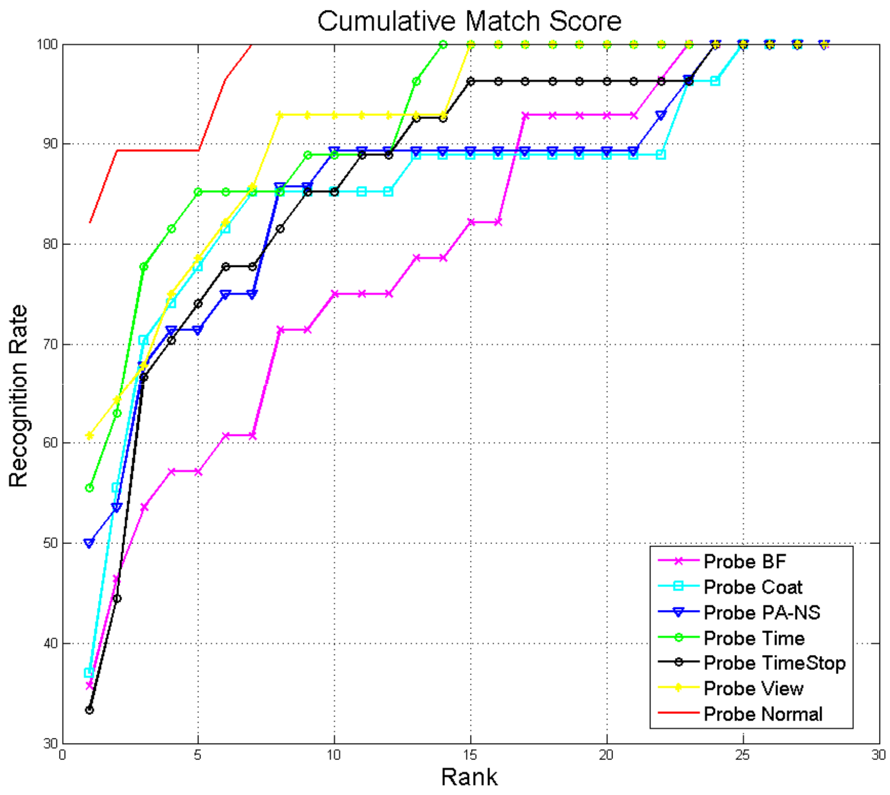



*Changing view angle experiment*

# Results on the ACTIBIO database




*Using the GEI algorithm*




*Using the GEI & SoftBiometrics*

➲ **The improvement of the results with the use of the soft biometrics is obvious.**

- The gait recognition algorithm deals with the random-path walking scenario, which is a brand new and novel approach in the whole research field of gait recognition / authentication.

- The experimental results demonstrate that the presented gait recognition system perform better than the state-of-the-art algorithms.

- The use of soft biometric enhance the performance of the gait recognition system.

- Novel methods were presented to improve the state-of-the-art gait recognition systems.

- Innovative biometrics were developed based on the users motion when responding to specific stimuli and demonstrated a very promising authentication potential.

➲ **Security systems using activity related biometrics can clearly enhance safety in critical applications.**

# Activity and Gait Recognition Group

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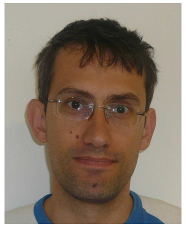

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# Publications

- **Book Chapters**
  - S. Argyropoulos, D. Ioannidis, D. Tzovaras, and M. G. Strintzis, “Distributed source coding for biometrics: A case study on gait recognition,” in Biometrics: theory, methods, and applications, N. V. Boulgouris, K. Plataniotis, E. Micheli-Tzanakou, Eds., IEEE/Wiley, 2009, ch. 22, pp. 559-578.
- **Journals**
  - D. Ioannidis, D. Tzovaras, I. G. Damousis, S. Argyropoulos, and K. Moustakas, “Gait recognition using compact feature extraction transforms and depth information,” IEEE Trans. on Information Forensics and Security, vol. 2, no. 3, pp. 623–630, Sep. 2007.
  - S. Argyropoulos, D. Tzovaras, D. Ioannidis, and M. G. Strintzis, "A Channel Coding Approach for Human Authentication From Gait Sequences," IEEE Trans. on Information Forensics and Security, vol. 4, no. 3, pp. 428-440, Sep. 2009.
- **Conferences**
  - D. Ioannidis, D. Tzovaras, K. Moustakas, "Gait Identification using the 3D Protrusion Transform," Image Processing, 2007. ICIP 2007. IEEE International Conference on , vol.1, no., pp.I -349-I -352, Sept. 16 2007-Oct. 19 2007
  - S. Argyropoulos, D. Tzovaras, D. Ioannidis, and M. G. Strintzis, "Gait authentication using distributed source coding," in IEEE Int. Conf. on Image Processing (ICIP 2008), San Diego, CA, Oct. 2008, pp. 3108-3111.
  - K. Moustakas, D. Tzovaras, G. Stavropoulos, “Gait Recognition Using Geometric Features and Soft Biometrics”, submitted for publication in IEEE Signal Processing Letters.
  - A. Drosou, K. Moustakas, D. Ioannidis, D. Tzovaras, “On the potential of activity-related recognition”, submitted for publication in International Conference on Computer Vision Theory and Applications.

# Thank you for your attention

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