Recognizing human behavior in video

Sergio Escalera

Index

1) Action/Gesture recognition
2) Features & methods (handcrafted)
3) Dynamic Time Warping
4) Deep learning modeling of videos

1) Action/Gesture recognition

- Actions/Gestures give us information about people behavior
- Many actions can be determined from a particular pose (**still images**)
- Some actions/gestures are visible analyzing temporal changes in pose (**image sequence**)

Why is action recognition hard?

- Lots of diversity in the data (view-points, appearance, motion, lighting…)

Drinking Smoking

- Lots of classes and concepts

1) Action/Gesture recognition

Dataset: PASCAL VOC Action Classification

- Person location given
- Classify into one of 9 categories

Applications: Video Search

- useful for TV production, entertainment, education, social studies, security,…

TV & Web: e.g. *"Fight in a parlament"*

Home videos: e.g. *"My daughter climbing"*

Sociology research: e.g.

Manually analyzed smoking actions in 900 movies

Surveillance: e.g. *"Woman throws cat into wheelie bin"* 260K views in 7 days

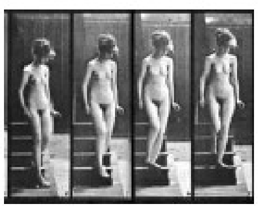
- … and it's mainly about people and human actions

1) Action/Gesture recognition

Human actions: Historic overview

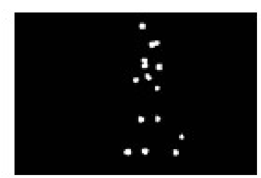
15th century studies of anatomy

17th century emergence of *biomechanics*



19th century emergence of *cinematography*

1973 studies of human motion perception

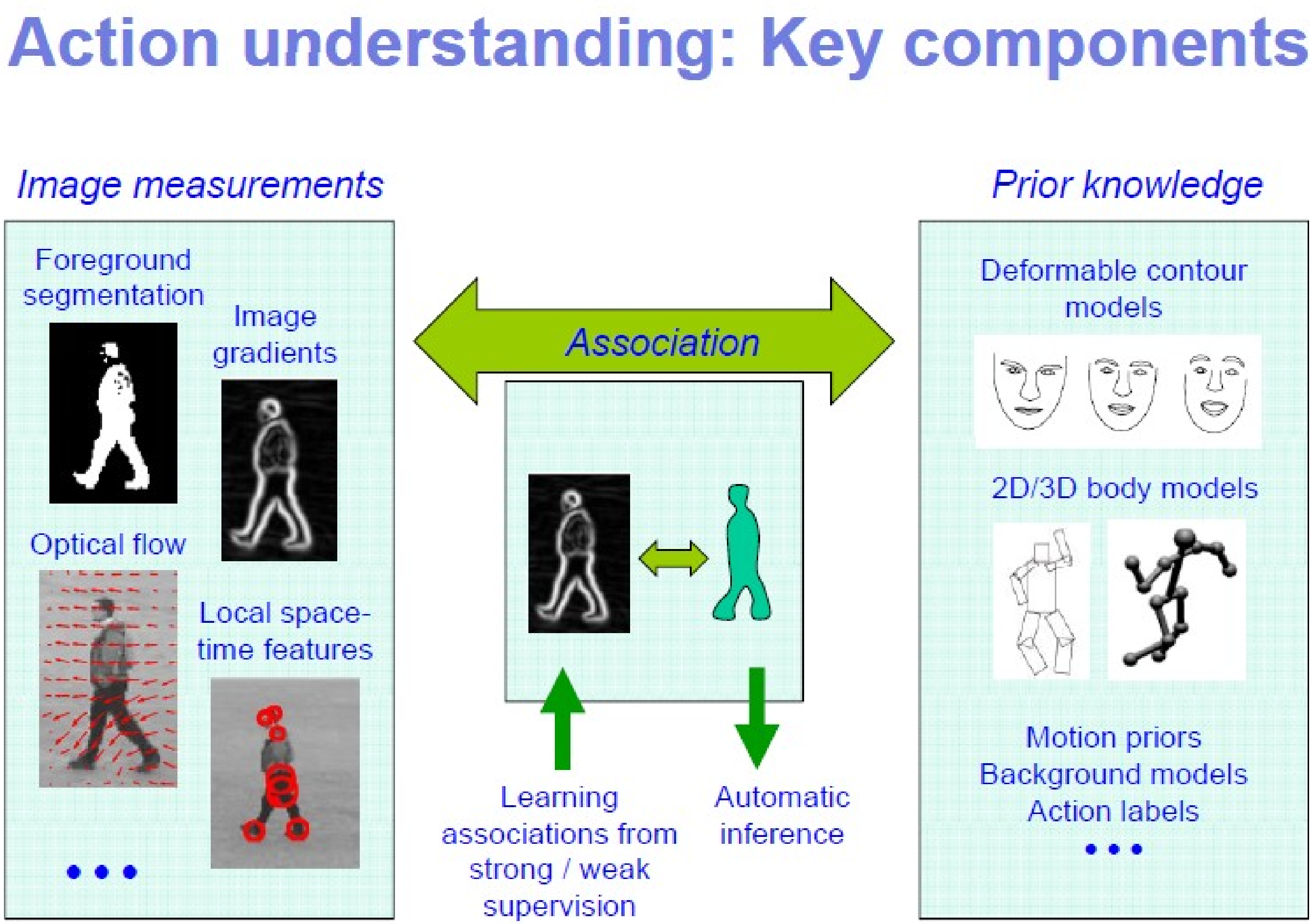


Cognitive basis
Cinematics
2D-3D
Etc.

Modern computer vision

Deep Learning

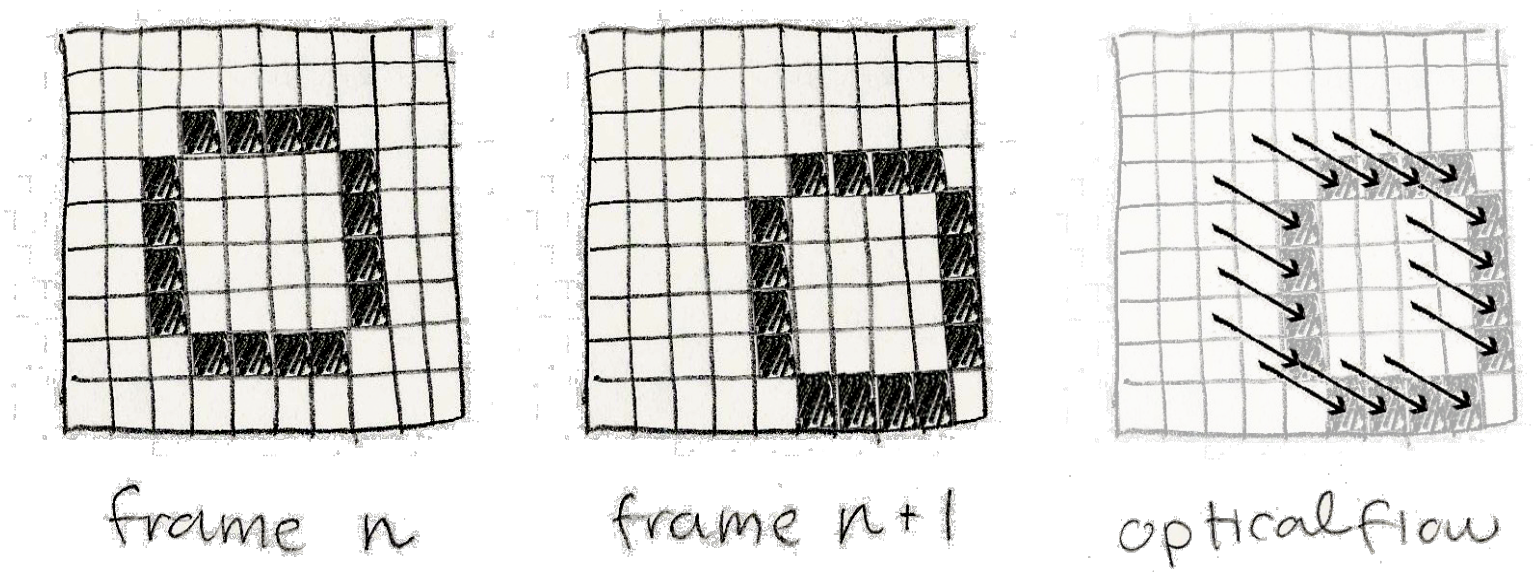
1) Action/Gesture recognition
(can be represented within the Pattern Recognition pipeline)



2) Features & methods

- Based on optical flow

Optical flow (OF) vectors indicate the translation of pixels between a pair of subsequent frames (n, $n + 1$).



2) Features & methods

- Based on optical flow

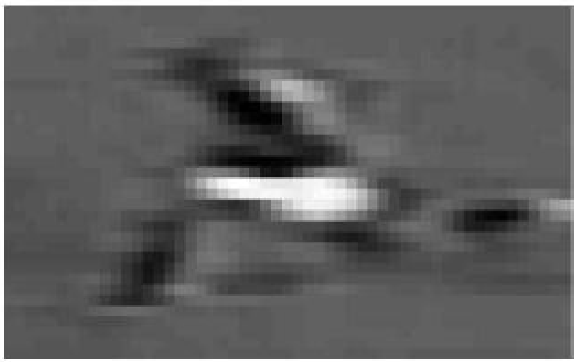
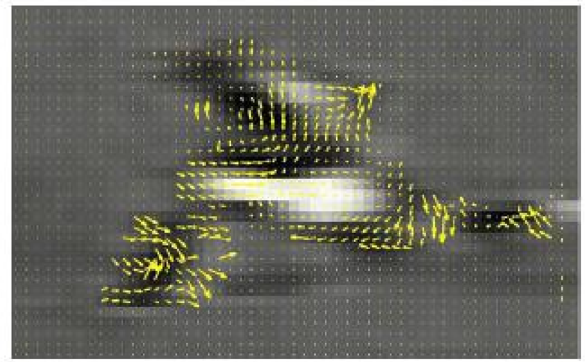
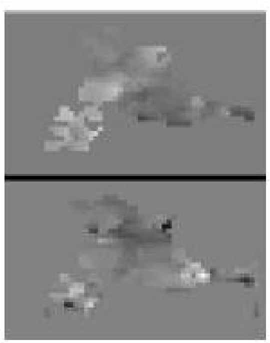


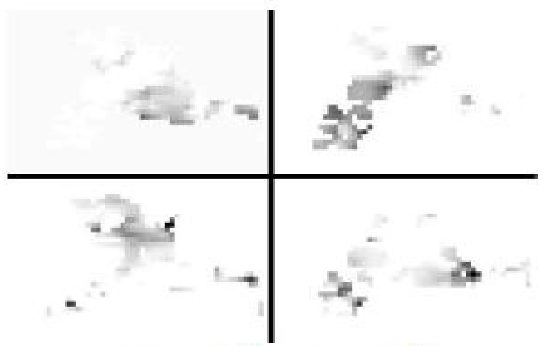
Image frame



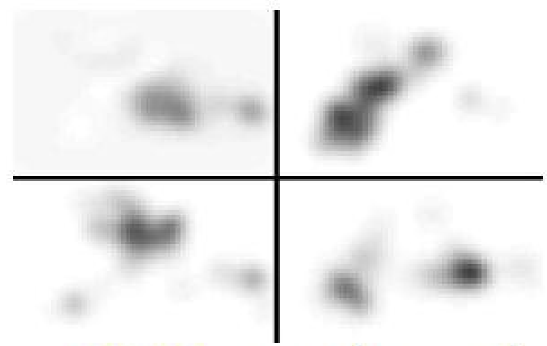
Optical flow $F_{x,y}$



F_x, F_y



$F_x^-, F_x^+, F_y^-, F_y^+$

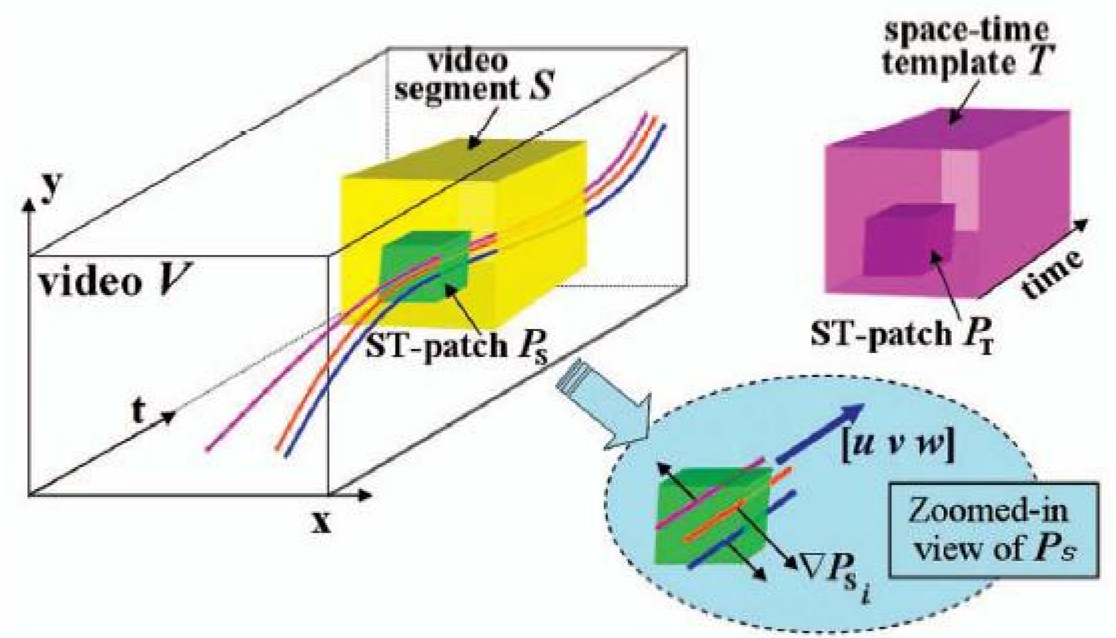


blurred $F_x^-, F_x^+, F_y^-, F_y^+$

[Efros, Berg, Mori, Malik, ICCV 2003]

2) Features & methods

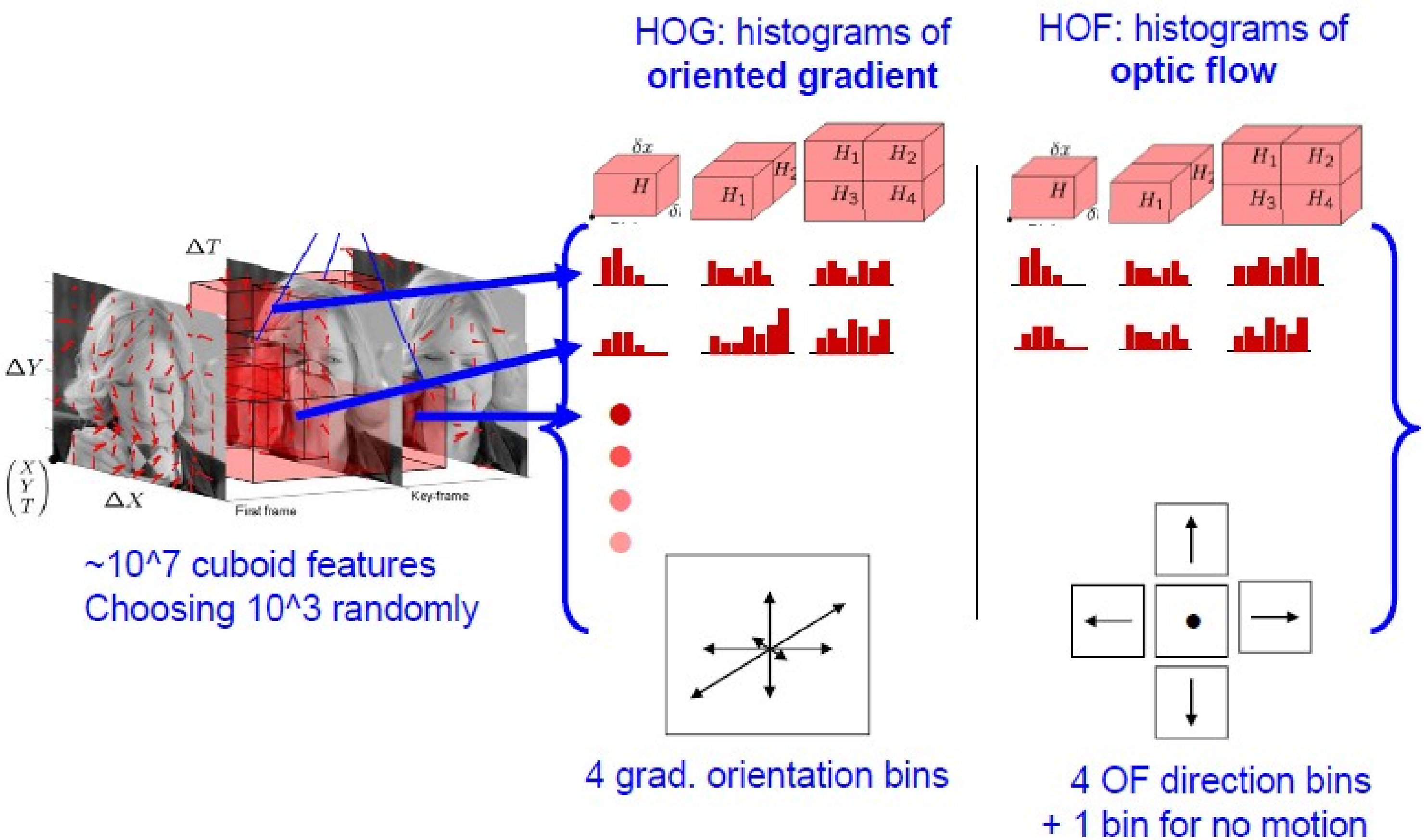
- Spatio-Temporal
  - Motion estimation from video is a often noisy/unreliable
  - Measure motion consistency between a template and test video



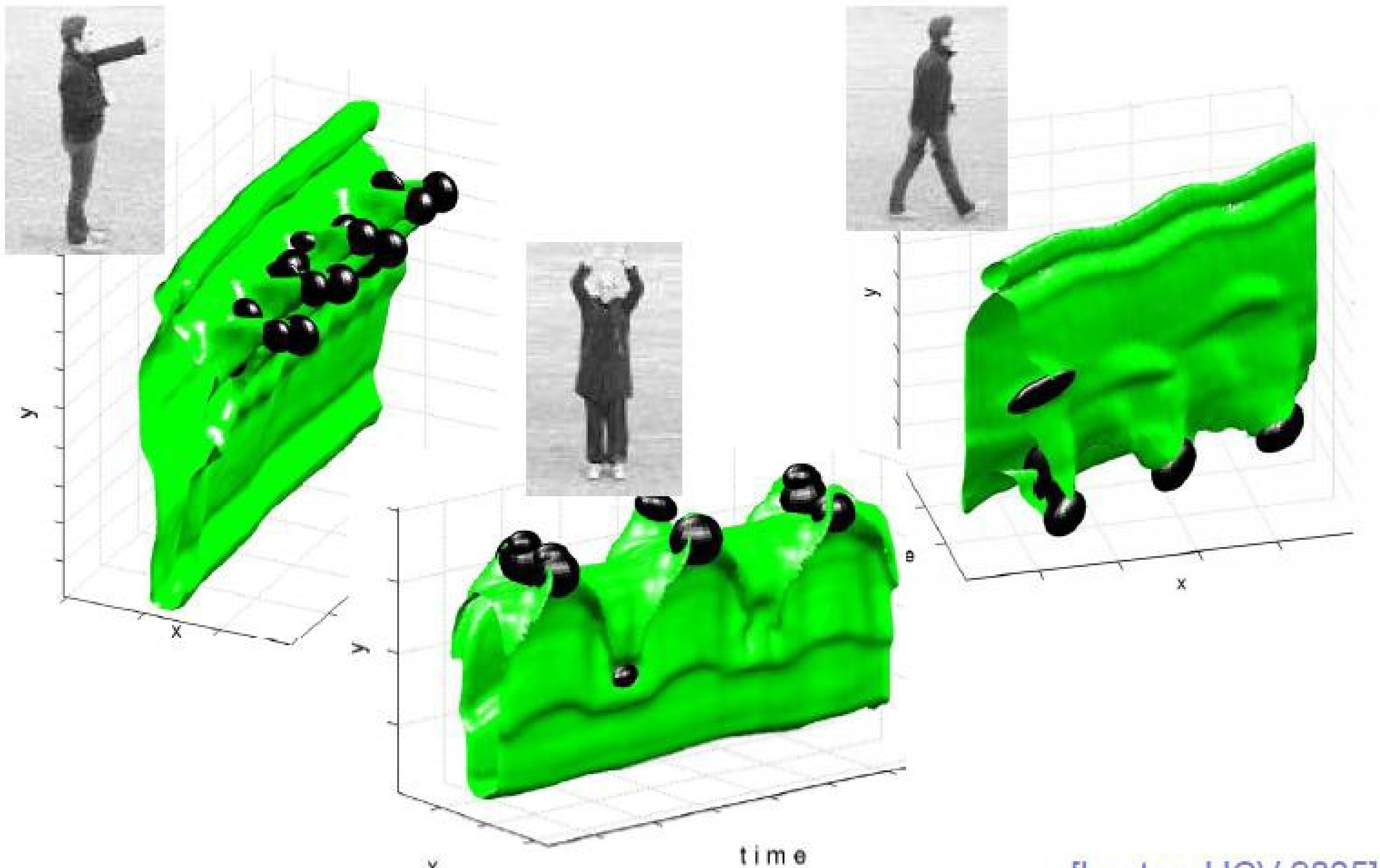
[Schechtman and Irani, PAMI 2007]

2) Features & methods

Histogram features

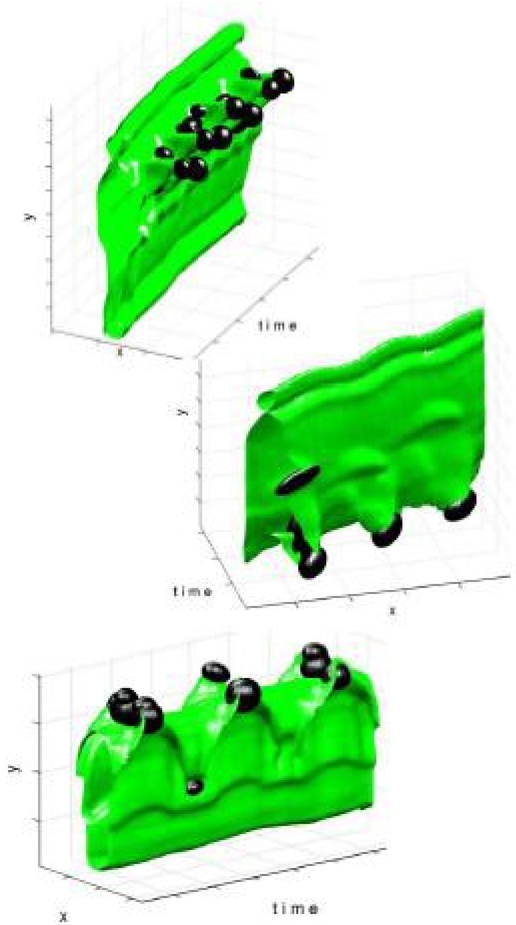


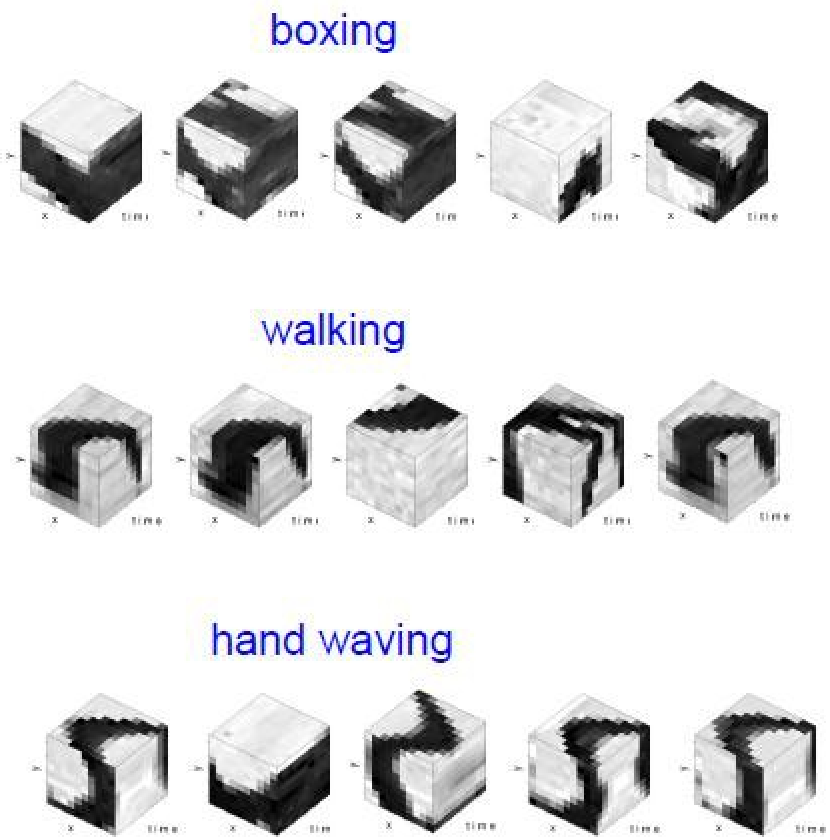
2) Features & methods
STIPS



[Laptev, IJCV 2005]

2) Features & methods



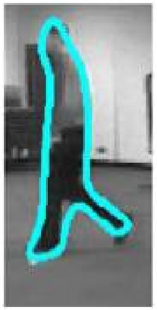


[Laptev, IJCV 2005]

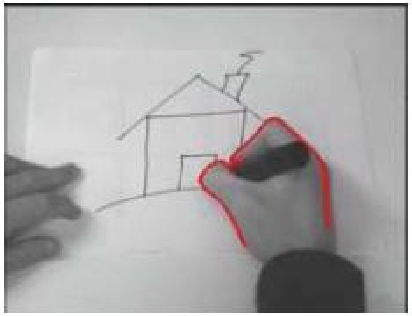
2) Features & methods

Where are we so far ?

Temporal templates:
+ simple, fast
- sensitive to segmentation errors

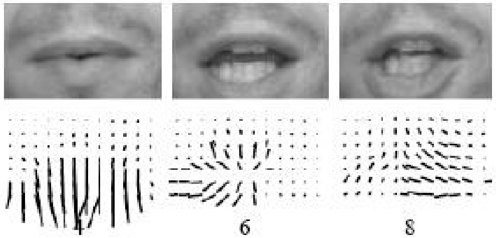


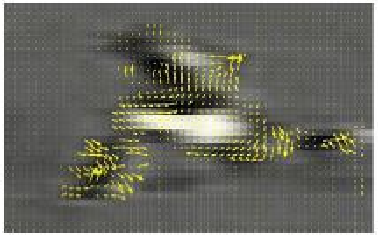
Active shape models:
+ shape regularization
- sensitive to initialization and tracking failures



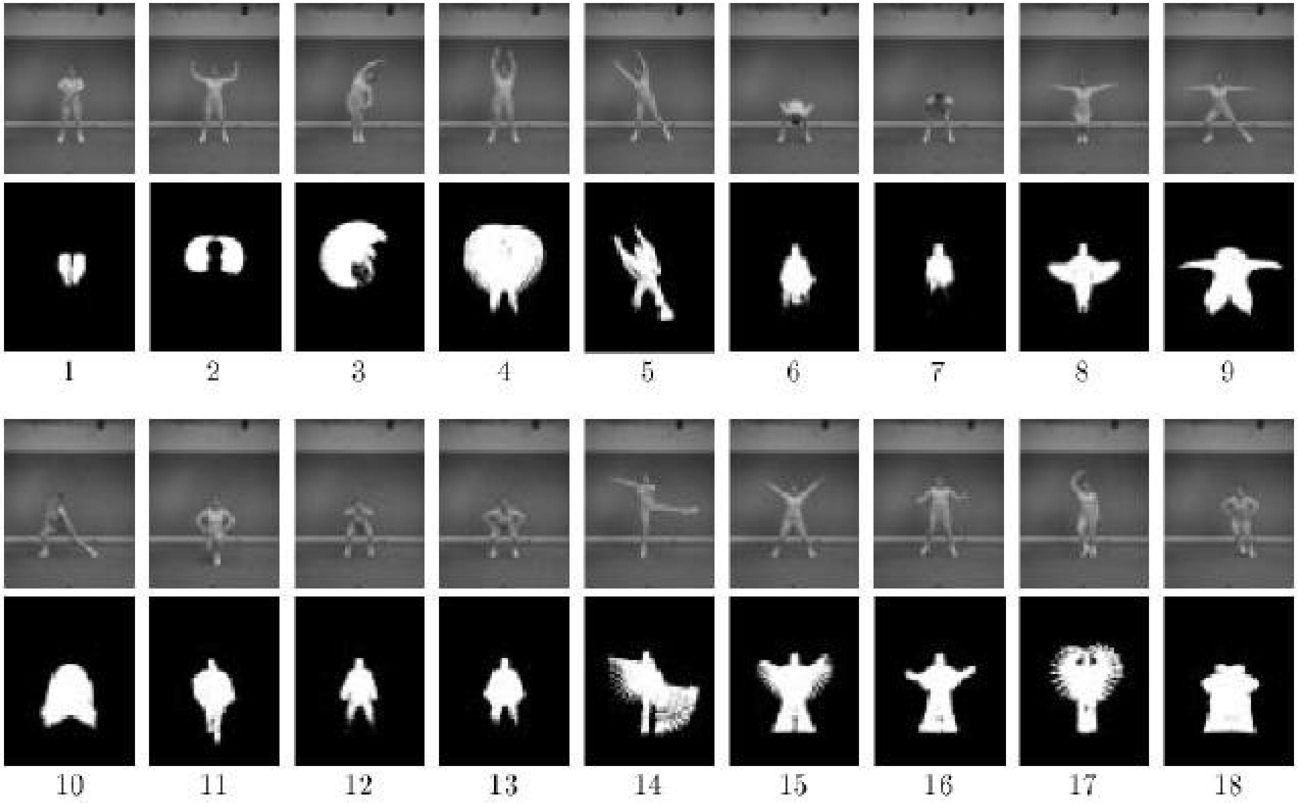
Tracking with motion priors:
+ improved tracking and simultaneous action recognition
- sensitive to initialization and tracking failures

Motion-based recognition:
+ generic descriptors; less depends on appearance
- sensitive to localization/tracking errors





2) Features & methods

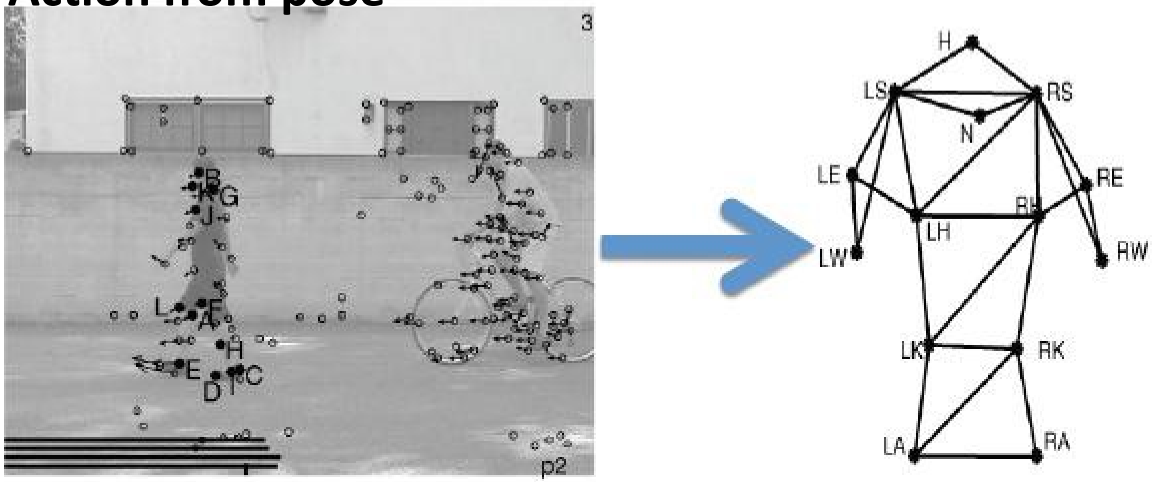


Nearest Neighbor classifier: 66% accuracy

[A.F. Bobick and J.W. Davis, PAMI 2001]

2) Features & methods

Action from pose

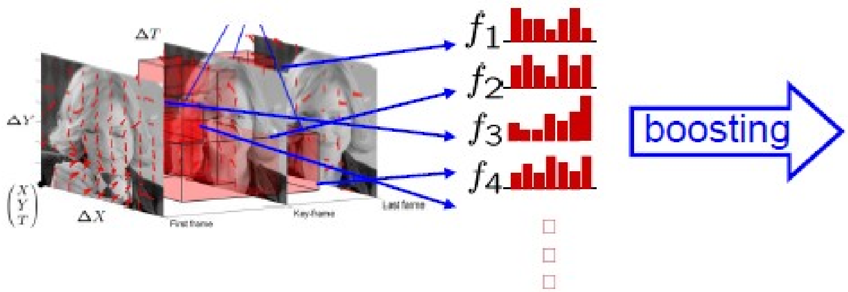


- Detect corners in images/video
- Assess likelihood under action-specific pose model
- Discriminate between walking directions, bicycle riding

Song, Goncalves & Perona NIPS 2001, PAMI 2003

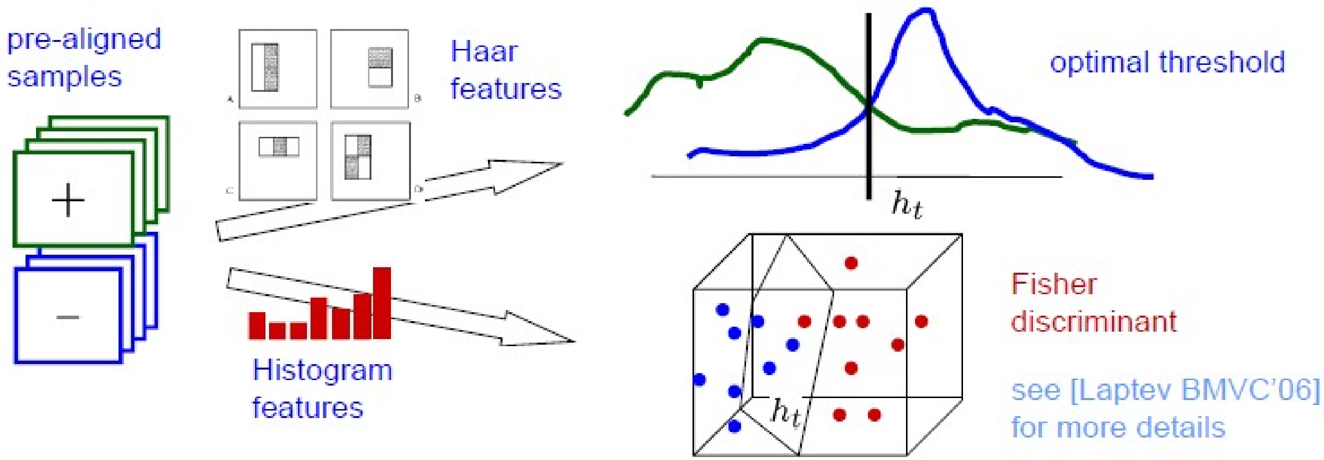
2) Features & methods

Action learning



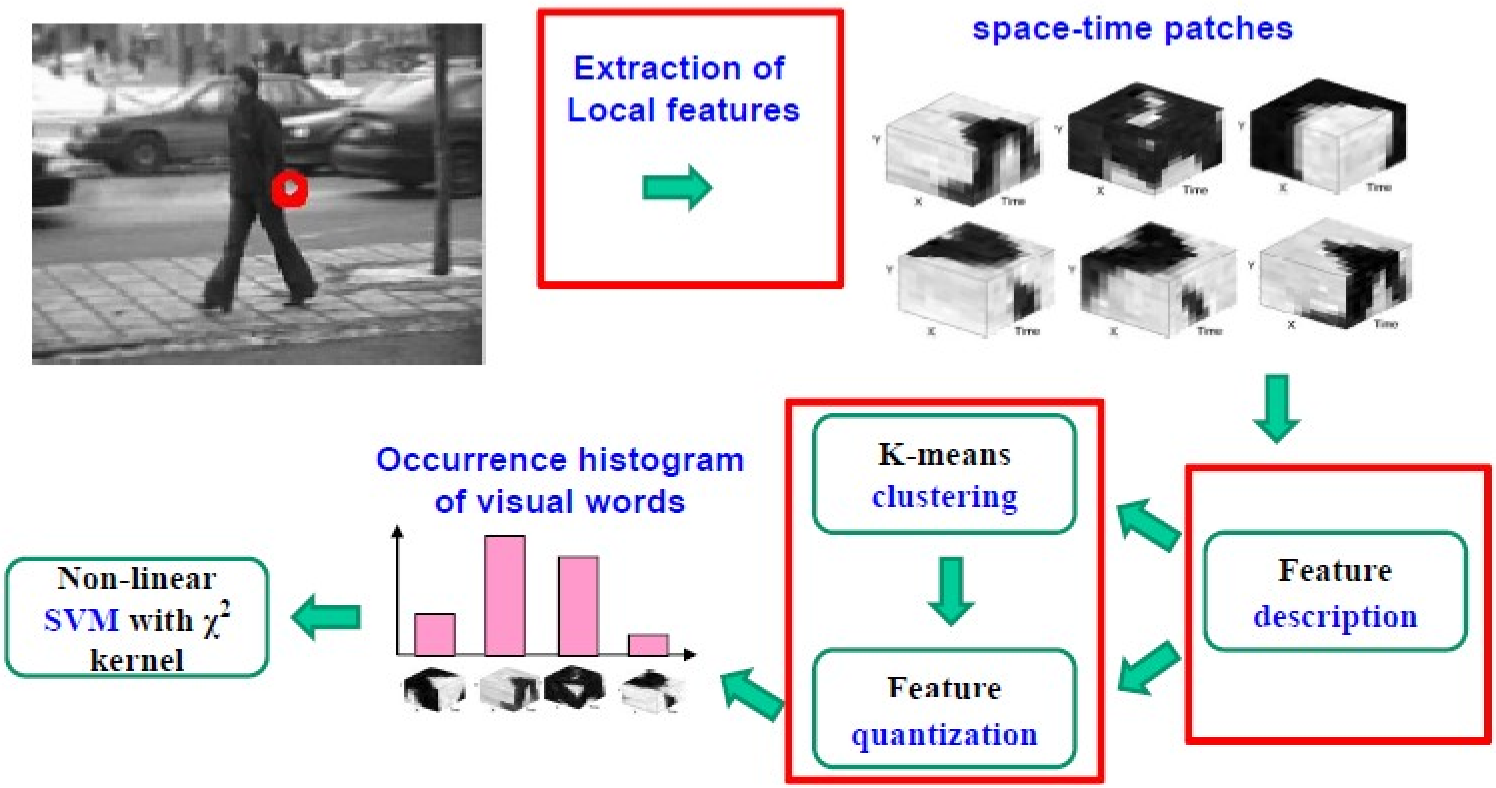
$$H(z) = \mathrm{sgn}\left(\sum_{t=1}^{T} \alpha_t h_t(f_t)\right)$$

AdaBoost:
- Efficient discriminative classifier [Freund&Schapire'97]
- Good performance for face detection [Viola&Jones'01]

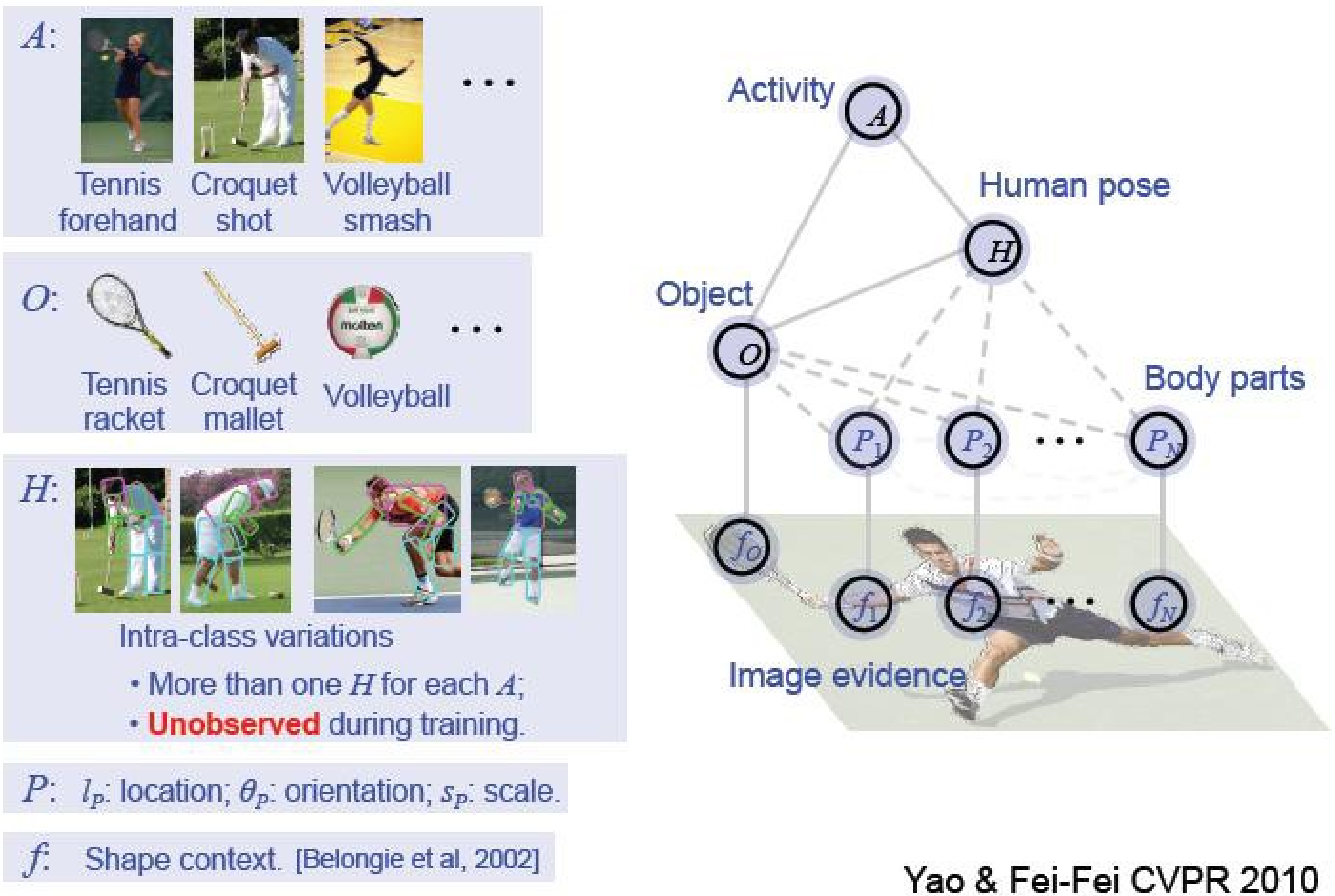


2) Features & methods

Bag of space-time features + SVM [Schuldt'04, Niebles'06, Zhang'07,…]

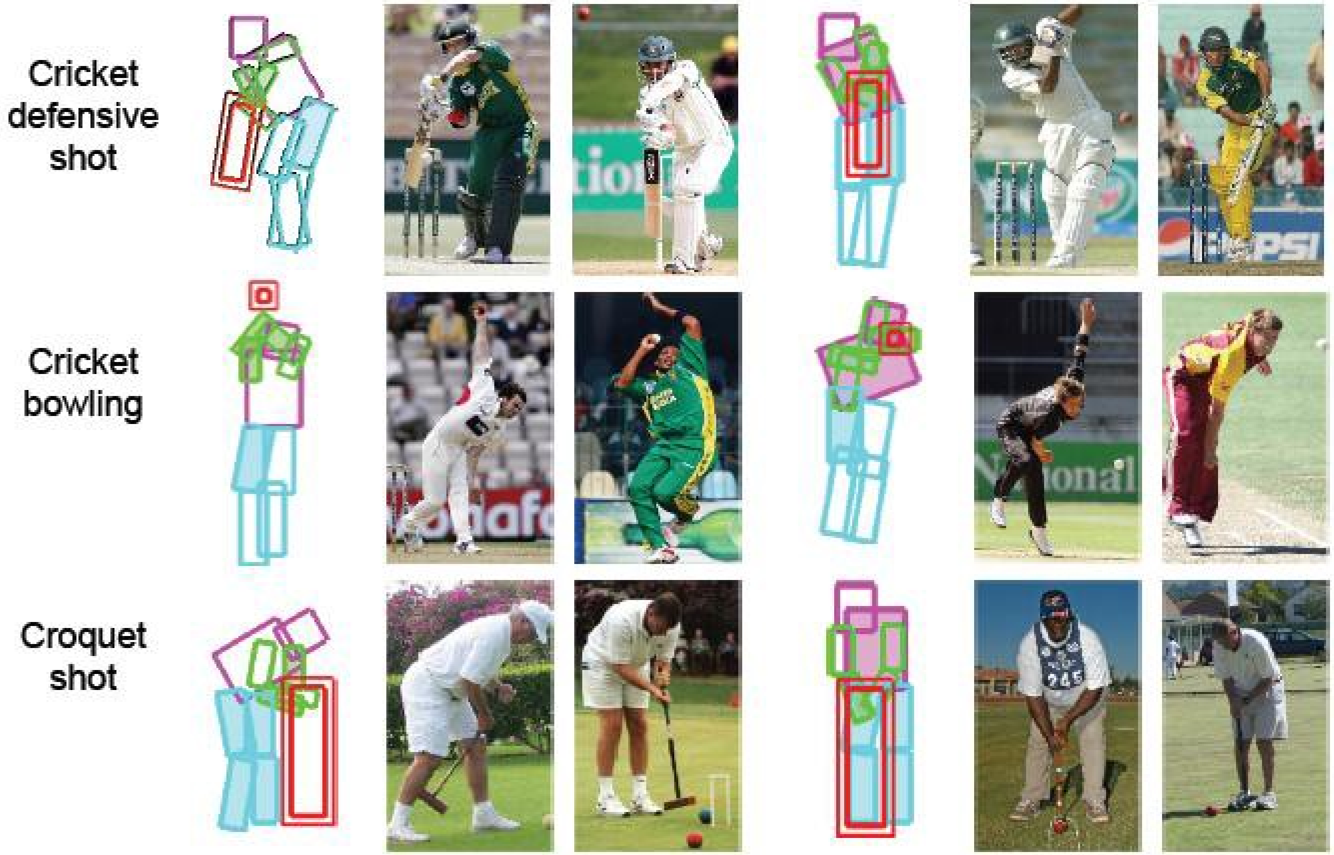


2) Features & methods



Yao & Fei-Fei CVPR 2010

2) Features & methods



2) Features & methods

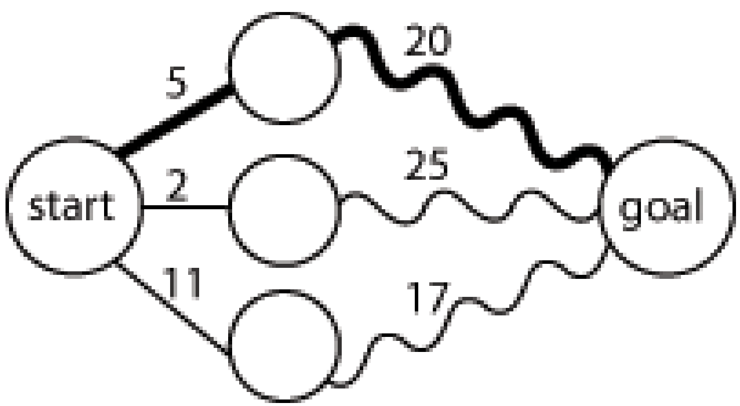
Perform Gesture Recognition from hand tracking

- Pruning Methods
    - Matching discriminative feature vectors with gesture models by eliminating large number of hypothesis → Reduces time complexity subproblems
- Deal with the Subgesture problem
- Dynamic Time Warping Based approach (DTW)
    - We will see how DTW works next

Jonathan Alon, Vassilis Athitsos, Quan Yuan and Stan Sclaroff , "A Unified Framework for Gesture Recognition and Spatiotemporal Gesture Segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), Vol. 31, No. 9, pp 1685-1699, 2009*

3) Dynamic Time Warping

- Dynamic programming
- **Dynamic programming** is a method for solving complex problems by breaking them down into simpler subproblems
- The term *dynamic programming* was originally used in the 1940s by Richard Bellman to describe the process of solving problems where one needs to find the best decisions one after another.
- e.g. path finding:



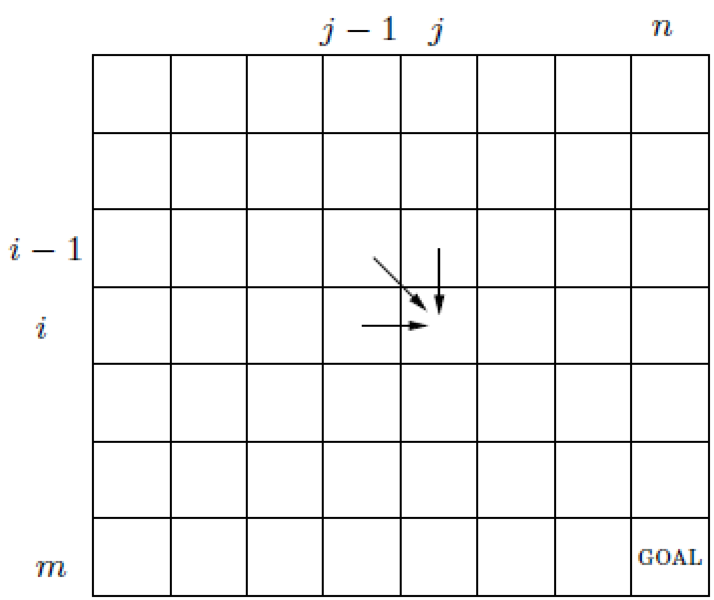
3) Dynamic Time Warping

- Example: text editing

for $i = 0, 1, 2, \ldots, m$:
  $E(i, 0) = i$
for $j = 1, 2, \ldots, n$:
  $E(0, j) = j$
for $i = 1, 2, \ldots, m$:
  for $j = 1, 2, \ldots, n$:
    $E(i, j) = \min\{E(i-1, j) + 1, E(i, j-1) + 1, E(i-1, j-1) + \mathtt{diff}(i, j)\}$
return $E(m, n)$

```
E X P O N E N – T I A L
– – P O L Y N O M I A L
```

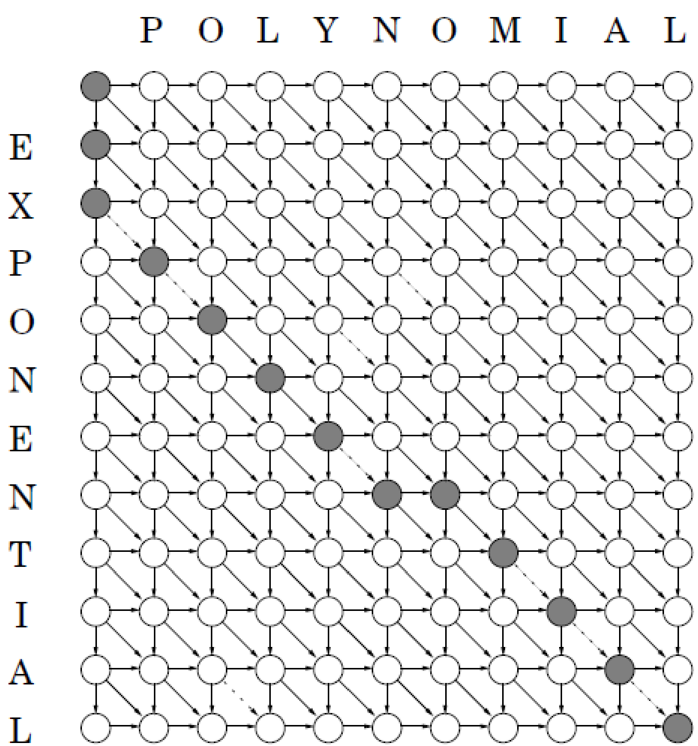
$O(mn)$



		P	O	L	Y	N	O	M	I	A	L
	0	1	2	3	4	5	6	7	8	9	10
E	1	1	2	3	4	5	6	7	8	9	10
X	2	2	2	3	4	5	6	7	8	9	10
P	3	2	3	3	4	5	6	7	8	9	10
O	4	3	2	3	4	5	5	6	7	8	9
N	5	4	3	3	4	4	5	6	7	8	9
E	6	5	4	4	4	5	5	6	7	8	9
N	7	6	5	5	5	4	5	6	7	8	9
T	8	7	6	6	6	5	5	6	7	8	9
I	9	8	7	7	7	6	6	6	6	7	8
A	10	9	8	8	8	7	7	7	7	6	7
L	11	10	9	8	9	8	8	8	8	7	6

3) Dynamic Time Warping

for $i = 0, 1, 2, \ldots, m$:
    $E(i, 0) = i$
for $j = 1, 2, \ldots, n$:
    $E(0, j) = j$
for $i = 1, 2, \ldots, m$:
    for $j = 1, 2, \ldots, n$:
        $E(i, j) = \min\{E(i-1, j) + 1, E(i, j-1) + 1, E(i-1, j-1) + \mathtt{diff}(i, j)\}$
return $E(m, n)$



E	X	P	O	N	E	N	—	T	I	A	L
—	—	P	O	L	Y	N	O	M	I	A	L

It can exist different ways (**working paths**)

3) Dynamic Time Warping

- Dynamic Time Warping
- Algorithm for measuring similarity between two sequences
  - Considering variations in time or speed
  - Objective is to find the optimal match
  - Data which can be analyzed
    - Any linear representation
    - *Audio*
    - *Video*
    - *Graphics*

```
int DTWDistance(char s[1..n], char t[1..m]) {
    declare int DTW[0..n, 0..m]
    declare int i, j, cost

    for i := 1 to m
        DTW[0, i] := infinity
    for i := 1 to n
        DTW[i, 0] := infinity
    DTW[0, 0] := 0

    for i := 1 to n
        for j := 1 to m
            cost:= d(s[i], t[j])
            DTW[i, j] := cost + minimum(DTW[i-1, j  ],    // insertion
                                        DTW[i  , j-1],    // deletion
                                        DTW[i-1, j-1])    // match

    return DTW[n, m]
}
```

Sakoe, H. and Chiba, S., *Dynamic programming algorithm optimization for spoken word recognition*, IEEE Transactions on Acoustics, Speech and Signal Processing, 26(1) pp. 43– 49, 1978, ISSN: 0096-3518.

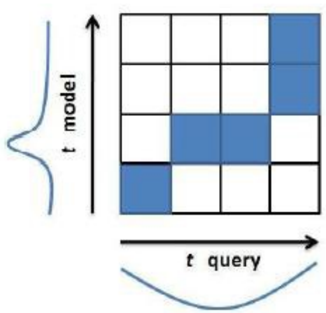
C. S. Myers and L. R. Rabiner. A comparative study of several dynamic time-warping algorithms for connected word recognition. The Bell System Technical Journal, 60(7):1389-1409, September 1981.

L. R. Rabiner and B. Juang. Fundamentals of speech recognition. Prentice-Hall, Inc., 1993 (Chapter 4)

3) Dynamic Time Warping

- Sign Language Recognition

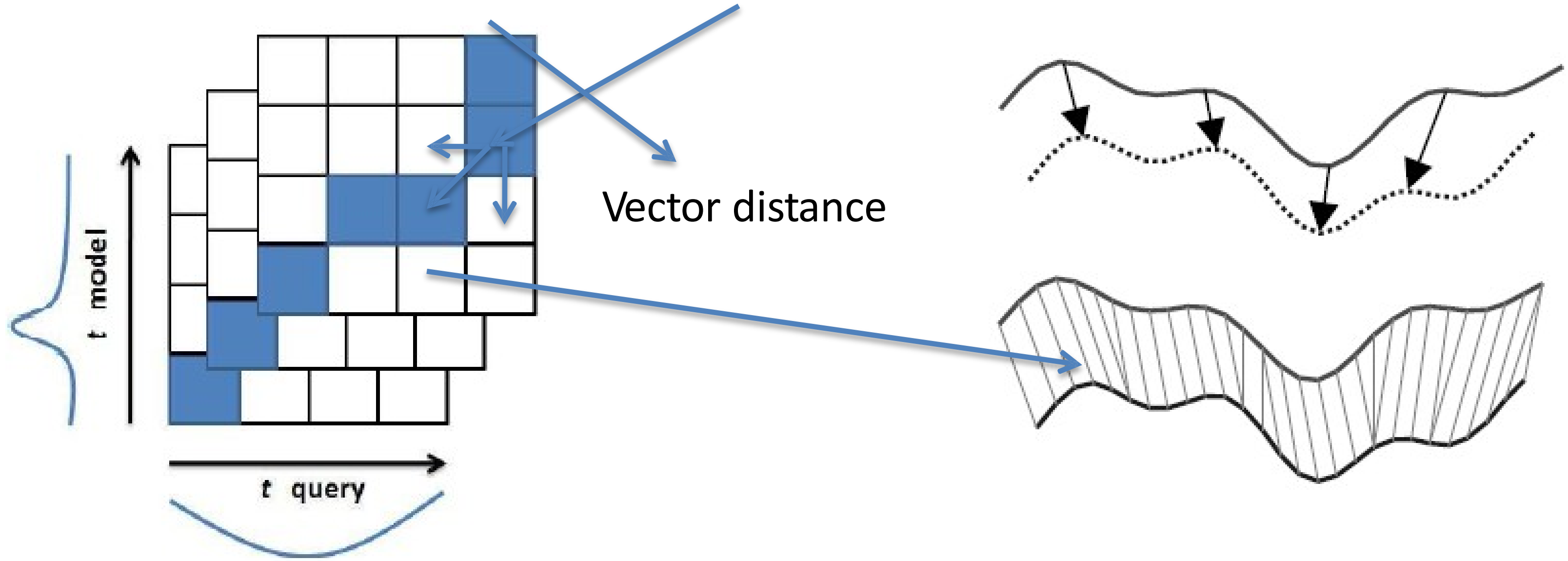
Face detection
Skin color modeling Noise
removing
Blob detection and tracking Dynamic Time
Warping



3) Dynamic Time Warping

- Multiple candidates

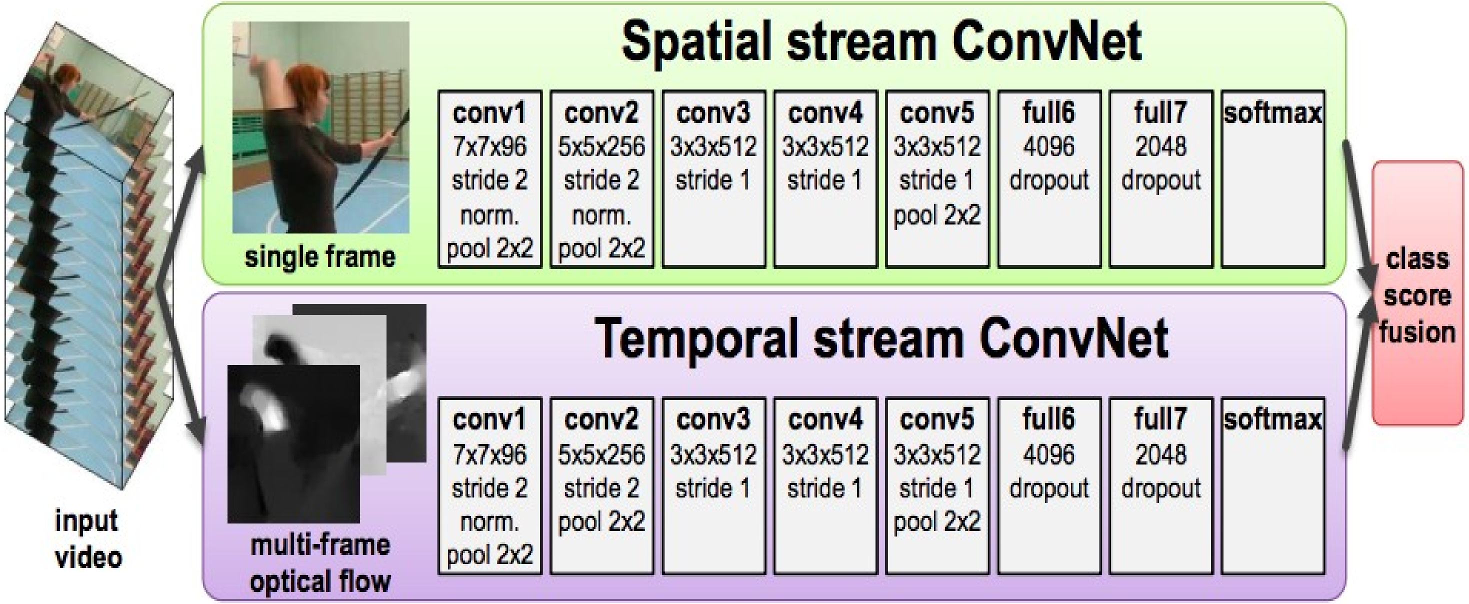
$$\gamma(i,j,k) = d(i,j,k) + \min\{\gamma((i-1,j-1),(i-1,j),(i,j-1)\times\{1,..,K\})\}$$



- Multiple candidates
  - Candidates can appear and disappear
- Sub-patterns can be detected from a large sequence
- Distances can be changed to cost or probabilities
- Gesture match sequence requires from threshold distance/cost
  → Learnt or empirically set

4) Moving to Deep learning

Until the apparition of the Two-stream ConvNet, hand-crafted methods dominated state-of-the-art of action classification.

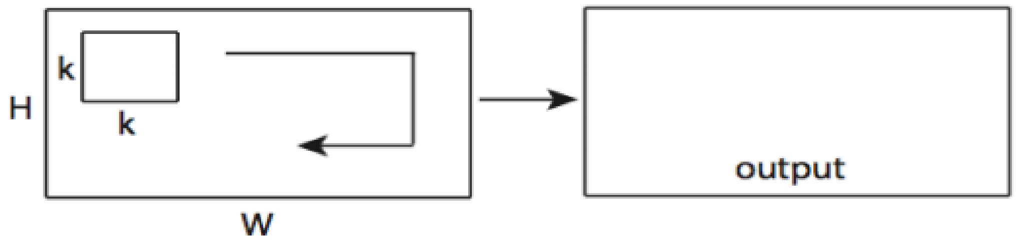


Karen Simonyan and Andrew Zisserman. "Two-stream convolutional networks for action recognition in videos". In: Advances in Neural Information Processing Systems. 2014, pp. 568–576.

4) Moving to Deep learning

Must know: 2D vs 3D convolutions

Convolving a $k \times k$ filter (or kernel) on a $H \times W$ grayscale image produces a 2D response map (output).

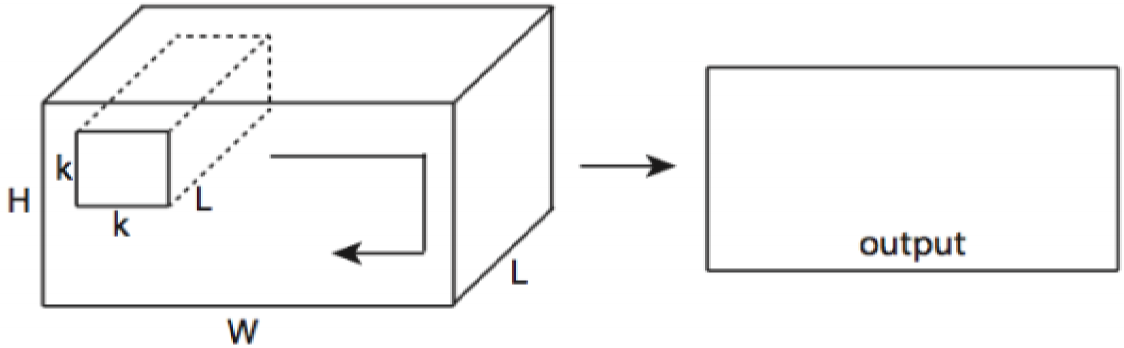


2D convolution

4) Moving to Deep learning

Must know: 2D vs 3D convolutions

Convoling a $k \times k \times L$ filter (or kernel) on a $H \times W \times L$ stack of grayscale images also produces a 2D response map (output).



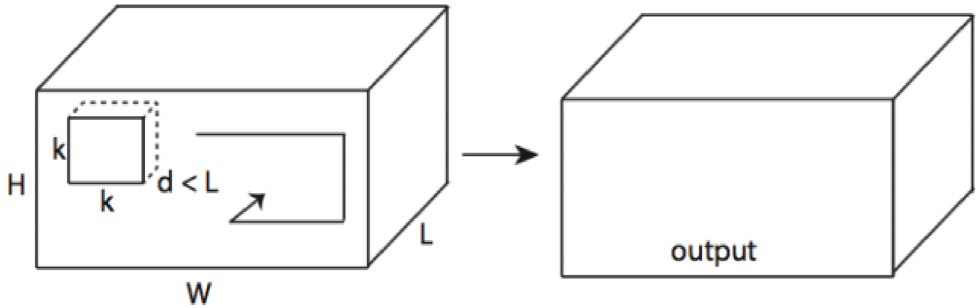
2D convolution on multiple frames

The temporal information is merged (or "lost") after the first convolutional layer.

4) Moving to Deep learning

Must know: 2D vs 3D convolutions

Convoling a $k \times k \times d$ filter (or kernel) on a $H \times W \times L$ stack of grayscale images, where $d < L$, produces a 3D response map (output).



3D convolution

The temporal structure is mantained throughout subsequent network layers.

4) Moving to Deep learning

Taxonomy: action classification architectures

In the current SOTA, action classification (AC) methods can be roughly categorized following this taxonomy:

1. Two-stream ConvNets
2. 3D ConvNets
3. ConvNet + LSTM
4. Two-stream Inflated 3D ConvNets
5. Transformer-like architectures

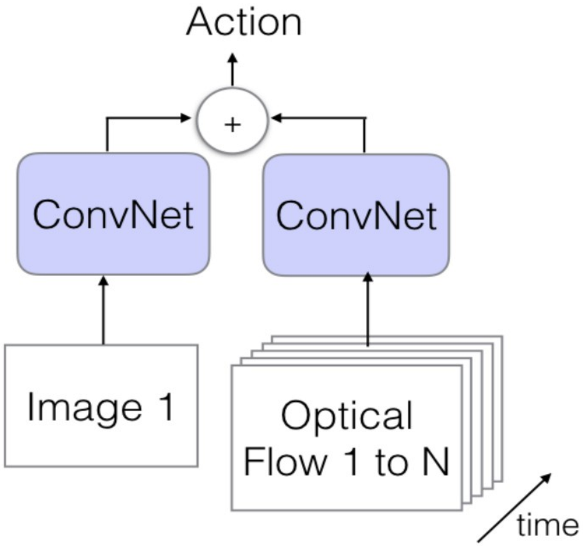
Taxonomy (1/5): Two-stream ConvNets

Two separate ConvNets – namely *streams* – process, respectively, appearance (RGB frames) and motion (pre-computed *optical flow* stacks). Whereas RGB frames are $H \times W \times 3$, OF stacks are $H \times W \times 2$. During **training**, the network learns to *classify individual RGB frames or OF stacks* centered at the corresponding frame.

During **test**, the *video-level prediction* is got from averaging class scores from several frames from each stream and performing a weighted sum of both streams.

+ Appearance stream can re-use pre-trained on image classification.
+ Motion stream rapidly trained from scratch.

– Temporal information in motion stream is dropped after the 1st conv layer.
– Ignores long-term temporal information.
– Complexity



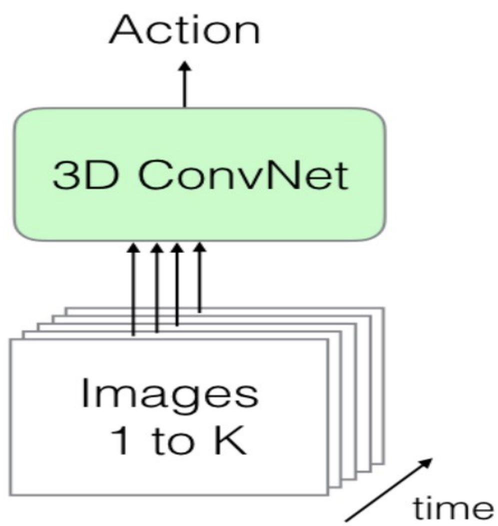
Taxonomy (2/5): 3D ConvNets

Convolutional layers and pooling kernels are extended in time, i.e. inputs are a $K \times H \times W \times 3$ tensor and filter (output) response maps are each a 3-D tensor. During **training**, the network learns to *classify short video snippets*, e.g. $K = 16$ frame clips.

The net is able to model local spatiotemporal information, e.g. motion-based features. During **test**, for *video-level prediction* class scores from several K -frame clips are averaged.

+ Models very rich but local spatiotemporal features.

– Harder to train than Two-stream ConvNets → more data needed.
– Ignores long-term temporal information.
– Do not re-use of powerful pre-trained image-based ConvNets.



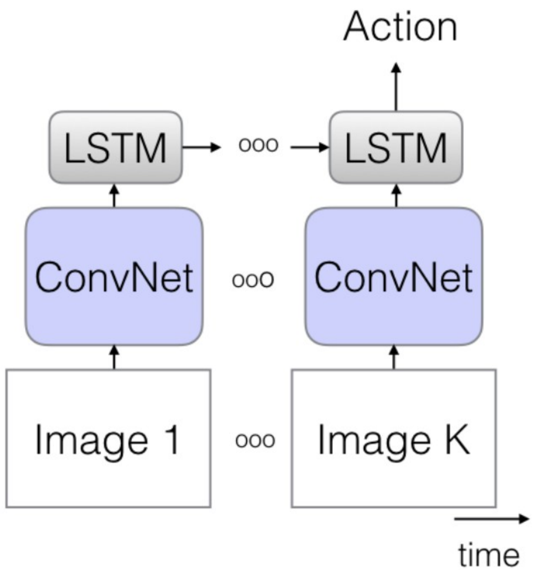
Taxonomy (3/5): ConvNet + LSTM

Individual frames are input to a ConvNet $g\ (\boldsymbol{X}\ ;\ \boldsymbol{\theta}_g\ )$ with shared parameters $\boldsymbol{\theta}_g$. The sequence of outputs $\mathbf{z}_i = g\,(\mathbf{X}_i;\ \boldsymbol{\theta}_g),\ 1 \leq i \leq K$, is input to a LSTM.

Recursively, the LSTM outputs a hidden state $\boldsymbol{h}_i$ after receiving $(\mathbf{z}_i\ ,\ \boldsymbol{h}_{i-1})$. During **test**, a video-level prediction in form of class score distribution is produced: $\mathbf{y} = \mathrm{softmax}(f\,(\boldsymbol{h}_K\,;\ \boldsymbol{\theta}_f\,))$, where $f\,(\,\cdot)$ is a feed-forward net and $\mathbf{y} \in \mathrm{R}^C$.

- \+ Long-term temporal information is modeled.

- – Larger K values → smaller batch size.
- – Recurrency difficults GPU-parallelization.
- – In practice, K very large does not work properly…
- – Useful with HARD sequencial dependencies



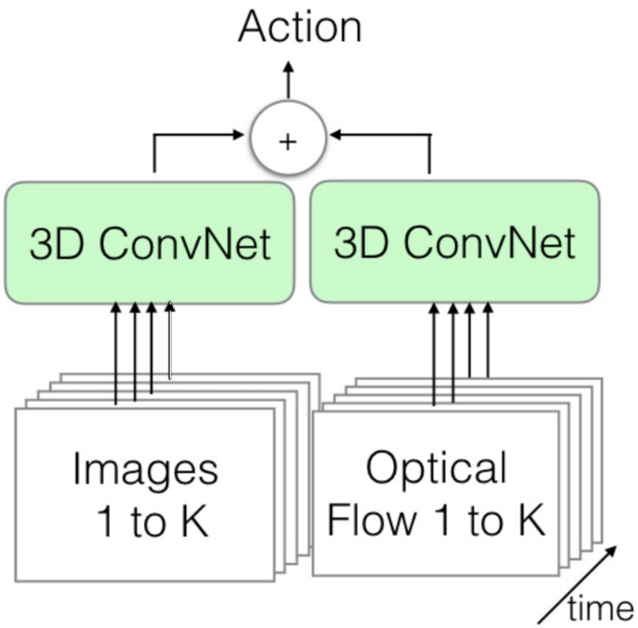
Taxonomy (4/5): Two-stream I3D ConvNets

Put together the best of 3D and Two-stream ConvNets: it *inflates* all the filters and pooling kernels from $N \times N$ to $N \times N \times N$ and includes an OF-based stream.

Given the inflation, the 3D filters are initialized from pre-trained 2D filter weights by repeating them N times along time dimension and rescaling them by dividing by N.

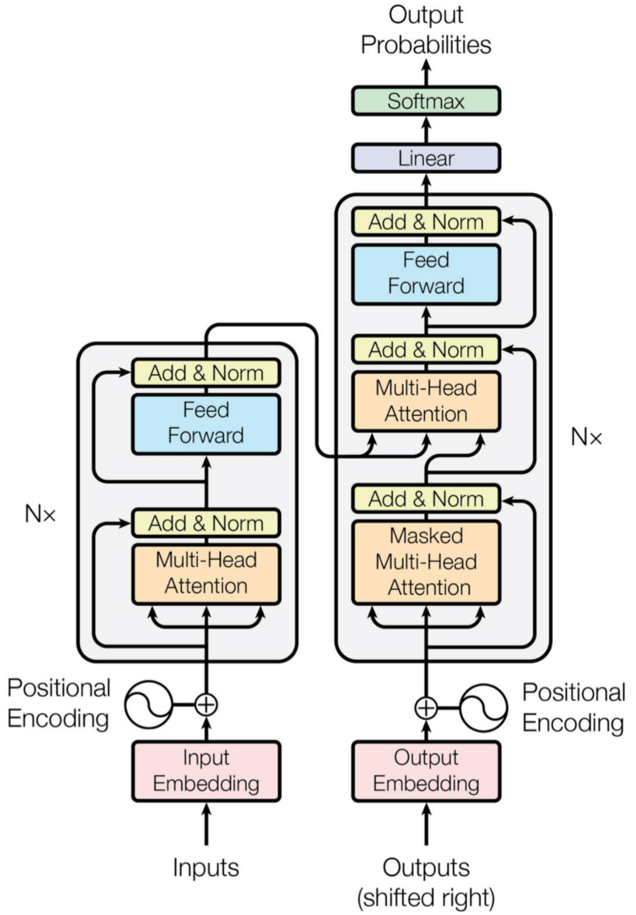
+ All the ones from 3D and Two-stream ConvNets.
+ Performance.

– Ignores long-term temporal information.
– Complexity



Taxonomy (5/5): Transformer-like architectures

It encodes frame-based or spatio-temporal input features (depending on the input backbones) and take benefit of self-attention mechanism.



+ Can model any kind of input
+ Avoid recurrent modeling
+ Can exploit long terms relationships

– Pretrain helps but training is hard and tricky
– Complexity / difficult end-to-end modeling