



Smart Mobile Platform

Lyapunov Optimization for Time-Varying Queueing Systems

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Problem Solving for **Utility Maximization**

- Linear Programming
- Convex Programming
 - . .

No Consideration on Time

What if our optimal solution introduces **delays**?

- Harmful for real-time mobile systems
- <u>Tradeoff</u> between <u>utility</u> and <u>delay</u>



Time Modeling

- Time Modeling w/ Queue
- Lyapunov Drift
 Formulation w/ the
 Queue Values



step 2

Time-Average Optimization

Under Queue Stability







Queuebased Model



Tradeoff

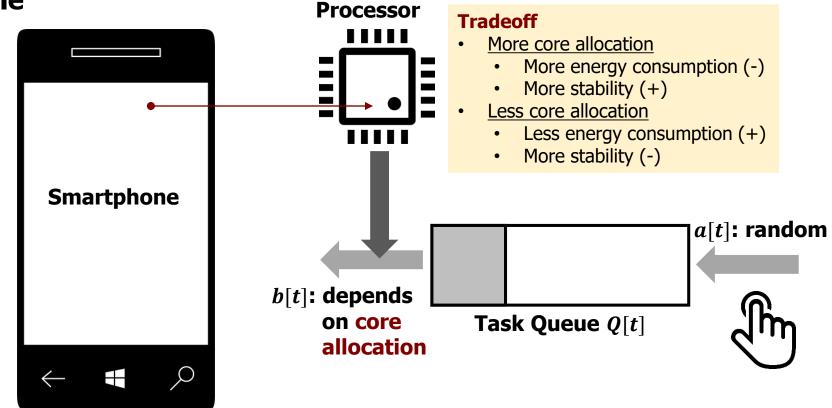




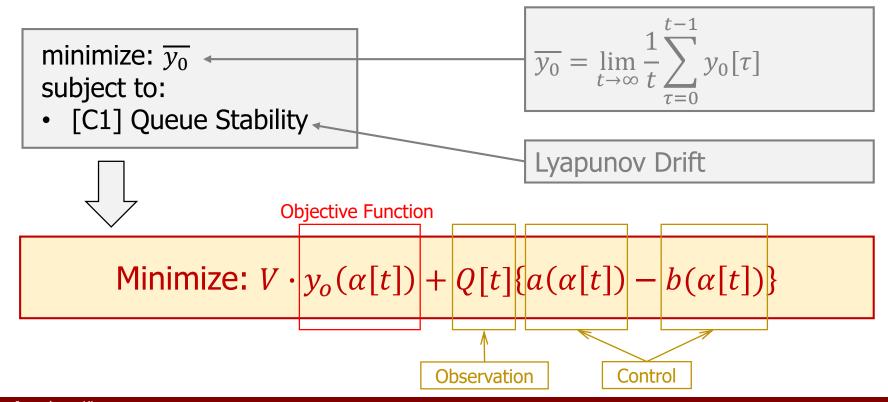
- Energy
- Quality
- PSNR
- Accuracy
- •



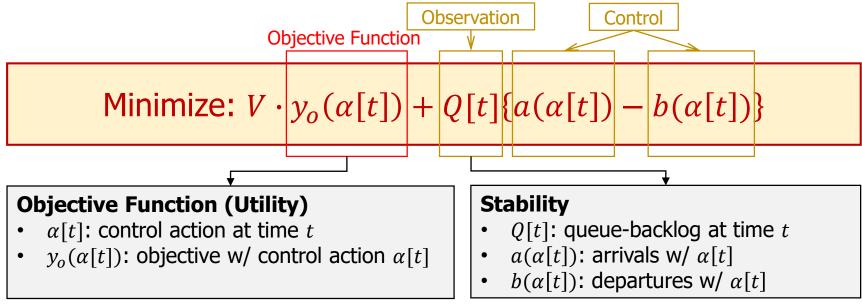
Example



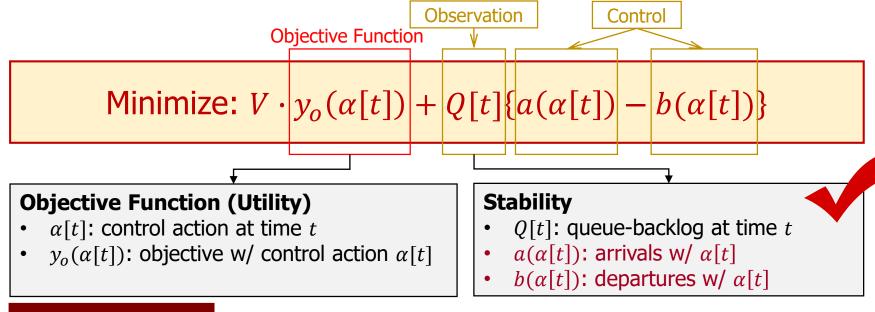










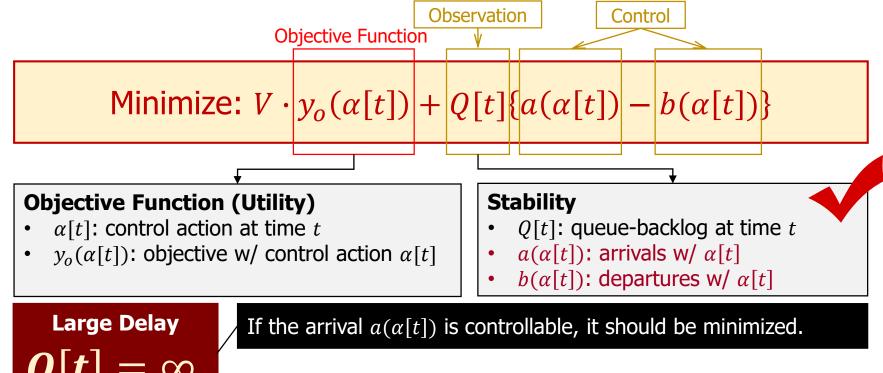


Large Delay

$$Q|t|=\infty$$

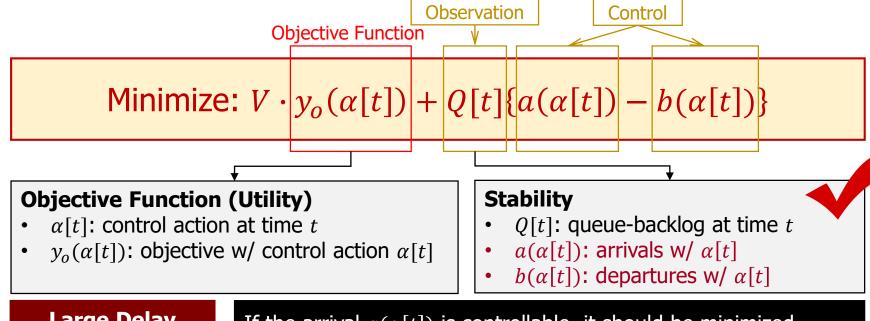


Time-Average Optimization subject to Queue Stability





Time-Average Optimization subject to Queue Stability



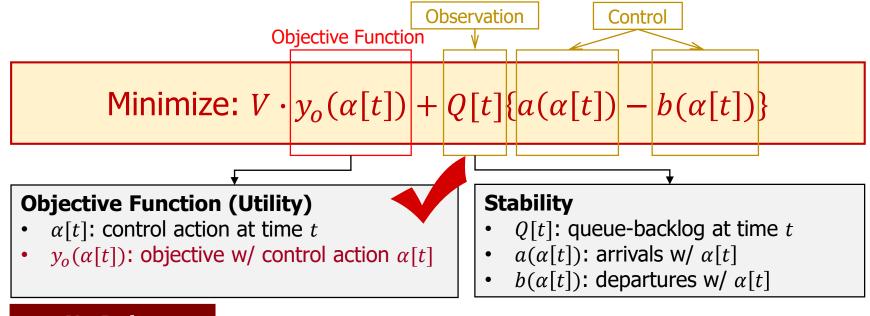
Large Delay



If the arrival $a(\alpha[t])$ is controllable, it should be minimized.

If the departures $b(\alpha[t])$ is controllable, it should be maximized.

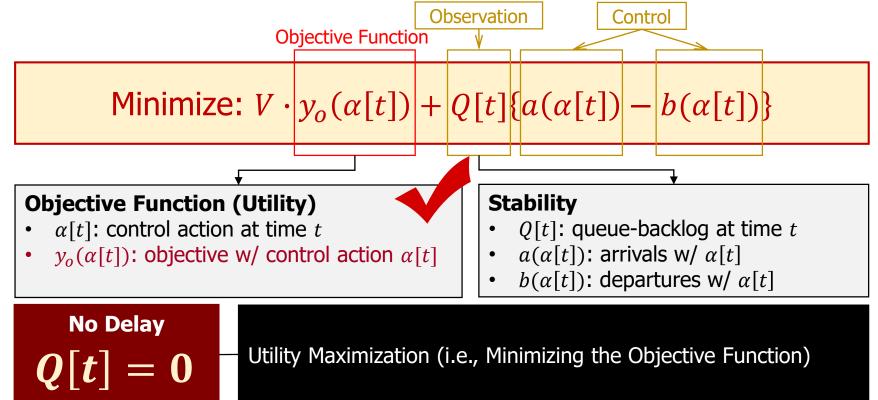




No Delay

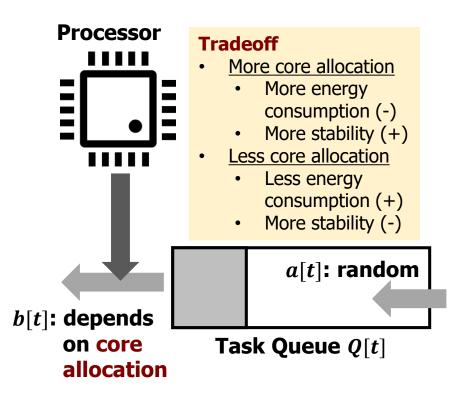
$$Q[t] = 0$$

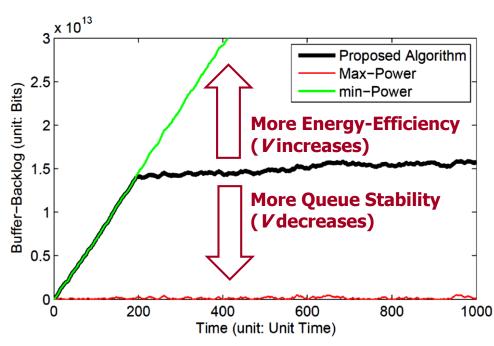






Research #1 (Core Allocation)

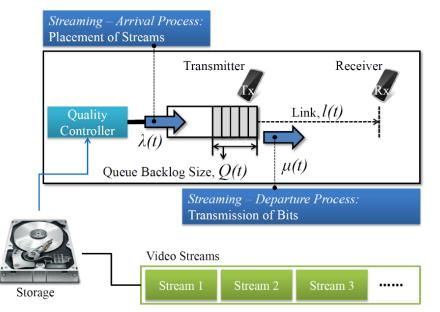






Research #2 (Adaptive Wireless Video Streaming)

Maximization of Time-Average Video Quality subject to Queue Stability



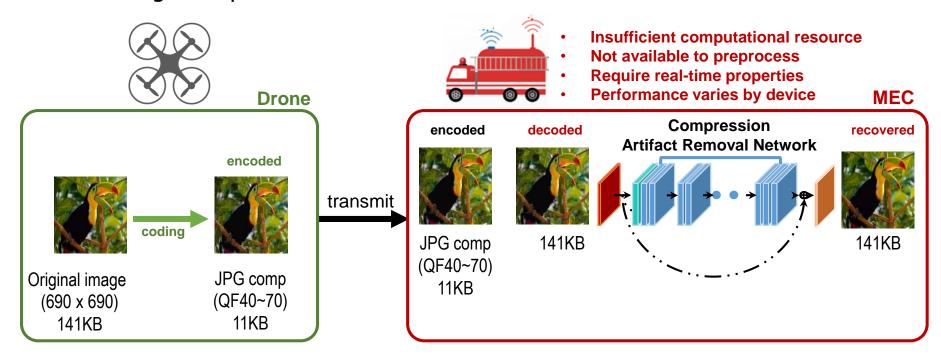
Tradeoff

- High compression on chunks
 - Low quality on chunks (-);
 - More stabilization on queues (+)
- Less compression on chunks
 - High quality on chunks (+);
 - Less stabilization on queues (-)

<u>J. Kim</u>, G. Caire, and A.F. Molisch, "Quality-Aware Streaming and Scheduling for Device-to-Device Video Delivery," <u>IEEE/ACM Transactions on Networking</u>, 24(4):2319-2331, August 2016.



JPEG image compression to reduce transmission overhead

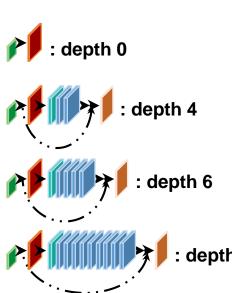




Research #3 (Depth-Adaptive Deep Super-Resolution Network)

Shallow faster lower performance

• Tradeoff between speed and performance over depth



Officiallow, faster, fe	D CC	Beeper, Stower, migner performance						
Depth	0	4	6	8	11	14	17	20
PSRN (dB)	30.4	32.56	33.01	33.229	33.379	33.435	33.495	33.523
00114	0.0000	0.04	0.040	0.040	0.00	0.00	0.004	0.000

- Op	•	_	•	•	''	'T		20
PSRN (dB)	30.4	32.56	33.01	33.229	33.379	33.435	33.495	33.523
SSIM	0.8682	0.91	0.916	0.918	0.92	0.92	0.921	0.922
Processing time (CPU)	0.002	0.321	0.5468	0.7725	0.994	1.317	1.622	1.96
Processing time (GPU)	0.001	0.01	0.012	0.0152	0.0189	0.0224	0.0262	0.0305
# of parameters	0	75K	148K	222K	333K	444K	555K	665K
	_		_		_	_		

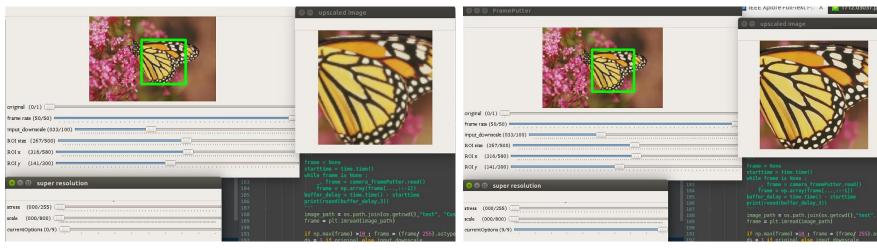
(processing time have measured on butterfly, 512 x 768)

Deener slower higher performance



Research #3 (Depth-Adaptive Deep Super-Resolution Network)

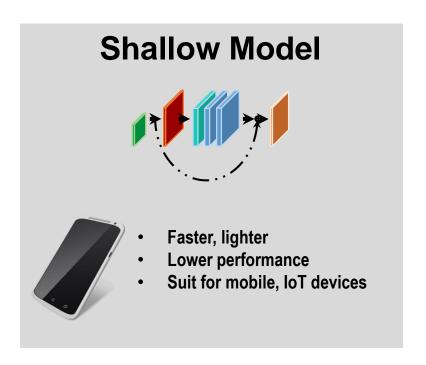
Super-resolution task

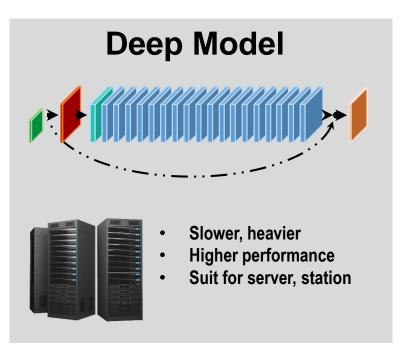


Depth 0 Depth 20



- Research #3 (Depth-Adaptive Deep Super-Resolution Network)
 - Model selection

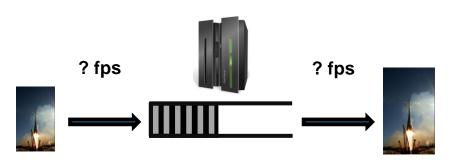






Research #3 (Depth-Adaptive Deep Super-Resolution Network)

Dynamic model adaptation



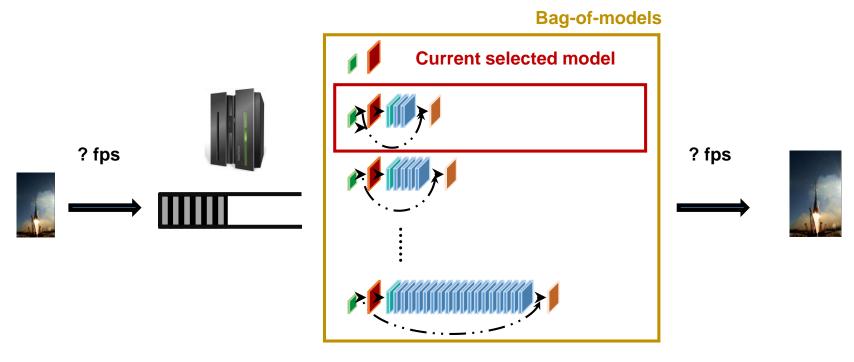
- Input rate (or image size) is unfixed.
- Required resolution of image is changed.
- Performance of system fluctuates frequently during running time.



 Service provide do not have any information about clients.

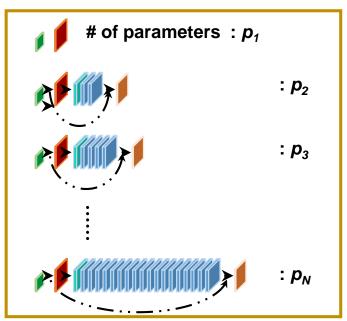


Adaptation with bag-of-models





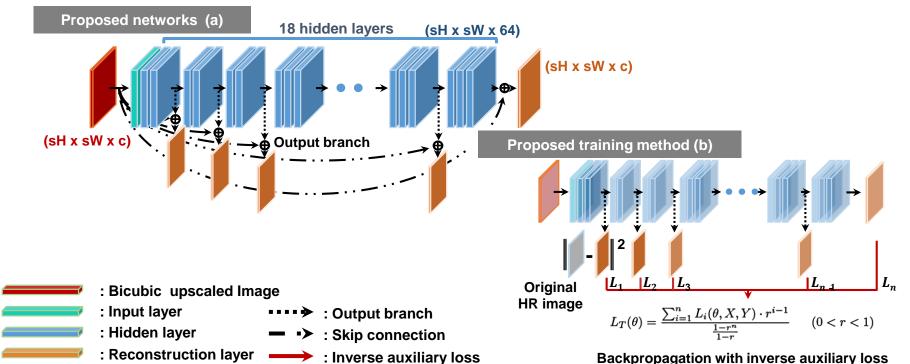
- Limitation to the adaptation with bag-of-models
 - Additional memory is required in proportion to the number of models.
 - Model switching may cause computational overhead.



Bag of models **Unload previous model** model switching Load next model



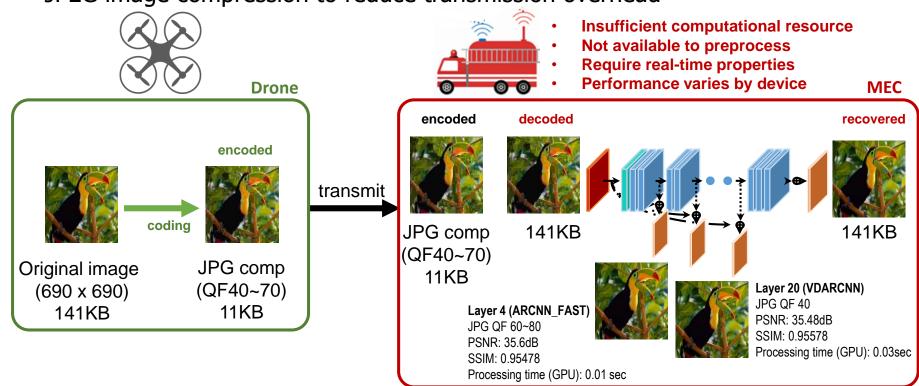
Overall architecture of the proposed SR network





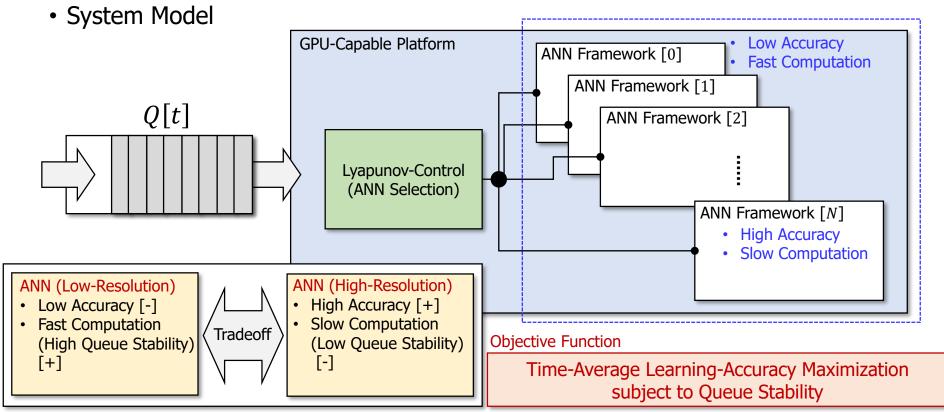
Research #3 (Depth-Adaptive Deep Super-Resolution Network)

JPEG image compression to reduce transmission overhead





Research #4 (Stabilized Computer Vision Platform)





Research #4 (Stabilized Computer Vision Platform)

Maximization of Time-Average Learning-Accuracy subject to Queue Stability

$$\alpha^*[t] \leftarrow \underset{\alpha[t] \in A}{arg \max}[V \cdot Accuracy(\alpha[t]) - Q[t] \{ \underbrace{a(\alpha[t])}_{\substack{\text{Not} \\ \text{Controllable}}} - b(\alpha[t]) \}]$$

$$\bigcirc$$

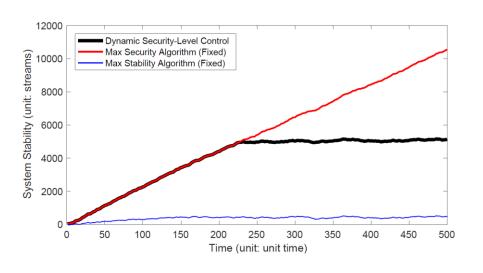
$$\alpha^*[t] \leftarrow \underset{\alpha[t] \in A}{arg\max} \{V \cdot Accuracy(\alpha[t]) + Q[t]b(\alpha[t])\}$$

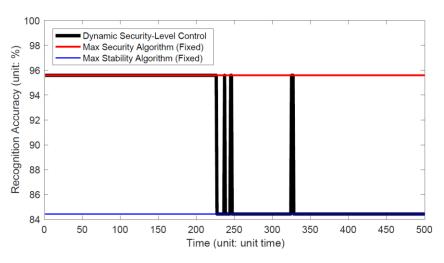
- Semantical Description
 - If the queue is near empty $(Q[t] \cong 0)$,
 - Select the $\alpha[t]$ which can maximize $V \cdot Accuracy(\alpha[t])$, i.e., high learning-accuracy ANN will be selected.
 - If the queue is near overflow $(Q[t] \cong \infty)$,
 - Select the $\alpha[t]$ which can maximize $b(\alpha[t])$, i.e., fast computation (i.e., low learning-accuracy) ANN will be selected.



Research #4 (Stabilized Computer Vision Platform)

• Surveillance Platforms with Parallel Deep Learning Frameworks

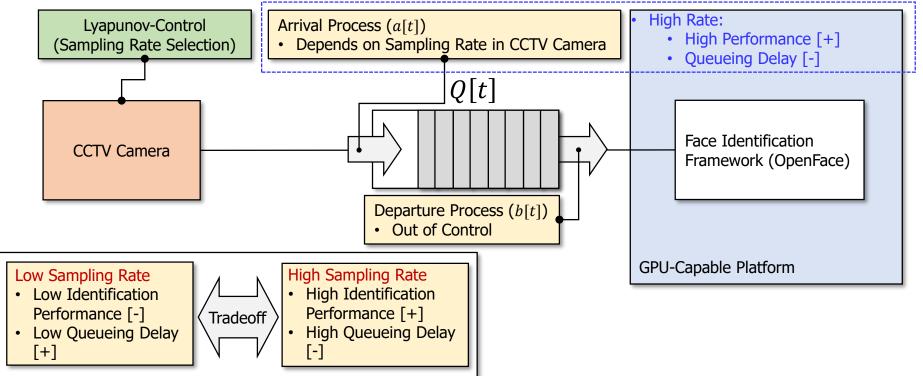






• Research #5 (Stabilized Computer Vision Platform: Revisited)

System Model





Research #5 (Stabilized Computer Vision Platform: Revisited)

Maximization of Time-Average Learning-Accuracy subject to Queue Stability

$$\alpha^*[t] \leftarrow \underset{\alpha[t] \in A}{arg \max}[V \cdot Accuracy(\alpha[t]) - Q[t]\{a(\alpha[t]) - b(\alpha[t])\}]$$
Not
Controllable

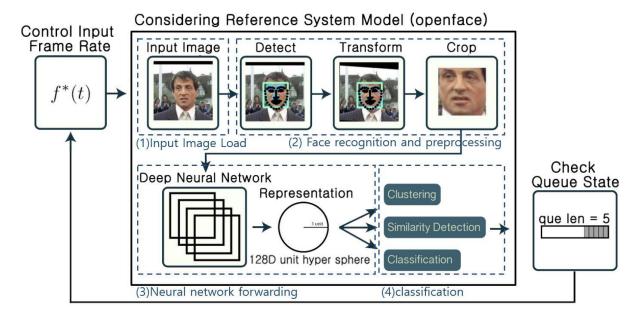


$$\alpha^*[t] \leftarrow \underset{\alpha[t] \in A}{arg \max} \{V \cdot Accuracy(\alpha[t]) - Q[t]a(\alpha[t])\}$$

- Semantical Description
 - If the queue is near empty $(Q[t] \cong 0)$,
 - Select the $\alpha[t]$ which can maximize $V \cdot Accuracy(\alpha[t])$, i.e., high learning-accuracy ANN will be selected.
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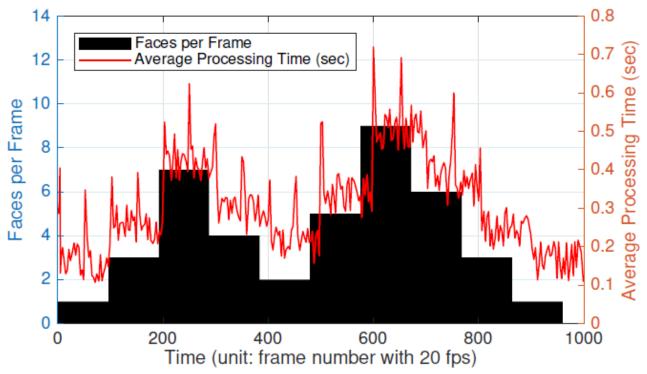
- Research #5 (Stabilized Computer Vision Platform: Revisited)
 - Block Diagram





Research #5 (Stabilized Computer Vision Platform: Revisited)

Implementation





• Research #5 (Stabilized Computer Vision Platform: Revisited)

Implementation

