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Implications for Global and Local Visual Processing in Individuals with Learning Disabilities

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Abstract

Visual processing in humans is done by integrating and updating multiple streams of global and local sensory input. When this is not done smoothly, it becomes difficult to see the “big picture”, which has been found to have implications on emotion recognition, social skills, and conversation skills in individuals with Autism Spectrum Disorder (ASD) and other learning disabilities. Previous research in this field has aimed to direct ASD patients toward normative processing of the global features by developing and evaluating a filter which is intended to decrease local interference, or the prioritization of local details. This work attempts to utilize the filter to, not only shift eye gaze toward normative fixation areas or “hotspots”, but also to maintain focus on those areas. To operationalize these measures, location and duration of participants’ fixations were recorded during a free viewing task. An algorithm was then implemented that would isolate these areas and calculate whether a participant’s fixation was within those bounds. Statistical analysis revealed that, overall, participants did not have a significantly higher likelihood of hitting a hotspot in a filtered image as opposed to a raw one. In addition, participants' hit duration was not significantly different when viewing a filtered image as opposed to a raw one. However, there were some clinically significant findings among individual participants that warrant further investigation. Building on this work, we plan to conduct research that will help to understand how the spatial frequency in raw and filtered images affects the ability of the filter to redirect global processing. These findings will eventually be used to improve the image filter and conduct further research in this field.

Keywords: visual processing, local interference, global processing, digital image processing, Autism Spectrum Disorder (ASD), learning disabilities

Implications for Global and Local Processing in Individuals with Learning Disabilities

Visual processing in humans is done by integrating and updating multiple streams of global and local sensory input (Fink et al., 1997; Gerlach & Poirel, 2018; Liechty et al., 2003; Navon, 1969). According to Van der Hallen and colleagues (2015), when this is not done smoothly, it becomes difficult to see the “big picture”. This has been found to have implications on emotion recognition (Baumann & Kuhl, 2005), social skills (Guillon et al., 2014; Hill et al., 2014; Klin et al., 2002; Rice et al., 2012), and conversation skills (Dube & Wilkinson, 2014; Klin et al., 2007) in individuals with Autism Spectrum Disorder (ASD) (Guy et al., 2016; Hayward et al., 2018; Katagiri et al., 2013; Rinehart et al., 2000) and other learning disabilities (Foxton et al., 2003; Gargaro et al., 2018).

Assistive technology has improved the quality of life for many individuals with disabilities, but there is still much to be done (Dawe, 2006; Kientz et al., 2013). Sensory overload is a key complaint of neurodivergent (ND) individuals and has been researched extensively (Ayres & Robbins, 2005; Dunn, 1997; Dunn et al., 2002; Gonthier et al., 2016; Kojovic et al., 2019; Matsushima & Kato, 2013; Robertson & Baron-Cohen, 2017). Computation allows significant offloading and augmentation of the cognitive load that visual processing places on ND individuals.

Many examples of this type of accessibility have been conducted that illustrate the importance of developing technology with ND populations in mind. For example, Rello and Bigham (2017) found that certain background colors significantly improved reading performance in individuals with dyslexia. Shinohara and colleagues (2018) stress the importance of social accessibility in assistive technology. The focus of assistive technology should be on engineering environments and devices that can combat this issue.

Previous research in this field has aimed to direct ASD patients toward normative processing of the global features by developing and evaluating a filter which is intended to decrease local interference, or the prioritization of local details (Boyd et al., 2022; Cibrian et al., 2020; Sean et al., 2019).

In a study with a low-fidelity filter, Cibrian and colleagues (2020) found that grayscale images were more effective than raw images in guiding attention towards global features. They also found that desaturating non-salient areas serves to highlight salient areas in ND individuals. Additionally, the duration of fixations in hotspots was significantly longer in filtered images, indicating that duration of fixations is a valid measure of visual attention.

These findings were used to develop a high-fidelity filter that would alter an image's spatial frequency and luminance to guide ND individuals toward more global processing. In that study, Boyd and colleagues (2022) found that high luminance and low spatial frequency yielded increased hits in hotspots.

Both the low- and high-fidelity filters in lab and field studies have shown some promise, but significant impact of the filter has not been found yet. This prompted the improvement of the image filter by altering luminance in pixels. In this study, we examine how the improved filter impacted the eye gaze of ND individuals as well as neurotypical (NT) individuals. Specifically, we were interested in whether the filter could (1) guide eye gaze towards normative fixation areas and (2) maintain eye gaze in those areas to encourage global processing. We hypothesize that, with the improvement of the filter, we will be able to shift and maintain eye gaze in normative fixation areas, thereby guiding attention towards globally salient areas of the image.

Method

Participants

A sample of seven participants took part in this study. Participants were recruited via flyers in email messages. Six participants self-identified as neurodivergent (ND) with learning disabilities, two of whom identified with a diagnosis of ASD. The remaining participant identified as neurotypical (NT) and did not choose to disclose any learning disabilities. Five individuals in the sample identified as female and two identified as male. The average age was 22.42 (*SD* = 3.41). Detailed participant demographics can be found in **Table 1**.

Materials

Open-Source Image Database. The images used were taken from an open-source online database of seven hundred images and their corresponding eye gaze heatmaps (Xu et al., 2014). The heatmaps were created using a model based on the aggregate of three seconds of natural viewing by twenty NT adults (Xu et al., 2014). Four hundred images were picked from the repository, of which, two hundred had social content and two hundred had no social content. An image with social content was any image that had a living being in it (e.g., people, faces, animals, etc.). An absence of these characteristics classified the image as nonsocial.

High-Fidelity Image Filter. Researchers who have used these images in visual perception work defined specific semantic areas and described three levels of visual attention based on eye fixations between groups as semantic, object, and pixel (Wang et al., 2015). They found that NTs focused more on semantic features while participants who had ASD focused on pixel-level features. These findings were leveraged to develop a high-fidelity filter to direct visual attention to salient global features as identified by the NT heatmaps.

Image characteristics, like spatial frequency and luminance, were altered to blur and desaturate non-salient areas. Spatial frequency is the distribution of light versus dark in an image. High spatial frequency images have abrupt spatial changes, such as edges, and features generally correspond to fine detail. In contrast, low spatial frequency represents global information about the shape, such as general orientation and proportions. See **Figure 1** for a representation of low and high spatial frequency. Research has shown that lower spatial frequencies guide individuals toward more global attention, which is what the filter intends to utilize in order to emulate NT visual processing (Burton & Moorhead, 1987). Luminance is the measure of how bright an image is, or the intensity of the light in the image. Images with high luminance will have more light and color while images with low luminance will be desaturated. See **Figure 2** for a representation of low and high luminance. Foundational work in visual perception has shown that individuals with ASD tend to focus on bright contrast at the pixel level, so dimming certain non-relevant areas will allow for more attention to globally salient areas in the image (Wang et al., 2015). The filter takes these findings into account to produce images with low spatial frequency and high luminance standardized across hotspots (Boyd et al., 2022). See **Figure 3** for a raw, unfiltered image compared to a filtered image.

Eye Tracker. Eye gaze was measured using an EyeLink Portable Duo, a commercial eye tracker made for research purposes. The tracker was mounted on a PC that showed the image stimuli and, as images were shown, participants' eye gaze data was recorded.

Measures

The eye tracker recorded participants' fixation location as (X, Y) coordinates and duration in milliseconds for each free viewing trial. Location measured where a participant's eye gaze fell. From this data, hit count could be derived, which was a measure of how many times a participant fixated inside a hotspot. Hotpots are rectangular bounding boxes algorithmically drawn (using Python image processing) around pixels that were at or above a grayscale threshold of twenty out of 255 (Boyd et al., 2022). For a visual representation of grayscale, see **Figure 4**. Duration measured how long attention was maintained at that location.

Experimental Design

This was a two by two, within subjects design with alternating treatment conditions. The dependent variable was eye gaze, as measured by fixation location and duration. The independent variables were filter condition (raw or filtered) and social content (social or nonsocial). There were four hundred images total, two hundred raw, one hundred of which were social and one hundred of which were nonsocial. The remaining two hundred images were the filtered pairs of the raw images.

The basic design was that participants would see the raw version of each image and its filtered pair in a predetermined order. The first paradigm had eight blocks, each made of twenty-five filtered and twenty-five raw images. Since each image was classified as either social or nonsocial, there were either thirteen or twelve of each kind in a filtered or raw condition. Therefore, each block had four categories of images: filtered and social, filtered and nonsocial, raw and social, and raw and nonsocial. See **Table 2** for a visual representation of the paradigm.

The first paradigm was successful in NT individuals that were tested prior to the study, however, was extremely challenging for the first ND participant. She was only able to participate in blocks one and two, so the paradigm was changed to be significantly shorter and all social stimuli were removed. See **Table 3** for a visual representation of the paradigm.

P1 and P7 were tested on paradigm one while P2, P5 and P6 were tested on paradigm two. P3 and P4 were unable to participate in eye tracking due to inability to calibrate on the eye tracker.

Procedure

Eye Tracker Setup. The EyeLink Portable Duo was used in remote mode, which allows participants to move their head for the duration of the study. This is essential in special needs populations as it increases comfort. There were two laptops, one was the host PC which ran the eye tracking software and the other was a display PC, which displayed the image stimuli. The eye tracker was mounted on the display PC which was set at a height perpendicular to the participants' eye gaze (this will vary based on height of the participant). The researcher sat diagonally from the participant to monitor activity on the host PC.

Participant Setup, Calibration, and Experiment. After initial recruitment efforts, participants who were interested in being part of the study were brought into the California Community Opportunities office or Chapman University offices where they were greeted by the research team. After providing informed consent, participants were calibrated on the eye tracker. Then, they did the free viewing trials. After the conclusion of the study, participants were compensated with a $50 Amazon gift card.

Results

Data Cleaning

Data Viewer & Excel. Data was collected in Data Viewer, EyeLink's data collection software. Fixation coordinates, duration, and other pertinent trial information was exported from this software to an Excel document where a majority of the cleaning took place. Upon initial exploration, the coordinates from the data files did not seem to map well to the image.

Conversation with the EyeLink team revealed that the display PC used a different scale for the image presentation, so the coordinates were offset. To solve this issue, the coordinates were transformed down 240 pixels and left 560 pixels by subtracting these values from the x and y coordinates respectively. Then, excess text on each row was removed (e.g., fil_non.jpg → fil_non). IF statements were utilized to populate binary columns for filter condition (0 = raw, 1 = filtered), social content (0 = nonsocial, 1 = social), and group identification (0 = NT, 1 = ND).

Python Programming. Using the OpenCV image processing package in Python, an algorithm to bound hotspots was developed. The program would take in a NT heatmap, from the OSIE database by Xu and colleagues (2014) and draw a bounding rectangle, or hotspot, around each pixel at or above a grayscale threshold of twenty out of 255 (Boyd et al., 2022). For a visual representation of grayscale, see **Figure 4**. For a visual representation of the hotspots, see **Figure 5**.

To calculate whether a given fixation was inside any hotspot, another program was developed in Python. This program took every fixation coordinate, matched it to its appropriate image, checked whether it was in any hotspot in that image, and returned a data frame populated with a column denoting whether it was in or out of a hotspot (0 = out of a hotspot, 1 = inside a hotspot). The cleaned data frame consisted of the following columns: image number, participant ID, participant age, filter condition, social content, fixation number, and fixation duration. See **Table 4** for a preview of the data frame.

Cleaning in R. The final data frame was loaded into R for statistical analysis. Further cleaning took place in R due to issues with data population. P1 was removed from analysis because she only saw blocks one and two of paradigm 1. All social stimuli were removed from

P7's data because P2, P5, and P6 did not see any social stimuli. The resulting data frame had nine columns and 4,125 rows.

Data Analysis

Once the final data frame was prepared, the data was modeled using logistic and linear regressions on the independent variable (IV) of filter condition and the dependent variables (DV) of fixation location (in or out of a hotspot) and hit duration in milliseconds. Since the independent variable of fixation location was binary, a logistic regression was implemented. Fixation hit duration was a continuous variable, so linear regression was implemented. See **Table 5** for regression results.

Logistic Regression Analysis. The findings of the logistic regressions are all follows. Overall, participants did not have a significantly higher likelihood of hitting a hotspot in a filtered image as opposed to a raw one, $\beta = 0.00$, $SE = 0.02$, $t = 0.08$, $p = 0.94$. Furthermore, the association between the filter condition and hitting a hotspot was no different in the NT participant as compared to the ND group, $\beta = 0.02$, $SE = 0.02$, $t = 0.81$, $p = 0.42$.

When examining differences between the NT and ND groups, we found that the participant in the NT group was 8% ($OR = 1.08$) more likely to hit a hotspot than participants in the ND group, $\beta = -0.08$, $SE = 0.02$, $t = -3.44$, $p < 0.01$. Specifically, the NT participant did not have a significantly higher likelihood of hitting a hotspot in a filtered image as opposed to a raw one, $\beta = 0.00$, $SE = 0.02$, $t = 0.16$, $p = 0.87$. ND participants did not have a significantly higher likelihood of hitting a hotspot in a filtered image as opposed to a raw one, $\beta = 0.02$, $SE = 0.01$, $t = 1.51$, $p = 0.13$.

We were interested in examining the ND finding further, so we ran regressions for each participant in the ND group. We found that the effect carried and no participants experienced an increased likelihood of hitting a hotspot when viewing a filtered image. Specifically, P2 did not have a significantly higher likelihood of hitting a hotspot in a filtered image as opposed to a raw one, $\beta = 0.30$, $SE = 0.20$, $z = 1.46$, $p = 0.14$. P5 did not have a significantly higher likelihood of hitting a hotspot in a filtered image as opposed to a raw one, $\beta = 0.32$, $SE = 0.18$, $z = 1.78$, $p = 0.07$. It should be noted that this finding is marginally significant. P6 did not have a significantly higher likelihood of hitting a hotspot in a filtered image as opposed to a raw one, $\beta = -0.20$, $SE = 0.24$, $z = -0.86$, $p = 0.39$.

Linear Regression Analysis. The findings of the linear regressions are all follows. Participants' hit duration was not significantly different when viewing a filtered image as opposed to a raw one, $\beta = 31.56$, $SE = 27.13$, $t = 1.16$, $p = 0.24$. Furthermore, the association between the filter condition and hit duration was no different in the NT participant as compared to the ND group, $\beta = -24.34$, $SE = 33.88$, $t = -0.72$, $p = 0.47$.

When examining differences between the NT and ND groups, we found that the participant in the NT group experienced 122.52 ms longer hit duration than participants in the ND group, $\beta = -122.51$, $SE = 31.94$, $t = -3.84$, $p < 0.01$. Specifically, NT participant's hit duration was not significantly different when viewing a filtered image as opposed to a raw one, $\beta = 42.89$, $SE = 24.43$, $t = 1.76$, $p = 0.08$. It should be noted that this finding is marginally significant. ND participants' hit duration was not significantly different when viewing a filtered image as opposed to a raw one, $\beta = 7.20$, $SE = 6.95$, $t = 1.04$, $p = 0.30$.

We were interested in examining the ND finding further, so we ran regressions for each participant in the ND group. We found that P5 experienced 33.89 ms longer hit duration in filtered images than in raw images, $\beta = 33.89$, $SE = 10.42$, $t = 3.25$, $p < 0.01$. However, P2's hit duration was not significantly different when viewing a filtered image as opposed to a raw one, β

= -2.22, $SE = 13.73$, $t = -0.16$, $p = 0.87$. Additionally, P6's hit duration was not significantly different when viewing a filtered image as opposed to a raw one, $\beta = -16.06$, $SE = 12.10$, $t = -1.33$, $p = 0.18$.

Descriptive Statistics/Clinical Significance

In order to determine whether there were any other notable differences in hits and hit duration between the filtered and raw images, we examined descriptive statistics for each group. The total number of hits in raw and filtered images was calculated as well as the mean hit duration for each group. The delta was calculated by subtracting the number of hits in filtered images from the number of hits in raw images. For the number of hits, the NT participant had a delta of -10 (10 more hits in raw images) and the ND group had a delta of 21 (21 more hits in filtered images). For the hit duration, the NT participant had a delta of 27.14 (27.14 ms longer hits on average in filtered images) and the ND group had a delta of 1.52 (1.52 ms longer hits on average in filtered images).

Discussion

Statistical analysis revealed that, overall, participants did not have a significantly higher likelihood of hitting a hotspot in a filtered image as opposed to a raw one. In addition, participants' hit duration was not significantly different when viewing a filtered image as opposed to a raw one. This indicates that the filter was not able to shift eye gaze to normative fixation areas or maintain attention in those areas. However, due to the significance of the duration finding in P5’s linear regression, we can conclude that the filter was successful in maintaining attention in hotspots in his case. There were marginally significant findings, including the duration finding in P7’s linear regression and the hotspot hit finding in P5’s logistic regression. The descriptive statistics reflected increased hotspot hits in filtered images for the ND group and longer average hit duration in filtered images for both groups. These findings, taken together, do hold some clinical significance and warrant further investigation.

Aside from the statistical modeling and descriptive statistics, qualitative data was collected from P3, who was unable to calibrate on the eye tracker. Pseudo trials were run to gauge the effect of the filter. In these trials, the participant was shown a raw image then its filtered pair, and asked what they thought the purpose of the filter was. P3 was shown **Figure 6**. When she was shown the raw image and asked what the image was about, she said “container,” and when she was shown the filtered image, she said “pantry.” This indicates a shift towards global processing since the container is a small object, a local detail, and the pantry is the big picture, the global idea. She also mentioned that the “black and white” images, filtered images, were “easier to look at” because “you don’t have to focus that hard.” Due to physical limitations, P4 was unable to provide qualitative data.

Limitations of this study include significant cognitive and physical load on ND participants. P1 was not able to complete the free viewing task due to short attention span and cognitive load on the free viewing task. P2 had visual impairments and her glasses prevented her from being able to look directly at the stimuli. P3 and P4 were unable to calibrate with the eye tracker due to physical limitations. P6 experienced fatigue with the free viewing task and continuously closed her eyes.

Additionally, since the sample size (n = 7) was small, we can expect that the models would not be able to detect accurate effects. Much data was thrown out due to paradigm inequalities, which further decreased the sample size. However, there is hope that, with a larger population, larger effects would be detected.

Taken together, these findings indicate promise for future implementations of computing in assistive technology. The main focus should be on offloading the cognitive load of visual processing and engineering environments with less sensory overload.

Next steps should be to examine the effect of spatial frequency and luminance on visual attention. Furthermore, specific hotspot bounds should be calculated using a different algorithm so that more accurate hit counts and duration can be determined.

Tables

Table 1. Participant Demographics

P ID	Gender	Age	Group
1	Female	24	ND
2	Female	18	ND
3	Female	19	ND
4	Male	26	ND
5	Male	27	ND
6	Female	21	ND
7	Female	22	NT

Table 2. Paradigm 1

Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Block 8
25 fil - 12 social - 13 nonsocial **25 raw** - 13 social	**25 fil** - 13 social - 12 nonsocial **25 raw** - 12 social	**25 fil** - 12 social - 13 nonsocial **25 raw** - 13 social	**25 fil** - 13 social - 12 nonsocial **25 raw** - 12 social	**25 fil** - 12 social - 13 nonsocial **25 raw** - 13 social	**25 fil** - 13 social - 12 nonsocial **25 raw** - 12 social	**25 fil** - 12 social - 13 nonsocial **25 raw** - 13 social	**25 fil** - 13 social - 12 nonsocial **25 raw** - 12 social

- 12 nonsocial	- 13 nonsocial	- 12 nonsocial	- 13 nonsocial	- 12 nonsocial	- 13 nonsocial	- 12 nonsocial	- 13 nonsocial

Table 3. Paradigm 2

Block 1	Block 2	Block 5	Block 6
25 fil - 13 nonsocial **25 raw** - 12 nonsocial	**25 fil** - 12 nonsocial **25 raw** - 13 nonsocial	**25 fil** - 13 nonsocial **25 raw** - 12 nonsocial	**25 fil** - 12 nonsocial **25 raw** - 13 nonsocial

Table 4. Data Frame Sample

	Image	P_ID	Group	Condition_nonbinary	Condition	Duration	Type_nonbinary	Type	Fixation_num	In_Out	Age
1	1001	P7	0	fil	1	195	non	0	1	1	22
2	1001	P7	0	fil	1	254	non	0	2	1	22
3	1001	P7	0	fil	1	262	non	0	3	1	22
4	1001	P7	0	fil	1	112	non	0	4	1	22
5	1001	P7	0	fil	1	102	non	0	5	1	22
6	1001	P7	0	fil	1	362	non	0	6	1	22
7	1001	P7	0	fil	1	416	non	0	7	1	22
8	1001	P7	0	fil	1	270	non	0	8	1	22
9	1001	P7	0	fil	1	184	non	0	9	0	22
10	1001	P7	0	fil	1	170	non	0	10	1	22

Table 5. Regression Results

Model #	Participant	IV	DV	Covariates/Control Vars	β (Coef)	SE	t-value	p-value
Model 1 - Logistic Reg	All	Condition	In Out	P ID, Image	0.00	0.02	0.08	0.94
	All	Group	In Out	P ID, Image	-0.08	0.02	-3.44	0.00
	All	Condition * Group	In Out	P ID, Image	0.02	0.02	0.81	0.42
Model 2 -	NT	Condition	In Out	Image	0.00	0.02	0.16	0.87

Logistic Reg								
Model 3 - Logistic Reg	ND	Condition	In Out	P ID, Image	0.02	0.01	1.51	0.13
Model 4 - Logistic Reg	P2	Condition	In Out	Image	0.30	0.20	1.46	0.14
Model 5 - Logistic Reg	P5	Condition	In Out	Image	0.32	0.18	1.78	0.07
Model 6 - Logistic Reg	P6	Condition	In Out	Image	-0.20	0.24	-0.86	0.39
Model 7 - Linear Reg	All	Condition	Duration	P ID, Image	31.56	27.13	1.16	0.24
	All	Group	Duration	P ID, Image	-122.51	31.94	-3.84	0.000131
	All	Condition * Group	Duration	P ID, Image	-24.34	33.88	-0.72	0.47
Model 8 - Linear Reg	NT	Condition	Duration	Image	42.89	24.43	1.76	0.08
Model 9 - Linear Reg	ND	Condition	Duration	P ID, Image	7.20	6.95	1.04	0.30
Model 10 - Linear Reg	P2	Condition	Duration	Image	-2.22	13.73	-0.16	0.87
Model 11 - Linear Reg	P5	Condition	Duration	Image	33.89	10.42	3.25	0.00
Model 12 - Linear Reg	P6	Condition	Duration	Image	-16.06	12.10	-1.33	0.18

Table 6. Sum of Hits

	Filter Condition	
Group	*Raw*	*Filtered*
NT	288	278
ND	471	492

Table 7. Mean of Duration of Hits

	Filter Condition	
Group	Raw	Filtered
NT	385.45	412.59
ND	289.59	291.11

Figures

Figure 1. Low Versus High Spatial Frequency

Low Spatial Frequency	High Spatial Frequency

Figure 2. Low Versus High Luminance

Low Luminance	High Luminance

Figure 3. High-Fidelity Filter Implementation

Raw Filtered

Figure 4. Grayscale

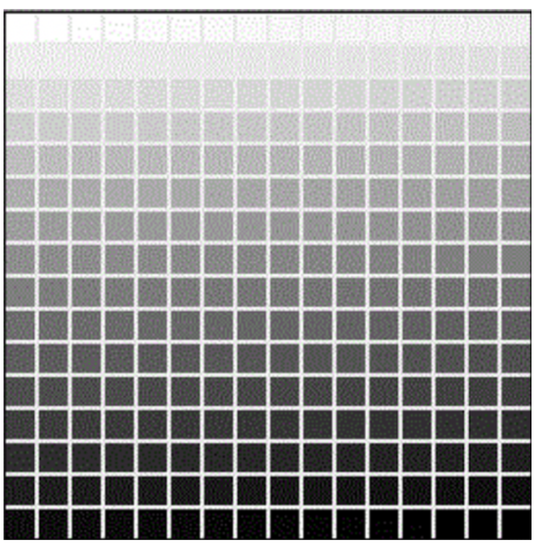


Figure 5. Hotspots/Bounding Rectangles

Image	Heatmap	Hotspots

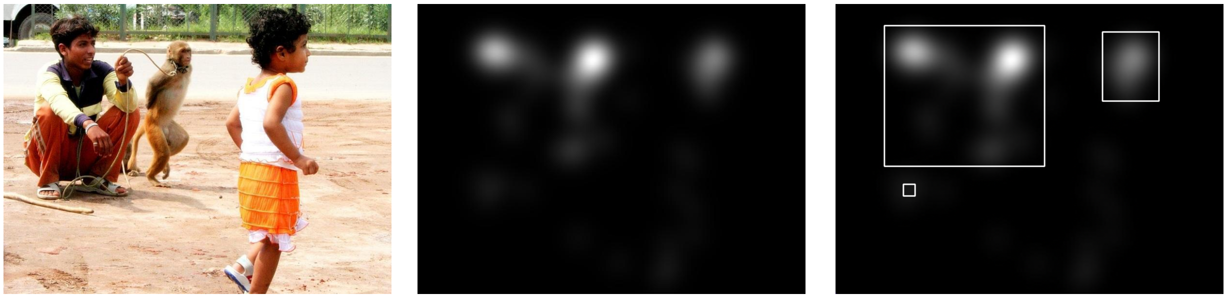
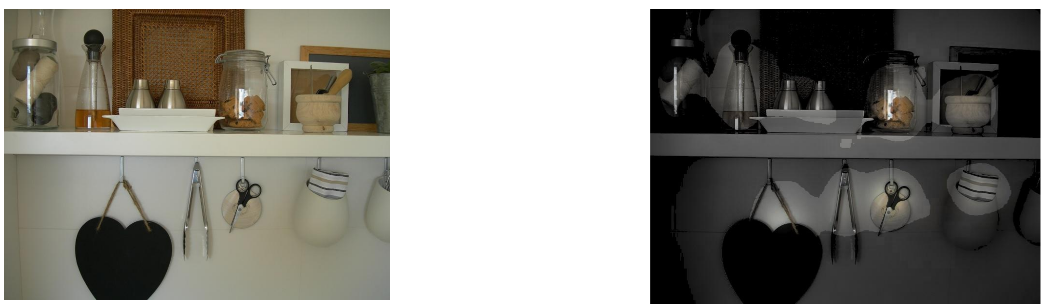


Figure 6. P3 Image

Raw	Filtered



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