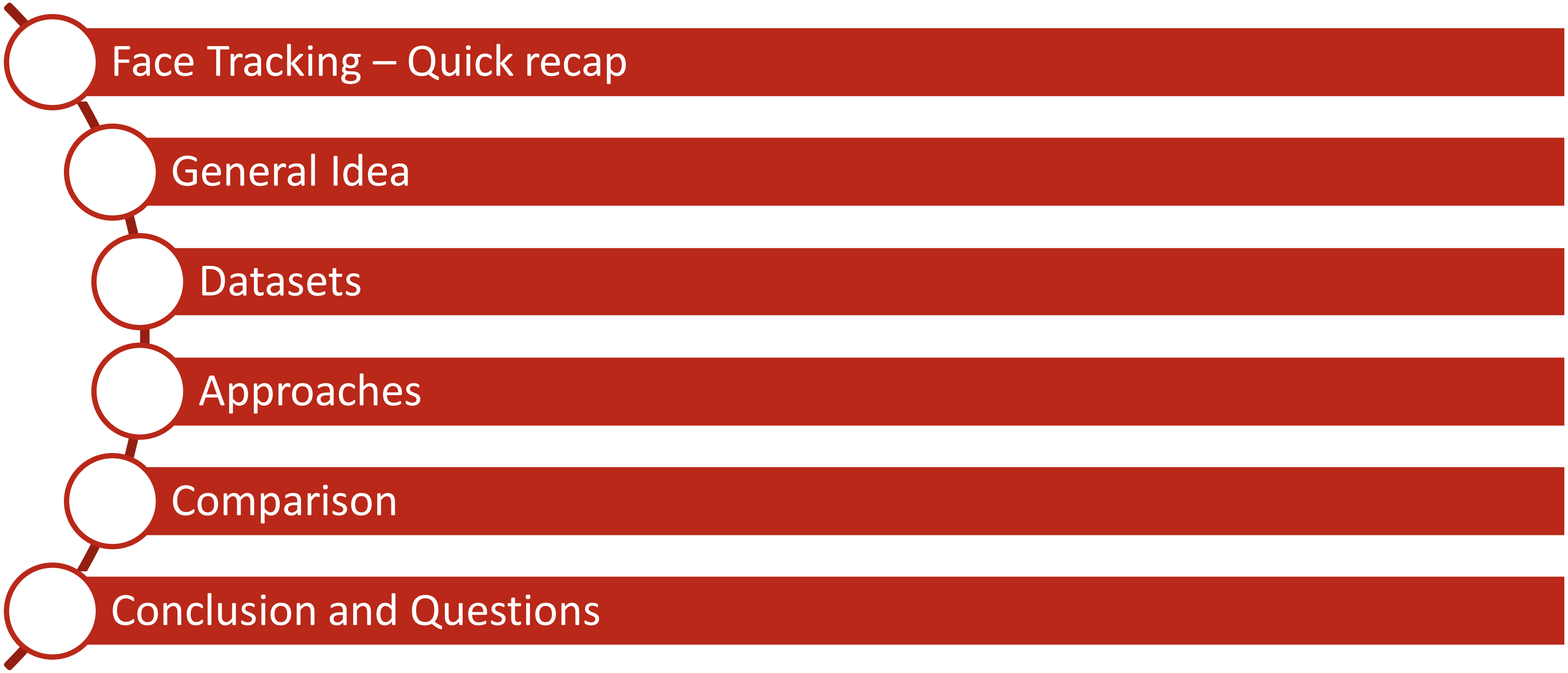
2D Image Processing & Augmented Reality
Winter Semester 2019/2020
Survey on Face Tracking with Deep Learning

Vinay Balasubramanian

v_balasubr18@cs.uni-kl.de

Supervisor: Jilliam Diaz Barros

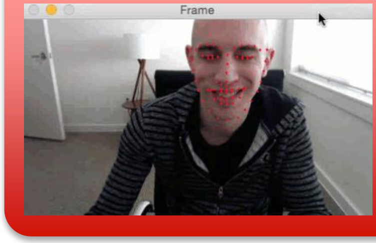
Outline



- Face Tracking – Quick recap
- General Idea
- Datasets
- Approaches
- Comparison
- Conclusion and Questions

Quick recap

Face Tracking



Tracking a face across all frames of a video.

Bounding-box or landmark based.

Applications - Face analysis, Person identification, Activity recognition, Expression analysis, Face modeling etc.

Challenges - Videos can be captured in unconstrained conditions.

May have illumination variations, large head poses, occlusions, etc.

Image source: Google

General Idea

- Video – Sequence of frames with temporal connection
- Sequence data? (Use RNN)

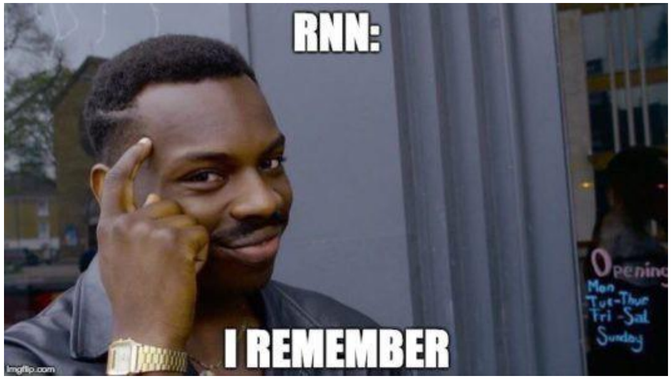
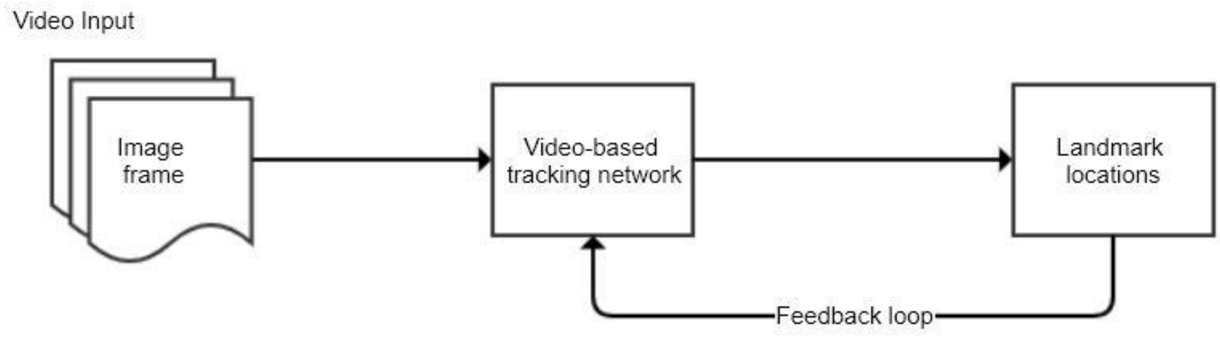


Image source: https://towardsdatascience.com/pytorch-basics-how-to-train-your-neural-net-intro-to-rnn-cb6ebc594677

General Idea

- Video – Sequence of frames with temporal connection
- Sequence data? (Use RNN)
- Give frames in temporal order, detect landmarks, feedback along with next frame.



Why Deep Learning?

- State-of-the-art in image processing tasks
- Operate directly on data
- Learn more generic features directly from data
- Domain knowledge is never obsolete

Datasets

- AFLW – Around 25k annotated face images. 21 points [AFLW]
- COFW – 1007 occluded face images. 29 points [COFW]
- Helen – 2000 training and 330 test images. 194 points [Helen]
- IBUG – 135 images with difficult poses and expressions. 68 points [IBUG]
- LFPW – 1432 images. 29 points [LFPW]
- LFW – 13233 images of 5749 people. 10 points [LFW]
- 300-W – 600 images in the wild. 68 points [300-W]
- 3D Menpo – 12k images, 280k video frames, with 2D and 3D landmarks. 84 points [3D-Menpo]
- FM – 2150 images of 6 videos. 68 points [FM]
- RWMB – 20 videos with motion blur. 68/98 points [RWMB]
- TF – 5000 frames of a person engaged in a conversation. 68 points [TF]
- 300-VW – 114 videos with 218,595 frames. 68 points [300-VW]

Approaches

- **RNN** [Jinwei Gu et al., 2017]
- **Two-stream network** [Hao Liu et al., 2017]
- **LSTM** [Qiqi Hou et al., 2017]
- **Encoder-Decoder network** [Xi Peng et al., 2018]
- **Deep reinforcement learning** [Minghao Guo et al., 2018]

Using RNNs [Jinwei Gu et al., 2017]

- **RNNs and Bayesian filters are operationally similar**

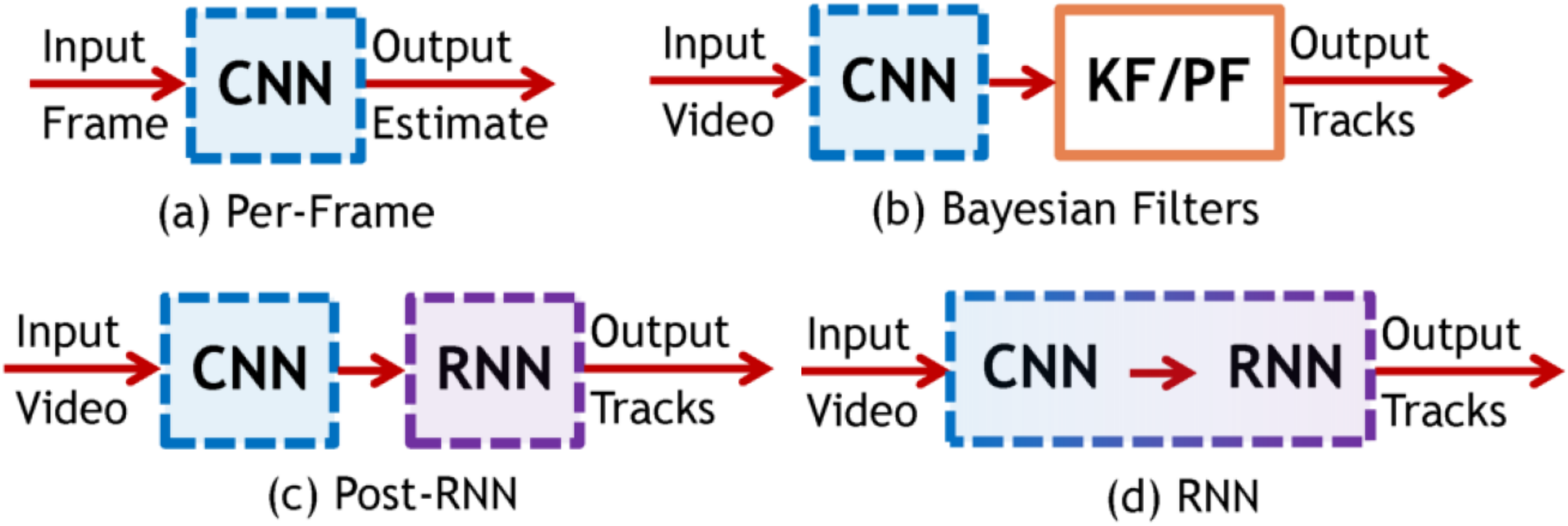
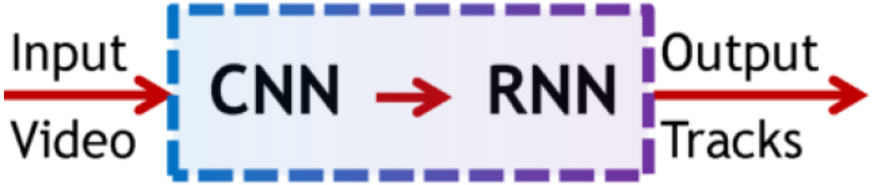


Image source: Jinwei Gu, Xiaodong Yang, Shalini De Mello, Jan Kautz: Dynamic Facial Analysis: From Bayesian Filtering to Recurrent Neural Network(2017).

Using RNNs [Jinwei Gu et al., 2017]



(d) RNN

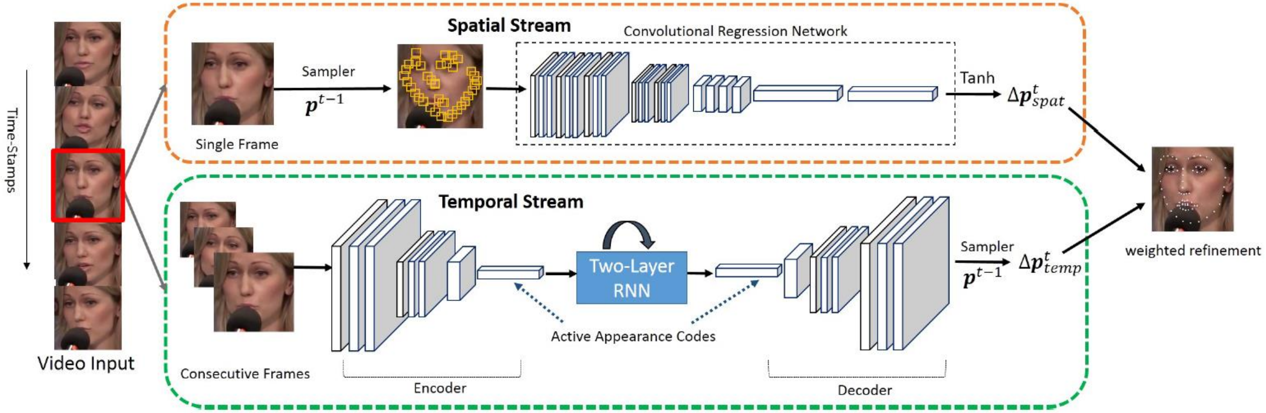
- FC-RNN is used to retain generalization of pre-trained CNN
- Trained end-to-end
- 300-VW dataset for facial landmark localization
- L2 loss function
- Evaluation - Area Under the Curve (AUC), Failure Rate (FR %)

Image source: Jinwei Gu, Xiaodong Yang, Shalini De Mello, Jan Kautz: Dynamic Facial Analysis: From Bayesian Filtering to Recurrent Neural Network(2017).

Two-stream network [Hao Liu et al., 2017]

- **Exploit both appearance information from still frames(spatial) and temporal information across frames(temporal)**
  - Spatial stream – Image pixels (still) -> landmark locations
  - Temporal stream – Compress video as active appearance codes

Two-stream network [Hao Liu et al., 2017]



- Spatial stream transforms local facial patches to shape residuals used to refine current face shape from previous.
- Temporal stream – Encoder-decoder network with 2-layer RNN. Capture facial dynamics in temporal dimension
- Final prediction is a weighted fusion of spatial and temporal streams shape updates

Image source: Hao Liu, Jiwen Lu, Jianjiang Feng, Jie Zhou: Two-Stream Transformer Networks for Video-based Face Alignment(2017).

Two-stream network [Hao Liu et al., 2017]

- Tested on 300-VW and TF datasets
- Evaluation – Normalized RMSE and Cumulative Error Distribution plots
- Weighted fusion – β_1 and β_2 = 0.5 yields the best performance

LSTMs [Qiqi Hou et al., 2017]

- **LSTM is used to exploit spatial and temporal information**

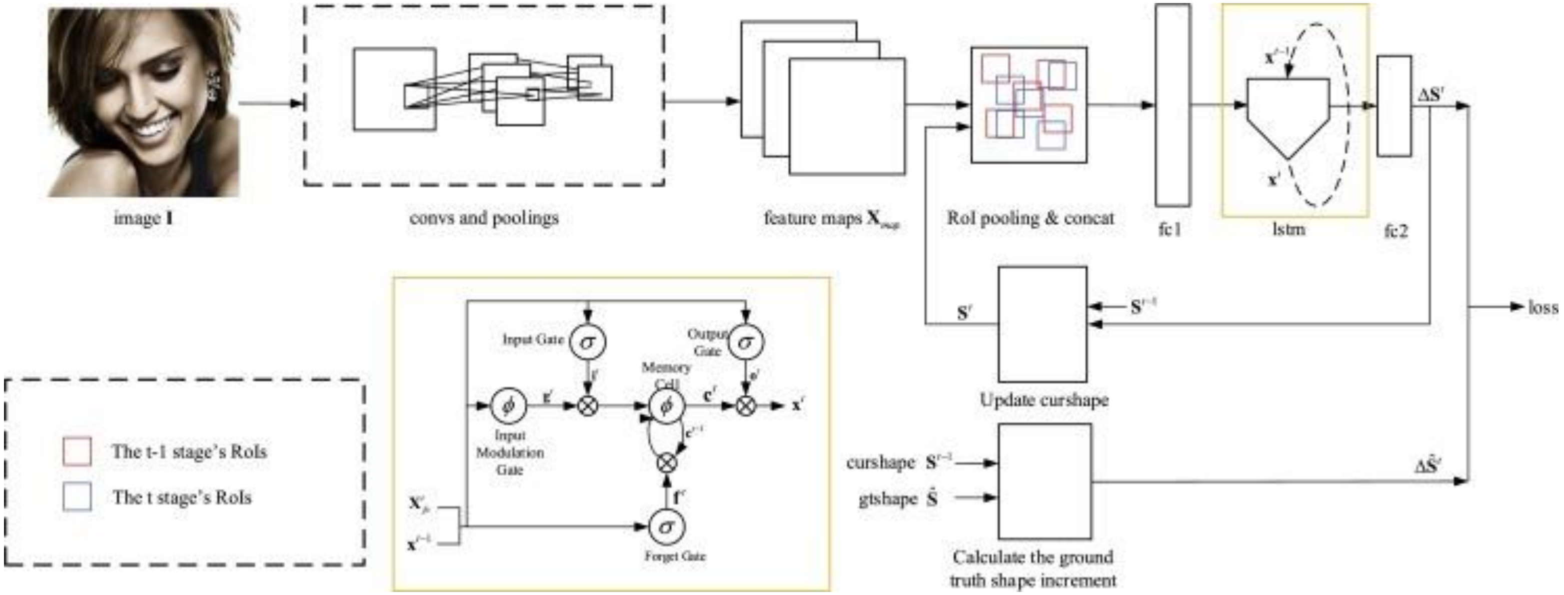
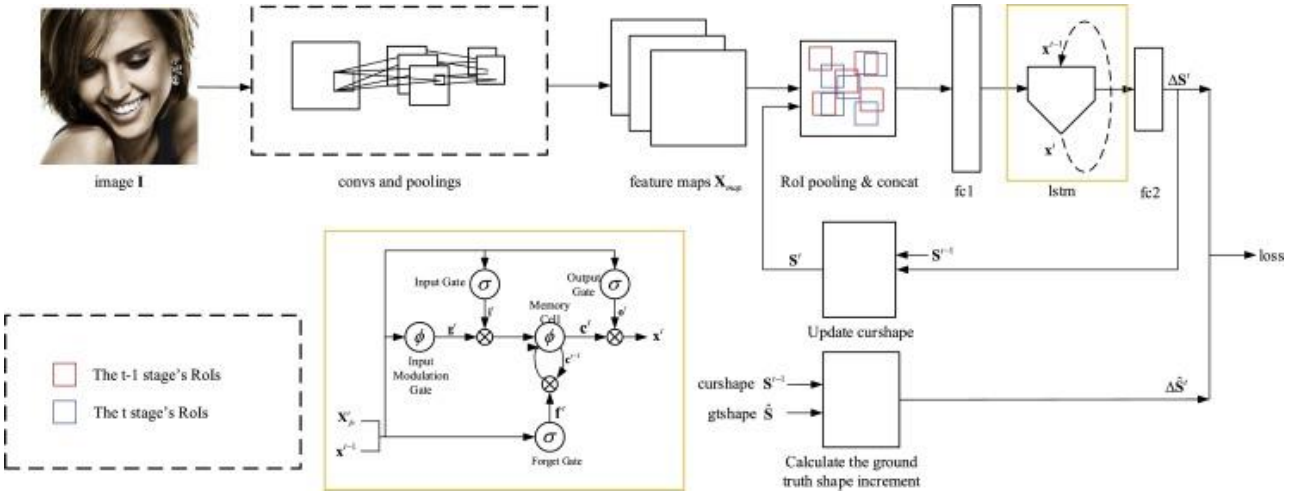


Image source: Qiqi Hou, Jinjun Wang, Ruibin Bai, Sanping Zhou, Yihong Gong: Face Alignment Recurrent Network(2017).

LSTMs [Qiqi Hou et al., 2017]



- Input – Image and Initial face shape
- Output – Predicted shape increment for the initial face shape
- Input -> several conv + max pooling -> ROI pooling for initial face shape -> concat -> FC layer -> LSTM -> predicted shape increment
- Update initial shape according to predicted shape increment

Image source: Qiqi Hou, Jinjun Wang, Ruibin Bai, Sanping Zhou, Yihong Gong: Face Alignment Recurrent Network(2017).

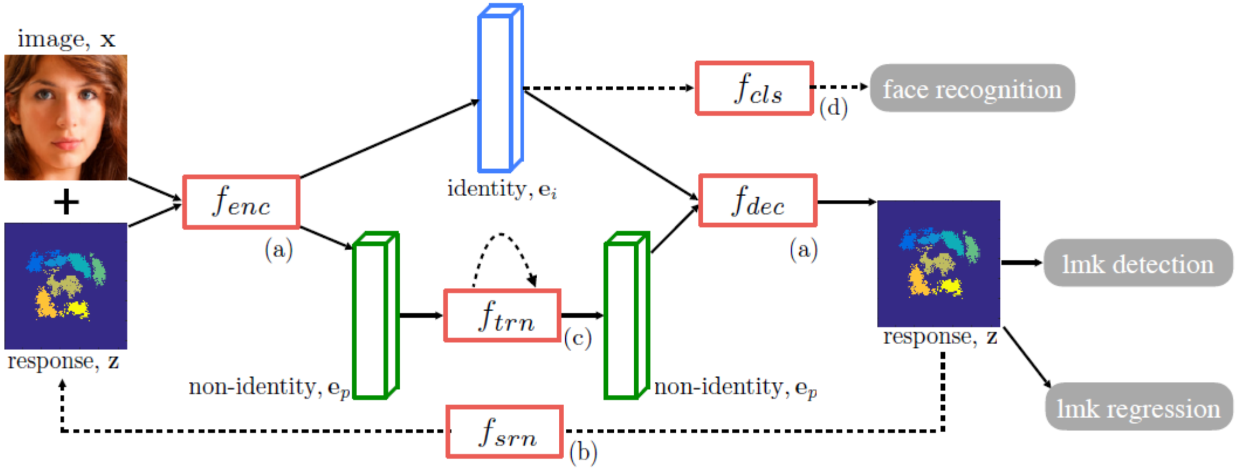
LSTMs [Qiqi Hou et al., 2017]

- **Landmark detection method**
- **Trained on COFW, LFPW, Helen, AFW**
- **Evaluated on – COFW, Helen, 300-W, 300-VW**
- **Evaluation – Point-to-point RMSE**
- **Runtime – 18ms**

Encoder-Decoder Network [Xi Peng et al., 2018]

- **Encoder – Image pixels -> Low dimensional feature space**
- **Decoder – Features in low dimensional space -> facial landmark heatmaps**
- **Feedback loop between the output(facial points) and the input**

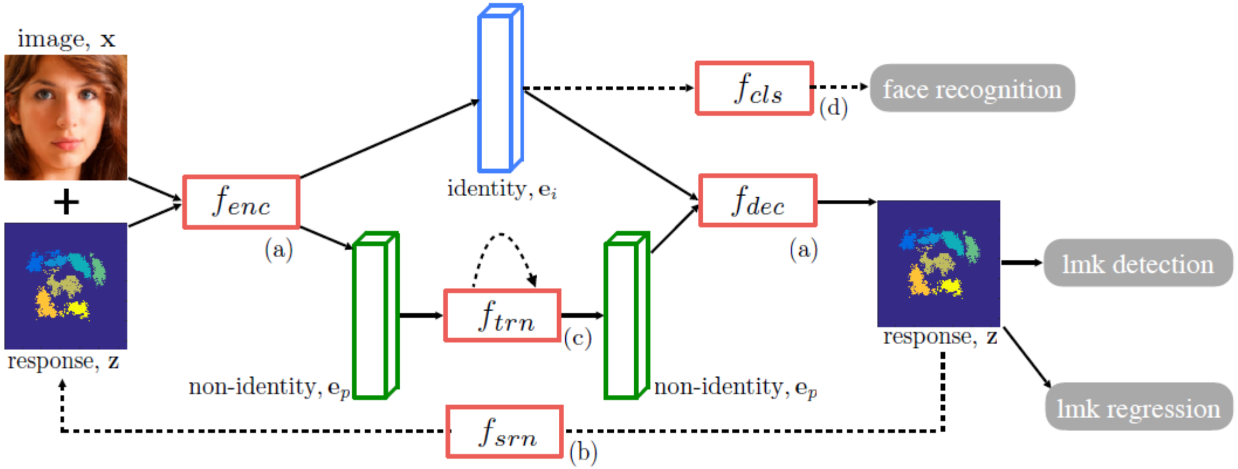
Encoder-Decoder Network [Xi Peng et al., 2018]



- Encoder -> Feature disentangling on low dimensional representation -> Decoder
- Disentangle temporal-variant and temporal-invariant factors
- Temporal-invariant: Person identity
- Temporal-variant: Pose, expression, illumination

Image source: Xi Peng, Rogerio S. Feris, Xiaoyu Wang, Dimitris N. Metaxas: RED-Net: A Recurrent Encoder-Decoder Network for Video-based Face Alignment(2018).

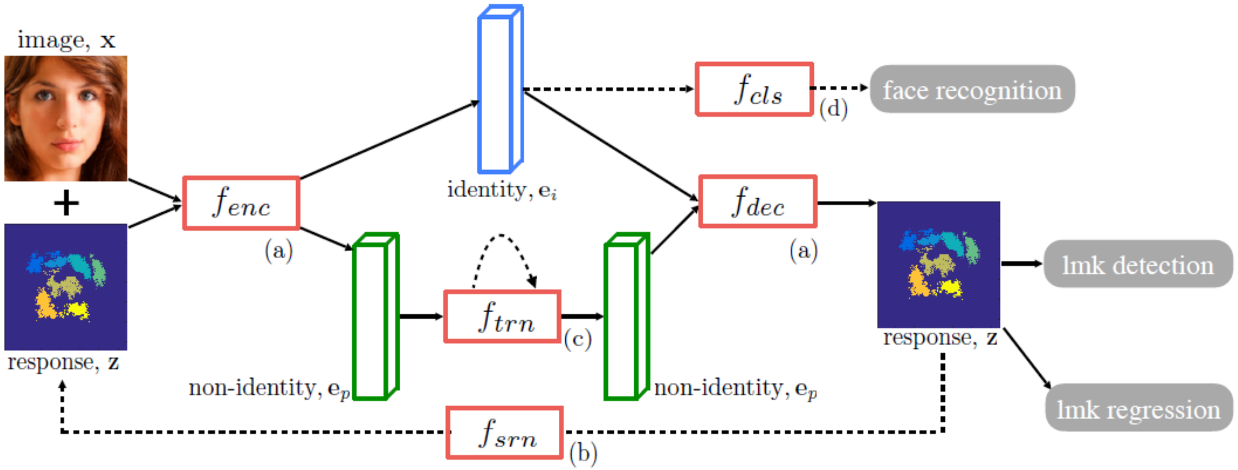
Encoder-Decoder Network [Xi Peng et al., 2018]



- Spatial recurrent learning: Coarse-to-fine landmark search
- Feedback loop: Previous prediction + image
- Landmark detection: Detect major landmarks
- Landmark regression: Refine predicted locations from previous detection step

Image source: Xi Peng, Rogerio S. Feris, Xiaoyu Wang, Dimitris N. Metaxas: RED-Net: A Recurrent Encoder-Decoder Network for Video-based Face Alignment(2018).

Encoder-Decoder Network [Xi Peng et al., 2018]



- **Temporal recurrent learning: Model non-identity factors (temporal-variant) using LSTM**

Image source: Xi Peng, Rogerio S. Feris, Xiaoyu Wang, Dimitris N. Metaxas: RED-Net: A Recurrent Encoder-Decoder Network for Video-based Face Alignment(2018).

Encoder-Decoder Network [Xi Peng et al., 2018]

- **Evaluated on – AFLW, LFW, Helen, LFPW, TF, FM, 300-VW**
- **Evaluation – Inter-ocular distance normalized RMSE**

Reinforcement Learning [Minghao Guo et al., 2018]

- **Bounding box generation and facial landmark detection are heavily dependent**
- **Two agents – bounding box Tracking and facial landmark Alignment**

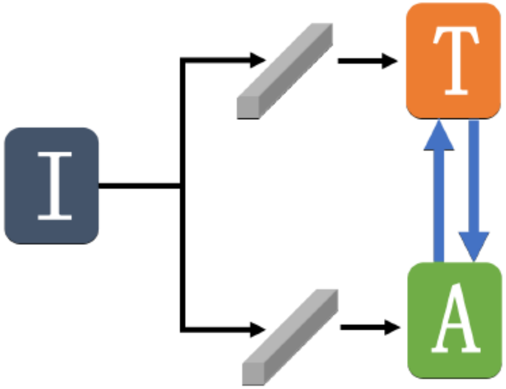
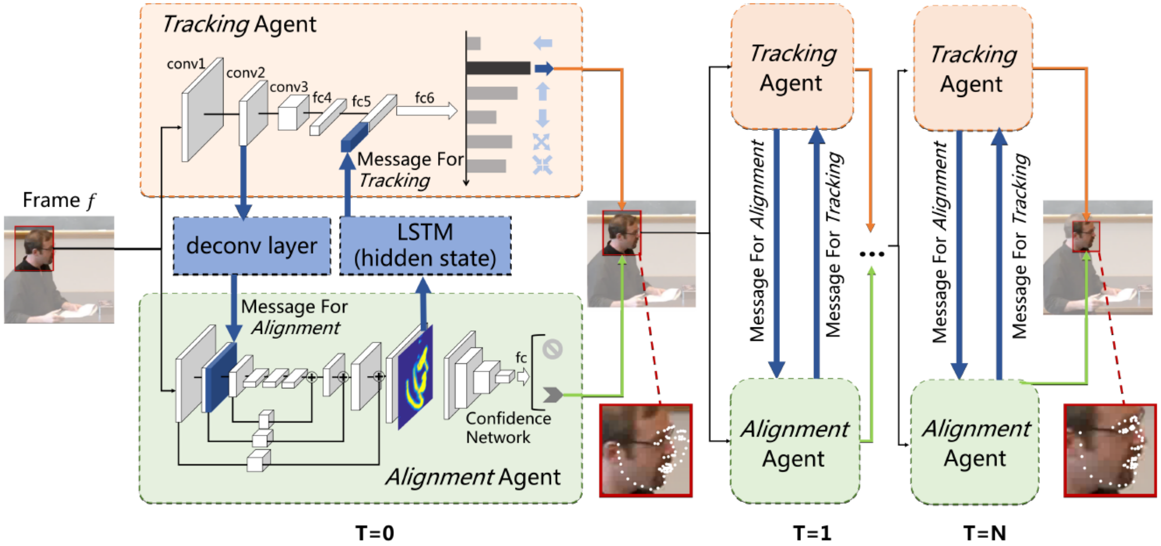


Image source: Minghao Guo, Jiwen Lu, and Jie Zhou: Dual-Agent Deep Reinforcement Learning for Deformable Face Tracking(2018).

Reinforcement Learning [Minghao Guo et al., 2018]

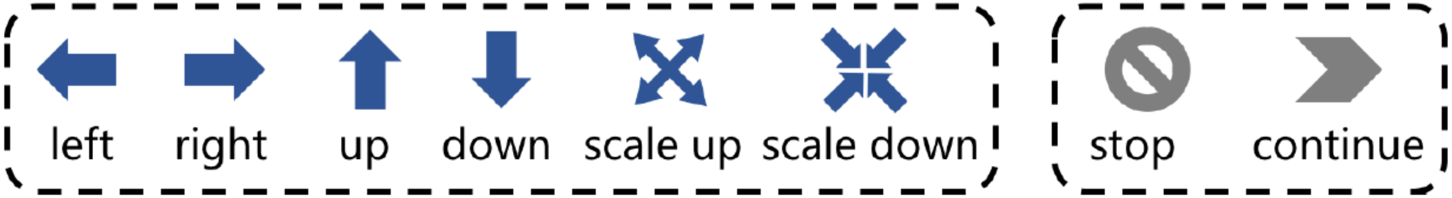


- **Communication channels between agents (Deep Q-learning)**
- **Current state initialized to terminal state of previous frame**
- **Agents decide sequence of actions based on observed state and received messages**

Image source: Minghao Guo, Jiwen Lu, and Jie Zhou: Dual-Agent Deep Reinforcement Learning for Deformable Face Tracking(2018).

Reinforcement Learning [Minghao Guo et al., 2018]

- Go to next frame when landmarks are finalized
- State – Current image region extracted by bounding box
- Action – Tracking agent(Movement), Alignment agent(stop/continue iterations)



- Reward – Landmark detection accuracy improvements

Image source: Minghao Guo, Jiwen Lu, and Jie Zhou: Dual-Agent Deep Reinforcement Learning for Deformable Face Tracking(2018).

Reinforcement Learning [Minghao Guo et al., 2018]

- Evaluated on Category 3 of 300-VW
- Supervised learning stage –
  - Alignment agent trained on 300-W
  - Tracking agent trained on 300-VW
- Reinforcement learning stage –
  - Whole network trained on 300-VW
- Evaluation – Normalized RMSE and cumulative error distribution plots
- DADRL-3D – Trained with 3D data from 3D Menpo. 3D landmarks.

Comparison

Approach	Evaluated on dataset	Evaluation metrics
RNN	300-VW	RMSE, AUC, FR
Two-stream network	TF, 300-VW	RMSE, CED plot
LSTM	COFW, Helen, 300-W, 300-VW	RMSE
Encoder-decoder network	TF, 300-VW, FM	RMSE
Reinforcement Learning	300-VW	RMSE and CED plot

$$RMSE_i = \frac{1}{Pd_i}\sum_{p=1}^{P}\sqrt{(x_{i,p}-\hat{x}_{i,p})^2+(y_{i,p}-\hat{y}_{k,p})^2}$$

Comparison

Approach	300-VW		TF		
	RMSE (68 landmarks)	RMSE (7 landmarks)	RMSE (68 landmarks)	RMSE (7 landmarks)	Runtime (ms)
RNN	6.16				
Two-stream network	5.59			**2.13**	33
LSTM	5.9				**18**
Encoder-decoder network	5.15	**5.29**	**2.77**	2.89	40
Reinforcement Learning	**3.09**				

Conclusion

- **RNN based approach**
  - FC-RNN to model temporal information.
- **Two-stream network**
  - Spatial and temporal streams
  - Least error on TF dataset for 7 landmarks
- **LSTM approach**
  - LSTM to model temporal information
  - Performs in real-time – 18ms
- **Encoder-Decoder approach**
  - Separate temporal-variant and temporal-invariant factors.
- **Reinforcement Learning approach**
  - Bounding box tracking ↔ Facial alignment.
  - Least error on the category-3 of 300-VW

References

Jinwei Gu, Xiaodong Yang, Shalini De Mello, Jan Kautz: Dynamic Facial Analysis: From Bayesian Filtering to Recurrent Neural Network(2017).

Hao Liu, Jiwen Lu, Jianjiang Feng, Jie Zhou: Two-Stream Transformer Networks for Video-based Face Alignment(2017).

Qiqi Hou, Jinjun Wang, Ruibin Bai, Sanping Zhou, Yihong Gong: Face Alignment Recurrent Network(2017).

Xi Peng, Rogerio S. Feris, Xiaoyu Wang, Dimitris N. Metaxas: RED-Net: A Recurrent Encoder-Decoder Network for Video-based Face Alignment(2018).

Minghao Guo, Jiwen Lu, and Jie Zhou: Dual-Agent Deep Reinforcement Learning for Deformable Face Tracking(2018).

References

[TF], Fgnet: Talking face video. Tech. rep., 2004.

[LFW], Gary Huang, Marwan Mattar, Tamara Berg, and Eric Learned-Miller. Labeled faces in the wild: A database for studying face recognition in unconstrained environments. Tech. rep., 10 2008.

[AFLW], Martin Ko▯stinger, Paul Wohlhart, Peter M. Roth, and Horst Bischof. Annotated facial landmarks in the wild: A large-scale, real-world database for facial landmark localization(2011)

[Helen], Vuong Le, Jonathan Brandt, Zhe Lin, Lubomir Bourdev, and Thomas S Huang. Interactive facial feature localization. In European conference on computer vision(2012)

[COFW], X. P. Burgos-Artizzu, P. Perona, and P. Dollar. Robust face landmark estimation under occlusion(2013)

References

[LFPW], Peter Belhumeur, David Jacobs, David Kriegman, and Neeraj Kumar. Localizing parts of faces using a consensus of exemplars. IEEE transactions on pattern analysis and machine intelligence(2013)

[FM], Xi Peng, Shaoting Zhang, Yu Yang, and Dimitris N Metaxas. Piefa: Personalized incremental and ensemble face alignment(2015)

[300-VW], Jie Shen, Stefanos Zafeiriou, Grigoris G Chrysos, Jean Kossai, Georgios Tzimiropoulos, and Maja Pantic. The rst facial landmark tracking in-the-wild challenge: Benchmark and results(2015)

[IBUG], [300-W], Christos Sagonas a, Epameinondas Antonakosa, Georgios Tzimiropoulosb, Stefanos Zafeirioua, and Maja Pantic. 300 faces in-the-wild challenge: database and results, 2016.

[3D-Menpo], Stefanos Zafeiriou, Grigorios G Chrysos, Anastasios Roussos, Evangelos Ververas, Jiankang Deng, andGeorge Trigeorgis. The 3d menpo facial landmark tracking challenge(2017)

References

[RWMB], Keqiang Sun, Wayne Wu, Tinghao Liu, Shuo Yang, Quan Wang, Qiang Zhou, Zuochang Ye, and Chen Qian. Fab: A robust facial landmark detection framework for motion-blurred videos(2019)

THANK YOU

QUESTIONS?