

A Marie Skłodowska-Curie Initial Training Network



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Naturalistic measurement of perceived video quality by measuring disruptions in free-viewing gaze patterns :

Case study of Interactive streaming

Yashas Rai, Gene Cheung, and Patrick Le Callet, in *Image Processing*, 2016. ICIP 16. Proceedings. (submitted)]





Agenda

- Why good quality estimation?
- Measuring quality naturalistically
- Modelling the Interactive Gaze System
- The GMM based HMM model
- Prediction Performance of the model
- Content dependence







Need for good quality metrics

Compress multimedia in such a way that distortions are cleverly embedded in the invisible areas

- Reduced size implies less storage space on cloud -> Better profits!
- More storage space for user-content on handheld devices!
- Efficient representation for faster transmission (broadcast and streaming)
 - Channels now approach Shannon limit whereas computing power is still increasing in a Moore Scale



Ground Truth quality of a video



- Quality assessment typically involves the subject examining a video sequence of several seconds and providing a quality score.
 - He is often searching for distortions in a very intricate manner.
- Attention Modulation in V4 (Response gain model):
 - Response to unattended stimulus reduces even though its within the receptive field Neuronal firing is 51% greater with attention [1]
 - Contrast detection thresholds 20%, Contrast Discrimination 40-50%, Orientation Discrimination 70% lower [1]
 - Attention influences motion processing by enhancing processing of relevant and suppressing the processing or irrelevant objects [2]
 - Tracking in the fovea task combined with a Number recognition in periphery More is the attention to the foveal task, more is the drop in performance of the peripheral task
 [3]

Do we examine videos in a similar manner when we freely watch videos at home?

- [1] J. Moran and R. Desimone, "Selective attention gates visual processing in the extrastriate cortex," Science, vol. 229, no. 4715, pp. 782–784, 1985.
- [2] J. Braun and B. Julesz, "Withdrawing attention at little or no cost: detection
- [3] B. Khurana and E. Kowler, "Shared attentional control of smooth eye movement and perception," Vision research, vol. 27, no. 9, pp. 1603–1618, 1987.



Subjective Experiment : Gaze contingency



Alter the quality in the visual peripery in real-time in accordance to gaze position.

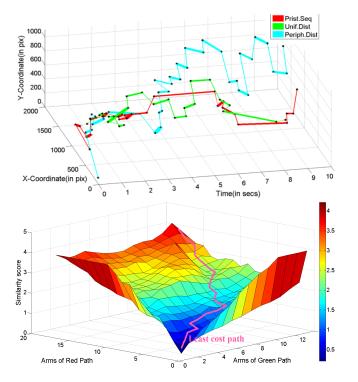
- **HEVC** distortions
 - 4 different Quantizations
 - Para and Peri-Fovea (5.09 and 10.9)

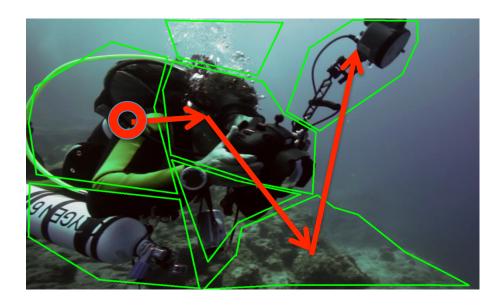


Measuring Disruptions



- Vector Similarity: measuring the difference in scan-path trajectories
- Comparing object transitions : D-B-B-C-C-C-A, D-D-C-B-A followed by Levenshtein similarity of string patterns.





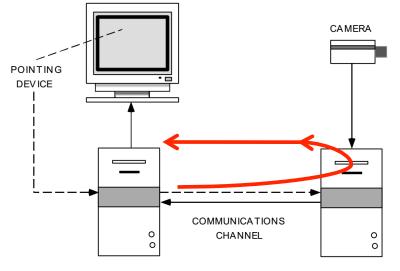




Interactive Video Streaming



- A reverse channel that transmits gaze data from the client end
- Virtual Reality, Panoramic Displays
- Practical considerations
 - Availability of a camera at the client end
 - Network delay
 - Real-time encoding





ENCODE/ TRANSMIT







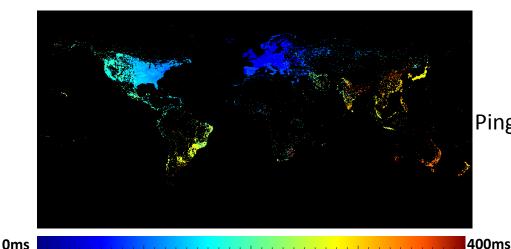
RTT delay

Round Trip Time: The time from which the user makes a head $\mathbf{\nabla}$ movement till the time the actual update happens on the display

- Eye Tracker Latency [<2 ms] Network Propagation Delay (x2) [180-190 ms] Encoding Delay [10 ms] [8.3 ms]
 - **Display Refresh Rate**

Considering wide geographies, we may consider the latency to be ~200

ms



Ping times from Oxford [folk.uio.no]



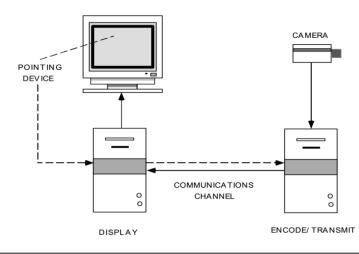






Goals of the research

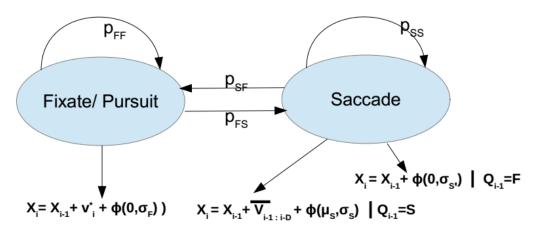
- Does the presence of peripheral HEVC artefacts/ uniform HEVC artefacts alter this prediction accuracy?
 - Same gaze model designed for the pristine sequence works here, as well?
 - HEVC artefacts introduce new Bottom-up effects?







Predicting future gaze locations



Types of Eye-movements

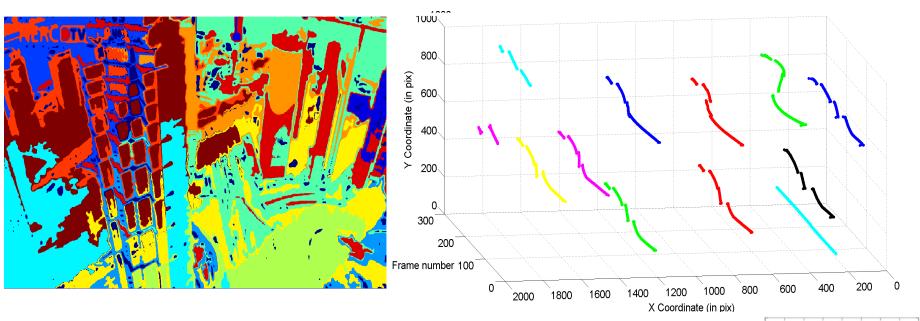
- Saccade Fast movement of the eye to attend to a different region
- Fixate Continue to gaze at the same position for detailed examination
- Pursuit Follow the trajectory of a moving object with the eyes

Terminologies:

- X_i and X_{i-1} are the (x,y) spatial locations
- Q_i and Q_{i-1} are the hidden states
- V_i is determined by the motion of the maximum likelihood object
- V_{i-1:i-D} indicates the average of the previous saccade speeds
- Φ() is the normal noise



Gaze prediction: Tracking objects under motion



Perceptually Optimised Video Compression

- Segmenting the image into discrete super-pixels using texture and color based super-pixelation.
- Motion consistency analysis in each region

[Anil K Jain and Farshid Farrokhnia, "Unsupervised texture segmentation using gabor filters," in Systems, Man and Cybernetics, 1990. Conference Proceedings., IEEE International Conference on. IEEE, 1990, pp. 14–19.]

[M.A. Hasan, Min Xu, Xiangjian He, and Changsheng Xu, "CAMHID: Camera motion histogram descriptor and its application to cinematographic shot classification," *Circuits and Systems for Video Technology, IEEE Transactions on*, vol. 24, no. 10, pp. 1682–1695, Oct 2014]



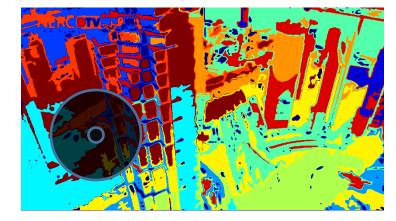


Determining the velocity v_i* of pursuit

- Due to the noise in the gaze data, we do not really know which object the user is actually tracking
- Consider all the objects within a radius of 2 degrees and take the one that maximizes the posterior probability

$$P_Q(X_{i+1}|X_i) = \max_{v_i \in M(X_i)} f_{\sigma_{F^2}}(X_{i+1} - X_i - v_i)$$

$$v_i^* = \arg \max_{v_i \in M(X_i)} f_{\sigma_{F^2}}(X_{i+1} - X_i - v_i)$$









Parameter estimation by training with real gaze data

- Gaze data from 30 observers
 - Estimate transition probabilities
 - Estimate the Gaussian processes
 - Estimate the state probabilities

 $[p_{FF}, p_{FS}, p_{SF}, p_{SS}]$ $[\sigma_F, \sigma_S, \sigma_{S'}]$ $[p_F, p_S]$

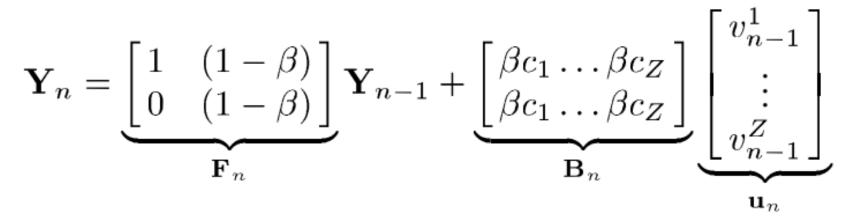
- Offline Learning: Baum Welch Forward-Backward propagation
- Online Learning: Forward only propagation







LDS based prediction of future locations



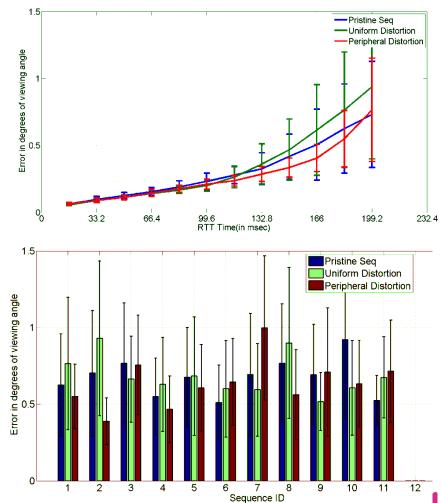
- Perform prediction only if in current as well as RTT seconds in future we have high chances of remaining in Fixation state
- Y_n contains the position and velocity vectors.
- V^z_{n-1} are the motion vector of surrounding pixels, each weighted by c_z





Prediction performance

- Peripheral or uniform distortions have no special effect on gaze predictability!
- The model trained for the pristine case could also predict these cases well!
- Can perform the prediction to within 1.5 degrees of viewing angle error (200ms)

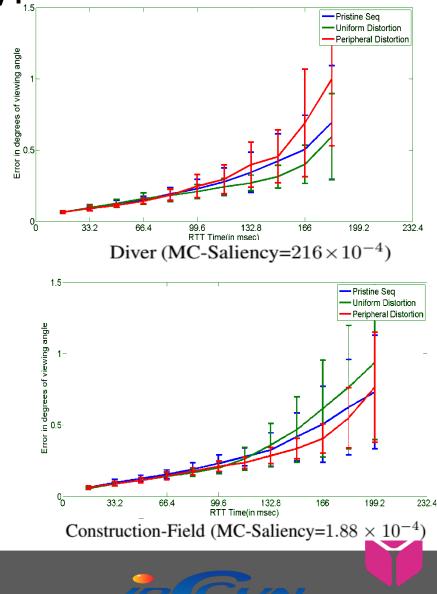






Prediction by sequence type

- Measuring temporal activity with MC-Saliency maps
- High temporal activity -> High prediction error for peripheral distortions
- Low temporal activity -> High prediction error for uniform distortions







Statistical test for verification

- Check how well the Kalman predictor predicts the gaze locations (Euclidean error)
- Is this error significantly higher, while predicting gaze data in case of peripheral / uniform distortion?

Table II					
		RTT = 100ms		RTT = 200ms	
Seq.ID		Pristine vs	Pristine vs	Pristine vs	Pristine vs
		Unif.Dist	Periph.Dist	Unif.Dist	Periph.Dist
1	Construction Field	0.23	0.69	0.78	0.86
2	Fountains	0.26	0.25	0.44	0.10
3	Library	0.48	0.53	0.69	0.26
4	Resid. Building	0.42	0.59	0.50	0.61
5	Tall Buildings	0.61	1.00	0.71	0.62
6	NTIA-Redgold	0.83	0.42	0.83	0.39
7	Diver	0.64	0.27	0.42	0.84
8	Lobsters	0.42	0.50	0.18	0.67
9	Evening Walk	0.53	0.83	0.33	0.54
10	Traffic Building	0.07	0.09	0.10	0.13
11	NTIA-Purple	0.17	0.16	0.81	0.43
12	Tree Shade	-	-	0.51	0.99





Key take-aways

- Peripheral as well as uniform distortions do not affect the prediction capabilities of the model
- Such a model maybe safely used for gaze prediction in interactive streaming systems
- Gaze disruption measurement can be used to test the annoyance of video distortions in a naturalistic manner!







Thank-You / Questions?



