OVERVIEW OF EYE TRACKING DATASETS

Stefan Winkler and Ramanathan Subramanian

Advanced Digital Sciences Center (ADSC), University of Illinois at Urbana-Champaign, Singapore

ABSTRACT

Datasets of images or videos annotated with eye tracking data constitute important ground truth for studies on saliency models, which have applications in quality assessment and other areas. Over two dozen such databases are now available in the public domain; they are presented in this paper.

***Index Terms*—** Eye fixations, saliency, visual attention

1. INTRODUCTION

Attention and saliency play important roles in visual perception. Consequently, a number of saliency-based quality assessment algorithms have been proposed in recent years, see e.g. [16,30]. While comparisons and reviews of saliency models are quite common [4, 21], information on eye tracking databases is harder to come by. There are over two dozen databases with eye tracking data for both images and video in the public domain. We review the content and purpose of each database and discuss their commonalities and differences.

2. DATABASES

An overview of the test material, subjects, viewing setup, and other experimental details of each database is provided in Table 1. Additional database specifics are discussed below. An up-to-date list of databases is available on the author's home page, http://stefan.winkler.net/resources.html.

2.1. Image Databases

- *Fixations in Faces (FiFA)* [8] was recorded to demonstrate that faces attract significant visual attention while viewing images through free-viewing, search, and memory tasks. Observers were found to fixate on faces with over 80% probability within the first two fixations.

- *IRCCyN/IVC Eyetracker 2006 05 (Image 1) Database* [25] was created to validate a bottom-up visual saliency model and involved free-viewing of natural color images of varying resolution.

This work is supported by the research grant for ADSC's Human Sixth Sense Programme from Singapore's Agency for Science, Technology and Research (A*STAR).

- *IRCCyN/IVC Berkeley (Image 2) Database* [40] was compiled for a database of hand-segmented images. First, users were asked to rate the importance of each object in the scenes. Additionally, eye fixation recordings (EFRs) were collected during free-viewing of the same images. Saliency was effective in predicting the main scene objects, but not the less important ones, suggesting that visual encoding of scenes involves the ability to quickly locate the main objects.

- *KTH Eye-tracking Dataset* [23] comprises complex photographic images and was used to validate a saliency model predicting interesting image regions. The study concluded that early eye fixations are observed especially in symmetrical image areas.

- *LIVE DOVES (A Database Of Visual Eye movementS)* [39] represents a large-scale eye movement database for calibrated natural images (devoid of semantically interesting objects).

- *McGill ImgSal Dataset* [27] aims to validate a frequency domain-based saliency detector incorporating scale-space analysis.

- *MIT CSAIL Saliency Database* [22] represents another publicly available, large-scale eye movement database to aid natural image-related visual attention studies. The EFRs are used to validate a supervised saliency model combining top-down and bottom-up cues.

- *MIT CVCL Search Model Database* [11] was recorded to understand task-oriented eye movement patterns of users. Observers were asked to perform a person detection task, and their eye movements were found to be consistent, even when the target was absent from the scene. The ground-truth eye movement data were used to evaluate three computational models for search guidance based on saliency, target features, and scene context respectively.

- *MIT Low-Resolution Saliency Database* [20] was compiled to study how image resolution affects consistency in eye fixations across observers. The study noted that eye fixations are biased towards the image center for all resolutions, and their consistency increases as image resolution is reduced, until the point where the scene gist can still be inferred by observers.

- *NUS Eye Fixation (NUSEF) Database* [36] contains a repository of eye fixations to study viewing patterns on semantically rich and diverse images, including faces, portraits, indoor/outdoor scenes, and affective content.

- *Toronto Dataset* [5] contains eye movement recordings while viewing natural scenes to validate a visual saliency model based on the principle of maximizing scene information.

- *TUD Image Quality Database: Eye-Tracking Release 1* [29] was created in a bid to integrate 'ground-truth' visual attention models in the computation of objective visual quality metrics. Empirical results demonstrated that including visual attention information improved performance of PSNR and SSIM.

- *TUD Image Quality Database: Eye-Tracking Release 2* [1, 3] was compiled to study the influence of a quality assessment task on image viewing. It found significant differences between visual attention patterns for the free-viewing and quality assessment task conditions.

- *TUD Image Quality Database: Interactions* [37] was designed to study the influence of image distortions on visual attention. The presence of distortions indeed caused a significant deviation in visual attention patterns, especially for low quality images.

- *Visual Attention for Image Quality (VAIQ) Database* [12] provides eye-tracking data for the uncompressed reference images from 3 image quality databases to validate the hypothesis that salient image regions should contribute more to objective image quality metrics.

2.2. Video Databases

- *Actions in the Eye Dataset* [33] was compiled to model human eye movements in the *Hollywood-2* and *UCF Sports* action datasets. Two subject groups were involved in the study – an active group of 12 subjects performed action recognition, while a second group of 4 subjects free-viewed the videos. Fixation patterns of free and active viewers did not deviate significantly.

- *Abnormal Surveillance Crowd Moving Noise (AS-CMN) Database* [38] comprises eye movements for surveillance-type videos, characterized by abnormal moving objects or camera motion. These eye movements are then employed for evaluating four dynamic saliency models.

- *DIEM Project* [34] was designed to show that motion predicts saliency better in videos compared to other low-level factors. The study could not conclude whether this phenomenon was involuntary or correlated to top-down factors such as scene semantics.

- *GazeCom Dataset* [10] was compiled to study the variability in eye movement patterns of users while viewing natural scenes (both images and video). The study concluded that typical images used in psychophysical experiments and professionally edited movies were not representative of natural viewing behavior.

- *IRCCyN/IVC SD 2008 11 (Video 1) Dataset* [35] was created to validate an error resilience method that is applied to preserve the region-of-interest (ROI) in a video from packet loss. The proposed approach was found to help retain an acceptable visual video quality by preventing temporal error propagation within ROIs.

- *IRCCyN/IVC SD 2009 12 (Video 2) Dataset* [13, 14] was recorded to validate a saliency model for objective video quality metrics. Empirical results confirmed that viewers perceived distortions in salient regions to be more annoying than those in non-salient regions.

- *SFU Video Database* [17] is a compilation of gaze-tracking data of subjects, who viewed a set of uncompressed video sequences twice. Significant differences were observed between the locations fixated by observers during the first and second viewings.

- *TUD Video Quality Database (Task Effect)* [2] was created to examine the effect of task on video-viewing behavior. One half of the participants were asked to evaluate the quality of the videos they viewed, while the other half were assigned a free-viewing task. As with images, a systematic difference in viewing behavior was observed between the two groups, and this difference was correlated to the video quality.

- *USC CRCNS Datasets* [6, 7, 18, 19] were designed to investigate the role of factors such as memory on visual attention in dynamic scenes. Eye movements were recorded as users viewed video content normally (original dataset) as well as scrambled into short MTV-style clips characterized by abrupt transitions. Analysis of saccades showed that the correlation between memory traces and attended scene locations was lowest immediately following the cut and monotonically increased thereafter.

- *USC Visual Attention Guided Bit Allocation (VAGBA) Dataset* [28] was compiled to demonstrate the utility of a saliency-based bit allocation strategy in video compression.

The recent *MIT Saliency Benchmark* [21] also deserves a mention here. The 300 images are public, but the fixations are not, which allows impartial benchmarking of saliency models using a common database and common evaluation methods.

The *Mouse Tracking Database* [32] contains mouse-tracking data from 40-60 observers for 91 images, which are correlated to eye tracking data.

Finally, there are a number of datasets where viewers were asked to manually label the “most salient object” (these were not included in the table). [31] provides datasets of 20,000 and 5,000 images labeled by 3 and 9 subjects, respectively; [26] provides more than 7 hours of video labeled by 23 subjects. While they are not based on eye tracking, the object segmentation data can also be used for similar purposes.

3. QUANTITATIVE COMPARISONS

We quantitatively compare the above datasets in several respects. The first is the number of viewers and the number of images or videos in the database. This is shown in Figure 1. Clearly, there is a trade-off between the amount of test material and the number of viewers, due to the amount of time needed for the experiments. NUSEF and MIT databases have the most images, Actions the most videos.

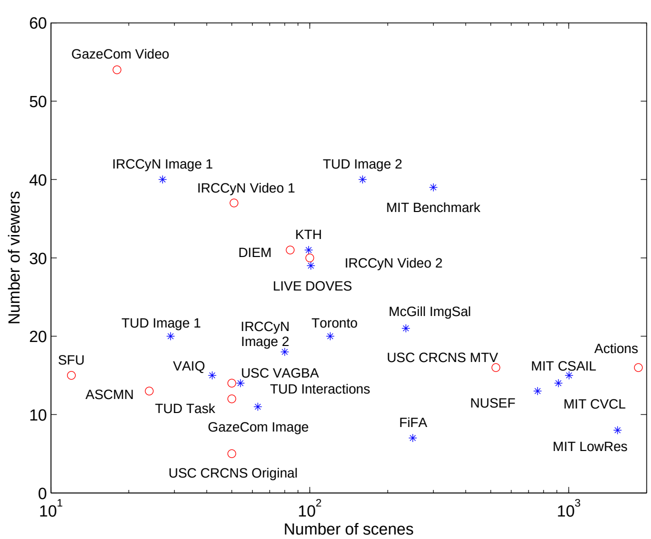

Fig. 1. Number of viewers vs. number of scenes (blue/stars: image databases, red/circles: video databases).

The other area where datasets exhibit quite a bit of variation is the viewing setup. In particular, the distance from the screen and the resolution of the test material vary widely (cf. Table 1). To represent this data in a more meaningful way, we normalize the viewing distance with respect to the vertical size (height) of the image/video (not necessarily identical to the screen height), and we compute the angular resolution in pixels per degree (ppd) of visual angle. This is shown in Figure 2. The sweet spot for most experiments seems to be a viewing distance of about 2-3 times image height and about 30-40 ppd. Some stand out because of their relatively low resolution (e.g. Actions, SFU), which may result in individual pixels becoming visible to viewers. Others sit subjects quite close to the screen (e.g. GazeCom).

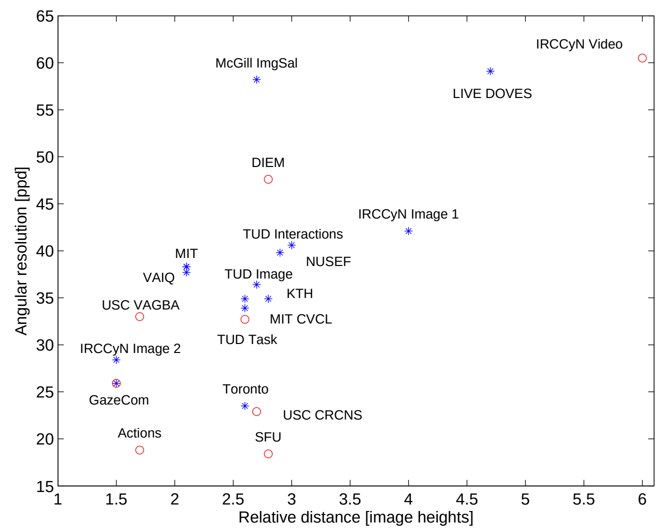

Fig. 2. Pixels per degree of visual angle vs. relative distance (multiples of image height) (blue/stars: image databases, red/circles: video databases).

Finally, Figure 3 shows the total viewing time aggregated over all subjects and scenes, as an indication of the overall amount of eye tracking data and fixations provided in each dataset. DIEM and Actions databases have a clear lead with 160 and 90 hours, respectively, whereas the datasets at the opposite end contain less than one hour of eye tracking data.

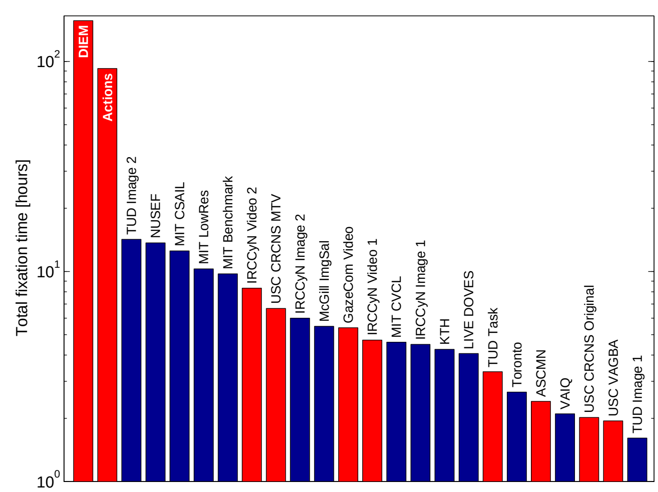

Fig. 3. Total aggregate viewing time over all subjects and scenes (blue: image databases, red: video databases).

4. DISCUSSION

Engelke et al. [15] set out to compare fixation density maps (FDMs) across three independently conducted eye tracking experiments, namely VAIQ [12], TUD Image 1 [29], and IRCCyN Image 2 [40]. The study investigated the effect of presentation time and image content. They found that the FDMs are very similar, and the differences have negligible impact on the applications considered (visual saliency modeling, image quality assessment, and image retargeting).

Most of the eye tracking databases available actually show lightly compressed test material (e.g. JPEG images or MPEG video) to subjects. Only a few use uncompressed, artifact-free content, namely VAIQ [12], SFU [17], and USC VAGBA [28]. Some experiments were designed specifically with quality assessment in mind, by including a pre-determined set of quality degradations and quality tasks – these are TUD Image 2 [1], TUD Interactions [37], IRCCyN Video 2 [13], and TUD Task [2]. MIT LowRes [20] also includes specific degradations, but the task is only free-viewing.

Models of visual saliency are equally important for image and video quality assessment. Visual saliency models have been an active research topic for the past 15 years, and a multitude of computational models have been developed. As mentioned above, MIT's saliency benchmark [21] was created with the goal of providing a common platform for comparison. In a similar vein, Borji et al. recently carried out a comprehensive quantitative comparison of 35 saliency models [4], using synthetic patterns as well as a few image and video datasets. They find that some models consistently perform better; computational complexity analysis shows that certain models are fast and still exhibit competitive prediction performance.

Incorporating saliency aspects into quality assessment metrics has also been tried for a number of years (see e.g. [16, 30] for recent works on images and video), although the resulting improvements in quality prediction performance are limited. Several of the above-mentioned databases were actually created with this purpose in mind.

5. CONCLUSIONS

At least two dozen eye tracking databases for images and video are currently available in the public domain. This encouraging development greatly facilitates benchmarking of algorithms and helps make saliency models more comparable. We provided an overview and some quantitative analysis of these databases. An up-to-date list is available on the author's home page, http://stefan.winkler.net/resources.html.

In terms of future research, there are two areas that come to mind. The popularity of stereo 3D imaging systems has prompted recent studies of eye movements under stereoscopic viewing conditions – one example is [24], whose authors promise an upcoming release of their database. The other is audiovisual attention: Audio can play a crucial role in guiding eye movements when viewing images or video [9]. However, only few video databases include a soundtrack, for example DIEM [34] or GazeCom [10].

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Table 1. Eye tracking datasets at a glance (T is viewing time, D is viewing distance, d is screen diagonal, f is frequency).

Dataset	Year	Type	Scenes	Resolution	Users	Age	T [sec]	D [cm]	d [in]	Screen	Eye Tracker	f [Hz]	Restraint
FiFA [8]	2007	Image	250	1024×768	7		2	80		CRT	EyeLink 1000	1000	Chin rest
GazeCom Image [10]	2010	Image	63	1280×720	11	18-34	2	45	22	CRT	EyeLink II	250	Chin rest
IRCCyN Image 1 [25]	2006	Image	27	≈768×512	40		15			CRT	Cambridge Research	50	
IRCCyN Image 2 [40]	2010	Image	80	481×321	18	19-45	15	40	17	LCD	Cambridge Research	50	
KTH [23]	2011	Image	99	1024×768	31	17-32	5	70	18	CRT	Eyelink I		Headmount
LIVE DOVES [39]	2009	Image	101	1024×768	29	$\mu = 27$	5	134	21	CRT	Fourward Tech. Gen. V	200	Bite bar
McGill ImgSal [27]	2013	Image	235	640×480	21			70	17	LCD	Tobii T60	60	
MIT Benchmark [21]	2012	Image	300	≈1024×768	39	18-50	3	61	19		ETL 400 ISCAN	240	Chin rest
MIT CSAIL [22]	2009	Image	1003	≈1024×768	15	18-35	3	61	19				Chin rest
MIT CVCL [11]	2009	Image	912	800×600	14	18-40		75	21	CRT	ISCAN RK-464	240	Head rest
MIT LowRes [20]	2011	Image	1544	1024×860	8	18-55	3	61	19		ETL 400 ISCAN	240	Chin rest
NUSEF [36]	2010	Image	758	1024×860	13	18-35	5	76	17	LCD	ASL	30	
Toronto [5]	2006	Image	120	681×511	20		4	75	21	CRT			
TUD Image 1 [29]	2009	Image	29	varying	20	students	10	70	19	CRT	iView X RED	50	Chin rest
TUD Image 2 [1]	2011	Image	160	600×600	40		8	60	17	CRT	iView X RED	50	Head rest
TUD Interactions [37]	2011	Image	54	768×512	14	22-35		70	17	CRT	SMI	50/60	Chin rest
VAIQ [12]	2009	Image	42	varying	15	20-60	12	60	19	LCD	EyeTech TM3		
Actions [33]	2012	Video	1857	SD	16	21-41	<60	60	22	LCD	SMI iView X HiSpeed	500	Chin rest
ASCMN [38]	2012	Video	24	VGA-SD	13	23-35	2-76				faceLAB		
DIEM [34]	2011	Video	85	SD-HD	42	18-36	27-217	90	21		Eyelink 2000	1000	Chin rest
GazeCom Video [10]	2010	Video	18	720p	54	18-34	20	45	22	CRT	EyeLink II	250	Chin rest
IRCCyN Video 1 [35]	2009	Video	51	720×576	37		8-10	276	37	LCD	Cambridge Research	50	
IRCCyN Video 2 [13]	2010	Video	100	720×576	30		10	150	40	LCD	Cambridge Research		
SFU [17]	2012	Video	12	CIF	15	18-30	3-10	80	19	LCD	Locarna Pt-Mini	30	Headmount
TUD Task [2]	2012	Video	50	720p	12	students	20	60	17	CRT	EyeLink II	250	
USC CRCNS Orig. [18]	2004	Video	50	640×480	8	23-32	6-90	80	22	CRT	ISCAN RK-464	240	Chin rest
USC CRCNS MTV [6]	2006	Video	523	640×480	16	23-32	1-3	80	22	CRT	ISCAN RK-464	240	Chin rest
USC VAGBA [28]	2011	Video	50	1080	14	22-32	10	98	46	LCD	ISCAN RK-464	240	Chin rest