Gait Recognition

Using Static, Activity-Specific Parameters

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What is Gait Recognition

- Gait recognition is a relatively new identification method that recognizes people by their walking patterns or other discrimination features during the walking action.

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Inspiration

- It has been shown that humans have the ability to recognize people using only gait.
  - Kozlowski and Cutting, **Sex of a walker** (1977)
  - Cutting and Kozlowski, **Identifying friends** (1977)
  - Stevenage, Nixon, & Vince, **Identifying unknown people** (1999)

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Methods of Gait Recognition

- Model-Free Technique: Analyze the visual shape or motion a subjects makes as they walk
- Model-Based Techniques: Either model the person or model the walk of the person
- Example Papers
  - **Shape of motion,** Little & Boyd (1996)
  - **Eigenspace representation,** Murase & Sakai (1996)
  - **Canonical space,** Huang, Harris, & Nixon (1999)
  - **Image self-similarity,** BenAbdelkader, Cutler, Nanda, & Davis (2001)
  - **Area based metric,** Foster, Nixon, & Prugel-Bennett (2001)
  - **Symmetry analysis,** Hayfron-Acquah, Nixon, & Carter (2001)
  - **XYT**, Niyogi & Adelson (1994)
  - **Time-normalized joint-angle trajectories**, Tanawongsuwan & Bobick (2001)
  - **Evidence gathering**, Cunado, Nixon, and Carter (1999)
  - **Modeling walking and running**, Yam, Nixon, & Carter (2001)

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Current Limitations

- Manner in which results are reported
  - Recognition rates from limited databases
- Many techniques are simply performing visual template matching
  - Fundamental properties of gait or human body is not used
- Source of confusion is not being classified
  - Bad vision recovery or features with low discrimination
- Lack of generality of viewing conditions
  - Mostly only analyze gait from side view

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Our Approach

- Expected confusion metric
  - Instead of recognition rates
- Measure static body parameters as a subject walks
  - Fundamental properties of gait and human body
- Evaluate parameters in a relative error free recovery environment (motion-capture)
  - To determine the true discrimination power of the features void of measurement noise
- Evaluate parameters in various viewing environments and map between views
  - Instead of only the side view

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Expected Confusion

- Goal is not to report percent correct
- Rather, characterize the uncertainty in identity after measuring a feature
- Which is less sensitive to database size

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Expected Confusion

- To characterize the uncertainty in identification
  - Estimate
    - Probability density of a feature vector “x” for a population
    - Probability density of a feature vector “x” for an individual

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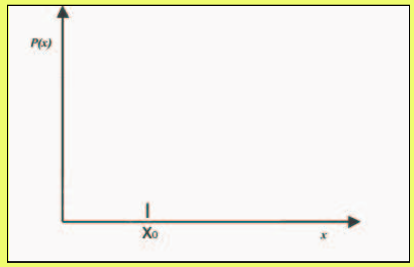
Expected Confusion

- Uniform density as an example
  - Measurement x_0



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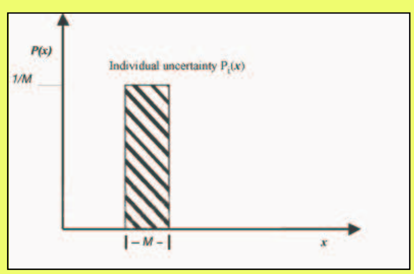
Expected Confusion

- Uniform density as an example
  - Measurement x_0
  - $P_i(x) = 1/M$



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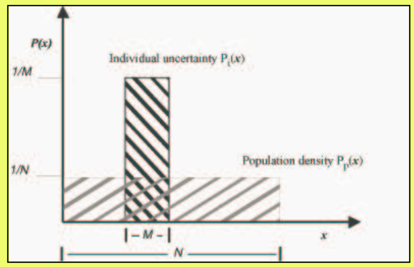
Expected Confusion

- Uniform density as an example
  - Measurement x_0
  - $P_i(x) = 1/M$
  - $P_p(x) = 1/N$
  - $N > M$



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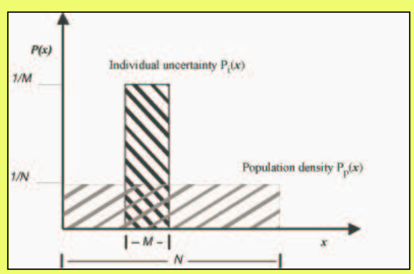
Expected Confusion

- Uniform density as an example
  - Measurement x_0
  - $P_i(x) = 1/M$
  - $P_p(x) = 1/N$
  - $N > M$
  - The uncertainty in identity is the area of overlap of these two densities



$$A(x_0) = \frac{M}{N}$$

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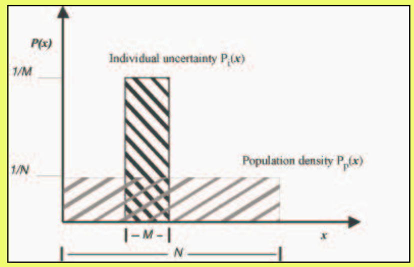
Expected Confusion

- Average uncertainty in identity, or Expected Confusion, is the expected value of the area of overlap over an entire population



$$E[A(x)] = \int_0^N A(x) P_p(x) dx$$
$$= \frac{M}{N}$$

Expected Confusion

- Our model
  - Individual variation: $N(x_0, \Sigma_i)$
  - Population variation: $N(\mu_p, \Sigma_p)$
  - Densities are estimated directly from the data
  - Population variation reasonably greater than the individual variation.

Expected Confusion

- Analytically applying this measure to the multidimensional Gaussian case

$$EC = \frac{|\Sigma_i|^{1/2}}{|\Sigma_p|^{1/2}}$$

Define: The ratio of the average individual variation of a feature vector to that of the population variation of the same feature vector.

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Expected Confusion

- Relationship to other metrics
  - Mutual Information
    - The negative natural log of the EC is the mutual information of two Gaussian densities
  - Area under a ROC curve
    - A dimensional varying scalar multiplied to the EC is equal to one minus the area under a ROC curve (Submitted to ICPR)

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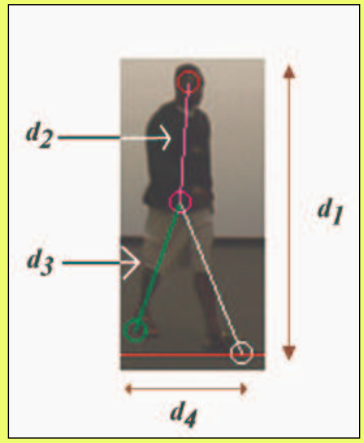
Static Body Parameters

- Active specific parameters
- Measure 4 distances
  - Head to ground (d_1)
  - Pelvis to head (d_2)
  - Foot to pelvis (d_3)
  - Left foot to right foot (d_4)
- Measured during double-support phase
- Form two feature vectors
  - $w = < d_1, d_2, d_3, d_4 >$
  - $s = < d_1, d_3 >$



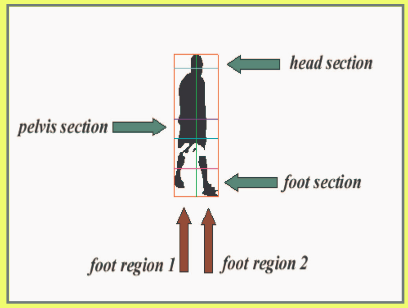
Motion-Capture Exploration

- Determine the discrimination power in the “absence” of measurement noise
- 3D-motion capture database
  - 20 subjects walking
  - 6 sequences per subject
  - 6 walk vectors per subject
- Results
  - **EC: W = .42%**
  - **EC: S = 2.5%**
- Establishes a discrimination baseline

Silhouette Body Part Labeling

- In order to find the features, we first label the
  - head
  - pelvis
  - feet

  in each image of a walking sequence, by analyzing the binary silhouette of the subject



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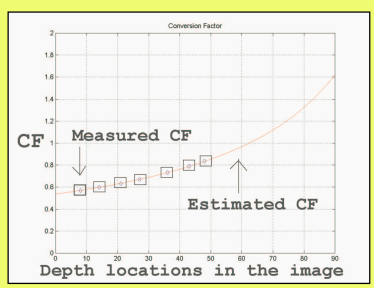
Depth Compensation

- Static body parameters are in units of pixels
- Convert to centimeters as a function of the subject's depth in the image
- Use subject of known height to estimate conversion factors for possible depth locations in the image



$$CF = \frac{\text{Actual Height (centimeters)}}{\text{Measured Height (pixels)}}$$

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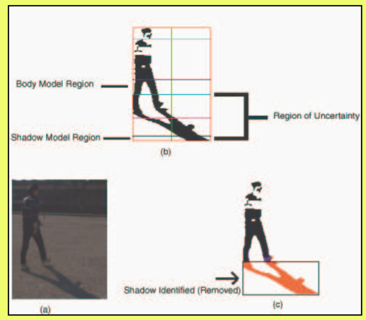
Shadow Removal

- To remove shadows in our outdoor experiments
  - Assume we know the general location of the shadow with respect to the subject
  - Sample the brightness distortion of each pixel in the known shadow and body regions, and model with a Gaussian density
  - Classify each pixel in a region of uncertainty as either belonging to the shadow or body density



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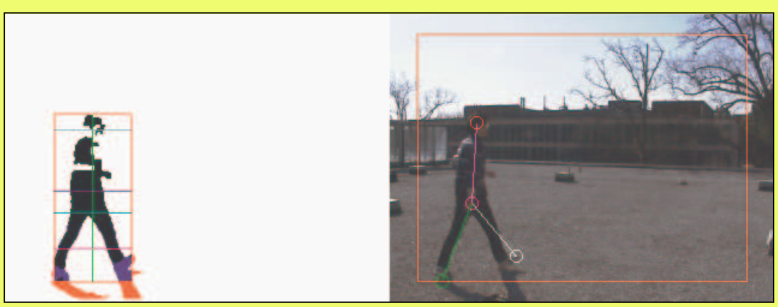
Example: Shadow Removal and Body Part Labeling



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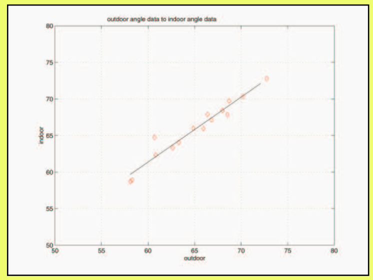
Cross-Condition Mapping

- Systematic differences between views
- Use linear regression to map parameters between views
- Use a small, yet representative, set of subjects to find the mapping
- Do not need real calibration, only relative information between views

Example: d_1 parameter



outdoor angle vs. indoor angle

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Viewing Conditions In Database

Indoor Angle: #Subjects: 18
#Trials: 6

Indoor Side Far: #Subjects: 18
#Trials: 3

Indoor Side Near: #Subjects: 18
#Trials: 3

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Viewing Conditions In Database

Outdoor Angle

Outdoor Side

#Subjects: 15
#Trials: 6

#Subjects: 15
#Trials: 3

Results:
Within View Expected Confusion

Viewing Condition	EC. W	EC. S	subjects/samples
→ Angle-view Indoors	1.53%	2.71%	18/6
→ Side-view-far Indoors	0.71%	2.57%	18/3
→ Side-view-near Indoors	0.43%	1.94%	18/3
→ Angle-view Outdoors	9.90%	14.2%	15/6
→ Side-view Outdoors	11.90%	19.8%	15/6

Motion Capture (baseline)	0.42% (w)	2.50% (s)

Results: Cross View Expected Confusion

(vs. Angle-view Indoors)

Viewing Condition	EC. W	EC. S	subjects/samples
Side-view-far Indoors	13%	9%	15/3
Side-view-near Indoors	37%	17%	15/3
Angle-view Outdoors	48%	31%	15/6
Side-view Outdoors	60%	47%	14/6

Motion Capture (baseline)	0.42% (w)	2.50% (s)

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Future Work

- Consider other parameters using our EC frame work
- Find a more robust mapping method to make the features view independent
- Analyze the effects of speed on the features
- Test features on a larger database of subjects

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Conclusion

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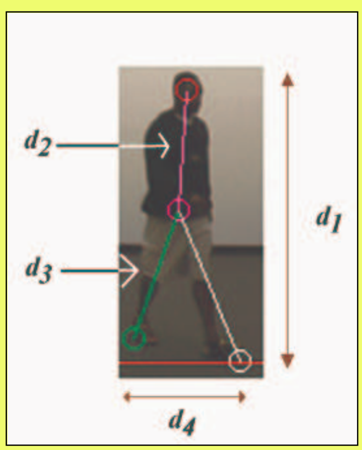
Questions & Answers



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