Measuring and Reducing Observational Latency when Recognizing Actions

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What This Talk is About

Novel Action Recognition Algorithm

- Parameterized to exploit accuracy/latency trade-off
- Temporally segmented and online
- Novel Dataset leveraging skeleton data from Microsoft Kinect
Outline

1. Introduction
   - Fundamentals
   - Dataset and Features

2. Temporally Segmented Action Recognition
   - Our Method
   - Baseline Models for Comparison
   - Results

3. Online Detection of Actions
   - Online Action Detection
   - Parameterizing Accuracy vs. Latency
Fundamental Criteria

High Accuracy
The system must be accurate at recognizing actions

Low Latency
A system that lags behind user actions will feel cumbersome

Goal: Understand and exploit the trade-offs between latency and accuracy
Why are Accuracy and Latency Important?

Fighters Uncaged Metacritic Reviews (Avg. score: 32/100)
- ...responds very badly to your moves...
- ...sub-par controls...
- ...entirely ruined by how it actually plays and controls...
- ...frustrates far more than it excites...
- ...fails to register most of the movements, and huge lag problems...
- ...it’s inexcusable that a game whose sole interaction is hand-to-hand combat should not be able to tell the difference between dodging and headbutting.
- ...unresponsive and downright inaccurate controls...
- Poor motion controls...
- ...poor movement recognition...
- You have more luck controlling a lifeless rock.
Computational Latency
Time till the system finishes computation on the observations

Observational Latency
Time till system observes enough frames to make an accurate prediction of the action being performed
Contributions

- A novel system for multiway on-line classification that addresses both latency and accuracy
  - Recognizes on minimal frames (canonical pose)
  - Parameterized to exploit accuracy/latency trade-off
- A new dataset containing skeleton pose estimation of sixteen actions
Novel Dataset

- Microsoft Kinect sensor using OpenNI
- 16 individuals performing 16 actions
- 5 repetitions of each action per person
- 15 joints per frame (position and orientation)
- Actions drawn from game Mirror’s Edge

Gameplay from Mirror’s Edge
Features

- 555 pairwise Euclidean distances between joints (position/rotation invariant)
  - Within current frame
  - Between current and previous frame (captures motion)
  - Between current frame and first frame (captures overall change, easy to estimate)
- Features clustered by 5 clusters per pairwise distance
  - Improves training time substantially
Finding Canonical Poses

Novel Action Recognition Algorithm

- Want to classify with as few observations as possible
- Action is recognized when actor assumes unambiguous pose
- Train on maximum likelihood class over all frames of video
Deriving Action Class Probability

\[
P[I = T | \bar{x}] = \frac{\exp \left( \max_{f \in F} \bar{x}_f \cdot \theta_T \right)}{\sum_c \exp \left( \max_{f \in F} \bar{x}_f \cdot \theta_c \right)}
\]

\[
\max(v_1, v_2, \ldots, v_N) \approx \log(e^{v_1} + e^{v_2} + \ldots e^{v_N})
\]

\[
P[I = T | \bar{x}] = \frac{\sum_{f \in F} \exp \left( \bar{x}_f \cdot \theta_T \right)}{\sum_c \sum_{f \in F} \exp \left( \bar{x}_f \cdot \theta_c \right)}
\]
1. Process frames into feature vectors
2. Learn weight parameters $\theta_1, \ldots, \theta_f$
3. For each action class $c \in \{1, \ldots, N_A\}$, find feature vector $\tilde{x}_{f \cdot c}^*$ such that $\tilde{x}_{f \cdot c}^* \cdot \theta_c$ has the highest value
4. Label the video with class $c^*$, where $c^* = \arg \max_c \tilde{x}_{f \cdot c}^* \cdot \theta_c$
Baseline - Bag of Words

- BoW works well on a wide variety of classification tasks
- Computed using (undiscretized) pairwise distance features
- Frames each assigned to one of 1000 clusters
- Videos represented by normalized histogram of cluster frequencies
- Classification performed by SVM based on histogram intersection kernel
Baseline - Conditional Random Field

- CRFs well-suited for streams of observations
- Chain structured CRF model with pairwise Potts model potentials

\[
P[l = T|x] = \frac{\exp \left\{ - \log \sum_y \exp(C_T(y; x)) \right\}}{\exp \left\{ - \log \sum_k \sum_y \exp(C_k(y; x)) \right\}}
\]
Accuracy vs. BoW and CRF over varying video length

Accuracy vs. BoW with cropped training samples

- LR
- BoW
- CRF

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Reducing Latency in Action Recognition
Average Std. Deviation of Features by Frames

**frame 5**

Balance

Punch

**frame 30**

Balance

Punch

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Reducing Latency in Action Recognition
Online Detection of Actions

- Closer to real-world classification tasks
  - Real world actions must be picked out of stream
  - Must classify as quickly as possible to ensure low latency
- Apply Canonical pose detector per frame and return a classification when any probability exceeds an empirically chosen threshold $T$
- If no frame in an action video has a action probability greater than $T$, the video is considered a missed detection

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Reducing Latency in Action Recognition
Online classifier confusion matrix

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<th>climbladder</th>
<th>climbup</th>
<th>duck</th>
<th>hop</th>
<th>kick</th>
<th>leap</th>
<th>punch</th>
<th>run</th>
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Reducing Latency in Action Recognition
Temporally Segmented vs. Online classification

**Instant**
- Vault
- Punch
- Kick

**Continuous**
- Run
- Ladder
- Balance

*Temporally segmented vs. Online classification frame*

**Actions**
- vault
- twistright
- twistleft
- stepright
- stepleft
- stepfront
- stepback
- run
- punch
- leap
- kick
- hop
- duck
- climbup
- climbladder
- balance

*Frame of classification*

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Reducing Latency in Action Recognition
Modifying the Learning Criterion

- Weights trained in situation where all frames of action are visible
- Does not match real world
- Modify the loss to penalize for detecting later in the action
- Parameterize new loss function to offer latency/accuracy trade-off
Modifying the Loss to Improve Online Detection

- Bias learner to classify earlier by adding weighted sum of loss terms on truncated observation sequence
- $M = 10, 15, 20$
- $\gamma \cdot m$ is linear scaling factor
- Higher weight on longer video sequences to avoid overfitting on noisy short videos

$$L_{Online}(\theta) = L_{Full}(\theta) + \sum_{m \in M} (\gamma \cdot m)L_{M}(\theta) + \alpha R(\theta)$$
Online Latency vs. Accuracy over a range of $\gamma$
Conclusion

- We out-perform baselines for temporally segmented action recognition
- Online classification achieves good accuracy for large number of actions
- Contributed a parameterized technique for biasing learning in favor of low latency or high accuracy
Future Work

- Collect new dataset using Kinect SDK
- Capture and detect actions with transitions
- Gesture spotting from unsegmented stream of frames
Dataset available at
www.cs.ucf.edu/~smasood/datasets/UCFKinect.zip

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