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► To cite this version:

Waqas Ellahi, Toinon Vigier, Patrick Le Callet. HMM-Based Framework to Measure the Visual Fidelity of Tone Mapping Operators. IEEE International Conference on Multimedia & Expo Workshops (ICMEW), Jul 2020, London, United Kingdom. hal-02612844

HAL Id: hal-02612844

<https://hal.science/hal-02612844>

Submitted on 19 May 2020

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HMM-BASED FRAMEWORK TO MEASURE THE VISUAL FIDELITY OF TONE MAPPING OPERATORS

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ABSTRACT

Recent advancements in the image capturing techniques and post processing software generate High Dynamic Range (HDR) images. Such images retain maximum information of the scene by capturing more realistic visual contents, which are often missed in traditional image capturing techniques. In this regard, tone mapping operators (TMOs) play a significant role in displaying HDR image contents on a traditional Low Dynamic Range (LDR) display. These operators tend to introduce artifacts in the original HDR image to change its brightness and contrast in such a way that it can destroy the important textures and information of the image. The assessment of these TMOs is a challenging topic to select best the best technique considering different perceptual and quality dimensions. In this paper, we propose to compare TMOs through their impact on visual behavior in comparison with HDR condition. This study is the first of its kind to utilize hidden markov model (HMM) as a similarity measure to evaluate perceived quality of TMO. The findings suggest that the proposed HMM-based method which emphasizes on temporal information produce better evaluation metric than the traditional approaches which are based only on visual spatial information.

Index Terms— scanpath, eye movements, visual attention, hidden markov model, tone mapping operators

1. INTRODUCTION AND BACKGROUND

High Dynamic Range (HDR) imaging has gained significant attention in recent years both in industry and academia. The is mainly due to the fact that HDR images are visually more realistic and appealing as they represent a larger dynamic range of the visual content present in the real world. The HDR technologies are arguably considered a major development in display technologies since the transition from black and white to color displays [1, 2]. However, most of the common imaging devices are only capable to work only with standard dynamic range (SDR) images, leading to a loss of luminance and contrast.

When the dynamic range is lower than the one of the content, the source image is processed with a tone mapping operator (TMO) to compress the dynamic range before rendering. The goal of this technique is to reproduce HDR content on SDR display while preserving details, contrasts and quality. As a consequence, several techniques have been developed in the past utilizing simple global operations such as linear scaling and clipping [3, 4] to more local advance operators that exploit properties of the human visual system [5, 6, 7, 8, 9]. TMOs can be also perceptually optimized using visual saliency and visual attention to locally adjust the contrast, preserve details and chromaticity [10]. The quality evaluation of tone mapping operators is a challenging topic due to the consideration of multi- perceptual dimensions such as naturalness, colorfulness, brightness, fidelity, and artistic intent. Several studies have assessed these dimensions through subjective experiments [11, 12, 13] and different objective metrics for HDR content have been proposed [14, 15, 16].

The use of eye tracking experiment is proven to be a good methodology in measuring visual fidelity. Indeed, Narwaria et al. [11] showed that tone mapping operators modify visual attention by comparing the similarity between saliency maps (computed from eye data obtained during the visualisation of HDR and tone-mapped images). The current study performs the comparison of saliency maps and investigates their impact on pre- and post tone mapping. The findings suggest that some salient areas in HDR image are not seen after tone-mapping (and vice versa). However, the dynamic aspect of visual behavior, e.g. scanpaths, is not considered with saliency-based framework. Indeed, temporal aspect in visual attention can reveal the way a content is visually perceived, semantically processed and qualitatively assessed.

Scanpath modeling is a challenging task which has been more recently raised with new analytical tools to compare visual behaviour of different conditions or populations. To cater this issue, probability based approaches are developed by assuming that eye movement parameters are random variables generated by underlying stochastic processes. The set of gaze positions is modeled as bivariate gaussian distribution and hidden markov models (HMMs) are utilized to introduce

the temporal component of gaze behavior [17, 18, 19]. This in turn will determine the percentage of transitions from one ROI to another ROI. These techniques have been used for the study of scanpath in face recognition [17], the classification of scanpath according to different visual task [19] or different population with visual field losses [18].

The main contribution of the paper is a new HMM based similarity measure in order to evaluate the quality of HDR and TMO generated scanpaths. This paper is structured as follows. First, we explain HMMs in the context of gaze behavior modeling. Then, we illustrate the application of this technique for TMOs benchmarking. Finally, we conclude our method in the last section.

2. HMM TOOLS FOR THE MEASURE OF VISUAL SCANPATH SIMILARITY

2.1. HMM used as eye movement modeling

The proposed work utilizes HMMs as a statistical approach to produce the sequence of observation through the set of stochastic process. These observed sequences are then predicted by estimating the transition among different states. It is a data-driven technique and integrates influences stemming from bottom-up mechanisms, top-down mechanisms, and viewing biases into a single model [19]. In this work, the eye position is observed using estimated ROI of the image which is set as the hidden state of HMM. Following the technique used in Chuk et al. [17], the transition matrix represents the saccadic movements of the participant. The emission densities (the distribution of fixation points in each ROI) are modeled as two-dimensional Gaussian distributions. The initial state of the model, i.e., the probability distribution of the first fixation, is modeled with the prior values. The parameter K which represents the number of ROI in context of scanpath must be selected according to the gaze data instead of setting the parameter with prior information.

The variational approach to Bayesian inference allows simultaneous estimation of complexity of model and its parameters [20], which automates the process of finding number of states (K) in HMM model [17]. An HMM is trained on eye movement data which enables to compare and visualize the gaze behavior of different groups of observers, in different experimental conditions. The individual HMMs of the similar gaze pattern behaviour is clustered by VHEM [21, 22] into joint HMM. For each cluster, the VHEM algorithm produced a representative HMM, which summarizes the common ROIs and transitions in the cluster.

2.2. Measure of similarity

In the proposed work, similarity is evaluated using sequence of steps. The steps involved in this process are presented in Fig. 1. Initially, each of the observers eye movement is modeled using HMM for one condition (C1). The HMM of each

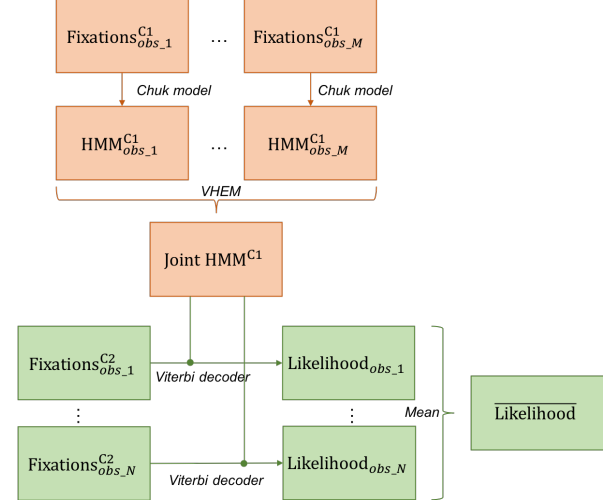


Fig. 1: Scanpath similarity evaluation framework.

observer is then clustered into single Joint HMM by using VHEM. The similarity between the scanpath (i.e. sequence of fixations) of second condition (C2) and the joint clustered is determined by computing the likelihood using Viterbi decoder. The mean likelihood of all observers is considered as a similarity score between the two conditions.

Table 1: Characteristics of subjective experiment

Features	HDR test	TMO test
# of images	11	88
Image resolution	760x900 to 1620x1080	
Image duration	10 seconds	
Distance	3 times of display height	
# of Observers	37	48
Display model	Sim2 HDR47E	TvLogic LVM401
Display resolution	1920x1080 pixels	
Eyetracker	SMI Hi-Speed	

3. APPLICATION OF BENCHMARKING TMOs

3.1. Dataset

The publicly available dataset "Eye-Tracking on High dY-namic range iMAges" (ETHyma) [11] is analyzed in this study. The dataset contains 11 HDR images, captured in different environmental conditions, i.e. indoor and outdoor scenes with varying illumination conditions. A total of 88 TMOs images were computed using 8 different TMO methods. These methods are referred in Table 1, column 4-11, where each column presents the output of these TMO methods using proposed and state-of-the-art techniques. The HDR stimuli were displayed on an HDR display (Sim2 HDR47E S 4K) and the tone mapped contents are presented on a stan-

Table 2: Similarity scores for the studied dataset. (Red cells represent similarity scores higher than the baseline, discussed Section 3.3. Results of green cells are discussed in Section 3.4 to highlight the interest of the framework.)

Images	Metrics	Baseline Likelihood	TMOs algorithms							
			ash[7]	chi [5]	dra [3]	dur [6]	ica [8]	linear	rei [9]	tum [4]
Apartment	KLD ↓	-	0.1624	0.3320	0.2391	0.3597	0.1309	0.1412	0.1712	0.2236
	HMM ↑	-13.34	-13.53	-13.60	-13.61	-13.63	-13.51	-13.41	-13.45	-13.47
	Corr ↑	-	0.8684	0.7798	0.8010	0.7440	0.8769	0.8761	0.8843	0.8531
	NSS ↑	-	1.0238	0.8137	1.1442	0.9361	1.0092	1.1543	1.2349	1.2286
Atrium_Night	KLD ↓	-	0.0917	0.1528	0.1150	0.0796	0.1541	0.1074	0.1543	0.1261
	HMM ↑	-13.09	-13.08	-13.23	-13.10	-13.15	-13.19	-13.12	-13.11	-13.21
	Corr ↑	-	0.8315	0.7451	0.8321	0.8758	0.7174	0.8616	0.7443	0.7281
	NSS ↑	-	0.8512	0.7626	0.9471	0.9414	0.7972	0.9478	0.6961	0.6130
Oxford_Church	KLD ↓	-	0.2331	0.3275	0.1880	0.2333	0.1887	0.1897	0.1086	0.1808
	HMM ↑	-12.74	-12.94	-13.03	-13.06	-13.03	-13.06	-12.94	-12.61	-12.69
	Corr ↑	-	0.9273	0.8663	0.9302	0.9100	0.8833	0.9027	0.9134	0.8882
	NSS ↑	-	1.2413	1.2006	1.2647	1.0502	1.3077	1.3967	1.6129	1.4484
Big_for_Map	KLD ↓	-	0.1996	0.1094	0.1880	0.1340	0.1086	0.1350	0.1092	0.2327
	HMM ↑	-13.02	-13.10	-13.17	-13.36	-13.26	-13.29	-13.39	-13.22	-13.25
	Corr ↑	-	0.8018	0.8709	0.7494	0.8376	0.8793	0.8496	0.8764	0.7378
	NSS ↑	-	1.1877	0.9602	0.6817	0.8068	0.9608	0.7904	1.1687	0.8693
Dani_Belgium	KLD ↓	-	0.1775	0.1278	0.2162	0.1589	0.2152	0.2013	0.2025	0.2288
	HMM ↑	-13.03	-13.12	-12.96	-13.23	-13.15	-13.03	-12.98	-13.17	-13.11
	Corr ↑	-	0.7239	0.8279	0.6537	0.8185	0.7045	0.8241	0.7544	0.7393
	NSS ↑	-	0.8347	1.1032	0.7022	1.0347	0.8727	1.2562	0.8626	0.7540
lampickaHDR	KLD ↓	-	0.2234	0.1485	0.1645	0.2338	0.5603	0.1619	0.0821	0.2884
	HMM ↑	-12.68	-13.00	-13.01	-13.35	-13.27	-13.08	-13.24	-12.84	-13.29
	Corr ↑	-	0.9154	0.8306	0.8322	0.6259	0.8719	0.7600	0.9367	0.5663
	NSS ↑	-	1.2041	0.9626	0.9040	0.8113	1.0356	0.8568	1.2953	0.7550
memorial_o876	KLD ↓	-	0.1125	0.1092	0.0729	0.0801	0.0565	0.0773	0.0551	0.1037
	HMM ↑	-12.31	-12.35	-12.63	-12.54	-12.40	-12.53	-12.35	-12.49	-12.33
	Corr ↑	-	0.9037	0.7787	0.9156	0.8978	0.9362	0.9147	0.9335	0.8886
	NSS ↑	-	1.2283	0.7700	1.0032	0.9547	0.8890	1.0938	1.0564	1.2794
moto	KLD ↓	-	0.7040	0.1932	0.1353	0.1967	0.2049	0.2216	0.3256	0.1876
	HMM ↑	-13.39	-13.50	-13.41	-13.56	-13.48	-13.32	-13.39	-13.68	-13.55
	Corr ↑	-	0.8894	0.9066	0.9048	0.8633	0.9086	0.9014	0.8253	0.8551
	NSS ↑	-	1.4345	1.5737	1.3882	1.4694	1.5536	1.8779	1.1869	1.3414
forest_path	KLD ↓	-	0.3322	0.4180	0.1626	0.1235	0.1458	0.1791	0.1679	0.1265
	HMM ↑	-13.47	-13.84	-13.83	-13.75	-13.67	-13.68	-13.83	-13.79	-13.61
	Corr ↑	-	0.8224	0.8475	0.9295	0.9447	0.9461	0.8724	0.9408	0.9475
	NSS ↑	-	1.3002	1.1029	1.5537	1.3769	1.5853	1.2878	1.6714	1.4998
rend02_oC95	KLD ↓	-	0.1488	0.0989	0.1080	0.0869	0.0978	0.0765	0.1187	0.0716
	HMM ↑	-12.90	-12.97	-12.91	-13.04	-12.91	-12.96	-12.94	-13.06	-12.96
	Corr ↑	-	0.8431	0.8617	0.8927	0.9404	0.9078	0.9212	0.8792	0.9263
	NSS ↑	-	1.0016	1.0149	1.1647	1.4003	1.1596	1.2397	1.0846	1.3691
treeUnil	KLD ↓	-	0.0835	0.0963	0.1867	0.1437	0.0637	0.1939	0.1188	0.1965
	HMM ↑	-13.19	-13.38	-13.29	-13.43	-13.36	-13.25	-13.31	-13.31	-13.10
	Corr ↑	-	0.9540	0.9297	0.8172	0.8268	0.9540	0.8527	0.9092	0.8737
	NSS ↑	-	1.0772	1.1153	0.8824	0.9030	1.2082	1.1491	1.2066	1.3509

dard LCD screen. Each image was viewed by the participant during 10 seconds. The eye movements were recorded using SMI Hi-Speed tracker with a frequency of 500Hz. Thirty seven observers participated in the HDR experiment and 48 did the TMO experiment. The characteristics of this subjective experiment are presented in Table.1.

3.2. Similarity metrics

In this section, we present the obtained scores of similarity for our framework compared with state-of-the-art saliency-based metrics: Kullback-Liebler divergence (KLD), 2D correlations (Corr) and Normalized scanpath saliency (NSS) [23]. These metrics are calculated after the computation of fixation maps. These maps are computed by convolving a Gaussian kernel with standard deviation of one degree of visual angle across the observer's fixation locations. The proposed framework is applied with C1 as the HDR condition compared with the different tone mapping techniques. The HMM model is applied on eye fixations extracted from raw gaze data for each observer during HDR experiment [24]. In addition, each HMM is then clustered into single joint HMM by using VHEM. The likelihood is calculated using Viterbi decoder by passing joint HMM parameters and fixation points recorded during TMOs experiment. The similarity score between HDR and TMOs is estimated by taking mean of likelihood of all observers for each TMOs. In this study, the maximum value of states in HMM, K , is set to 7. The scores of the proposed framework with the ones of all the other similarity / dissimilarity metrics are presented Table 2.

Table 3: Pearson correlation coefficients (PCC) between similarity metrics. (* indicates a p-value < 0.05 and ** indicates a p-value < 0.001).

PCC	KLD	HMM	Corr	NSS
KLD	1.0000	-0.3957**	-0.2755*	0.0581
HMM	-0.3975**	1.0000	0.1300	-0.1472
Corr	-0.2755*	0.1300	1.0000	0.6811**
NSS	0.0581	-0.1472	0.6811**	1.0000

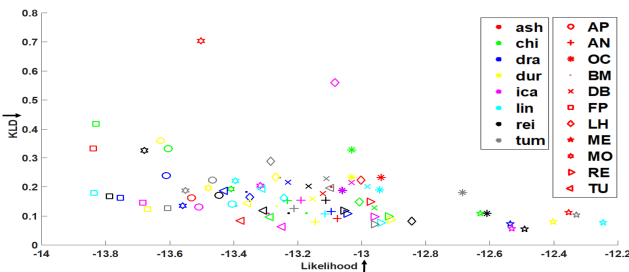


Fig. 2: Relationship between scores of KLD and HMM metrics

In addition, a baseline likelihood score on individual HDR scanpaths is also calculated to validate this method. The baseline likelihood is estimated by providing the fixation points of each observer for HDR condition and joint HMM parameter to the Viterbi decoder. The final score is taking a mean of all likelihood for all observers. This baseline can be interpreted as the similarity score between one observer and a model of all scanpaths for the same condition. It is thus expected that the likelihood score for the TM condition would be lower than the baseline.

3.3. Validation of the framework

The similarity metrics are compared between each other through the computation of Pearson's correlation coefficients (PCC) presented Table 3. The proposed framework shows a strong significant negative correlations with KLD metric. The relationship between KLD and HMM likelihood scores is also presented Fig. 2. These results ensure the validity of the proposed framework which is correlated with existing metrics used to measure visual fidelity.

Concerning the baseline, the obtained scores seem to validate the previous assumption except for a few values (highlighted in red in Table 2). These specific cases could be explained by a low inter-observer congruency for HDR baseline condition and further analysis should be done to better understand these outcomes.

3.4. Benchmarking of TMOs through dynamic visual fidelity

The similarity scores detailed in Table 2 show a strong correlation between saliency-based metrics and the proposed HMM-based one, except for some specific tone-mapped contents. The moto and rend02.oC95 are selected as test images to investigate these results through the comparison of the performance between HMM and KLD. The performed analysis of KLD suggests that Drago and Tumblin methods offer the best performance among all for moto and rend02.oC95 images respectively. Whereas with the HMM-based framework, iCAM06 method offers best performance for moto and Chiu method for rend02.oC95 image (see Table 2-highlighted green cells). Saliency maps, HDR joint HMM states and transition matrix as well as scanpaths for TMO condition are depicted on Fig 3 and 4. We can see that most performant TMOs with our framework seem to lead to more similar saliency maps than the best ones with KLD metric. In addition, the scanpaths for iCAM06 (resp. Chiu) TMO fit better the joint HMM on HDR condition than Drago (resp. Tumblin) TMO. From these observations, we can see that HMM-based framework outperforms KLD metric and better reveals visual attention similarity for both spatial (i.e salient) and temporal (i.e. scanpath) information.

One limitation of this proposed framework is that HMM based on Chuck methodology perform well with image con-

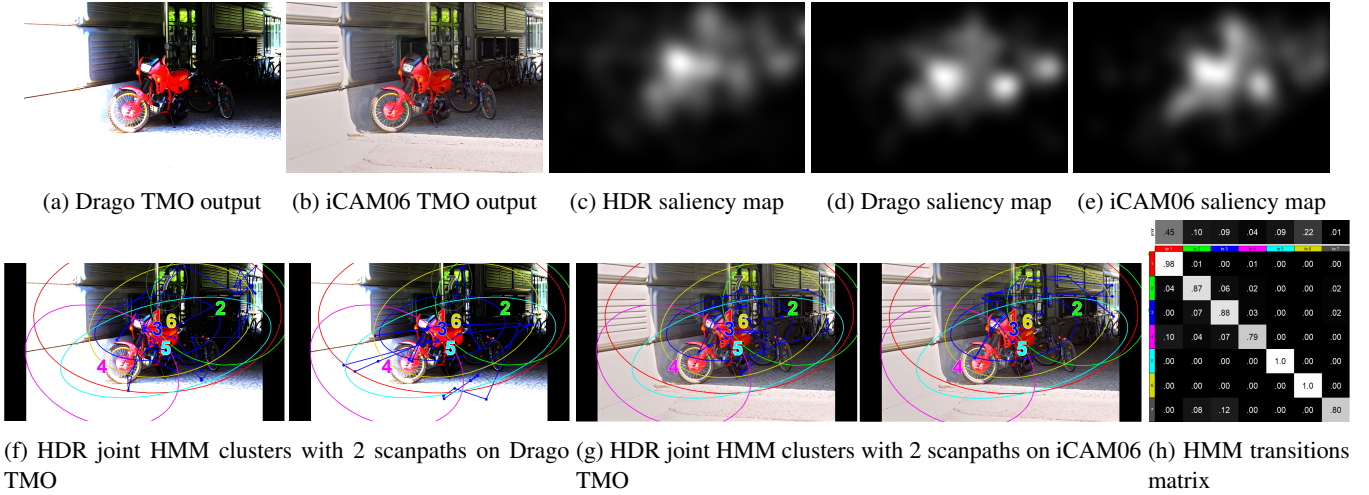


Fig. 3: Tone-mapped images, saliency maps, scanpaths and HDR joint HMM model for moto content.

tent with clear regions of interest and, thus, low visual attention dispersion. Therefore, future work should be needed to deeper assess the impact of content, inter-observer congruency and HMM meta-parameters as number of states (i.e regions of interest) on the similarity metric performance. Different HMM techniques can be also further tested and compared for similarity evaluation through this framework.

4. CONCLUSION

In this paper, an HMM based framework is proposed to measure the similarity of visual behaviour between two conditions of experiment. The framework is then applied and validated for the comparison of visual attention in HDR and tone-mapped images. The proposed framework provides promising results due to the capability of HMM to analyse eye data considering both the spatial and sequential aspects. On the contrary, other saliency models do not reflect the dynamic (saccadic) nature of visual scanpaths.

5. ACKNOWLEDGMENT

The work in this paper was funded from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No 765911, European Training Network on Real Vision project.

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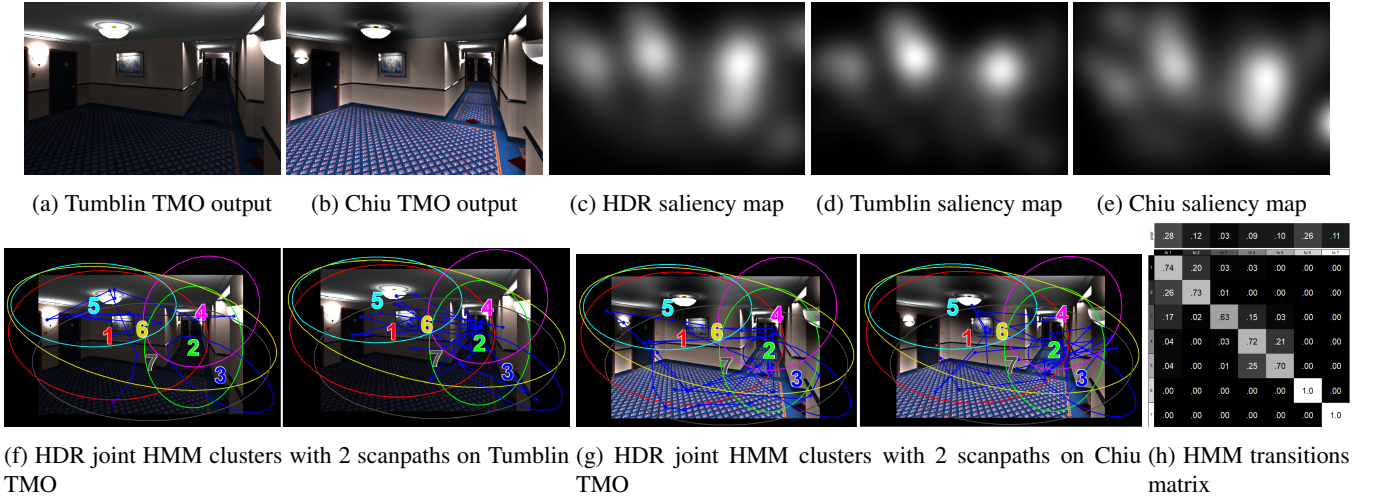


Fig. 4: Tone-mapped images, saliency maps, scanpaths and HDR joint HMM model for rend02_oC95 content.

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