Hidden Markov Models for Gait-based Human ID

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The Original Image Sequence from the USF Database

- The following are sample images from the sequence 02463C0AL: of person with ID 02463, walking on Concrete, (6º sequence) wearing a shoe of type A, and obtained from the Left camera. (Image indices 050, 052, 054, ..., 100 below). The sequences obtained under different conditions (Shoe type B, Right Camera, Grassy surface) are used as probes.

- The corresponding background subtracted images are below.

- In general the HMM framework allows any feature vector to be used as an observation. In the experiments reported, we have used a vector form of the binary background subtracted images above as the observation.

The HMM Framework, Training and Testing

- Given the observation sequence, \( O = \{ O_1, O_2, ..., O_T \} \), we would like to find a parameter set, \( \theta = (A, B, \pi) \), that maximizes \( P(O | \theta) \), the conditional probability.
- \( A \) is the transition matrix. \( B \) is the probability of an observation conditional on the state index. The probability of the observation given the exemplar (state) is an exponential function of the distance between the \( i^{th} \) observation and the \( j^{th} \) exemplar.

\[
P_j(O_i) = \alpha e^{-\| \theta_j - \theta_i \|^2}
\]

\[
D(O_j, E) = \frac{O_j^T E}{\sqrt{O_j^T O_j} \sqrt{E^T E}}
\]

- Starting with a predefined (diagonally dominant) value for \( A \), a constant value for \( \pi \) and initial estimate of the exemplars, the Expectation-Maximization algorithm can be used to refine the estimates of the exemplars \( (B) \), and \( A \).

\[
E[\pi] = \arg \max \prod_{i=1}^{T} P(O_i | \theta) \rightarrow E[\pi] = \arg \max \prod_{i=1}^{T} D(O_i | E)
\]

\[
A[\theta] = \arg \max P(O | \theta) \rightarrow \text{Baum-Welch Algorithm}
\]

\[
ID = \arg \max \text{Pr}(X | \lambda_{p}), \text{ where } \lambda_{p} \text{ is the HMM for the } p^{th} \text{ person.}
\]

- A sequence \( X \) can be identified by finding the HMM parameters \( \lambda_{p} \) from the gallery that maximize the probability of the observation conditional on \( \lambda_{p} \).

Overview and Details

- Identify “cycles” from the sum of the observations plotted against frame index by using band-pass filters which admit frequencies corresponding to that of gait.
- We divide each cycle into 6 adjacent regions and group together observations from each region of all cycles and take an “average” to obtain Exemplars.

Results, and Future work

- The Cumulative Match Characteristics plot on the left indicates the number of probes for which the correct match figured within the top \( n \) (\( n \in \{1, 2, 3, ..., 20\} \)) ranks.
- The bar graph on the right compares the performance of our algorithm with that of the baseline algorithm provided by the University of South Florida.
- Future work: We would like to incorporate high level observation vectors obtained using 3-D models for humans, to represent dynamics of gait leading to a robust and efficient representation in the current HMM framework.