Predicting Human Behavior from Public Cameras with Convolutional Neural Networks

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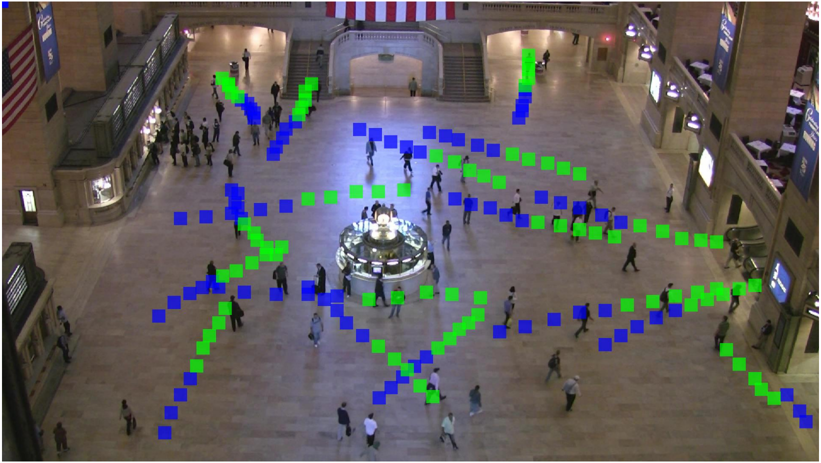
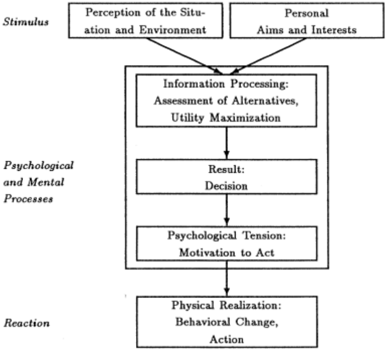
Aim



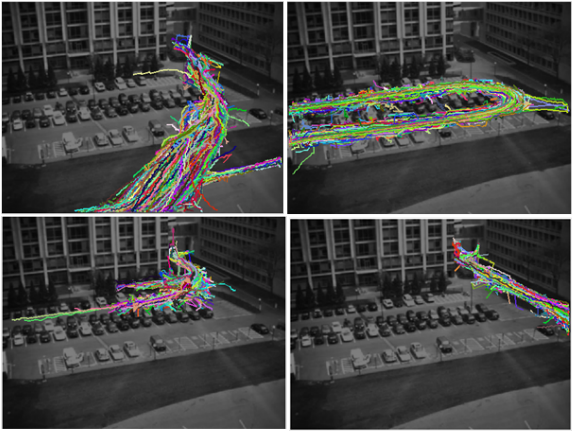
Prediction of pedestrian trajectories through the scene [Yi et al., 2016]

Related Work I.



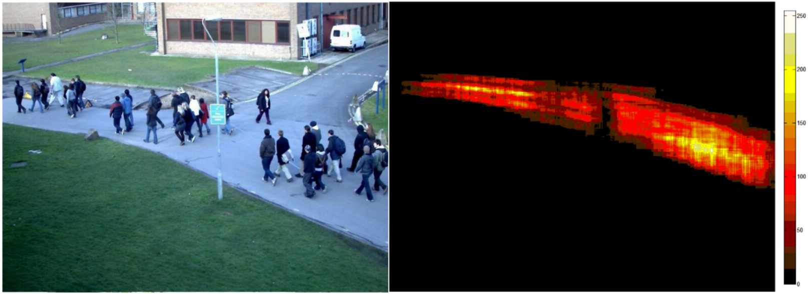
Graph of decision making of individual pedestrian based on "social force" model [Helbing and Molnar, 1995]

Related Work II.



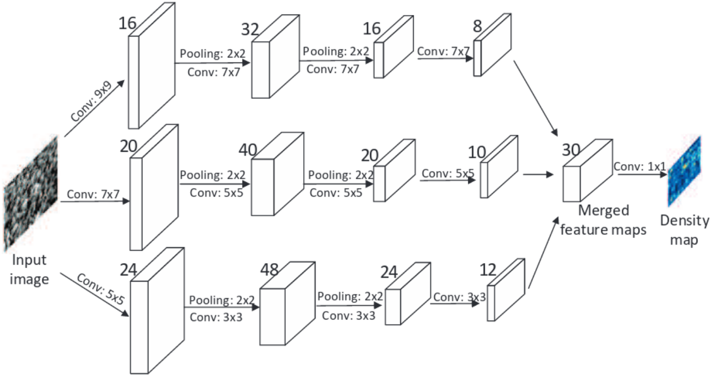
Cluster trajectories used model by Dual-HDP [Wang et al., 2009]

Related Work III.



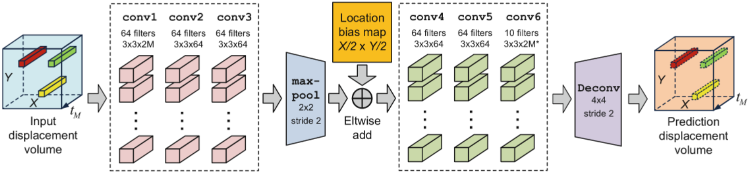
Constructed flow map of the scene by multiview face detector [Xing et al., 2011]

Related Work IV.



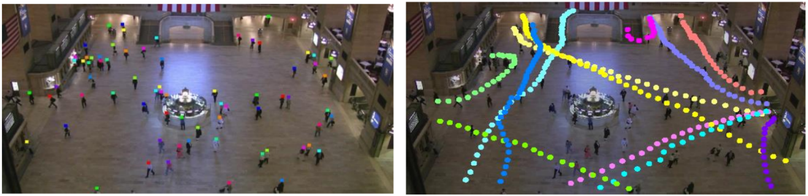
Multicolumn Convolutional Neural Network [Zhang et al., 2016]

Related Work V.



Behavioral Convolutional Neural Network [Yi et al., 2016]

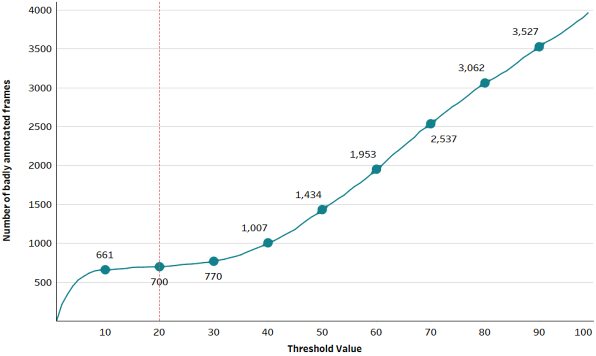
Dataset I.



A one-hour surveillance video with the exact walking paths of 12,684 pedestrians [Yi et al., 2016]

Dataset II.

- Full HD images
- Badly annotations
  - Remove non-annotated sequences
  - Select threshold on number of annotations

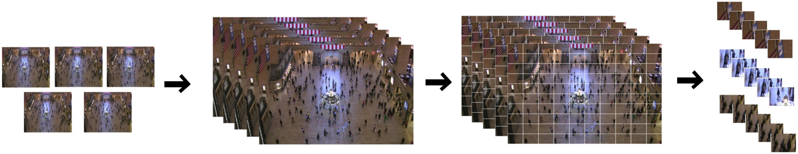


Current approach

- Behavioral-CNN
- Uses pedestrian encoding
  - Need to correctly extract position of pedestrian in test time
  - Construction of volume of displacement vectors for each pedestrian
  - Very sparse input and output
  - Needs special learning scheme
- Predicting same sparse volume
  - Needs a lot of computational power
  - Needs a lot of space

Our approach I.

- No special encoding
- Split the image (9×8 patches)



Process of segmenting input into smaller patches.

Our approach II.

- No special encoding
- Split the image (9×8 patches)
- Predict pedestrian mask
  - Predict entire patch (a)
  - Classify each pixel (b)
- Pedestrian representations (6×6 pixels)

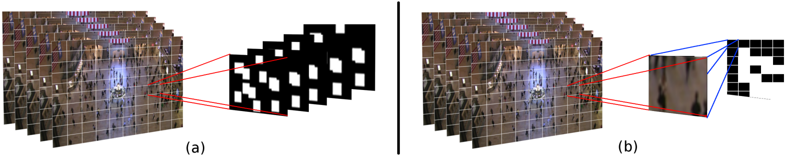


Illustration of our prediction schemes

Our approach III.

- Simple convolutional encoder
  - simple linear architecture

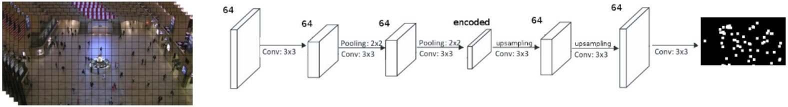


Illustration simple encoder architecture

Our approach IV.

- Multi-column convolutional encoder
  - multiple layers extracting low level features
  - each simultaneous layer with different filter size

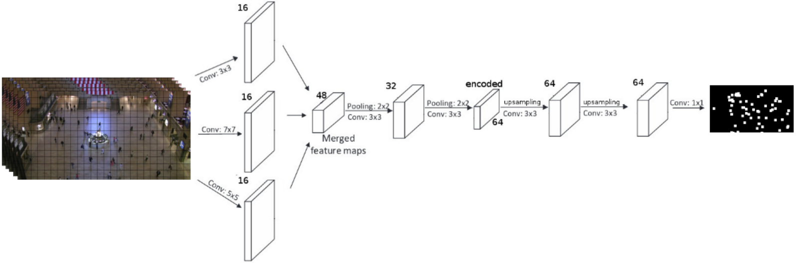


Illustration column encoder architecture

Results I.

- Use **MSE** to make results comparable to [Yi et al., 2016]
- Post processing step to extract pedestrian locations
  - Threshold pedestrian mask
  - Find contours
  - Pick top and left most pixel as pedestrian representation

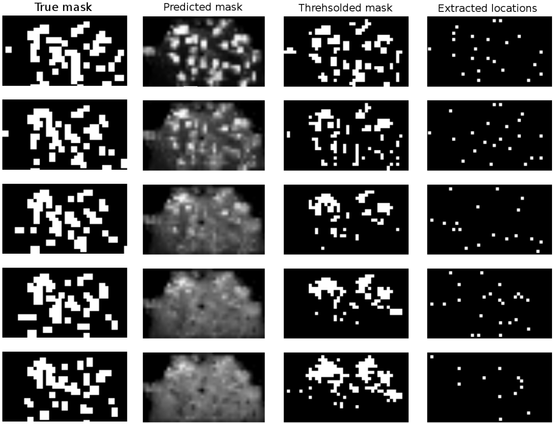
Posprocessing step needed to extract exact pedestrian coordinates

Results II.

architecture	1 frame	2 frame	3 frame	4 frame	5 frame
simple encoder	5.805	13.112	13.899	14.010	15.472
column encoder	3.946	11.766	12.101	12.002	12.621
simple encoder + sparsity	4.900	13.761	14.189	14.510	15.706
column encoder + sparsity	3.401	11.102	**11.336**	11.919	12.803
simple encoder + penalization	4.605	12.779	13.860	14.217	15.873
column encoder + penalization	4.070	11.690	12.093	12.370	12.110
column classifier	3.245	11.042	11.711	**11.893**	12.829
column encoder ensemble	3.103	11.983	12.622	12.891	13.209
column classifier ensemble	**3.015**	**10.814**	*11.519*	*11.978*	**12.780**

Final *MSE* for various types of tested model architectures predicting 1 to 5 frames ahead

Results III.



Sample prediction of our best model. Each row represents one step ahead in prediction

Conclusion

- Prediction of one and two frames ahead
- Need of post-processing step
  - Find good threshold
  - Extract pedestrian coordinates from blobs
- Find good splitting windows size
- Pedestrian representation
  - Merging of pedestrians

Future work

- Find better representation of pedestrian
  - Autoencoder
  - CNN to extract coordinates
- Recurrent Neural Network to reduce sparsity
  - Predict coordinates
  - Time series prediction

Thank you for your attention!

Section methodology

- Heavily based on Deep Learning Book [Bengio et al., 2014] and Stanford cs231n course notes [Li et al.,]

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- *The main purpose of a neural network is to approximate some arbitrary function* f'
- Each layer defined as function which we stack to approximate given function

Section methodology

- Heavily based on Deep Learning Book [Bengio et al., 2014] and Stanford cs231n course notes [Li et al.,]
- *The main purpose of a neural network is to approximate some arbitrary function f'*
- Each layer defined as function which we stack to approximate given function
- $y = f(\vec{w}x)$, where w are weights...
- $\vec{y} = \hat{f}(W^T x + \vec{b})$, where W are layer weights... b represents the bias vector...

Rosenblatt neuron

$$output = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases} \tag{1}$$

Equation 3.1 - Rosenblatt neuron

$$output = \begin{cases} 1 & \text{if } \sum_j w_j x_j + b > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Next equation 3.2 - redefinition of previous function

Filling empty annotations

- Same as constructing special encoding in test time
- Head-and-Shoulders or face detectors
    - Problem with occlusion
- Pixel-wise segmentation
- Special features with various machine learning algorithms
- Neural networks

LeNet [LeCun et al., 1990]

- Do not describe history
- Various examples of CNNs in context of behavioral modeling

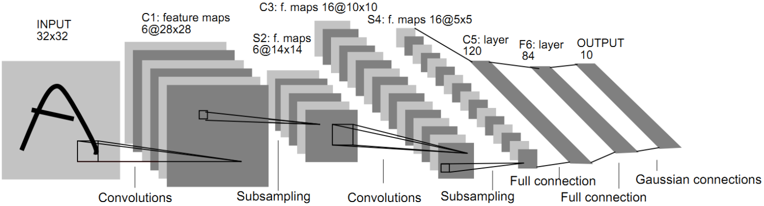

Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Hand-written digit recognition with a back-propagation network [LeCun et al., 1990]

Pixel representation

- The current annotation is on the head
- Imperfect edges

MSE as define in [Yi et al., 2016]

$$MSE = \frac{1}{NM'} \sum_{i}^{N} \sum_{j}^{M'} ||I_i^j - I_i'^j||_2 \times 100\%$$

where N is the number of samples, M' is the number of predicted frames, I is the volume containing normalized annotated positions of each pedestrian and I' is predicted volume of normalized pedestrian locations.

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