

2D Image Processing & Augmented Reality

Winter Semester 2019/2020

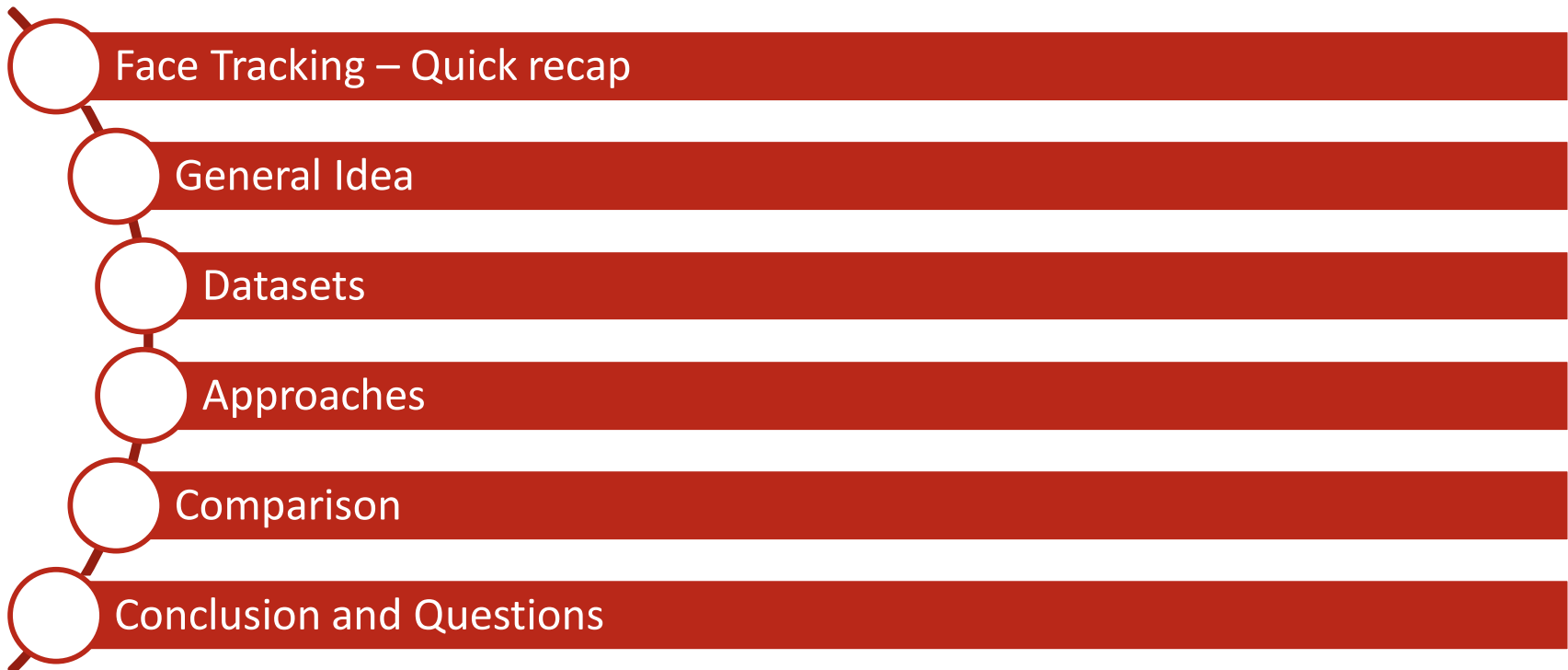
Survey on Face Tracking with Deep Learning

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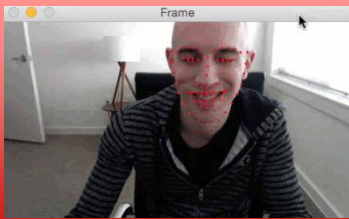
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Outline



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.

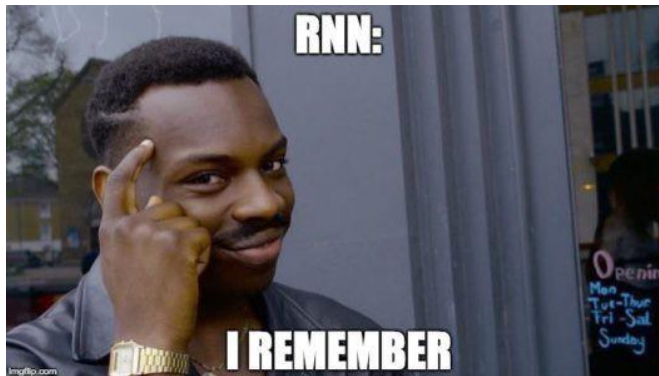


Challenges - Videos can be captured in unconstrained
conditions.

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

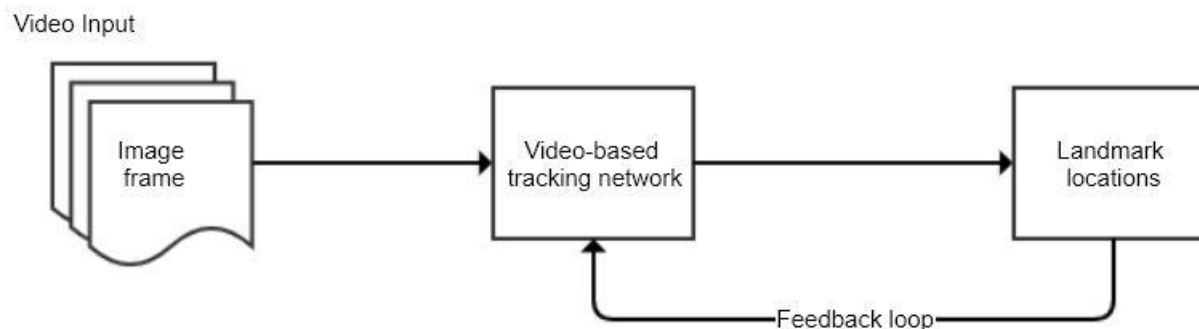
General Idea

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



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**
- **Computational efficiency**
- **Domain knowledge is never obsolete**

Datasets

- AFLW
- COFW
- Helen
- IBUG
- LFPW
- LFW
- 3D Menpo
- 300-W
- BIWI
- FM
- RWMB
- SynHead
- TF
- 300-VW

Approaches

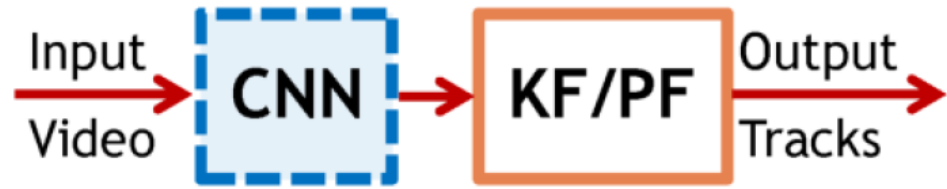
- RNN
- Two-stream network
- LSTM
- Encoder-Decoder network
- Deep reinforcement learning

Using RNNs

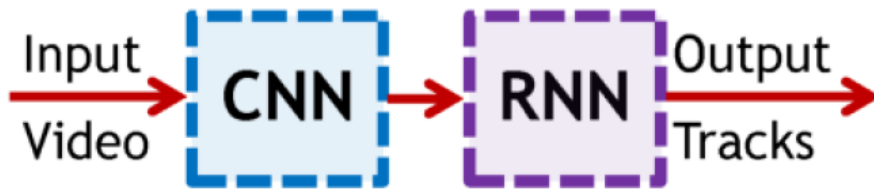
- RNNs and Bayesian filters are operationally similar



(a) Per-Frame



(b) Bayesian Filters

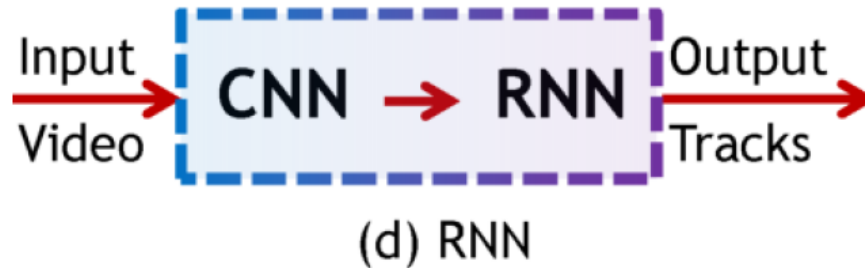


(c) Post-RNN



(d) RNN

Using RNNs

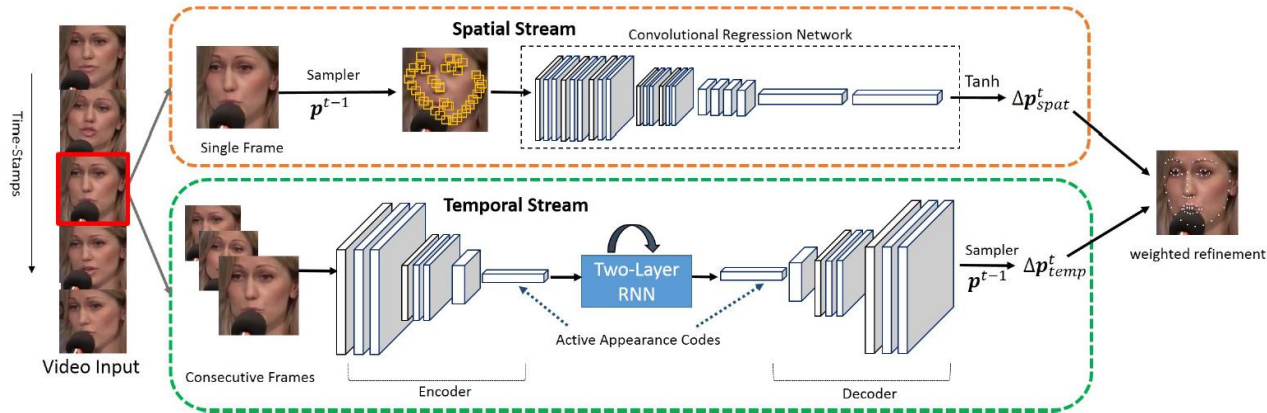


- FC-RNN is used to retain generalization of pre-trained CNN
- Trained end-to-end
- **SynHead** dataset for head pose estimation
- **300-VW** dataset for facial landmark localization
- L2 loss function
- Evaluation - Area Under the Curve (AUC), Failure Rate (FR %)

Two-stream network

- 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



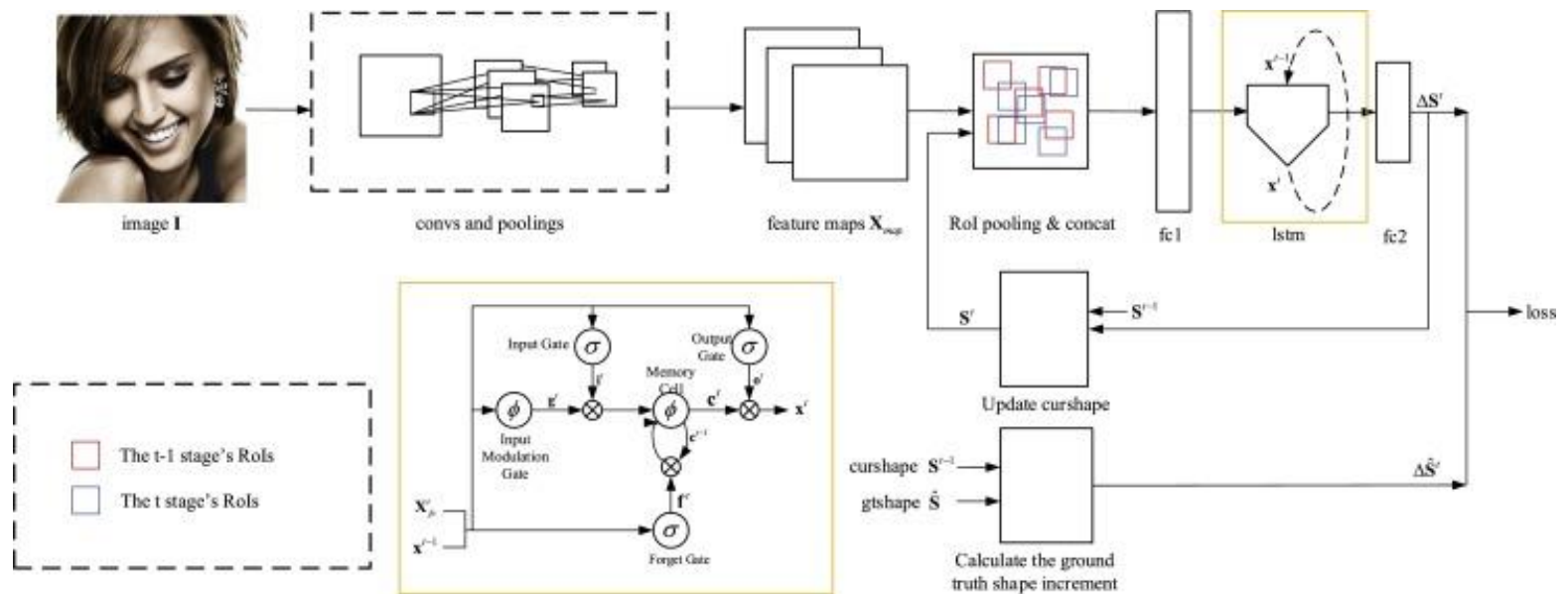
- Spatial stream transforms local facial patches to shape residuals used to refine current face shape from previous.
- Temporal stream – Encoder-decoder network with 2-layer RNN. Capture facial dynamics in temporal dimension
- Final prediction is a weighted fusion of spatial and temporal streams shape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

Two-stream network

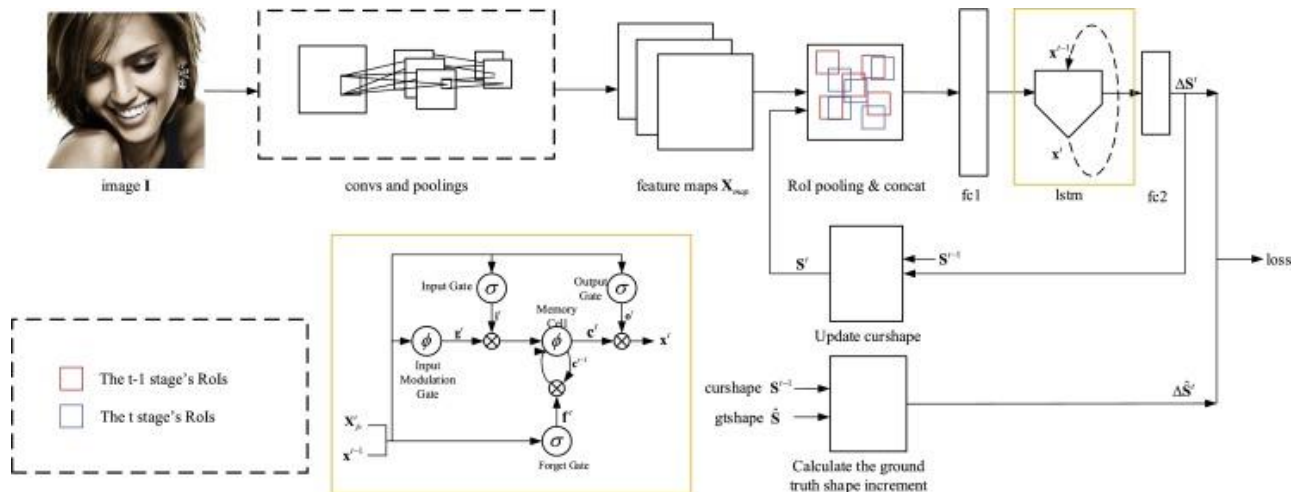
- Tested on **300-VW** and **TF** datasets
- Evaluation – Normalized RMSE and Cumulative Error Distribution plots
- Weighted fusion – β_1 and $\beta_2 = 0.5$ yields the best performance

LSTMs

- LSTM is used to exploit spatial and temporal information



LSTMs



- 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

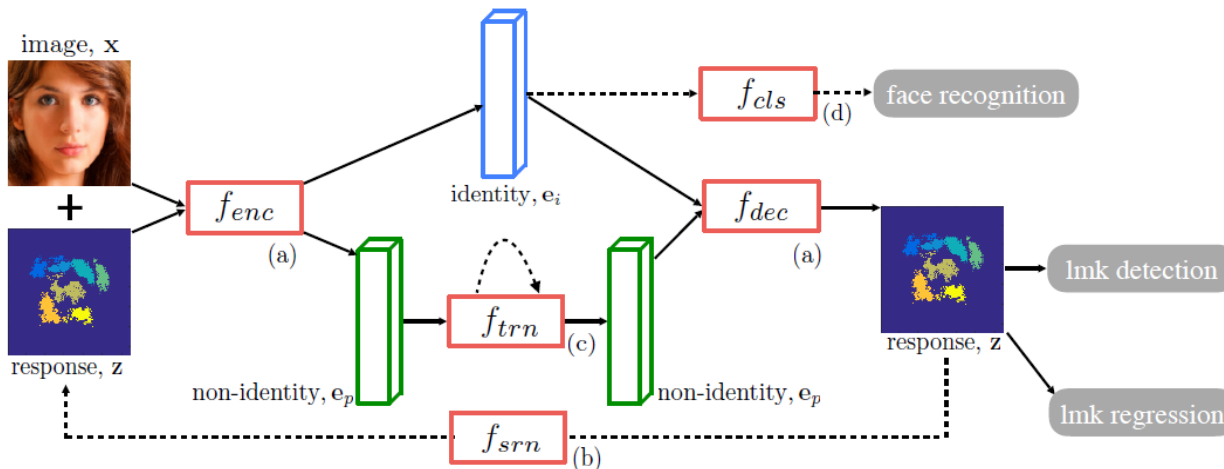
LSTMs

- 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

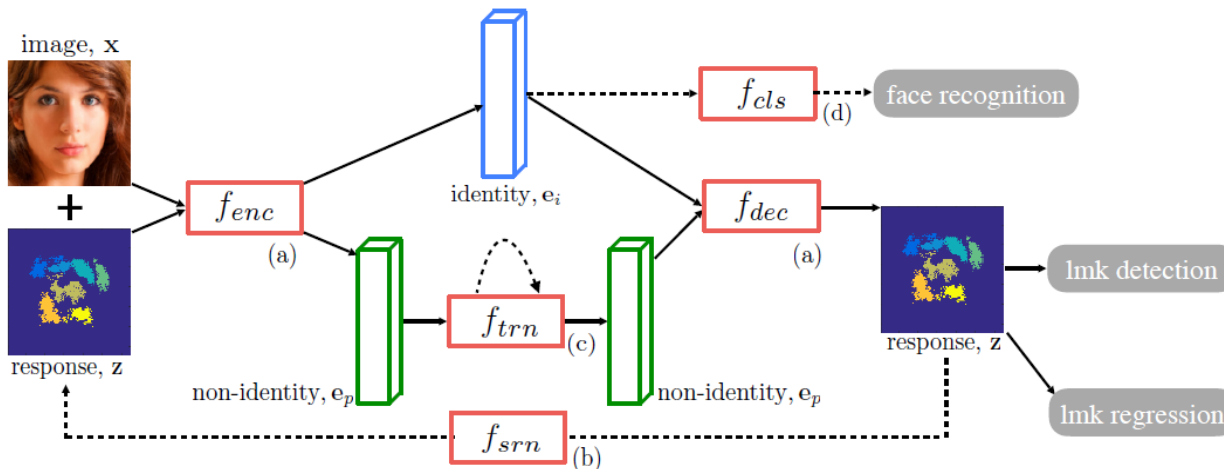
- **Encoder – Image pixels -> Low dimensional feature space**
- **Decoder – Features in low dimensional space -> facial landmark heatmaps**
- **Feedback loop between the output(facial points) and the input**

Encoder-Decoder Network



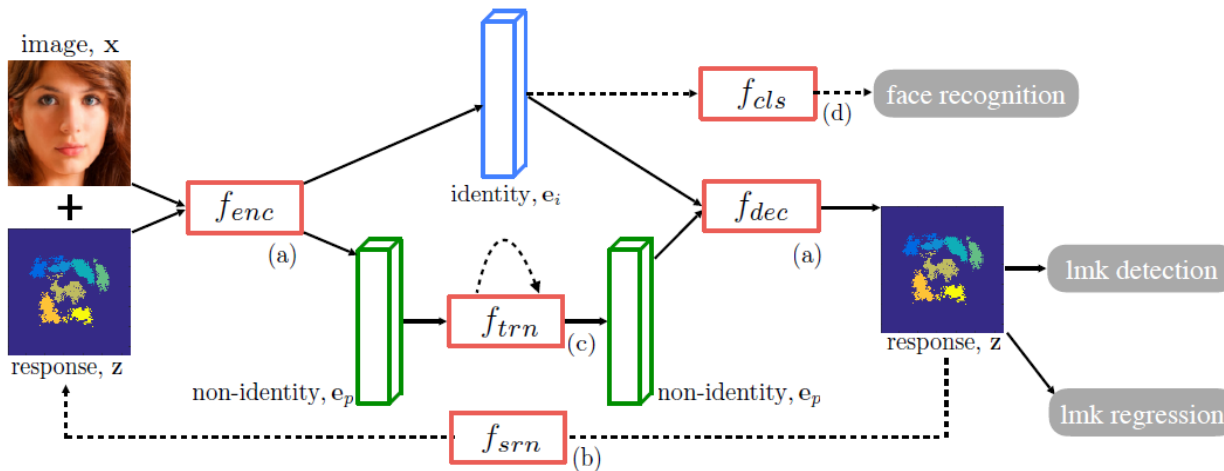
- Encoder -> Feature disentangling on low dimensional representation -> Decoder
- Disentangle temporal-variant and temporal-invariant factors
- Temporal-invariant: Person identity
- Temporal-variant: Pose, expression, illumination

Encoder-Decoder Network



- **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**

Encoder-Decoder Network



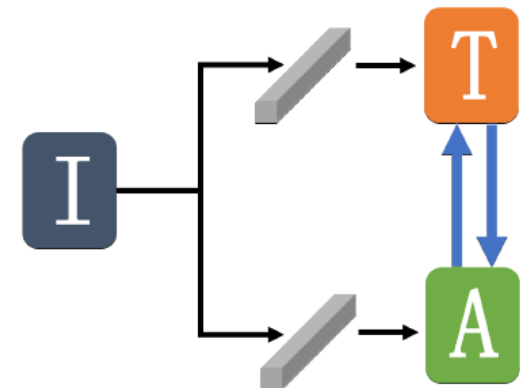
- Temporal recurrent learning: Model non-identity factors (temporal-variant) using LSTM

Encoder-Decoder Network

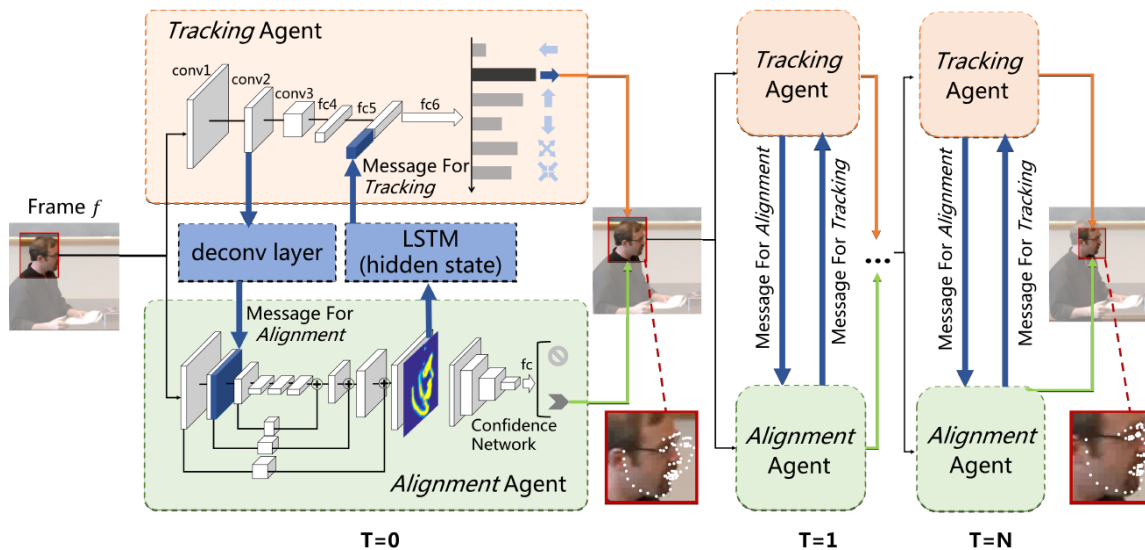
- Evaluated on – **AFLW**, **LFW**, **Helen**, **LFPW**, **TF**, **FM**, **300-VW**
- Evaluation – Inter-ocular distance normalized RMSE

Reinforcement Learning

- Bounding box generation and facial landmark detection are heavily dependent
- Two agents – bounding box **T**racking and facial landmark **A**lignment



Reinforcement Learning



- 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

Reinforcement Learning

- 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

Reinforcement Learning

- 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
Dynamic Facial Analysis using RNN	300-VW	RMSE, AUC, FR
Two stream transformer network	TF, 300-VW	RMSE, CED plot
Face alignment recurrent network	COFW, Helen, 300-W, 300-VW	RMSE
Recurrent encoder-decoder network	TF, 300-VW, FM	RMSE
Dual agent deep reinforcement learning	300-VW	RMSE and CED plot

Comparison

Approach	300-VW		TF		Runtime(ms)
	RMSE(68 landmarks)	RMSE(7 landmarks)	RMSE(68 landmarks)	RMSE(7 landmarks)	
Dynamic Facial Analysis using RNN	6.16				
Two stream transformer network	5.59			2.13	33
Face alignment recurrent network	5.9				18
Recurrent encoder-decoder network	5.15	5.29	2.77	2.89	40
Dual agent deep reinforcement learning	3.09				

References

1. Jinwei Gu, Xiaodong Yang, Shalini De Mello, Jan Kautz: Dynamic Facial Analysis: From Bayesian Filtering to Recurrent Neural Network(2017).
2. Hao Liu, Jiwen Lu, Jianjiang Feng, Jie Zhou: Two-Stream Transformer Networks for Video-based Face Alignment(2017).
3. Qiqi Hou, Jinjun Wang, Ruibin Bai, Sanping Zhou, Yihong Gong: Face Alignment Recurrent Network(2017).
4. Xi Peng, Rogerio S. Feris, Xiaoyu Wang, Dimitris N. Metaxas: RED-Net: A Recurrent Encoder-Decoder Network for Video-based Face Alignment(2017).
5. Minghao Guo, Jiwen Lu, and Jie Zhou: Dual-Agent Deep Reinforcement Learning for Deformable Face Tracking(2018).

THANK YOU

QUESTIONS?