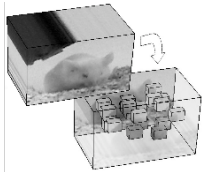


Standard Features



(image from Dollar et al. 2004)

- Local space-time patch features are clustered, treated as bag-of-words
- Ignores any information outside the local neighborhood defined by the patch

Standard Datasets

Low resolution videos of simple behaviors
Example: KTH dataset

160 x 120 pixels

6 behaviors characterized by broad cyclic motion:
Boxing, Clapping, Waving, Walking, Running, and Jogging



Our Dataset

1280 x 720 pixels

10 activities of daily living:

Dial Phone, Answer Phone, Drink Water, Eat Snack Chips, Lookup in Phonebook, Write on Whiteboard, Peel Banana, Chop Banana, Eat Banana, Use Silverware

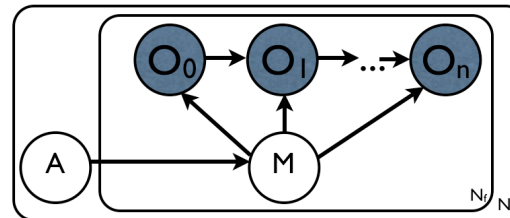


Feature Velocity Dynamics

- KLT Tracker gives us velocity histories of tracked keypoints



- Each feature's velocity history is an observation sequence



$$P(A, O) = \sum_M P(A, M, O) =$$

$$P(A) \prod_f \sum_i P(M_f^i | A) P(O_{0,f} | M_f^i)$$

$$\prod_{t=1}^{T_f} P(O_{t,f} | O_{t-1,f}, M_f^i)$$



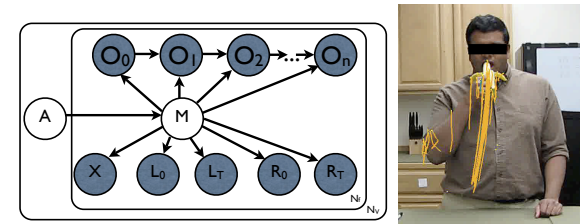
Model	Performance on KTH	Performance on new dataset
Temporal Templates (Bobick and Davis 2001)	X	33%
Cuboids (Dollar et al. 2004)	66%	36%
Space-Time Interest Points (Laptev et al. 2008)	80%	59%
Feature Velocity Dynamics (Us)	74%	63%

Augmentations

- Feature Velocity Dynamics directly represent the motion of a single point.
- How can we add information to this feature that will increase its descriptive power?
- What information would we want to add?



- All augmentations are codebooked
- Each mixture component has a distribution over each augmentation



$$P(A, L_0, L_T, R_0, R_T, X, O) =$$

$$\sum_M P(A, M, L_0, L_T, R_0, R_T, X, O) =$$

$$P(A) \prod_f \sum_i P(M_f^i | A) P(L_{0,f} | M_f^i) P(L_{T,f} | M_f^i)$$

$$P(R_{0,f} | M_f^i) P(R_{T,f} | M_f^i) P(X_f | M_f^i)$$

$$P(O_{0,f} | M_f^i) \prod_{t=1}^T P(O_{t,f} | O_{t-1,f}, M_f^i)$$

STIP features (Laptev et al. 2008) 55% Our method with augmentations 89%

