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# FIXED PATTERN NOISE NON-UNIFORMITY CORRECTION THROUGH K-MEANS

# CLUSTERING

by

# Andres Imperial

# A thesis submitted in partial fulfillment of the requirements for the degree

of

# MASTER OF SCIENCE

in

Computer Science

Approved:

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2021

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### ABSTRACT

### Fixed Pattern Noise Non-Uniformity Correction through K-Means Clustering

by

Andres Imperial, Master of Science Utah State University, 2021

Major Professor: John Edwards, Ph.D. Department: Computer Science

Fixed pattern noise removal from imagery by software correction is a practical approach compared to a physical hardware correction because it allows for correction post-capture of the imagery. Fixed pattern noise presents a unique challenge for de-noising techniques as the noise does not present itself where large number statistics are effective. Traditional noise removal techniques such as blurring or despeckling produce poor correction results because of a lack of noise identification. Other correction methods developed for fixed pattern noise can often present another problem of misidentification of noise. This problem can result in introducing secondary artifacts that can disrupt the imagery and leave the resulting image worse than the uncorrected image. This underlying issue of poor noise identification stems from strong assumptions globally and locally in the imagery. A proposed approach utilizing image intensity clustering will blend local and global information to find a nuanced correction value on a row-by-row basis. The proposed algorithm's evaluation will be against multiple other correction methods developed for fixed pattern noise removal through a synthetic suite of imagery. The suite is founded on clean images and expanded by varied synthetic noise types introduced by algorithmic means. Images will be evaluated pixel by pixel, row mean by row mean, and with and without a scene intensity bias correction for validation of noise correction.

(86 pages)

### PUBLIC ABSTRACT

# Fixed Pattern Noise Non-Uniformity Correction through K-Means Clustering Andres Imperial

Imagery obtained with poorly calibrated sensors is often corrupted with fixed pattern noise. Fixed pattern noise presents itself through a non-uniform distribution and therefore is hard to target in noise removal. Traditional noise removal techniques assume that the noise is uniformly distributed and subsequently produces inadequate corrections. Noise correction methods that target fixed pattern noise rely on dynamically identifying present noise and adjust correction values appropriately using nearby information or general assumptions about the image's composition. If noise identification is not accurate, the correction values will also suffer from low accuracy. Inaccurate correction values can affect the imagery's quality, and in some cases, produce a corrected image worse off than an uncorrected image. The proposed algorithm utilizes local and global information to find more accurate correction values on a row-by-row basis. This paper will also introduce a standard dataset and evaluation metrics for comparison against other established non-uniformity correction methods.

# CONTENTS

ABSTRACT iv									
PU	JBLIC ABSTRACT								
LIS	ST OF TABLES								
LIS	ST OF EIGURES								
	LIST OF FIGURES X								
AC	CRONYMS xi								
1	INTRODUCTION       1         1.1       Overview and Motivation       1         1.1.1       Contributions       2								
2	RELATED WORK52.1Related Work52.1.1Common Denoising Techniques52.1.2Scene Mean/Median NUC Method62.1.3Midway Histogram NUC Method92.1.4Median Ratio NUC10								
3	EVALUATION       12         3.1       Evaluation       12         3.1.1       Common Evaluation Metrics       12         3.1.2       Evaluation Metrics       12								
4	DATA       15         4.1       Data       15         4.1.1       Standard Dataset       15         4.1.2       Noise Generation       15								
5	ALGORITHM195.1Clustering Non-Uniformity Correction195.1.1Clustering195.1.2Correction195.1.3Correction Value per Cluster205.1.4Primed Correction20								
6	RESULTS       21         6.1       Results       21         6.1.1       Algorithm Performance       21         6.1.2       Performance by Noise Types       23         6.1.3       Primed Correction       26								

7	DISCUSSION							
	7.1 Discussion							
		7.1.1	Correction Validation	29				
		7.1.2	Correction Discussion	32				
8	CON	NCLUS	ION	35				
	8.1	Conclu	usion	35				
		8.1.1	Final Contributions	35				
		8.1.2	Future Work	36				
REFERENCES								
APPENDICES								
	Α	Scene	Correction Metrics	40				
		A.1	Pixel RMSE Metric	40				
		A.2	Row RMSE Metric	49				
		A.3	Pixel Bias RMSE Metric	58				
		A.4	Row Bias RMSE Metric	67				

# LIST OF TABLES

Table		Page
6.2	Best correction method by noise type. Percentages are representative of best correction by the pixel RMSE error metric across fifty different scenes per noise type. Abbreviations can be found in the acronyms section	23
6.1	Summary of results across noise types and correction methods. Correction method abbreviations can be found in the acronyms section	24

# LIST OF FIGURES

Figure		Page
1.1	Pushbroom/scanner style imaging.	1
2.1	Common denoising techniques applied to fixed pattern noise	6
2.2	Median NUC example	8
2.3	Midway NUC example	10
2.4	Ratio NUC example	11
6.1	Bi-directional bar chart highlighting best performers for both RMSE metrics. X-axis is the count of scenes in which the given correction performed best by the given metric (Pixel RMSE on the left and Row RMSE on the right). Scenes consisted of all seven different noise types.	21
6.2	Comparison of median ratio correction with and without global correction component.	22
6.3	The noisy image followed by the best and worst corrections for Scene 24	25
6.4	Bar chart highlight performance improvement by pixel error metric when primed correction is utilized.	26
6.5	Line charts highlighting the average row intensity (y-Axis), by row index (x-Axis) for scene 31 corrupted by GNPN noise.	27
7.1	Scene 10 with GNPN corrected by midway histogram correction plotted against truth image without and with bias offset applied.	30
7.2	Scene 31 with GNPN corrections and uncorrected with image differences in respect to the truth image. The image differences' (d-f) image intensities are scaled in order to highlight noise. Image (g-i) are zoomed in sections to highlight left over noise.	31
7.3	These scene have low or repetitive content with no outstanding features and offer the median scene correction its best environment.	34
8.1	Comparison of clustering information between truth image and noisy image.	37

### ACRONYMS

- AN Agminated Noise
- AWGN Additive White Gaussian Noise
- CN Clustering NUC
- FPN Fixed Pattern Noise
- GNPN Global Non-Periodic Noise
- GPN Global Periodic Noise
- LNPN Local Non-Periodic Noise
- LPN Local Periodic Noise
- MCN Median Scene Primed Clustering NUC
- MIDCN Midway Histogram Primed Clustering NUC
- MIDN Midway Histogram NUC
- MN Median Scene NUC
- NUC Non-Uniformity Correction
- PBN Periodic Banding Noise
- RCN Ratio Primed Clustering NUC
- RMSE Root Mean Squared Error
- RN Median Ratio NUC
- SN Single Noise

### CHAPTER 1

### INTRODUCTION

### 1.1 Overview and Motivation



Fig. 1.1: Pushbroom/scanner style imaging.

Non-uniformity noise, also called fixed pattern noise(FPN), for push broom and scanner style imaging is a significant cause of image quality degradation. These scanning-style sensors are prone to producing noise due to their individual detector elements being responsible for their specific line in a given image. Even with periodic calibration, these detector elements often have a different response to the photometric energy in a scene, thus causing FPN in the resulting image. The form of FPN highlighted in this paper is that of line noise; this form of noise is some value offset, either positive or negative, added to all samples in a given line of imagery. The generation of FPN typically stems from a poorly calibrated equalization or a change of sensor response from time of calibration to time of in-field imaging for a scanner or push broom style imaging device [1]. These instances of line noise can lower image quality, hampering a viewer from seeing finer details or may even make the same in-scene material appear as though they were different. Lower image quality can also cause issues in other image processing techniques, such as image registration, classification, and other image analysis methods.

Line noise non-uniformities have been particularly difficult to correct because of their non-random or non-statistical model conforming nature. Most noise correction techniques rely on 'large number' statistics to find and correct noise that is assumed to be randomly distributed or to be following a statistical pattern such as a Gaussian pattern throughout a scene. However, with fixed pattern noise, the noise presents itself in a non-uniform pattern that does not conform to a 'large number' statistical model. While correction algorithms for uniform types of noise can be applied to FPN and may address some of the present noise, a more tailored algorithm can increase accuracy in corrections across various scenes.

Often current algorithms that address line noise need many registered images stemming from hyperspectral imagery, a closed sensor aperture sensor equalization, or fine-tuned parameters. The algorithm presented by this paper uses the information from a single static scene to properly correct fixed pattern noise while also avoiding an introduction of secondary artifacts. Secondary artifacts are non-uniformities introduced in an initial step of image processing and are a significant issue with most current non-uniformity correction algorithms. Some such artifacts are introduced by algorithms that overcorrect pixels due to in-image objects and patterns, while others may propagate and transform original noise to secondary noise artifacts.

#### 1.1.1 Contributions

The proposed algorithm's main contribution averts these issues by avoiding the assumptions that the previous algorithms make about a given image's signal and noise structure. The proposed algorithm uses image clustering to avoid making these broad assumptions that local correction algorithms fall victim to; instead, the approach that the proposed algorithm takes is a blend of utilizing local and global information. The algorithm then corrects pixels in a given row based on their associated clusters and cluster participation in the target line. This approach allows for increased subtlety in the correction values and avoids shifting the image's overall contrast, which is often heavily manipulated in other correction algorithms. Once the original image's pixel clusters are derived, they can then provide the information to calculate the proper correction values. These correction values then adjust mean line values towards the mean of their associated clusters, which may be a weighted combination of multiple cluster origins.

This research also introduces a collection of standard dataset imagery that offers an environment to assess and validate non-uniformity correction algorithms' performance. A standard dataset will allow for better and more objective baselines in a research field that lacks a dataset where corrections can be evaluated against 'truth' imagery. This standard dataset will consist of 50 land satellite images representing a variety of scene compositions. Scenes will vary from one another through a blend of the following: low to high overall intensity, containing minimal or multiple features, having a uniform, repeating, or nonuniform composition, and having symmetrical or asymmetrical structure. The variance in scene composition will offer insight into the stability and how a correction method will handle scenes with these base attributes. These base images will expand to another 350 test images by applying seven different noise introducing algorithms. The noise types will consist of global periodic noise, local periodic noise, global non-period noise, local nonperiodic noise, single noise, banding noise, and agminated noise. The variation of noise will offer an opportunity to assess algorithms' pros and cons by noise structure.

The following research introduces the development and use of metrics with the standard dataset. Given an extensive standard dataset of 400 images multiplied for every algorithm being evaluated, visual analysis quickly becomes hard to manage. The use of error metrics to resolve a score for a correction regarding the 'truth' image will provide insight into performance and remove any perceptual bias of human analysis. Utilizing these metric scores will allow for a quick narrowing of top algorithms for given scene compositions or noise types. Metrics based on root-squared mean error(RMSE) calculations are utilized in this paper for objective comparisons against 'truth' images.

By introducing the proposed clustering algorithm, standard dataset, and utilization of error metrics, this paper looks to progress the research environment for FPN. The proposed clustering algorithm highlights the faults in strict local or global derived corrections and looks to offer a better, more stable correction. The introduced dataset offers various image compositions corrupted with unique noise types and looks to remove selective scene use for validating correction methods in future research. Metrics used in conjunction with the introduced standard dataset will contribute to the unbiased evaluation of algorithms and start conversations about what defines an accurate correction.

# CHAPTER 2

## RELATED WORK

### 2.1 Related Work

#### 2.1.1 Common Denoising Techniques

Standard techniques for denoising focus on correcting noise in the form of additive white Gaussian noise (AWGN) [2]. This noise has uniform power across the scene with an overall Gaussian/Normal distribution. The typical correction for this form of noise is done using local information through the application of spatial filters. Since these filters use local information, they often maintain accurate signal information while smoothing out any noise. Commonly used methods here are the Gaussian blur (mean filter), despeckling (median filter) [3], and bilateral filtering [4]. Some of the issues with these filters are that if the noise is not uniform throughout the scene, the filters will mistake noise for signal and propagate present noise. Another issue with these filters is that when deriving pixel correction values from nearby pixels, a blurring effect is introduced, obscuring fine details. Input parameters in the form of the filter size amplify the blurring effect; larger filter sizes can filter out stronger noise signals. These drawbacks' depictions are in Figures 2.1a and 2.1b produced by GIMP denoising tools. The despeckling algorithm from GIMP (Figure 2.1a) utilizes the median pixel value from nearby pixels dependent on filter size. Another standard local correction for AWGN is mean filtering, as seen in Figure 2.1b in the form of a Gaussian blur, a weighted mean of nearby pixels.



(a) GIMP despeckle algorithm applied (b) Gaussian blur applied to image with to image with fixed pattern noise.

Fig. 2.1: Common denoising techniques applied to fixed pattern noise

As seen with these correction techniques for AGWN, the image is blurred while leaving behind remnants of line noise. Even with a large filter radius applied to the Gaussian blur, artifacts from the original noise are present while blurring all finer details beyond recognition.

#### 2.1.2 Scene Mean/Median NUC Method

The scene mean non-uniformity correction method relies on using statistical mean or median methods for its correction [1]. In this paper we have utilized the median method as it minimizes the effect of outlier pixels in an image. For the rest of the paper we will refer to this correction method as the 'scene median', but the mean can be substituted for its computation. The algorithm assumes that the median of all samples for a line is the same as the median for the entire scene. This algorithm works well for handling scenes with large amounts of striping noise but relies on the assumption that the scene's median is representative of all rows. This algorithm is also an attractive approach to non-uniformity correction because of its simple implementation and low computational complexity.

The base assumption is often not valid with images presenting prominent uniform features, such as lakes, rivers, roads, and other like features. Significant secondary artifacts are produced when large uniform objects present themselves in a given line and contain an average value that does not coincide with the given average for the whole scene. These artifacts present themselves as an over-correction of the given line in either a lightening or darkening fashion. Suppose a line contains an object with an average luminance greater than that of the scene. In that case, the line will be assumed to have a noise offset that is brightening the line, and thus the assumed correction will be a negative offset in order for the line's average to converge with that of the scene. This correction will darken the image for where this light object is present. This artifact will also present itself when an overall dark object is locally present in a scene as seen in Figure 2.2c where the correction method has over-corrected the upper and lower part of the image by brightening and darkening the respective parts of the image. Large objects/features in an image with a significant difference in average luminance than the rest of the scene will create an inadequate correction for the entire image. Utilizing the row and scene median statistic in the implementation instead of the mean helps avoid outlier pixel values affecting the adjustment values.



(a) Image with introduced line noise.



(b) Comparison of average row luminance.



(c) Image corrected with median NUC.

Fig. 2.2: Median NUC example

Highlighting potential secondary artifacts using synthetic sample imagery is shown in Figure 2.2. We can observe striping noise from left to right in the uncorrected imagery with large uniform bodies of water in the upper section of the imagery containing an average value far less than the rest of the given scene. When the median non-uniformity correction algorithm corrects this image, it perceives the water as a negative noise offset and, in turn, over-lightens rows trying to compensate for the large amounts of dark water. The dark water also gives the entire scene a low average compared to the image's non-water sections. The correction for this scene composition will result in the darkening of the imagery that is non-water sections. The 'truth' image's line highlights the true dynamic range of the imagery in the presented line chart 2.2b. Analyzing the imagery from top to bottom (low to high in terms of line count), you can see each row's average luminance generally increases. With the assumption of the median/mean scene algorithm, that the average row luminance is that of the scene's average, the plot of the 'corrected' image line shows a rise (brightening) of the truth's dark rows and a decline (darkening) of the bright rows. These corrections disrupt that original dynamic range of the image and introduce significant secondary artifacts.

### 2.1.3 Midway Histogram NUC Method

This statistical non-uniformity correction method utilizes line histogram information to infer a given row's correct luminance. The midway histogram correction's base assumption is that neighboring lines have nearly equal histograms [5] and that a target line's correction is derived with this information. In efforts to not correct a line with inadequate local information, the midway histogram correction utilizes a window around a target line and Gaussian weighting of adjacent lines to produce the proper equalization. This method utilizes a single static scene's information alone for its derived correction. The most crucial parameter to this method is the window size around the target line and will dictate the amount of local information to contribute to the resulting correction [5].

This algorithm's issue is that its local correction nature allows it to fall victim to noise prevalent in a confined area. The window size parameter has crucial bounds that must fall within to maintain proper correction values, but these bounds also inhibit its ability to avoid dense local noise. If the window size is too small, it may not obtain enough line information unaffected by noise for a proper correction. However, if the window is too large, the window may begin to sample lines that contain content that does not correctly reflect the target row's content. The Gaussian weighting helps minimize the impact of non-alike rows that are more distant from the target row, but if noise is pervasive throughout the window, the row's correction will be tainted and inaccurate.





(a) Comparison of average row lumi-(b) Image corrected with median NUC.

Fig. 2.3: Midway NUC example

We have a better result than the scene median algorithm by utilizing the same truth image with introduced noise from above and applying the midway histogram algorithm to the image. The midway histogram algorithm did a far better job maintaining the truth image's general luminance pattern while smoothing out and minimizing the introduced noise. Although the results are improved over that of the scene mean/median algorithm, the midway histogram correction still has some leftover artifacts in areas where the window spans many rows that are more affected by noise and thus introduces the original noise into the target row by an incorrect adjustment value. This noise propagation is presented in Figure 2.3a as abnormal spikes deviating away from the truth image's row luminance.

### 2.1.4 Median Ratio NUC

According to Leather [1], the median ratio NUC method assumes that adjacent samples in a scene across many lines will have a median ratio of approximately 1. This algorithm's highlight is that it can avoid making assumptions about the scene's global radiance with relation to a specific line like those assumptions made in the scene median correction al-

gorithm. This algorithm does its most optimal corrections in imagery where the spatial resolution is fine enough that a majority of adjacent pixels are imaging the same object [1]. In scenes where the previous condition holds and given enough lines in the imagery to form a substantial collection of adjacent sample ratios, hundreds to thousands, any outliers will be non-influential on the final correction ratio. As noted in Leathers [1] this method alone only provides a locally accurate non-uniformity correction. The correction may propagate noise as the algorithm moves across the image, either picking up additional noise or having present noise in the correction ratio taper off. An adjustment for this method starts the algorithm in the center of the image, working out towards the edges. This adjustment to the correction method will mitigate any secondary artifacts, but local noise propagation will still be present to an extent. The median ratio correction algorithm's downfall is its assumption that any given line in an image is supposed to have a ratio of approximately 1 to any other line in the given scene. This assumption is not valid for imagery where the general pixel intensity increases from one end of the imagery to the other. In Figure 2.4b we can see an example of a scene where the general row intensity increases from top to bottom. As a result of this composition, the method encounters a situation where the correction adjustment value trends to zero.



(a) Comparison of average row lumi- (b) Image corrected with median ratio nance. NUC.

Fig. 2.4: Ratio NUC example

# CHAPTER 3 EVALUATION

### 3.1 Evaluation

#### 3.1.1 Common Evaluation Metrics

Identification and quantification of noise present in a given scene are essential for a correction's fitness measure. This identification of noise in a scene is often made through a closed aperture calibration image. This calibration image is a response to a uniform black body source and allows one to identify any noise introduced by the sensor. However, these calibration images are often not an available resource for downstream image correction and thus are not included in this paper's approach to non-uniformity correction.

Other common image quality evaluation approaches include peak signal-to-noise ratio (PSNR) and structure similarity index measure (SSMI). The PSNR metric is based on the mean squared error and offers a value describing the objective difference between two images' pixel values. The SSIM metric offers insight into the change of an image's overall composition by factoring in the changes to the images' average, variance, and covariance. These evaluation approaches require two images to compare: a corrected image and a ground truth image free of the corrupting noise.

Due to that lack of a standard dataset, a set of data with uncorrected images and their ground truth counterparts, PSNR and SSIM are often not viable metrics. The most common evaluation metric is a visual comparison and analysis by the human eye [1, 2, 5-7]. Quantitative measurements do not always capture an accurate representation of image quality, and often a visual comparison will highlight edge and texture presentation better than a quantitative measure. [2]

### 3.1.2 Evaluation Metrics

### **Root Squared Mean Error**

The RSME is a standard quality metric to assess an image's reconstruction compared to its 'truth' image [8]. The RSME is utilized in two different formats for assessing the quality of tested non-uniformity correction algorithms. The first utilizes the metric on a pixe-by-pixel basis defined as:

$$M = \left[\left(\sum_{j=0}^{M} \sum_{i=0}^{N} (b_{i,j} - c_{i,j})^2\right)/N\right]^{1/2}$$

Where 'M' is the output metric score, N is the number of columns in an image, M is the number of rows in an image,  $b_{i,j}$  is the pixel value in the truth image and  $c_{i,j}$  is the corresponding pixel value in the corrected image.

Given that the striped fixed pattern noise introduces itself on a per line basis, a second evaluation technique utilizes the RSME on a row mean basis and is defined as:

$$M = [(\sum_{i=0}^{N} (\bar{b}_i - \bar{c}_i)^2)/N]^{1/2}$$

Where 'M' is the output metric score, N is a line number in a given image,  $\bar{b}_i$  is the mean of the line at index 'i' in the truth image and  $\bar{c}_i$  is the mean of the corresponding line in the corrected image.

### **Bias Correction Metric**

This alternative metric builds off the RSME metric by introducing a bias correction before calculating the RSME. This correction involves taking the median of the truth image  $\tilde{b}$  and finding the median of the corrected image  $\tilde{c}$ . Utilizing the difference of these two values a correction can be applied so that  $\tilde{c} = \tilde{b}$ . This approach looks to isolate the underlying image composition by removing any general offset that has been introduced to the corrected image through correction. This alternative metric highlights imagery that may contain a good scene representation to human analysis despite being offset from the 'truth' image's intensity.

### Metric Utilization

These quality metrics will give objective benchmarks that we can use for quality assessment of images where a ground truth image exists. The pixel-based metric will offer insight on image reconstruction by the most fundamental image element. In contrast, the row-based metric will offer an evaluation on row-by-row correction and could provide insight for applications where row statistics are more important than pixel statistics.

Also, for other imagery where a ground truth image does not exist, a visual comparison for image quality, correction, and secondary artifact introduction will be utilized.

# CHAPTER 4 DATA

### 4.1 Data

### 4.1.1 Standard Dataset

With the absence of a standard dataset for evaluating non-uniformity noise correction, the generation of such a dataset is presented as a contribution from this paper's research. The dataset will encapsulate various scene compositions and various stripe noise presentations. Utilizing the noise analysis done by Liu [9] on real-world data, this synthetic dataset will highlight the following noise: local, global, periodic, non-periodic, single, agminated, and banding noise. Local noise describes noise present in a subsection of the image, while global noise describes noise that is persistent throughout the entire image. Periodic noise displays a reoccurring pattern of noise in the corrupted part of the imagery, either local or global. Single noise describes an occurrence of noise that only affects one line within a local region and displays no patterned behavior with other occurrences of noise in the image.

Creating and utilizing a standard dataset of imagery allows for an environment where the objective ground truth image is available. Utilizing the truth image to measure nonuniformity corrections provides an objective metric for comparing algorithms. Visual points of comparison will supplement the standard dataset and proposed metric.

### 4.1.2 Noise Generation

This section will describe and highlight the methodology used to generated the variety of synthetic noise introduced to the standard dataset images.

[jme] General noise algorithm parameters are as follows:

1. Input: Truth Image B

- 2. Max Noise Offset (o)
- 3. Length of Noise Section (l)
- 4. Period Interval Length (p)
- 5. Local Noise Start (s)
- 6. Height of Image  $(B_h)$
- 7. Random Number (r)
- 8. Max Noise Offset (m)
- Local Periodic Noise: Noise that presents itself in a subsection of the image through a repeating pattern. The algorithm is:

```
i = s
do
for All columns in row_i
N(column, row_i) = B(column, row_i) + o
i \neq p
while i < B_h and i < s + l
```

• Local Non-Periodic Noise: Noise that presents itself in a subsection of the image through a non-repeating pattern.

```
i = s
do
for All columns in row_i
N(column, row_i) = B(column, row_i) + o
i \neq r \mod p
while i < B_h and i < s + l
```

• Global Periodic Noise: Noise that presents itself throughout the image through a repeating pattern.

```
i = 0
do
for All columns in row_i
N(column, row_i) = B(column, row_i) + o
i \neq p
while i < B_h
```

• Global Non-Periodic Noise: Noise that presents itself throughout the image through a non-repeating pattern.

i = 0do for All columns in  $row_i$  $N(column, row_i) = B(column, row_i) + o$  $i \neq r \mod p$ while  $i < B_h$ 

• Single Noise: Noise that affects a single line with no pattern to other noise in the imagery.

```
i = r \mod B_h
do
for All columns in row_i
N(column, row_i) = B(column, row_i) + o
i \neq r \mod B_h
while i < B_h
```

• Agminated Noise: Noise characterized by a sudden change in noise intensity offset that remains consistent for an indeterminate period.

• Periodic Banding Noise: Noise that is characterized by a sudden change in noise intensity offset that remains consistent for multiple periods.

```
i = 0

do

if i \mod p == 0

o = r \mod m

for All columns in row_i

N(column, row_i) = B(column, row_i) + o

++i

while i < B_h
```

### CHAPTER 5

### ALGORITHM

### 5.1 Clustering Non-Uniformity Correction

#### 5.1.1 Clustering

The basis for this correction algorithm starts with the clustering of the image values through a gray value k-means approach. K-means is a clustering method that takes a sample space and organizes it into k partitions minimizing each cluster's variance [10, 11]. The Kmeans algorithm works through an iterative method assigning each sample to a centroid. After distributing all samples to their closest centroid, new centroids are computed by taking the mean of all samples for a given centroid. After reassigning samples to the resulting centroids, the algorithm repeats for a given number of iterations.

### 5.1.2 Correction

Calculating a row-by-row correction is done utilizing the resulting clustering information obtained from the clustering step. The correction method is based on the median scene correction but adjusted to derive correction values from individual clusters and combine them for a single correction value per row. The following equation shows the calculation for a row's correction value:

$$C_{i} = \sum_{j=0}^{K} \left( \widetilde{G}_{j} - \widetilde{l}_{i,j} \right) * \left( s_{i,j} / w_{i} \right)$$

Where  $C_i$  is the correction offset value to be applied to all pixels in the target row, where K is the number of clusters,  $\tilde{G}_j$  is the median of the  $j^{th}$  cluster at a global scope, where  $\tilde{l}_{i,j}$  is the median of the  $j^{th}$  cluster at a local scope of the  $i^{th}$  row, where  $s_{i,j}$  is the sample population of  $\tilde{l}_{i,j}$ , where  $w_i$  is the sample population for the  $i^{th}$  row or the width of the image.

### 5.1.3 Correction Value per Cluster

Clustering on a noisy image is expected to produce poor clustering information. Imperfect clustering information stems from pixels corrupted by noise that reside near cluster bounds and are assigned incorrectly according to their actual signal. The proposed algorithm utilizes the median statistic to mitigate pixels clustered by noise. An alternative implementation could utilize a mean statistic but is susceptible to outlier features such as in-scene glints. The median statistic being affected by incorrectly clustered pixels decreases as samples increase for a given cluster. The correction values are weighted by the participation of that cluster in a given row to mitigate poor correction values. This weighting targets local clusters with a small population containing incorrectly clustered pixels and minimizes potential incorrect values. The weighting is defined as the number of samples in the local cluster for a given row divided by the number of total samples in that given row.

### 5.1.4 Primed Correction

One approach to mitigating noise in the uncorrected image resulting from corrupted clustering information is to perform clustering on an image that another non-uniformity correction has already corrected. A pre-corrected image may provide a better scene for generating accurate clustering information. The best primed images have mitigated highfrequency noise and allow the clustering algorithm to identify general features and overall composition of the image instead of picking up on noise embedded in these areas. Using the clustering information from the pre-corrected image and applying it to the uncorrected image allows for better correction of high-frequency noise that may have otherwise been incorrectly clustered. Using the clustering correction method on primed images offers a flexible approach to various scenes and noise types. If a correction method works well at mitigating high-frequency noise but struggles with maintaining overall image composition, primed clustering correction can offer a solution.

# CHAPTER 6

## RESULTS

### 6.1 Results



#### 6.1.1 Algorithm Performance

Fig. 6.1: Bi-directional bar chart highlighting best performers for both RMSE metrics. X-axis is the count of scenes in which the given correction performed best by the given metric (Pixel RMSE on the left and Row RMSE on the right). Scenes consisted of all seven different noise types.

Figure 6.1 shows the two top performers on the synthetic dataset were the midway histogram correction and the midway histogram primed cluster correction. The base clustering algorithm placed third in both metrics with the scene mean and scene mean primed clustering correction coming in at fourth and fifth. Median ratio and its primed correction

method placed last having no best performances over the other correction methods for all scenes.

For the pixel RMSE metric the midway histogram primed cluster correction performed best and the base midway histogram correction performing second best. These results are reversed for the row RMSE metric. This performance difference among metrics is likely attributed to the clustering method's correction that takes into account sub-row correction values while the midway correction is based on whole row correction techniques. The difference in these approaches allows the clustering correction to minimize outliers on a pixel by pixel basis.

The worst performer was the median ratio correction and its primed correction counterpart. The median ratio method had correction issues that lead to severe detrending, as seen in 6.2a, despite mitigation techniques such as starting from the center of the image and working outward. Another mitigation technique is to add a global component to the correction value. Leathers [1] recommends utilizing the scene mean correction value as a global component, but the inclusion of this value introduced secondary artifacts produced by the scene mean method into the final correction as seen in 6.2b.



(a) Median ratio corrected image with no global correction component shows severe detrending to zero intensity.



(b) Median ratio corrected image with global correction component shows secondary artifacts introduced by the secondary correction component.

Fig. 6.2: Comparison of median ratio correction with and without global correction component. Table 6.1 shows that the results for the midway correction method produced an average standard deviation often less than two and greater than zero showing the algorithm's stability. Its primed correction counter part also produced low standard deviation numbers often less than three and greater than one. Error averages in noise types where the midway histogram primed clustering correction performed better were often one point or fractional of a point better, and at times with higher standard deviation numbers.

### 6.1.2 Performance by Noise Types

Table 6.2 summarizes the best performing correction methods for all scenes of a given noise type. The best performers where the midway histogram and the midway histogram primed clustering corrections. The base midway histogram correction performed greater than 50% on local periodic noise, single noise, and the truth imagery. These noise type categories have the least amount of noise present and therefore limit the potential for local noise propagation, which is one of the weaknesses in midway histogram's correction method. The midway histogram primed clustering correction performed the best in noise type categories that contain a lot of noise variability throughout the scene.

Noise Type	Best Method	Percentage			
AN	N Midway Histogram				
GNPN	Midway Histogram Primed Clustering	88%			
GPN	GPN Midway Histogram Primed Clustering				
LNPN	Midway Histogram Primed Clustering	66%			
LPN	Midway Histogram	60%			
PBN	Midway Histogram Primed Clustering	44%			
SN	Midway Histogram	66%			
Truth	Midway Histogram	62%			

Table 6.2: Best correction method by noise type. Percentages are representative of best correction by the pixel RMSE error metric across fifty different scenes per noise type. Abbreviations can be found in the acronyms section.

				C	Correctio	n Method	l		
Measure	Noise Type	MN	MIDN	RN	CN	MCN	MIDCN	RCN	UC
	AN	$14 \pm 9$	$8 \pm 1$	$24 \pm 12$	$8 \pm 1$	$12 \pm 7$	$8\pm 1$	$13 \pm 2$	$8 \pm 1$
	GNPN	$14 \pm 9$	$4 \pm 2$	$25 \pm 11$	$8\pm 2$	$12 \pm 7$	$4\pm 2$	$13 \pm 3$	$9\pm 2$
Pixel	GPN	$14 \pm 10$	$2\pm 0$	$21 \pm 12$	$5 \pm 1$	$11 \pm 7$	$2 \pm 1$	$10 \pm 3$	$5 \pm 1$
Dirrol	LNPN	$14 \pm 10$	$2 \pm 1$	$19 \pm 13$	$3 \pm 1$	$11 \pm 7$	$2 \pm 1$	$8\pm3$	$4 \pm 1$
Pixel PixelBias	LPN	$14 \pm 10$	$1\pm 0$	$18 \pm 14$	$2 \pm 1$	$11 \pm 7$	$2 \pm 1$	$7\pm3$	$2\pm 0$
	PBN	$14 \pm 9$	$10 \pm 1$	$27 \pm 11$	$9 \pm 1$	$12 \pm 7$	$9\pm 1$	$15 \pm 4$	$10 \pm 1$
	SN	$14 \pm 10$	$1\pm 0$	$17 \pm 14$	$2 \pm 1$	$11 \pm 7$	$2 \pm 1$	$6 \pm 3$	$0\pm 0$
	TRUTH	$14 \pm 10$	$1\pm 0$	$16 \pm 14$	$2 \pm 1$				
	AN	$14 \pm 10$	$8 \pm 1$	$24 \pm 12$	$8\pm 2$	$12 \pm 7$	$8\pm 2$	$12 \pm 2$	$8 \pm 1$
PixelBias	GNPN	$14 \pm 10$	$2\pm 0$	$25 \pm 12$	$7\pm2$	$11 \pm 7$	$3 \pm 1$	$13 \pm 3$	$8\pm 2$
	GPN	$14 \pm 10$	$2\pm 0$	$21 \pm 13$	$5 \pm 1$	$11 \pm 7$	$2 \pm 1$	$10 \pm 3$	$5 \pm 1$
DivolDiag	LNPN	$14 \pm 10$	$2\pm 1$	$20 \pm 14$	$3 \pm 1$	$11 \pm 7$	$2 \pm 1$	$8 \pm 3$	$3 \pm 1$
FIXEIDIAS	LPN	$14 \pm 10$	$1\pm 0$	$18 \pm 15$	$3 \pm 1$	$11 \pm 7$	$2 \pm 1$	$7\pm3$	$2\pm 0$
	PBN	$14 \pm 10$	$10 \pm 1$	$27 \pm 11$	$9 \pm 1$	$12 \pm 7$	$9\pm 1$	$15 \pm 4$	$10 \pm 1$
	SN	$14 \pm 10$	$1\pm 0$	$17 \pm 15$	$2 \pm 1$	$11 \pm 7$	$2 \pm 1$	$6\pm3$	$0\pm 0$
	TRUTH	$14 \pm 10$	$1\pm 0$	$17 \pm 15$	$2 \pm 1$				
	AN	$14 \pm 9$	$8 \pm 1$	$21 \pm 8$	$8 \pm 1$	$12 \pm 7$	$8\pm 1$	$13 \pm 2$	$8 \pm 1$
	GNPN	$14 \pm 9$	$4 \pm 1$	$23 \pm 8$	$7\pm2$	$12 \pm 7$	$3\pm 2$	$13 \pm 3$	$8 \pm 2$
	GPN	$14 \pm 9$	$2 \pm 0$	$19 \pm 9$	$5 \pm 1$	$11 \pm 7$	$2 \pm 1$	$10 \pm 3$	$5 \pm 1$
Bow	LNPN	$13 \pm 9$	$2 \pm 0$	$17 \pm 10$	$3 \pm 1$	$11 \pm 7$	$2 \pm 1$	$8 \pm 3$	$3 \pm 1$
Row	LPN	$13 \pm 9$	$1\pm 0$	$16 \pm 10$	$2 \pm 1$	$11 \pm 7$	$2 \pm 1$	$7\pm3$	$2\pm 0$
	PBN	$14 \pm 9$	$10 \pm 1$	$25 \pm 7$	$9 \pm 1$	$12 \pm 6$	$9\pm 1$	$15 \pm 3$	$10 \pm 1$
	SN	$13 \pm 9$	$0\pm 0$	$14 \pm 11$	$2 \pm 1$	$11 \pm 7$	$2 \pm 1$	$6 \pm 3$	$0\pm 0$
	TRUTH	$13 \pm 9$	$0 \pm 0$	$14 \pm 11$	$2 \pm 1$				
	AN	$14 \pm 9$	$8 \pm 1$	$22 \pm 8$	$7\pm2$	$11 \pm 7$	$7\pm 2$	$12 \pm 2$	$8 \pm 1$
	GNPN	$14 \pm 9$	$2 \pm 0$	$23 \pm 9$	$7\pm2$	$11 \pm 7$	$2 \pm 1$	$12 \pm 3$	$8 \pm 2$
	GPN	$14 \pm 9$	$1\pm 0$	$19 \pm 9$	$5 \pm 1$	$11 \pm 7$	$2 \pm 1$	$10 \pm 3$	$5 \pm 1$
BowBing	LNPN	$13 \pm 9$	$2 \pm 0$	$18 \pm 11$	$3 \pm 1$	$11 \pm 7$	$2 \pm 1$	$8 \pm 3$	$3 \pm 1$
HOWDIAS	LPN	$13 \pm 9$	$1\pm 0$	$16 \pm 11$	$2 \pm 1$	$11 \pm 7$	$2 \pm 1$	$7\pm3$	$2\pm 0$
	PBN	$14 \pm 9$	$10 \pm 1$	$25 \pm 7$	$9\pm1$	$11 \pm 7$	$9\pm 1$	$14 \pm 3$	$10 \pm 1$
	SN	$13 \pm 9$	$0\pm 0$	$15 \pm 12$	$2\pm1$	$11 \pm 7$	$2 \pm 1$	$\overline{6\pm3}$	$0\pm 0$
	TRUTH	$13 \pm 9$	$0\pm 0$	$15 \pm 12$	$2 \pm 1$				

Table 6.1: Summary of results across noise types and correction methods. Correction method abbreviations can be found in the acronyms section.



Fig. 6.3: The noisy image followed by the best and worst corrections for Scene 24.


Fig. 6.4: Bar chart highlight performance improvement by pixel error metric when primed correction is utilized.

Figure 6.4 shows when utilizing the primed clustering correction method the resulting image contained less error on average than the base correction method. Figure 6.4 highlight results for standard error deviation on primed correction, showing a similar behavior of minimizing the standard deviation for the median scene and median ratio methods. In the midway histogram primed correction the standard deviation was elevated over the base correction method. On average the primed corrections did not minimize standard deviation or elevate standard deviation past the base clustering method's score, the same is also said for the error.



(g) Clustering vs Truth

(h) Uncorrected vs Truth

Fig. 6.5: Line charts highlighting the average row intensity (y-Axis), by row index (x-Axis) for scene 31 corrupted by GNPN noise.

Figure 6.5 highlights average row intensity trends in comparison to the truth image. Figure 6.5h displays the average row intensities as a blue line, as seen the line has some variability on the line by line scale with is apart of the natural scene variability. The line plot also displays a trend of average row intensity, starting at the top of imagery (left side of graph) at 160 and ending at the bottom of the imagery (right side of graph) at 110. The noisy image is plotted on the same graph and highlights the added noise to the image seen as spikes in row intensity. The presence of these spikes throughout the plot indicate noise throughout the image. Error metrics found in tables A.1 and A.2 show the best performer for this scene to be midway primed clustering (Figure 6.5d) with an error of 2.10 for both metrics and the worst performer to be median ratio 6.5e with an error of 15.59 and 15.47 for each metric respectively. The midway primed clustering (Figure 6.5d) plotting highlights the low error metric as the two lines lie closely to one another. The closely trending lines lead to a low error metric and increase similarity to the truth image but the small spikes are still seen on the corrected image's line indicated variability on a line by line basis which can make the resulting image appear not smooth (Figure 7.2h). The trend data in Figure 6.5b shows a brightening of rows from 200-750 and a darkening of rows from 900-1600 with another brightening of the last rows from 1750 to the end of the image in relation to the truth image. These difference in image intensity trends produced a pixel RMSE error of 7.55, which is three times more than the error of the midway primed clustering correction. The median primed correction plot lacks the sharp spikes that are seen in the midway clustering correction plot; the lack of spikes can increase perceived smoothness, particularly on a local level (Figure 7.2i).

# CHAPTER 7 DISCUSSION

#### 7.1 Discussion

#### 7.1.1 Correction Validation

With a large resulting pool of corrected images development of an algorithmic metric and utilization of the metric to evaluated results is necessary. While the developed error metrics can quickly identify top performers and other corrections that may have had issues, it can not properly account for human perception. As seen in Figure 7.2 the median scene primed clustering correction appears at first glance to be the best because of its smooth appearance, but the derived metrics and error difference image 7.2f offer insight to potential problems. If the resulting corrected image is sent directly for human analysis Figure 7.2c may be the best correction, but if the imagery is to have more image processing done to it or some statistical analysis, the midway histogram primed clustering correction offers an image with minimal error that may prove to be the best for such applications. These situations can occur when a correction method corrects high frequency noise but introduces a secondary low frequency noise. This secondary noise may have a large impact on the statistics of the image but can be hard for human eyes to perceive. While this low frequency error may be hard for human eyes to perceive it can have large impacts on the overall image composition.



Fig. 7.1: Scene 10 with GNPN corrected by midway histogram correction plotted against truth image without and with bias offset applied.

Figures 7.1a and 7.1b highlight the potential for other error metrics to play a role in non-uniformity correction evaluation. Figure 7.1a shows the average line intensity trends significantly higher than that of the truth image and generates a large error metric of 10.68(A.1). If the corrected image is adjusted for a bias, defined as the difference between both image medians, the resulting plot 7.1b shows a much closely trending line and produces an error metric of 4.08(A.3). This application of bias can create a plot that is much easier to judge and allow for comparison of underlying image composition and intensity trends.

The utilization of error metrics with an applied bias did not reveal much insight from numbers alone but has offered a way to more easily compare correction plots. For situations where underlying trends are of most importance the use of a bias to level the intensities between two images will offer the best environment for evaluation.



(g) Oncorrected image (ii) Midway primed (i) Median scene primed

Fig. 7.2: Scene 31 with GNPN corrections and uncorrected with image differences in respect to the truth image. The image differences' (d-f) image intensities are scaled in order to highlight noise. Image (g-i) are zoomed in sections to highlight left over noise.

The collection of figures in 7.2 exemplify that correction validation may be subject dependent on what attributes are of most importance. While error was minimized with the midway histogram primed clustering correction upon visual comparison some noise remnants are still visible as seen in Figure 7.2b. This left over noise and rough appearance leaves an argument open for the median scene primed clustering correction being the better image as seen in 7.2c. The correction made by the median scene primed clustering correction 7.2b. But when analyzing the average row intensity trend data in 6.5b we can see significant trend differences. These error differences are highlighted in Figures 7.2e-7.2d. These figures

visually highlight the error difference the image and the truth image. The corrections shown in Figures 7.2b and 7.2c both are visually better than the uncorrected image seen in Figure 7.2a, but looking at the image diff 7.2f the amount of introduced noise is more than the uncorrected image 7.2d. These kinds of scenes and corrections offer a starting point for conversations on whether a visual metric or an error metric is more important for correction validation.

## 7.1.2 Correction Discussion

## Midway Histogram Primed Clustering

The best performing correction by number of best scenes is the midway histogram primed clustering correction. This correction is considered best because of its low error values and consistent correction behave that prevents it from introducing large amounts of error. This correction is a combination of the midway histogram correction and the clustering correction. Both of these corrections had the next lowest numbers in terms of error values and standard deviation. The combination of these corrections then offer no surprise that resulting error values and standard deviation are also very low. The midway histogram primed correction excelled in keeping the corrected image very close to the truth image in value but did have some issues reducing the noise to a point where it is completely undetectable to human eyes. This noise propagation issue is present in both the base midway histogram correction and base clustering correction but for different reasons. The midway histogram correction has a noise propagation issue because of its limited local information. The correction relies on having enough local rows around it not corrupted by noise to produce an accurate correction. Though when given a locale of an image where noise is persistent the information collected from nearby rows may have too much noise corruption and thus propagate the noise to the corrected image. The clustering correction's noise propagation issue stems from the inaccurate clustering information it obtains. All inaccurate clustering information has an affect on the correction value, although in most situation some inaccuracy is fine because of the use of median statistics and clustering participation weights. But when given enough in accuracy these mitigation techniques begin to breakdown and noise propagation occurs. Although noise propagation occurs with the midway histogram primed correction, this method rarely amplifies noise or introduces secondary artifacts.

#### Median Scene Primed Clustering

The median scene primed correction had limited amount of scenes where it excelled. These scenes are one where the median scene correction was able to mitigate present noise and allow the clustering algorithm to generate accurate results. These scene are one that have uniform composition throughout the scene, often these scenes are low in content 7.3aor have repetitive content and no outstanding features 7.3b. The scenes with this kind of composition keep the median scene correction from introducing secondary artifacts. Secondary artifacts are often generated from outstanding features or in areas of an image where the general composition changes quickly. The severity of these secondary artifacts are dependent on the contrast levels of a given feature or composition shift. When such issues are not present the median scene correction is able to mitigate noise quite well and produce a smooth image where the clustering algorithm can generate clustering information that does not propagate noise. A downside to this correction method was that most imagery displays a focal point around a distinctive feature. Another issue when secondary artifacts were not introduced is that the median scene priming often changed the scene composition to a degree that the clustering would propagate these new composition attributes. These new composition attributes are often presented in low frequency noise, either lightening or darkening significant portions of the image.



(a) Low scene content

(b) Repetitive scene content

Fig. 7.3: These scene have low or repetitive content with no outstanding features and offer the median scene correction its best environment.

#### Median Ratio

The median ratio correction and median ratio primed correction both did the worst out of all other corrections by error values and visual evaluation. The main issue with this correction is its assumption, the assumption that all lines have a median ratio of 1 to one another does not allow for much change in an image. As scene in row intensity line plots for the test imagery it is apparent that these images have a intensity changes from one edge to another. These image composition changes can be seen as noise and when correcting for them the correction can quickly trend the image to zero intensity. As an additive part to this correction an introduction of a global correction term is used to avoid the trend to zero situation. The recommended global correction term when a laboratory calibration value is not available is the median scene correction value [1]. The addition of this correction term keeps the correction from trending to zero but introduces any secondary artifacts produced by the median correction and produces a noise amplification effect.

# CHAPTER 8

## CONCLUSION

## 8.1 Conclusion

Fixed pattern noise is an image degradation issue that can present itself in a variety of manners creating a challenge that may not be solved by a single correction method. Through analysis of the results stemming from the standard dataset and mix of correction approaches a single correction method does solve all scenes. The results become harder to interpret also when factoring in human perception as a qualifying metric. It can frequently occur that a scene appearing to be the best corrected may not be the one with the least amount of error. Whether this distinction is of importance depends on specific downstream application.

Creating a blend of local and global information to form a nuanced correction value drives the best performance of the clustering correction method. The stability that the clustering method displays permitted minimal error introduction in scenes with good and poor corrections. The method's heavy reliance on accurate clustering information created issues where local noise would be propagated, possible boosts to clustering accuracy are up for future research.

With different noise presence, scene composition, and fitness tests the best correction method may vary from scene to scene. It is important to compare and contrast the pros and cons of each potential method and having a set of standard imagery allows for better selection per application.

## 8.1.1 Final Contributions

Row correction through image clustering has strong merit but relies heavily on hitting a threshold of accurately clustering the signal over the noise. This clustering accuracy requirement is something that can be help with priming the image by applying a different correction method that can mitigate noise that may disrupt the clustering algorithm. Utilizing the clustering information from the primed image and applying it to the original uncorrected image allows potential for greater clustering results while avoiding any secondary artifacts or noise introduced in the primed image.

The generation of a standard dataset that spans multiple types of fixed pattern noise with a variety of scene compositions offer an environment where correction methods can be exercised. The lack of previous standard datasets combined with the issue of the unknown optimal noise correction for real world data created a research environment where objective non-uniformity correction comparison was non-existent. While the utilization of RSME based metrics may not properly account for human perception as seen in Figure 7.2 it does offer high level insight at a quick glance.

#### 8.1.2 Future Work

#### **Clustering Correction Method**

The clustering correction method's downfall is its susceptibility for clustering strong noise over the true signal producing poor clustering information resulting in a poor overall correction. For improved results research involving alternative clustering methods that can provide better clustering accuracy is a priority. For other applications where multiple registered images containing non-matching noise pattern may offer an environment where multi-dimensional clustering is a viable approach. As seen in Figure 8.1 the optimal clusters are shown in Figure 8.1a but the noise signal was clustered in the GNPN image seen as lateral lines in Figure 8.1b.

Another potential approach for better clustering accuracy could stem from incorporating spatial information into the clustering algorithm. Potential applicable algorithms may be DBSCAN [12], mean-shift [13], or super-pixel based clustering algorithms. The inclusion of spatial information may allow for better robustness toward line noise in uniform areas. Uniform areas are the most susceptible to continuous inaccurate clustering and given that a uniform area is large enough the line correction value will be severely affected. A potential issue with spatial clustering could relate to these areas of uniformity, since the line noise is continuous it in itself has some spatial affinity, the case is even greater for banding noise. Care will have to be take to avoid this attribute of spatial affinity for any line and banding noise, particularly in uniform sections of imagery.



(a) Clustering information given scene (b) Clustering information given scene 19's truth image where k=5. 19's GNPN image where k=5.

Fig. 8.1: Comparison of clustering information between truth image and noisy image.

## Metrics

RMSE based metrics offer high level insight to correction performance but do convey how humans perceive the image. Further metric development that can more accurately measure how humans may perceive will allow better correction method selection given a situation where the corrected image will go directly to human analysis. RMSE based metrics may have the best chance at identifying the best correction method for images that will continue to have more image processing applied to it downstream, this notion could still use more validation.

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APPENDICES

# APPENDIX A

# Scene Correction Metrics

A.1 Pixel RMSE Metric

Scene	Median	Midway	Ratio	Cluster	Cluster	Cluster	Cluster	AN
AN	AN	AN	AN	AN	Median AN	Midway AN	Ratio AN	Uncorrected
1	16.52	14.11	16.61	13.10	15.89	13.19	14.58	14.03
2	5.47	8.67	18.11	7.44	4.74	7.42	11.83	8.62
3	12.67	9.37	26.05	9.98	10.98	9.67	10.63	9.25
4	4.97	10.57	19.43	9.81	6.07	9.73	12.40	10.64
5	5.14	11.67	21.98	11.55	5.56	11.54	14.90	11.73
6	22.16	9.18	21.77	8.27	21.25	8.04	11.13	9.28
7	15.45	9.35	20.60	8.03	12.91	8.02	14.53	9.30
8	6.57	7.21	13.99	6.97	7.45	6.93	11.40	7.18
9	3.15	9.33	19.49	8.90	3.22	9.00	14.68	9.25
10	12.09	8.20	21.48	8.43	12.21	8.27	15.08	8.22
11	28.09	8.74	29.24	6.52	15.62	6.61	14.43	8.37
12	15.22	8.36	24.40	7.65	13.95	7.82	18.57	7.88
13	12.24	7.45	20.64	7.45	11.49	7.31	13.91	7.36
14	11.80	8.80	21.46	7.59	10.61	7.60	15.71	8.65
15	11.67	8.08	25.70	7.86	10.06	7.99	17.52	7.72
16	15.50	10.67	24.21	9.09	15.21	9.69	17.08	9.72
17	22.25	8.78	26.70	7.17	18.83	7.47	15.27	8.67
18	17.26	9.28	28.18	6.71	15.70	6.67	13.55	9.03
19	42.19	8.91	33.97	6.63	36.96	6.49	14.52	8.68
20	16.63	8.86	16.24	11.01	17.17	11.20	11.80	8.74
21	6.04	10.00	18.63	9.41	6.47	9.47	14.58	9.84
22	24.45	8.65	27.91	7.73	23.12	7.68	12.05	8.62
23	40.90	8.69	33.88	15.86	31.07	15.76	15.43	8.83
24	11.73	9.20	25.65	8.14	10.37	8.07	17.81	9.13
25	21.43	10.20	27.26	7.68	17.52	8.43	16.35	10.21
26	37.32	10.26	37.99	9.13	26.98	9.02	17.68	10.31
27	9.29	7.32	19.49	6.48	8.92	6.31	12.10	7.35
28	14.60	8.81	30.06	8.14	11.58	8.18	15.43	8.89
29	24.39	9.11	21.88	8.88	19.50	8.16	11.23	9.16
30	17.07	9.50	16.45	8.67	15.79	8.60	10.03	9.22
31	8.15	10.84	20.10	10.23	7.88	10.16	14.41	10.86
32	9.56	9.34	16.03	8.80	9.22	8.79	12.31	9.29
33	6.66	9.29	17.25	7.78	5.42	7.70	13.27	9.16
34	25.53	9.10	19.35	8.86	18.00	8.96	11.63	8.77
35	2.83	6.93	15.48	5.98	3.05	5.96	11.23	6.90
36	11.22	9.01	22.50	8.57	11.16	8.53	11.72	9.03
37	11.97	10.97	17.41	10.12	10.85	10.08	12.47	11.02
38	38.98	8.50	82.66	8.67	19.68	8.64	10.64	8.49
39	18.89	7.07	16.56	6.10	15.21	6.04	11.67	6.99
40	5.56	4.75	10.46	4.19	5.24	4.22	7.63	4.65
41	17.15	6.20	78.67	6.85	10.51	6.80	18.64	6.10
42	12.17	8.19	20.68	8.75	11.27	8.74	13.33	8.17
43	6.78	7.52	14.13	7.44	6.44	7.36	10.09	7.56
44	7.16	11.24	22.90	9.59	8.78	9.38	13.08	11.31
45	3.38	8.94	17.38	8.17	2.93	8.13	9.25	8.97
46	6.87	7.00	12.76	6.55	6.76	6.54	9.44	6.96
47	6.73	10.29	21.05	9.29	6.96	9.27	15.24	10.28
48	16.52	6.91	26.78	5.80	12.24	5.96	11.76	6.86
49	11.64	9.91	28.85	9.53	8.60	9.41	12.71	9.98
50	1.77	9.11	18.00	8.32	1.64	8.28	11.34	9.21

Scene GNPN	Median GNPN	Midway GNPN	Ratio GNPN	Cluster GNPN	Cluster Median GNPN	Cluster Midway GNPN	Cluster Ratio GNPN	GNPN Uncorrected
1	10.42	3.26	18.06	6.63	9.79	2.78	12.01	7 21
2	5 46	3.88	16.05	6.18	4 54	2.63	9.56	7.76
3	12 67	3 65	34.08	6.87	9.78	2.60	10.43	7.70
0	3 91	2 99	14 75	5 57	3.84	2.07	8.63	6.91
5	4 01	2.55	16.47	5.84	1 24	1.88	9.65	6.03
6	25 69	7.69	38.10	12 52	20.74	5.60	15 36	13 58
7	15 /2	3.42	24.00	6.12	12.61	2.63	15.00	7 1/
8	6 51	2 7/	1/ 17	5 78	6.62	2.00	10.57	6 15
9	3 19	3.60	17 78	6.98	2 9/	2.27	14 20	7.46
5 10	15.15	10.68	31.03	15 20	14.02	0.16	22 33	16.46
10	28.97	6.46	27.40	7 53	16.82	6.14	14 66	0.40
12	15 51	1 80	22.05	6.96	14.25	0.14 1 55	16.00	7.62
12	11 47	4.05	22.00	7 77	10.50	4.00 5.02	12 44	9.02
1.0	1415	4.70 8.54	22.34	12.50	12.39	7 1 7	21 20	14.21
14	12.40	7 1 4	29.31	10.17	11.61	7.17	20.01	14.21
16	17.20	0.04	20.21	12.10	16.65	7.20	10.41	12 55
17	22.50	9.04	20.00	13.10	10.05	7.04	19.41	13.55
10	22.50	4.07	27.00	0.12	16.99 16.4E	0.11 6.25	12.10	9.22
10	10.23	7.11 F 26	23.94	9.13	10.45	0.20	13.94	11.59
19	42.91	5.20	39.20	8.28	38.24	4.14	14.47	9.79
20	17.48	5.03	24.66	9.38	17.70	4.27	14.18	9.84
21	8.22	8.15	29.63	12.48	7.79	0.39	19.50	13.85
22	24.50	4.21	29.66	7.59	23.22	3.73	11.83	8.74
23	40.42	4.55	32.70	14.42	30.84	12.68	16.16	9.06
24	12.11	7.06	24.40	10.49	11.52	6.03	17.78	12.06
25	21.54	3.53	28.43	6.82	17.39	3.85	14.66	7.44
26	36.42	4.55	38.71	6.95	26.11	4.32	16.64	8.68
27	9.99	6.83	26.17	10.27	9.60	5.36	15.45	12.38
28	14.31	4.48	27.58	8.82	11.41	3.00	14.46	9.29
29	23.87	8.33	33.88	12.68	19.76	6.70	17.69	14.12
30	18.62	8.68	27.85	12.71	17.30	7.15	16.53	14.13
31	8.20	3.14	15.59	4.42	7.55	2.10	6.85	6.83
32	10.27	3.45	17.40	6.39	9.04	2.46	9.77	7.38
33	6.63	3.63	15.61	5.90	5.35	2.40	9.41	7.37
34	25.24	3.99	21.17	5.63	19.38	3.96	12.70	5.85
35	3.51	3.60	17.27	6.02	2.89	2.19	10.83	7.87
36	11.06	3.17	22.50	5.84	10.91	2.57	8.55	7.28
37	10.65	2.57	16.27	5.45	9.24	2.25	7.32	6.04
38	38.52	4.13	84.40	8.19	18.96	2.77	13.72	8.75
39	19.06	3.48	17.71	5.84	15.16	4.23	12.73	6.18
40	5.84	3.18	16.34	5.58	5.36	2.31	9.57	6.44
41	17.39	4.43	54.63	8.66	9.58	3.69	19.07	8.92
42	12.81	4.44	27.09	8.85	11.98	3.33	16.99	9.16
43	5.67	3.51	15.98	6.55	4.66	2.60	10.02	7.37
44	6.13	3.99	17.46	6.90	5.30	2.86	9.38	8.54
45	2.89	2.72	12.70	5.65	2.88	1.53	6.30	6.31
46	7.06	4.54	19.37	7.51	6.56	2.58	10.41	9.20
47	7.66	4.54	19.46	7.89	7.20	3.69	12.87	9.11
48	17.27	4.95	31.17	8.71	12.45	3.12	14.84	9.94
49	11.50	2.61	22.36	5.39	8.76	1.78	9.99	5.92
50	1.77	2.91	13.70	5.66	1.42	1.54	7.44	6.66

Scene GPN	Median GPN	Midway GPN	Ratio GPN	Cluster GPN	Cluster	Cluster	Cluster Ratio	GPN
		_			Median GPN	Midway GPN	GPN	Uncorrected
1	10.45	2.05	15.09	4.37	9.80	1.98	9.53	4.72
2	4.71	2.08	10.79	3.58	4.31	1.13	6.26	4.72
3	13.14	2.54	33.81	5.76	9.72	2.25	8.39	5.01
4	3.69	1.74	10.20	3.84	3.80	1.25	6.26	4.50
5	3.73	1.44	11.46	4.13	4.20	1.91	8.61	3.98
6	23.56	3.42	33.42	6.54	20.08	2.18	12.35	7.59
7	15.40	2.23	21.34	4.14	12.56	1.90	13.28	4.69
8	6.28	1.98	10.77	4.11	6.59	1.82	8.00	4.26
9	2.90	2.43	11.96	4.39	2.93	1.83	10.11	4.85
10	12.75	4.55	20.94	8.17	11.84	3.68	14.33	8.89
11	28.27	3.93	26.57	5.23	15.95	4.03	13.16	6.04
12	15.28	3.88	19.29	4.74	14.02	3.56	14.74	5.12
13	11.45	2.77	18.30	5.90	10.33	4.32	8.08	5.67
14	12.39	4.15	21.21	7.24	10.97	2.99	14.76	8.16
15	11.66	3.87	20.74	5.24	10.49	3.58	13.61	6.90
16	16.12	5.49	19.61	7.42	15.46	4.51	13.80	7.45
17	22.21	2.70	25.09	4.80	18.71	2.25	12.71	5.79
18	17.28	3.74	19.53	5.40	15.56	3.29	10.09	6.81
19	42.36	3.16	37.75	5.09	37.86	2.74	14.12	6.29
20	16.75	2.84	20.37	6.84	17.33	2.85	10.86	6.32
21	6.55	3.79	17.69	6.62	6.40	2.86	12.39	7.58
22	24.37	2.41	27.20	4.88	23.05	2.49	9.53	5.37
23	40.52	2.41	31.23	12.70	30.52	12.37	15.23	5.72
24	11.13	3.38	17.80	5.84	10.49	2.72	12.51	6.95
25	21.38	2.10	26.45	4.66	17.37	2.02	13.11	4.89
26	36.81	2.60	37.11	4.95	26.11	3.25	15.62	5.45
27	9.05	2.97	17.33	5.58	8.63	1.83	9.52	7.08
28	14.02	2.38	23.19	5.29	11.20	1.53	11.92	5.77
29	24.07	3.77	29.58	7.61	18.53	3.28	12.69	8.18
30	17.61	4.51	21.06	7.79	16.00	3.43	10.88	8.18
31	8.00	2.03	11.91	3.37	7.48	1.52	5.49	4.48
32	9.94	2.24	13.95	4.26	8.99	1.69	7.45	5.01
33	6.36	2.51	11.66	3.75	5.31	1.62	6.43	5.01
34	25.15	3.21	20.66	3.91	19.04	2.82	11.86	4.02
35	3.03	2.08	11.62	4.21	2.83	1.31	7.97	5.18
36	11.22	1.86	18.55	3.92	10.99	1.75	6.50	4.72
37	10.49	1.55	13.25	3.58	9.07	1.94	4.58	4.03
38	38.79	2.24	83.68	5.72	19.06	1.94	12.21	5.36
39	18.76	2.30	16.75	3.94	15.02	2.85	11.77	4.06
40	5.54	1.82	11.37	3.58	5.15	1.25	6.83	4.04
41	17.02	2.76	53.93	5.54	9.46	2.68	16.88	5.99
42	12.18	2.41	21.86	5.94	11.67	2.34	12.60	5.77
43	5.31	1.85	10.78	4.19	4.40	1.38	7.53	4.63
44	5.80	2.29	12.56	3.20	5.09	1.52	6.71	5.75
45	2.69	1.55	9.13	2.81	2.96	1.11	4.18	4.25
46	6.80	2.66	13.48	4.90	6.45	1.49	7.49	5.79
47	6.88	2.38	13.28	4.85	6.90	2.06	9.15	5.56
48	16.79	2.62	26.82	5.44	12.02	2.47	11.19	6.35
49	11.64	1.56	20.22	3.50	8.79	1.32	7.84	4.01
50	1.38	1.73	9.52	3.74	1.39	1.15	5.22	4.51

Scene LNPN	Median	Midway	Ratio LNPN	Cluster LNPN	Cluster	Cluster	er Cluster Ratio LNF	
	LNPN	LNPN			Median	Midway	LNPN	Uncorrected
					LNPN	LNPN		
1	10.45	1.83	12.47	3.61	9.84	2.21	7.98	3.29
2	4.62	2.09	8.27	2.79	4.26	1.67	5.11	3.38
3	13.78	2.27	36.99	3.25	9.95	2.09	7.51	3.22
4	3.69	1.49	7.67	2.38	3.83	1.46	3.58	3.13
5	3.73	1.24	8.96	3.18	4.15	1.78	4.76	2.82
6	23.24	3.65	35.02	5.48	20.26	3.45	12.39	5.72
7	15.46	2.04	20.80	2.92	12.51	1.95	12.73	3.26
8	6.28	1.81	8.46	3.24	6.59	1.97	6.18	3.16
9	2.96	2.27	9.62	3.43	3.01	1.98	8.19	3.47
10	12.01	5.41	22.59	6.69	11.61	4.58	14.67	7.71
11	28.01	3.77	26.60	4.25	15.83	3.58	12.75	4.31
12	15.17	3.70	18.74	3.64	13.90	3.37	14.37	3.55
13	11.75	2.53	17.02	4.19	10.52	3.75	6.13	3.51
14	11.93	4.56	17.56	6.09	10.74	3.79	12.37	6.75
15	11.58	3.94	17.75	4.52	10.56	3.91	11.06	5.10
16	15.65	5.74	18.46	5.93	15.29	5.11	12.67	5.77
17	22.13	2.47	22.45	3.51	18.68	2.58	10.77	3.89
18	17.05	3.80	18.06	3.72	15.39	2.96	8.90	4.93
19	41.92	3.09	38.43	3.62	37.38	2.37	13.47	4.38
20	16.62	2.75	18.63	7.53	17.13	5.03	9.52	4.42
21	6.03	4.16	13.31	5.29	6.39	3.86	9.47	5.89
22	24.36	2.40	26.46	3.90	23.06	2.67	8.89	4.07
23	40.60	2.04	32.01	12.40	30.30	12.29	14.85	3.87
24	11.08	3.49	16.02	4.13	10.27	2.84	11.24	5.09
25	21.38	1.92	24.92	3.80	17.31	3.18	12.02	3.27
26	37.05	2.36	37.12	4.15	26.10	3.14	15.57	3.66
27	8.94	3.10	17.22	3.13	8.53	1.88	7.09	5.21
28	14.07	2.13	21.77	3.63	11.27	1.79	10.21	3.87
29	24.40	4.43	29.66	5.99	18.19	4.22	10.89	6.70
30	17.20	4.91	19.40	6.47	15.72	4.41	9.08	6.77
31	8.00	1.83	9.10	2.76	7.48	2.18	4.70	3.15
32	9.69	1.95	10.96	2.95	8.96	1.71	6.15	3.18
33	6.36	2.27	9.88	2.06	5.33	1.58	4.78	3.17
34	25.18	2.99	20.58	2.58	19.03	2.16	11.72	2.49
35	2.83	1.88	8.18	2.62	2.83	1.48	5.21	3.46
36	11.22	1.62	16.04	3.31	11.17	2.00	5.60	3.31
37	10.49	1.32	10.58	3.16	9.09	2.23	4.10	2.75
38	39.14	2.27	84.46	4.55	18.92	1.92	12.19	4.07
39	18.71	2.07	16.53	2.69	14.95	2.30	11.31	2.61
40	5.41	1.66	9.03	2.28	5.16	1.19	5.48	2.68
41	16.92	2.51	60.30	3.74	9.34	2.85	17.31	4.05
42	11.97	2.12	19.29	4.32	11.37	2.97	10.36	3.82
43	5.11	1.64	7.06	3.01	4.39	1.50	5.53	3.07
44	5.64	2.03	10.50	1.96	5.12	1.65	3.94	3.91
45	2.69	1.24	6.41	2.09	3.01	1.12	3.07	2.74
46	6.67	2.40	10.04	3.17	6.40	1.77	5.52	3.82
47	6.68	2.40	11.57	3.88	6.90	2.31	7.56	3.99
48	16.61	2.51	23.32	5.15	12.21	1.60	8.91	4.40
49	11.85	1.27	18.52	2.72	8.95	1.58	4.68	2.58
50	1.38	1.43	6.03	2.38	1.41	1.19	3.17	2.91

Scene LPN	Median LPN	Midway LPN	Ratio LPN	Cluster LPN	Cluster	Cluster	Cluster Ratio	LPN
					Median LPN	Midway LPN	LPN	Uncorrected
1	10.45	1.44	11.73	2.75	9.85	2.16	7.19	2.18
2	4.62	1.47	6.35	1.86	4.26	1.05	4.15	2.14
3	13.78	1.97	34.37	2.74	9.95	2.17	6.50	2.25
4	3.69	1.03	5.84	1.93	3.84	1.19	3.13	2.06
5	3.73	0.75	6.35	2.12	4.15	1.86	4.78	1.82
6	22.96	2.14	31.72	3.47	20.28	2.22	11.35	3.44
7	15.45	1.66	19.96	2.29	12.62	1.76	12.08	2.15
8	6.28	1.45	7.12	2.35	6.57	1.78	5.12	1.95
9	2.95	1.89	6.84	2.46	3.05	1.86	5.69	2.23
10	11.78	2.69	16.85	3.79	11.55	2.21	10.75	4.00
11	27.95	3.11	26.27	3.39	15.76	3.33	12.19	2.71
12	15.14	3.48	17.76	2.99	13.91	3.17	13.65	2.64
13	11.63	2.07	15.51	4.24	10.45	4.00	5.11	2.43
14	11.82	2.80	15.03	3.55	10.63	2.13	10.29	3.72
15	11.57	3.06	15.76	3.36	10.36	3.44	8.87	3.14
16	15.62	4.82	15.74	3.92	15.15	4.22	10.26	3.36
17	22.13	1.97	22.57	2.80	18.74	2.35	10.69	2.63
18	16.91	2.84	16.84	3.02	15.35	2.56	8.33	3.07
19	41.91	2.43	37.31	3.13	37.39	2.80	14.10	2.87
20	16.62	1.98	17.09	4.82	17.07	4.02	8.12	2.90
21	6.03	2.77	9.26	3.34	6.34	2.72	6.15	3.45
22	24.36	1.67	25.51	2.94	23.03	2.32	8.39	2.45
23	40.60	1.39	31.08	12.25	30.29	12.18	14.52	2.64
24	11.13	2.42	13.77	2.66	10.23	1.95	9.56	3.15
25	21.37	1.45	24.84	3.51	17.47	2.10	11.82	2.23
26	37.05	1.90	36.46	3.67	26.12	3.10	15.22	2.51
27	8.94	1.80	13.23	2.11	8.53	1.20	5.77	3.18
28	14.18	1.55	20.63	2.59	11.21	1.43	9.69	2.65
29	24.39	2.19	27.49	3.97	18.30	2.81	9.27	3.69
30	17.08	3.30	16.57	4.38	15.52	3.15	7.22	3.69
31	8.00	1.47	8.25	3.10	7.48	2.06	3.78	2.04
32	9.69	1.61	10.36	2.19	9.05	1.45	5.41	2.27
33	6.36	1.97	8.27	1.65	5.34	1.42	4.03	2.27
34	25.12	2.81	20.35	2.05	19.06	1.88	11.53	1.79
35	2.83	1.35	5.98	1.84	2.85	1.10	3.98	2.36
36	11.22	1.15	14.99	2.56	11.17	2.41	4.73	2.17
37	10.43	0.88	10.47	2.56	9.13	2.06	3.23	1.82
38	39.56	1.47	84.90	3.27	18.75	1.81	11.21	2.45
39	18.60	1.67	16.23	2.13	14.96	2.00	11.16	1.73
40	5.41	1.33	7.72	1.67	5.15	1.01	4.77	1.83
41	16.98	1.94	60.49	2.83	9.27	2.49	15.66	2.67
42	11.97	1.59	18.11	3.42	11.32	2.65	8.82	2.67
43	5.11	1.17	5.99	2.16	4.37	1.13	4.75	2.10
44	5.64	1.39	8.18	1.74	5.13	1.59	3.20	2.62
45	2.69	0.78	4.90	1.01	3.01	1.07	1.42	1.91
46	6.67	1.95	8.44	2.36	6.42	1.39	4.72	2.67
47	6.68	1.62	8.97	2.67	6.91	1.80	6.09	2.52
48	16.61	1.66	22.60	3.92	11.81	2.21	7.93	2.86
49	11.85	0.90	18.27	2.10	9.00	1.42	4.21	1.83
50	1.38	1.01	4.41	1.68	1.45	0.94	2.35	2.05

Scene PBN	Median PBN	Midway PBN	Ratio PBN	Cluster PBN	Cluster	Cluster	Cluster Ratio	PBN
					Median PBN	Midway PBN	PBN	Uncorrected
1	11.59	10.78	17.89	10.27	10.40	10.22	13.69	10.80
2	4.75	7.63	15.36	6.18	5.00	6.13	10.38	7.60
3	13.44	10.83	47.32	11.15	9.41	10.65	13.62	10.77
4	3.73	11.12	22.74	9.45	4.08	9.58	13.54	11.19
5	4.01	11.13	24.14	11.05	3.99	10.96	11.49	11.19
6	22.25	10.69	28.53	9.22	20.81	9.09	13.51	10.77
7	15.73	10.84	28.21	10.18	12.83	10.04	20.43	10.80
8	6.56	10.83	21.61	10.27	7.82	9.97	15.91	10.81
9	3.34	10.87	23.53	10.20	5.06	10.15	16.25	10.81
10	11.69	10.68	22.01	9.92	11.98	9.63	16.22	10.77
11	27.56	10.45	27.97	7.52	15.93	7.78	13.71	10.24
12	15.47	10.90	27.50	9.57	14.00	9.69	21.28	10.57
13	12.27	10.82	28.47	9.74	9.87	9.73	16.92	10.78
14	12.03	10.77	32.52	9.50	11.13	9.45	21.50	10.75
15	12.09	10.87	29.49	9.63	10.95	9.76	19.31	10.69
16	15.63	11.46	27.83	9.42	15.18	9.99	18.76	10.65
17	22.10	10.81	24.34	9.44	18.78	9.43	14.04	10.80
18	17.14	10.74	28.50	8.42	15.55	8.41	15.50	10.59
19	41.64	10.79	32.56	10.80	36.30	9.73	14.07	10.67
20	16.63	10.82	26.59	10.40	17.01	10.30	16.40	10.80
21	6.49	10.88	24.93	9.88	6.64	10.00	16.22	10.79
22	24.61	10.73	35.20	9.53	23.34	9.42	15.55	10.74
23	40.39	10.55	31.97	17.93	31.72	17.89	18.83	10.65
24	12.07	10.68	25.29	9.07	10.64	9.22	17.66	10.61
25	21.40	11.12	30.37	10.25	17.56	10.23	19.72	11.17
26	36.81	11.17	34.42	10.06	27.91	9.93	16.68	11.18
27	9.60	10.72	25.94	9.36	8.60	9.25	15.65	10.80
28	14.36	10.79	27.22	9.76	11.51	9.68	15.58	10.81
29	24.61	10.62	23.32	10.06	19.26	9.91	13.34	10.74
30	17.04	10.93	21.87	9.72	15.67	9.52	14.63	10.78
31	8.15	11.16	24.51	9.66	7.52	9.65	14.02	11.18
32	9.74	10.79	16.35	10.37	9.65	10.67	13.81	10.79
33	7.51	10.71	25.94	9.19	7.18	9.08	15.55	10.64
34	25.92	10.42	27.53	9.06	19.03	9.05	18.44	10.15
35	3.43	10.76	21.77	9.94	4.39	9.90	15.77	10.81
36	12.67	10.76	23.79	11.05	11.48	10.97	14.35	10.81
37	12.49	11.68	25.83	10.77	11.25	10.70	14.27	11.74
38	39.27	9.48	94.00	9.46	20.31	9.39	39.39	9.51
39	19.14	10.19	18.14	9.24	15.82	9.17	13.31	10.16
40	7.14	8.12	17.57	7.88	7.48	7.80	11.93	8.16
41	17.01	9.40	54.21	10.20	13.31	10.16	17.22	9.37
42	12.96	9.96	32.66	9.89	11.88	9.91	17.12	10.00
43	5.30	7.66	17.93	6.53	5.02	6.47	11.04	7.69
44	6.19	11.09	22.63	9.63	5.32	9.50	13.09	11.18
45	2.86	7.52	16.25	5.82	3.12	5.77	6.85	7.57
46	7.17	10.87	20.26	9.87	7.08	9.96	13.80	10.82
47	7.02	10.75	21.63	9.21	7.61	9.16	14.97	10.76
48	16.56	9.70	24.32	9.70	13.59	9.64	12.11	9.72
49	11.85	7.67	27.14	7.11	9.14	7.07	10.92	7.70
50	7.02	11.67	22.67	11.10	8.53	11.24	13.18	11.75

Scene SN	Median SN	Midway SN	Ratio SN	Cluster SN	Cluster Median SN	Cluster Midway SN	Cluster Ratio SN	SN Uncorrected
1	10.60	1.25	11.87	1.98	9.85	1.96	6.85	0.93
2	4.62	1.27	4.77	0.82	4.30	0.89	3.21	0.46
3	13.78	1.81	31.89	2.30	10.02	2.37	5.13	0.70
4	3.69	0.75	3.80	1.13	3.84	1.09	2.10	0.44
5	3.73	0.43	4.37	1.37	4.20	1.63	2.66	0.55
6	22.72	1.65	29.84	1.99	20.28	1.98	10.47	0.75
7	15.56	1.47	19.41	1.66	12.62	1.73	11.18	0.47
8	6.28	1.26	6.29	1.58	6.57	1.69	4.27	0.43
9	2.94	1.69	4.05	1.62	3.12	2.00	3.15	0.48
10	11.69	1.98	13.24	1.94	11.56	1.95	7.89	1.16
11	27.90	2.89	25.95	3.06	15.74	3.24	11.67	0.83
12	15.09	3.37	16.88	2.32	13.90	3.08	12.72	1.45
13	11.83	1.81	14.34	4.37	10.47	4.30	4.79	0.79
14	11.82	2.36	14.19	1.53	10.63	1.74	9.33	1.31
15	11.70	2.81	15.07	2.92	10.23	3.17	7.54	0.68
16	15.47	4.63	14.14	2.47	15.13	4.13	8.66	0.70
17	22.13	1.74	22.79	1.99	18.66	2.16	10.78	0.57
18	16.89	2.58	15.96	2.43	15.28	2.52	7.95	0.67
19	41.90	2.19	36.22	3.02	37.40	3.10	13.85	0.63
20	16.55	1.69	16.09	4.21	17.04	4.28	7.03	0.63
21	6.01	2.43	7.27	1.64	6.39	2.47	3.86	0.72
22	24.36	1.43	25.05	2.21	23.05	2.24	7.83	0.52
23	40.60	1.04	30.03	12.32	30.29	12.14	14.30	0.58
24	11.12	2.13	11.85	1.40	10.23	1.59	8.28	0.95
25	21.37	1.18	24.54	3.32	17.60	2.25	11.64	0.49
26	37.31	1.67	36.24	3.17	26.05	3.11	14.91	0.53
27	8.94	1.39	9.28	1.43	8.53	1.39	5.09	0.96
28	14.18	1.22	18.73	1.31	11.43	1.35	8.87	0.58
29	24.60	1.59	26.74	2.40	18.30	2.26	8.22	1.09
30	17.08	2.94	14.92	2.19	15.54	2.67	5.96	1.09
31	7.92	1.29	7.77	2.77	7.56	2.78	3.15	0.45
32	9.69	1.42	9.89	1.18	9.05	1.21	4.87	0.86
33	6.24	1.83	6.27	1.24	5.34	1.28	3.78	0.86
34	25.17	2.70	20.01	1.40	19.07	1.69	11.39	0.67
35	2.83	1.06	3.25	0.88	2.85	0.85	2.30	0.52
36	11.22	0.89	14.42	1.63	11.25	1.59	3.80	0.65
37	10.43	0.66	10.39	2.00	9.02	1.95	2.53	0.79
38	40.05	1.21	85.52	2.08	18.62	1.88	10.33	0.91
39	18.49	1.44	15.97	1.77	15.03	1.83	11.02	0.40
40	5.41	1.17	6.51	0.85	5.15	1.03	3.83	0.39
41	17.07	1.70	60.58	2.47	9.28	2.44	14.69	0.83
42	11.97	1.31	17.08	2.72	11.32	2.57	7.44	0.97
43	5.11	0.95	5.42	1.27	4.41	1.20	4.07	0.78
44	5.64	1.03	5.64	1.64	5.13	1.70	2.93	0.56
45	2.69	0.40	2.84	0.90	3.01	0.91	1.30	0.42
46	6.70	1.70	6.90	0.75	6.42	1.11	3.82	0.56
47	6.68	1.37	6.79	1.71	6.89	1.80	4.87	0.54
48	16.48	1.40	23.11	2.63	11.46	2.44	7.43	1.37
49	11.85	0.62	18.12	1.20	9.03	1.30	3.74	0.39
50	1.38	0.72	1.75	0.74	1.45	0.78	1.34	0.44

Scene Base	Median Base	Midway Base	Ratio Base	Cluster Base		
1	1.82	1.21	11.57	1.82		
2	0.76	1.26	4.68	0.76		
3	2.12	1.80	31.84	2.12		
4	1.06	0.73	3.73	1.06		
5	1.32	0.38	4.02	1.32		
6	1.92	1.63	29.61	1.92		
7	1.58	1.46	19.41	1.58		
8	1.53	1.25	6.28	1.53		
9	1.56	1.68	3.81	1.56		
10	1.69	1.92	12.94	1.69		
11	2.99	2.86	26.00	2.99		
12	2.25	3.35	16.78	2.25		
13	4.30	1.79	14.27	4.30		
14	0.91	2.31	13.93	0.91		
15	2.78	2.80	15.06	2.78		
16	2.33	4.62	14.00	2.33		
17	1.94	1.72	22.73	1.94		
18	2.35	2.56	15.99	2.35		
19	3.00	2.18	36.23	3.00		
20	4.19	1.68	16.01	4.19		
21	1.54	2.42	7.07	1.54		
22	2.16	1.42	25.01	2.16		
23	12.31	1.01	30.04	12.31		
24	1.16	2.10	11.81	1.16		
25	3.30	1.17	24.54	3.30		
26	3.16	1.65	36.24	3.16		
27	1.20	1.35	9.17	1.20		
28	1.22	1.21	18.65	1.22		
29	2.22	1.54	26.65	2.22		
30	1.99	2.91	14.70	1.99		
31	2.75	1.28	7.73	2.75		
32	0.95	1.39	9.73	0.95		
33	1.10	1.80	6.06	1.10		
34	1.27	2.68	19.98	1.27		
35	0.79	1.04	3.04	0.79		
36	1.56	0.86	14.28	1.56		
37	1.94	0.60	10.16	1.94		
38	1.83	1.17	85.48	1.83		
39	1.74	1.43	15.95	1.74		
40	0.78	1.16	6.45	0.78		
41	2.40	1.66	60.42	2.40		
42	2.59	1.26	16.91	2.59		
43	1.09	0.91	5.13	1.09		
44	1.64	1.02	5.47	1.64		
45	0.88	0.37	2.73	0.88		
46	0.71	1.69	6.71	0.71		
47	1.63	1.36	6.72	1.63		
48	2.41	1.32	22.78	2.41		
49	1.19	0.61	18.02	1.19		
50	0.66	0.70	1.50	0.66		

# A.2 Row RMSE Metric

Scene	Median	Midway	Ratio	Cluster	Cluster	Cluster	Cluster	AN
AN	AN	AN	AN	AN	Median AN	Midway AN	Ratio AN	Uncorrected
1	16.52	14.07	16.52	13.10	15.89	13.19	14.58	14.03
2	5.46	8.58	18.01	7.44	4.74	7.42	11.82	8.62
3	12.66	9.20	22.67	9.98	10.98	9.66	10.61	9.25
4	4.97	10.55	19.40	9.81	6.07	9.73	12.40	10.64
5	5.14	11.66	21.31	11.55	5.56	11.54	14.90	11.73
6	22.16	9.05	19.28	8.27	21.25	8.04	11.13	9.28
7	15.43	9.25	19.12	8.03	12.91	8.01	14.51	9.29
8	6.56	7.12	13.83	6.97	7.44	6.93	11.39	7.18
9	3.15	9.20	18.91	8.90	3.22	9.00	14.67	9.25
10	12.08	8.01	20.97	8.42	12.20	8.27	15.04	8.21
11	25.84	8.08	23.91	6.19	14.83	6.28	13.39	8.12
12	14.75	7.80	21.63	7.41	13.53	7.57	18.07	7.66
13	12.23	7.26	19.11	7.44	11.48	7.30	13.89	7.35
14	11.77	8.61	20.00	7.58	10.58	7.58	15.65	8.64
15	11.58	7.65	23.13	7.81	9.97	7.94	17.37	7.67
16	15.39	10.00	22.93	9.00	15.11	9.59	16.86	9.63
17	22.21	8.66	24.15	7.16	18.81	7.47	15.23	8.66
18	16.94	8.73	26.52	6.46	15.45	6.42	13.29	8.85
19	41.87	8.58	29.29	6.56	36.68	6.41	13.99	8.62
20	16.60	8.72	15.35	11.00	17.15	11.19	11.78	8.74
21	6.03	9.88	18.24	9.41	6.46	9.47	14.56	9.83
22	24.44	8.54	26.80	7.72	23.11	7.66	12.00	8.61
23	38.32	8.63	31.65	15.48	30.36	15.39	15.28	8.83
24	11.56	8.91	24.37	8.04	10.22	7.97	17.54	9.05
25	21.41	10.14	25.18	7.67	17.51	8.42	16.26	10.20
26	37.10	10.15	35.29	9.13	26.92	9.02	17.65	10.31
27	9.28	7.20	19.01	6.46	8.91	6.30	12.05	7.34
28	14.59	8.74	28.30	8.14	11.58	8.18	15.43	8.89
29	24.12	8.98	19.90	8.85	19.36	8.13	11.18	9.13
30	17.06	9.20	15.79	8.66	15.78	8.60	10.02	9.22
31	8.15	10.77	19.96	10.23	7.87	10.16	14.40	10.86
32	9.55	9.25	15.81	8.79	9.22	8.79	12.29	9.29
33	6.52	8.98	16.76	7.67	5.26	7.59	13.03	9.07
34	24.16	8.38	16.40	8.53	17.09	8.62	10.87	8.46
35	2.83	6.87	15.32	5.98	3.05	5.96	11.23	6.90
36	11.22	8.98	22.15	8.57	11.15	8.53	11.72	9.03
37	11.97	10.95	17.21	10.12	10.85	10.08	12.47	11.02
38	33.04	8.06	58.04	8.15	17.59	8.10	10.04	8.15
39	17.95	6.55	14.79	5.73	14.61	5.66	11.29	6.67
40	5.54	4.63	9.79	4.18	5.22	4.20	7.57	4.64
41	14.97	5.41	52.03	6.14	9.35	6.09	15.85	5.58
42	11.82	7.89	17.32	8.48	10.97	8.48	12.75	7.97
43	6.77	7.47	13.93	7.44	6.44	7.36	10.09	7.56
44	7.16	11.20	22.70	9.59	8.78	9.38	13.08	11.31
45	3.38	8.93	17.38	8.17	2.93	8.13	9.25	8.97
46	6.87	6.84	12.71	6.55	6.76	6.54	9.44	6.96
47	6.73	10.21	20.75	9.29	6.96	9.27	15.24	10.28
48	15.84	6.43	22.36	5.49	11.86	5.66	11.21	6.61
49	11.63	9.89	28.15	9.53	8.60	9.41	12.71	9.98
50	1.77	9.09	17.97	8.32	1.64	8.28	11.34	9.21

Scene GNNP	Median GNNP	Midway GNNP	Ratio GNNP	Cluster GNNP	Cluster Median	Cluster Midway	Cluster Ratio GNNP	GNNP Uncorrected
					GNNP	GNNP	10.00	
1	10.42	3.06	17.75	6.63	9.79	2.78	12.00	7.21
2	5.46	3.70	15.98	6.18	4.54	2.63	9.56	7.76
3	12.66	3.22	31.96	6.87	9.78	2.67	10.43	7.37
4	3.91	2.89	14.71	5.57	3.84	2.07	8.63	6.91
5	4.01	2.46	16.22	5.84	4.24	1.88	9.66	6.03
6	25.69	7.54	35.75	12.52	20.74	5.60	15.36	13.58
7	15.40	3.12	22.34	6.09	12.59	2.58	15.43	7.12
8	6.50	2.48	13.99	5.77	6.61	2.24	10.55	6.14
9	3.15	3.23	17.45	6.97	2.89	2.30	14.15	7.45
10	15.28	10.44	30.23	15.16	13.85	8.92	22.10	16.33
11	26.43	5.39	21.79	6.56	15.65	4.86	13.44	9.20
12	14.91	3.90	19.39	6.51	13.69	3.80	16.25	7.23
13	11.38	4.33	20.86	7.65	10.50	4.83	12.22	8.88
14	14.10	8.28	28.20	12.45	12.30	7.09	21.21	14.17
15	12.10	6.57	26.30	9.89	11.30	6.77	19.50	11.65
16	17.11	8.32	25.62	13.01	16.46	7.54	19.11	13.39
17	22.45	4.41	25.56	7.57	18.96	3.75	15.08	9.22
18	17.70	6.40	22.47	8.67	15.98	5.51	13.55	11.23
19	42.58	4.84	34.83	8.22	37.94	4.02	14.12	9.75
20	17.44	4.78	23.75	9.37	17.73	4.26	14.16	9.84
21	8.20	8.00	29.22	12.46	7.77	6.36	19.47	13.84
22	24.50	4.02	28.70	7.58	23.22	3.72	11.81	8.73
23	38.14	4.38	30.60	14.26	30.32	12.50	16.07	9.01
24	11.88	6.65	23.28	10.31	11.29	5.70	17.50	11.90
25	21.51	3.33	26.42	6.80	17.38	3.82	14.63	7.42
26	36.22	4.20	35.98	6.88	26.04	4.20	16.60	8.62
27	9.99	6.72	25.88	10.27	9.59	5.36	15.45	12.38
28	14.31	4.33	26.39	8.82	11.41	3.00	14.46	9.29
29	23.70	8.17	32.23	12.67	19.72	6.67	17.67	14.11
30	18.60	8.31	27.08	12.70	17.28	7.12	16.51	14.11
31	8.20	2.88	15.47	4.41	7.55	2.10	6.85	6.83
32	10.27	3.23	17.16	6.39	9.04	2.46	9.77	7.38
33	6.62	3.24	15.40	5.90	5.35	2.39	9.40	7.37
34	23.60	2.59	18.04	4.77	18.04	2.54	11.80	5.03
35	3.51	3.48	17.15	6.02	2.89	2.19	10.83	7.87
36	11.06	3.05	22.19	5.84	10.91	2.57	8.55	7.28
37	10.65	2.49	16.10	5.45	9.24	2.25	7.32	6.04
38	32.97	3.98	61.01	8.17	16.85	2.74	12.38	8.75
39	17.77	2.56	15.53	5.03	14.21	2.95	11.95	5.44
40	5.84	3.03	15.77	5.58	5.35	2.31	9.56	6.44
41	16.11	4.08	40.02	8.57	8.90	3.49	18.20	8.86
42	12.65	4.25	24.16	8.81	11.84	3.24	16.70	9.13
43	5.67	3.41	15.82	6.55	4.66	2.60	10.02	7.37
44	6.13	3.86	17.34	6.90	5.30	2.86	9.38	8.54
45	2.89	2.68	12.69	5.65	2.88	1.53	6.30	6.31
46	7.06	4.28	19.29	7.51	6.56	2.58	10.41	9 1 9
47	7 66	4.38	19 20	7.89	7 20	3.69	12.87	9 1 1
48	16.90	4 79	27 41	8 71	12.30	3.12	14 58	9.94
49	11 50	2 53	21.63	5.39	8 76	1.78	9 99	5.92
50	1 77	2.83	13.67	5.66	1 42	1 54	7 44	6.66

Scene GNP	Median GNP	Midway GNP	Ratio GNP	Cluster GNP	Cluster	Cluster	Cluster Ratio	GNP
					Median GNP	Midway GNP	GNP	Uncorrected
1	10.44	1.73	14.76	4.37	9.79	1.98	9.52	4.72
2	4.71	1.71	10.72	3.58	4.30	1.13	6.26	4.72
3	13.12	1.86	31.22	5.76	9.72	2.25	8.39	5.01
4	3.69	1.58	10.17	3.84	3.80	1.25	6.26	4.50
5	3.73	1.38	11.22	4.13	4.20	1.91	8.61	3.98
6	23.56	3.06	30.76	6.54	20.08	2.18	12.34	7.59
7	15.39	1.80	19.60	4.13	12.55	1.88	13.26	4.68
8	6.28	1.61	10.60	4.10	6.59	1.81	7.99	4.25
9	2.88	1.87	11.68	4.38	2.91	1.81	10.08	4.84
10	12.69	4.18	20.32	8.11	11.79	3.55	14.20	8.84
11	25.95	2.74	21.06	4.83	15.10	3.48	12.11	5.71
12	14.78	2.72	16.63	4.35	13.56	3.00	14.22	4.77
13	11.41	2.16	16.90	5.84	10.30	4.24	8.03	5.61
14	12.37	3.73	19.89	7.23	10.95	2.96	14.73	8.15
15	11.52	2.95	18.92	5.08	10.35	3.34	13.34	6.78
16	16.03	4.39	18.46	7.35	15.37	4.38	13.63	7.38
17	22.17	2.28	22.82	4.79	18.68	2.25	12.70	5.79
18	16.93	2.79	18.32	5.16	15.28	2.87	9.88	6.63
19	42.04	2.44	33.11	5.05	37.57	2.68	13.67	6.27
20	16.72	2.39	19.35	6.84	17.31	2.85	10.84	6.32
21	6.54	3.48	17.34	6.62	6.39	2.84	12.38	7.58
22	24.36	2.06	26.17	4.88	23.04	2.49	9.51	5.36
23	38.12	2.15	29.15	12.55	29.98	12.16	15.13	5.71
24	11.00	2.82	16.86	5.74	10.37	2.51	12.34	6.87
25	21.36	1.79	24.38	4.65	17.35	2.00	13.09	4.88
26	36.60	2.10	34.37	4.93	26.05	3.22	15.60	5.43
27	9.05	2.70	17.03	5.58	8.63	1.83	9.52	7.08
28	14.02	2.09	21.82	5.29	11.20	1.53	11.92	5.77
29	23.84	3.51	27.63	7.61	18.47	3.27	12.68	8.17
30	17.60	3.84	20.23	7.79	15.99	3.42	10.87	8.17
31	8.00	1.59	11.80	3.37	7.48	1.52	5.49	4.48
32	9.93	1.89	13.70	4.26	8.98	1.69	7.44	5.01
33	6.35	1.89	11.46	3.74	5.30	1.61	6.42	5.01
34	23.65	1.76	17.76	3.34	17.90	1.93	11.21	3.47
35	3.03	1.87	11.52	4.21	2.83	1.31	7.97	5.18
36	11.22	1.67	18.20	3.92	10.99	1.75	6.50	4.72
37	10.49	1.42	13.07	3.58	9.07	1.94	4.58	4.03
38	32.99	1.94	59.38	5.67	16.77	1.88	10.90	5.36
39	17.63	1.43	14.82	3.45	14.29	2.07	11.22	3.60
40	5.53	1.54	10.79	3.58	5.14	1.25	6.82	4.04
41	15.53	2.24	38.23	5.45	8.67	2.49	16.02	5.95
42	11.98	2.07	18.46	5.90	11.52	2.28	12.29	5.76
43	5.31	1.67	10.62	4.19	4.40	1.38	7.53	4.63
44	5.80	2.06	12.45	3.20	5.09	1.52	6.71	5.75
45	2.69	1.49	9.12	2.81	2.96	1.11	4.18	4.25
46	6.80	2.21	13.43	4.90	6.45	1.49	7.49	5.79
47	6.88	2.05	13.03	4.85	6.90	2.06	9.15	5.56
48	16.28	2.31	22.44	5.44	11.78	2.46	10.93	6.35
49	11.63	1.43	19.41	3.50	8.79	1.32	7.84	4.01
50	1.38	1.59	9.50	3.74	1.39	1.15	5.22	4.51

Scene LNNP	Median	Midway	Ratio LNNP	Cluster LNNP	Cluster	Cluster	r Cluster Ratio LNNF	
	LNNP	LNNP			Median	Midway	LNNP	Uncorrected
					LNNP	LNNP		
1	10.44	1.47	12.13	3.61	9.84	2.20	7.98	3.29
2	4.62	1.73	8.21	2.79	4.26	1.67	5.11	3.38
3	13.76	1.48	34.19	3.25	9.94	2.09	7.51	3.22
4	3.69	1.30	7.64	2.38	3.83	1.46	3.58	3.13
5	3.73	1.17	8.73	3.18	4.15	1.77	4.76	2.82
6	23.24	3.32	32.21	5.48	20.26	3.45	12.39	5.72
7	15.44	1.55	18.99	2.91	12.50	1.92	12.70	3.25
8	6.28	1.41	8.27	3.24	6.59	1.96	6.17	3.16
9	2.95	1.66	9.31	3.42	3.00	1.96	8.14	3.46
10	11.92	5.03	21.71	6.56	11.53	4.38	14.43	7.60
11	25.75	2.58	21.08	3.89	15.03	3.15	11.66	3.97
12	14.71	2.54	16.05	3.26	13.48	2.94	13.86	3.17
13	11.69	1.79	15.22	4.05	10.46	3.58	5.86	3.33
14	11.90	4.15	16.18	6.07	10.72	3.76	12.34	6.73
15	11.49	3.06	15.94	4.43	10.46	3.80	10.90	5.02
16	15.56	4.69	17.26	5.86	15.21	5.01	12.51	5.70
17	22.09	2.00	20.07	3.51	18.65	2.58	10.75	3.89
18	16.73	2.87	16.89	3.44	15.14	2.59	8.71	4.73
19	41.60	2.35	33.67	3.57	37.10	2.30	13.05	4.35
20	16.60	2.29	17.51	7.53	17.11	5.03	9.51	4.42
21	6.03	3.88	13.02	5.29	6.39	3.85	9.46	5.89
22	24.36	2.04	25.40	3.90	23.06	2.67	8.87	4.07
23	38.15	1 79	29.95	12 19	29 74	12.08	14 74	3.87
24	10.97	2 95	15.08	4 06	10 17	2 73	11.09	5.04
25	21.36	1.57	22 73	3 80	17.30	3 17	12.02	3 26
26	36.84	1.82	34 36	4 15	26.04	3 1 3	15 56	3 65
27	8 94	2.85	16.92	3 13	8 53	1.88	7 09	5 21
28	14.06	1 81	20.32	3.63	11 27	1 79	10.21	3.87
29	24.00	4.09	27.43	5.00	18 10	4 19	10.88	6.68
30	17 10	4.05	18 47	6.47	15 71	4.10	9.08	6.77
31	8.00	1.34	8 97	2 76	7 /8	2 18	4 70	3 15
32	0.00	1.52	10.70	2.70	9.05	1 71	6 15	2 1 9
32	9.09 6.35	1.55	9.67	2.95	0.95 5 22	1.71	4 77	2 17
24	0.33	1.50	9.07 17.70	2.05	17.07	1.37	4.77	3.17 2.12
25	23.11	1.57	27.75	2.23	2 0 2	1.70	E 21	2.15
26	2.03	1.04	0.09	2.02	2.03	2.00	5.21	2.40 2.21
27	10.40	1.40	10.27	2.16	0.00	2.00	3.00	2.31 2.75
20	22 10	1.10	10.37	3.10	9.09	1.23	4.10	2.75
20	17.66	1.90	14.61	4.50	14.03	1.04	10.79	4.07
39	17.00 E 20	1.24	0 41	2.21	14.27 E 17	1.71	10.05	2.13
40	5.39	1.34	8.41	2.28	5.14 0.45	1.19	5.47 16 F 4	2.08
41	14.91	1.93	43.82	3.59	8.45	2.00	10.54	3.99
42	11./3	1.75	15.57	4.29	11.10	2.91	10.04	3.82
43	5.11	1.42	6.91	3.01	4.39	1.50	5.53	3.07
44	5.64	1.//	10.38	1.96	5.12	1.65	3.94	3.91
45	2.69	1.18	<u>ь.39</u>	2.09	3.01	1.12	3.07	2.74
46	0.67	1.88	9.99	3.17	b.40	1.77	5.52	3.82
4/	0.68	2.07	11.31	3.88	6.90	2.31	1.56	3.99
48	16.03	2.19	18.56	5.15	11.95	1.60	8.67	4.40
49	11.85	1.12	17.61	2.72	8.95	1.58	4.68	2.58
50	1.38	1.26	6.01	2.38	1.41	1.19	3.17	2.91

Scene LNP	Median LNP	Midway LNP	Ratio LNP	Cluster LNP	Cluster	Cluster	Cluster Ratio	LNP
					Median LNP	Midway LNP	LNP	Uncorrected
1	10.44	0.94	11.38	2.75	9.85	2.16	7.19	2.18
2	4.62	0.88	6.28	1.86	4.26	1.05	4.15	2.14
3	13.76	0.96	31.39	2.74	9.94	2.17	6.50	2.25
4	3.69	0.75	5.81	1.93	3.84	1.19	3.13	2.06
5	3.73	0.64	6.13	2.12	4.15	1.86	4.78	1.82
6	22.96	1.51	28.74	3.47	20.28	2.22	11.34	3.44
7	15.44	1.04	18.13	2.28	12.62	1.75	12.07	2.14
8	6.28	0.90	6.92	2.35	6.57	1.78	5.11	1.95
9	2.94	1.08	6.53	2.45	3.05	1.85	5.67	2.23
10	11.75	2.04	16.17	3.74	11.52	2.13	10.61	3.96
11	25.72	1.75	20.76	3.25	15.04	3.18	11.18	2.54
12	14.69	2.22	15.06	2.58	13.50	2.77	13.19	2.19
13	11.61	1.20	13.93	4.18	10.43	3.94	5.03	2.32
14	11.79	2.13	13.46	3.55	10.61	2.12	10.28	3.71
15	11.49	1.85	13.85	3.32	10.30	3.40	8.78	3.09
16	15.56	3.54	14.52	3.89	15.09	4.18	10.16	3.32
17	22.09	1.35	20.13	2.80	18.71	2.35	10.68	2.63
18	16.63	1.60	15.76	2.90	15.14	2.40	8.20	2.95
19	41.59	1.39	32.48	3.09	37.11	2.75	13.60	2.85
20	16.60	1.26	15.90	4.82	17.05	4.02	8.10	2.90
21	6.03	2.33	8.91	3.34	6.34	2.72	6.15	3.45
22	24.36	1.10	24.42	2.94	23.03	2.32	8.36	2.45
23	38.15	1.00	29.00	12.02	29.72	11.95	14.39	2.64
24	11.04	1.62	12.83	2.62	10.15	1.90	9.44	3.12
25	21.36	0.95	22.67	3.51	17.46	2.10	11.81	2.23
26	36.83	1.18	33.69	3.67	26.07	3.10	15.21	2.50
27	8.94	1.32	12.90	2.11	8.53	1.20	5.77	3.18
28	14.17	1.05	19.10	2.59	11.21	1.43	9.69	2.65
29	24.12	1.71	25.20	3.97	18.19	2.81	9.26	3.69
30	17.07	2.29	15.58	4.38	15.51	3.15	7.21	3.69
31	8.00	0.79	8.11	3.10	7.48	2.06	3.78	2.04
32	9.69	1.07	10.09	2.19	9.05	1.45	5.41	2.27
33	6.35	1.08	8.05	1.65	5.33	1.41	4.02	2.27
34	23.73	1.35	17.62	1.83	18.03	1.61	11.01	1.53
35	2.83	0.98	5.89	1.84	2.85	1.10	3.98	2.36
36	11.22	0.81	14.60	2.56	11.16	2.41	4.73	2.17
37	10.43	0.65	10.27	2.56	9.13	2.06	3.23	1.82
38	33.29	0.96	60.13	3.20	16.45	1.71	10.08	2.45
39	17.58	0.73	14.42	1.86	14.32	1.71	10.79	1.42
40	5.39	0.91	7.06	1.67	5.14	1.01	4.76	1.83
41	14.84	1.15	43.03	2.67	8.40	2.30	14.87	2.63
42	11.73	1.04	14.19	3.37	11.11	2.58	8.41	2.67
43	5.11	0.84	5.81	2.16	4.37	1.13	4.75	2.10
44	5 64	0.98	8.07	1 74	5 13	1 59	3 20	2 62
45	2.69	0.68	4.88	1.01	3.01	1.07	1.42	1.91
46	6.67	1.27	8.39	2.36	6.42	1.39	4.72	2.67
47	6.68	1.08	8.69	2.67	6.91	1.80	6.09	2.52
48	16.03	1.12	17.63	3.91	11.51	2.20	7.64	2.86
49	11.85	0.66	17.35	2.10	9.00	1.42	4.21	1.83
50	1.38	0.76	4.38	1.68	1.45	0.94	2.35	2.05

Scene PBN	Median PBN	Midway PBN	Ratio PBN	Cluster PBN	Cluster	Cluster	Cluster Ratio	PBN
					Median PBN	Midway PBN	PBN	Uncorrected
1	11.58	10.73	17.69	10.27	10.39	10.22	13.68	10.80
2	4.74	7.52	15.28	6.17	4.99	6.12	10.38	7.60
3	13.42	10.69	44.09	11.14	9.41	10.65	13.59	10.77
4	3.73	11.10	22.69	9.45	4.08	9.58	13.54	11.19
5	4.01	11.12	23.68	11.05	3.99	10.96	11.49	11.19
6	22.25	10.58	25.75	9.21	20.81	9.09	13.48	10.77
7	15.72	10.75	26.37	10.18	12.82	10.03	20.42	10.80
8	6.56	10.77	21.45	10.27	7.82	9.97	15.90	10.81
9	3.33	10.75	22.98	10.19	5.05	10.14	16.24	10.80
10	11.67	10.53	21.49	9.91	11.97	9.62	16.19	10.76
11	25.51	9.85	22.98	7.16	15.21	7.43	12.74	9.98
12	14.95	10.36	24.41	9.29	13.50	9.39	20.63	10.32
13	12.25	10.68	27.06	9.73	9.85	9.72	16.91	10.78
14	11.98	10.60	30.54	9.48	11.07	9.43	21.38	10.73
15	11.97	10.51	27.35	9.55	10.84	9.68	19.08	10.61
16	15.52	10.85	26.42	9.33	15.07	9.89	18.51	10.57
17	22.06	10.71	22.08	9.44	18.76	9.43	14.02	10.79
18	16.84	10.26	27.11	8.24	15.30	8.22	15.28	10.45
19	41.31	10.44	27.71	10.69	36.01	9.60	13.58	10.57
20	16.60	10.69	25.52	10.39	16.99	10.29	16.37	10.79
21	6.47	10.77	24.33	9.87	6.62	9.99	16.20	10.78
22	24.59	10.61	33.96	9.49	23.32	9.38	15.46	10.69
23	38.07	10.48	29.36	17.35	30.93	17.31	18.43	10.64
24	11.88	10.33	24.09	8.93	10.46	9.08	17.38	10.50
25	21.38	11.05	28.40	10.23	17.55	10.22	19.65	11.16
26	36.60	11.06	31.50	10.06	27.85	9.93	16.66	11.17
27	9.59	10.65	25.45	9.35	8.60	9.24	15.63	10.79
28	14.35	10.73	25.65	9.76	11.50	9.68	15.58	10.81
29	24.32	10.51	21.36	10.04	19.14	9.88	13.28	10.72
30	17.03	10.66	20.86	9.71	15.66	9.51	14.57	10.77
31	8.15	11.09	24.40	9.66	7.52	9.65	14.01	11.18
32	9.72	10.70	16.20	10.36	9.63	10.65	13.79	10.78
33	7.32	10.38	25.45	9.06	6.99	8.94	15.34	10.52
34	24.51	9.66	24.69	8.62	17.90	8.61	17.66	9.77
35	3.43	10.72	21.57	9.94	4.39	9.90	15.77	10.81
36	12.66	10.73	23.39	11.05	11.48	10.97	14.35	10.81
37	12.49	11.67	25.66	10.77	11.25	10.70	14.27	11.74
38	33.18	8.67	65.63	8.55	17.60	8.46	33.19	8.85
39	18.26	9.60	16.38	8.79	15.22	8.71	12.79	9.75
40	7.00	7.97	16.54	7.79	7.35	7.70	11.77	8.08
41	14.89	8.55	36.54	9.35	12.12	9.30	16.06	8.72
42	12.25	9.43	27.58	9.35	11.30	9.38	16.12	9.58
43	5.29	7.62	17.74	6.53	5.02	6.47	11.04	7.69
44	6.19	11.03	22.46	9.63	5.32	9.50	13.08	11.17
45	2.86	7.51	16.24	5.82	3.12	5.77	6.85	7.57
46	7.17	10.76	20.21	9.87	7.08	9.96	13.80	10.82
47	6.99	10.66	21.22	9.19	7.58	9.13	14.92	10.74
48	15.66	8.93	19.92	9.13	12.90	9.06	10.91	9.22
49	11.85	7.64	26.48	7.11	9.14	7.07	10.92	7.69
50	7.02	11.65	22.63	11.10	8.53	11.24	13.18	11.75

Scene SN	Median SN	Midway SN	Ratio SN	Cluster SN	Cluster	Cluster	Cluster Ratio	SN
	10.00	0.01	11.10	1.00	Median SN	Midway SN	SN	Uncorrected
1	10.60	0.61	11.49	1.98	9.85	1.96	6.84	0.93
2	4.62	0.47	4.68	0.82	4.29	0.89	3.21	0.46
3	13.76	0.58	28.71	2.30	10.02	2.37	5.13	0.70
4	3.69	0.24	3.76	1.13	3.84	1.09	2.10	0.44
5	3.73	0.20	4.16	1.37	4.20	1.63	2.66	0.55
6	22.72	0.66	26.81	1.99	20.28	1.98	10.46	0.75
1	15.55	0.71	17.56	1.66	12.62	1.73	11.17	0.47
8	6.28	0.55	6.07	1.58	6.57	1.69	4.27	0.43
9	2.94	0.69	3.69	1.62	3.12	2.00	3.15	0.48
10	11.67	0.95	12.64	1.94	11.55	1.94	7.84	1.16
11	25.69	1.44	20.44	3.04	15.05	3.21	10.69	0.79
12	14.65	2.06	14.17	1.84	13.50	2.73	12.32	0.47
13	11.83	0.81	12.92	4.37	10.46	4.30	4.78	0.79
14	11.79	1.51	12.51	1.53	10.60	1.74	9.32	1.31
15	11.64	1.42	13.02	2.92	10.18	3.16	7.47	0.66
16	15.41	3.28	12.89	2.46	15.08	4.12	8.60	0.70
17	22.09	0.97	20.29	1.99	18.63	2.16	10.76	0.57
18	16.63	1.17	14.92	2.41	15.10	2.50	7.85	0.65
19	41.59	0.92	31.31	2.99	37.12	3.06	13.35	0.62
20	16.53	0.72	14.83	4.21	17.02	4.28	7.01	0.63
21	6.01	1.92	6.83	1.64	6.39	2.47	3.86	0.72
22	24.36	0.68	23.94	2.21	23.05	2.24	7.80	0.52
23	38.15	0.37	27.92	12.04	29.72	11.88	14.17	0.58
24	11.03	1.18	10.87	1.39	10.16	1.58	8.18	0.95
25	21.36	0.47	22.35	3.32	17.60	2.25	11.64	0.49
26	37.09	0.74	33.45	3.17	25.99	3.10	14.90	0.53
27	8.94	0.67	8.90	1.43	8.53	1.39	5.09	0.96
28	14.17	0.46	17.14	1.31	11.43	1.35	8.87	0.58
29	24.32	0.81	24.33	2.40	18.19	2.26	8.21	1.09
30	17.07	1.73	13.87	2.19	15.54	2.67	5.95	1.09
31	7.92	0.34	7.63	2.77	7.56	2.78	3.15	0.45
32	9.69	0.75	9.60	1.18	9.05	1.21	4.87	0.86
33	6.23	0.78	6.04	1.24	5.33	1.28	3.77	0.86
34	23.84	1.21	17.30	1.35	18.07	1.64	10.90	0.56
35	2.83	0.52	3.14	0.88	2.85	0.85	2.30	0.52
36	11.22	0.37	14.03	1.63	11.24	1.59	3.80	0.65
37	10.43	0.32	10.18	2.00	9.01	1.95	2.53	0.79
38	33.55	0.49	60.59	1.98	16.37	1.76	9.39	0.91
39	17.50	0.47	14.25	1.73	14.43	1.79	10.70	0.34
40	5.39	0.66	5.79	0.85	5.13	1.02	3.82	0.39
41	14.81	0.72	42.35	2.29	8.41	2.27	13.77	0.83
42	11.73	0.50	12.95	2.65	11.11	2.50	6.98	0.97
43	5.11	0.48	5.21	1.27	4.41	1.20	4.07	0.78
44	5.64	0.31	5.52	1.64	5.13	1.70	2.93	0.56
45	2.69	0.17	2.81	0.90	3.01	0.91	1.30	0.42
46	6.70	0.84	6.84	0.75	6.42	1.11	3.82	0.56
47	6.68	0.65	6.47	1.71	6.89	1.80	4.86	0.54
48	15.81	0.68	17.96	2.61	11.15	2.42	7.18	1.37
49	11.85	0.18	17.20	1.20	9.03	1.30	3.74	0.39
50	1.38	0.28	1.71	0.74	1.45	0.78	1.34	0.44

Scene Base	Median Base	Midway Base	Ratio Base	Cluster Base		
1	10.60	0.52	11.20	1.82		
2	4.62	0.44	4.60	0.76		
3	13.76	0.52	28.66	2.12		
4	3.69	0.18	3.69	1.06		
5	3.73	0.08	3.81	1.32		
6	22.72	0.60	26.55	1.92		
7	15.55	0.69	17.55	1.58		
8	6.28	0.53	6.06	1.53		
9	2.94	0.67	3.44	1.56		
10	11.67	0.85	12.36	1.69		
11	25.69	1.40	20.49	2.97		
12	14.64	2.05	14.10	1.78		
13	11.83	0.76	12.85	4.30		
14	11.79	1.44	12.23	0.91		
15	11 64	1 41	13.00	2 78		
16	15 41	3 28	12 75	2.33		
17	22.09	0.95	20.22	1 94		
18	16.63	1 13	1/ 95	2 3/		
19	11 59	0.90	31 32	2.94		
20	16 53	0.50	1/ 75	1 19		
20	6.01	1 90	6.63	1.54		
21	24.36	0.66	23 01	2.16		
22	24.30	0.00	27.91	12.10		
23	11 02	1 1 2	10.02	1 15		
24	21.05	0.44	22.25	2 20		
25	27.00	0.44	22.33	2 16		
20	0 0 A	0.72	0 70	1 20		
20	0.94	0.56	0.79	1.20		
20	14.17	0.42	24.22	2.22		
29	24.32	1.00	24.23	1.00		
30	17.07	0.21	13.04	2.99		
31 22	7.92	0.51	7.59	2.75		
32	9.09	0.09	9.44 F 02	0.95		
33	0.23	0.71	5.83	1.10		
34	23.84	1.19	17.28	1.20		
35	2.83	0.48	2.93	0.79		
30 27	10.42	0.29	13.03	1.04		
37	10.43	0.15	9.95	1.94		
38	33.55	0.38	00.52	1.72		
39	17.50	0.45	14.24	1.72		
40	5.39	0.64	5.72	0.78		
41	14.81	0.64	42.12	2.21		
42	11.73	0.37	12.75	2.51		
43	5.11	0.40	4.92	1.09		
44	5.64	0.24	5.34	1.64		
45	2.69	0.07	2.70	0.88		
46	6.70	0.81	6.65	0.71		
4/	6.68	0.63	6.39	1.63		
48	15.81	0.50	17.58	2.40		
49	11.85	0.13	17.09	1.19		
50	1.38	0.23	1.44	0.66		

# A.3 Pixel Bias RMSE Metric

Scene	Median	Midway	Ratio	Cluster	Cluster	Cluster	Cluster	AN
1	AN 10.61	AN 4 47				1 10	Ralio AN	4 22
1	10.01	4.47	9.04	3.51	9.90	4.10	0.23	4.33
2	4.03	0.37	10.03	1.22	4.32 11.04	1.20	10.00	8.33
3	13.00	10.77	20.09	11.31	2 90	10.74	10.90	10.09
4 E	3.09	10.10	19.39	9.50	3.89 E.62	9.48 12.05	12.23	10.23
5 6	3.73 22.72	12.14	22.12	7 10	20.02	12.95	15.75	12.19
0	22.72	0.91	22.19	7.10	20.92	0.00		8.94
/ 0	15.50	9.42	20.00	8.03	12.99	8.02 6.19	14.53	9.37
0	0.20	0.04	10.90	0.21	2 42	0.10	10.70	0.58
9	2.94	9.02	21 52	9.30	3.43 11 10	9.42 7 55	14.07	9.50
11	20 20	0.16	22.00	6.75	15.40	6.92	14.09	1.10
12	20.29	9.10	24 21	7.22	12.04	0.02	19 20	0.55
12	11.00	7 1 2	24.21	6 1 2	11 12	7.01 6.12	12.02	7.71
13	11.00	0.05	20.71	7 52	10.64	7.56	15.95	7.0Z
15	11.03	0.00	21.70	7.55 9.00	10.04	7.50 9.10	17 52	0.09
15	15 50		23.02	0.00	10.11	0.10	16.77	0.56
17	10.00	0.00	24.49	0.07	10.20	9.47	14.42	9.50
10	17.21	0.10	27.94	6.49	10.71	0.17 6.46	12 /1	0.03
10	11.51	9.31 0 0E	20.55	0.40 6 EE	25.00	0.40 6.46	13.41	9.04
19	41.97	0.00	40.90	11 01	17.09	11 20	11.40	0.04
20	6.02	0.02	19.60	0.41	£ 10	0 <i>1</i> 7	14.61	0.71
22	24.42	9.99 0 E7	20.00	7.50	0.40	5.47 7 5 4	14.01	9.04
22	24.42	0.37 9 42	20.39	15.96	23.12	15 76	15.10	0.55
23	11 22	0.45	25.65	9.00	10.27	7 02	17.62	0.50
24	21.32	9.24 10.41	27.00	7.54	17.52	7.93 9.41	16.49	9.10
25	27.22	10.41	27.20	9.06	29.14	0.41 9.05	17.62	10.20
20	8 97	7.03	10 0/	5.00	20.14 8 55	5.84	11.02	7.02
28	14 16	8 55	30.20	7.63	11 10	7 69	14.74	7.03 9.61
20	24.63	9 30	24.01	9.10	20.57	8.00	11 26	0.01
30	17.08	9.50	17.06	8 57	15.83	8 50	9 93	9.30
30	7 93	11 00	20.35	10.07	7.86	10.36	14 50	11 01
32	9 70	9.42	16.47	8 83	9 /3	8.82	12 36	9.36
32	6 52	9.42	17 27	7 78	5. <del>4</del> 5 5.37	7 70	13 27	9.30
34	25 53	9.00	18.85	8.86	18 12	8 96	11.23	8.77
35	2 83	6.93	15 55	5.98	2 82	5.96	11.23	6.90
36	11 22	9.01	22 50	8.57	11 16	8 53	11.20	9.03
37	10.43	9.11	16.68	8 14	9 91	8.07	10.85	9.00
38	40.41	8 95	84.03	9.46	20.04	9 10	10.00	9.00
39	18.86	6 75	15 95	5.25	15.00	5 22	10.70	6.72
40	5 43	4 62	10.46	4 19	5 16	4 22	7.63	4 53
40	17.32	6.20	70.69	6.69	10.34	6 67	17.93	6 24
42	12 17	8 1 9	21 41	8 75	11 40	8 78	13 44	8 17
43	5.11	6.71	14.16	6.26	4.45	6.18	9.38	6.74
44	5.64	10.07	22.24	8.23	4.88	8.12	12.39	10.18
45	2.69	8.60	17.38	7.99	2.82	7.96	9.11	8.62
46	6.70	6.82	12.62	6.25	6.52	6.19	9.13	6.77
47	6.68	10.46	21.70	9.56	7.03	9.51	15.51	10.45
48	16.52	6.91	31.00	5.80	12.24	5.96	12.62	6.86
49	11.86	10.10	28.90	9.53	8.75	9.41	12.57	10.18
50	1.38	9.01	18.32	8.32	1.45	8.28	11.34	9.11

Scene GNNP	Median GNNP	Midway GNNP	Ratio GNNP	Cluster GNNP	Cluster Median GNNP	Cluster Midway GNNP	Cluster Ratio GNNP	GNNP Uncorrected
1	10.61	2.34	17.86	6.35	9 90	2 67	11 89	6.86
2	4 63	2 34	15.88	5.68	4 29	1.81	9.22	7 12
2	13.87	2.59	32 27	7 31	10.52	2 76	10.75	7.34
3 1	3 69	1 97	14 75	5.34	3.84	1.83	8.63	6.65
5	3 73	1 70	16.47	5.84	4 24	1.88	0.00	5.82
6	22 72	3.24	38.26	10.9/	20.74	2.95	15 16	11 78
7	15 58	2.52	23.72	5 01	12 74	2.55	15.10	6.80
9	6 20	2.32	14 17	5.51	6.62	2.45	10.57	5.04
0	2.00	2.21	17 70	6.79	2.25	2.04	14.20	7.06
9	2.99	2.02	20.42	0.70	3.25	4.21	20 56	12.20
10	11.04	4.00	29.42	6.75	16.57	4.21	20.30	13.30
11	28.17	4.43	31.07	0.75	10.57	5.01	14.80	9.03
12	15.24	4.04	21.97	0.05	13.98	4.13	17.05	7.18
13	12.00	3.05	21.52	7.67	11.15	4.91	12.47	8.38
14	11.88	3.78	28.54	10.40	10.76	3.00	20.12	12.06
15	11.98	3.86	26.79	8.16	10.84	4.43	19.45	10.35
16	15.64	5.58	26.24	11.26	15.42	5.11	18.60	11.71
17	22.14	2.94	28.33	6.94	18.74	2.69	15.02	8.51
18	17.08	3.86	23.65	7.85	15.64	4.23	13.26	10.12
19	41.88	3.00	45.58	7.53	35.37	4.14	14.64	8.85
20	16.54	2.60	24.27	8.52	17.01	2.82	13.83	8.93
21	6.04	3.92	28.53	10.87	6.33	3.65	18.60	11.96
22	24.36	2.57	29.66	7.17	23.04	2.93	11.69	8.10
23	40.79	2.60	35.62	14.88	31.10	12.73	16.27	8.34
24	11.32	3.53	23.36	8.91	10.49	3.31	16.99	10.49
25	21.38	2.30	28.18	6.50	17.43	3.58	14.86	6.97
26	37.48	2.86	37.06	6.66	27.36	3.53	16.68	8.00
27	8.95	2.87	25.33	8.79	8.53	2.34	14.52	10.83
28	14.20	2.50	26.90	8.43	11.45	2.15	14.53	8.65
29	24.79	3.29	33.88	10.48	19.77	2.68	17.00	11.95
30	17.09	4.12	27.28	10.53	15.75	3.79	15.06	12.05
31	7.92	2.21	15.78	4.29	7.49	2.01	6.72	6.47
32	9.69	2.36	17.97	6.18	9.21	2.07	9.63	6.95
33	6.24	2.58	15.83	5.41	5.27	2.10	9.25	6.94
34	24.93	3.40	21.08	5.28	18.95	4.13	12.70	5.56
35	2.83	2.27	17.09	5.63	2.83	1.93	10.51	7.41
36	11.22	2.13	22.50	5.63	11.07	2.23	8.36	7.02
37	10.43	1.72	16.48	5.29	9.08	2.24	7.17	5 74
38	40.62	2 53	85.60	9.73	19.57	2 51	13.88	9.38
39	18.69	2.73	17 75	5 47	14 95	3.72	12 73	5.86
40	5 42	1.98	16 34	5 34	5 17	1 75	9.42	5.00
10	17.84	2.58	56 64	9.15	9.58	3.12	18.45	9.30
41 12	12 10	2.60	27 77	8 51	11 75	2 73	16.99	9.01
43	5 11	1 95	15 79	6.01	4 41	1.80	9 74	6.78
-5	5.64	2.07	17 72	6.36	5 12	2.15	0 11	7.96
44	2.60	1.62	12.00	5.30	2.12	1.52	9.11	6.04
45	6.70	2.02	10 12	6.96	6.42	2.00	0.30	0.04
40	6.69	2.12	10.46	7.27	6.07	2.23	12 52	0.40
47	16 74	2.79	19.40	1.31	0.97	2.03	12.33	0.39
40	11 07	2.57	33.00	0.23	11.9 <i>1</i>	2.50	13.30	9.00
49	1.00	1.00	21.02	5.24	0.91	1.78	9.85	0.50
50	1.30	1.80	113.70	5.45	1.42	1.54	1.20	0.30

Scene GNP	Median GNP	Midway GNP	Ratio GNP	Cluster GNP	Cluster	Cluster	Cluster Ratio	GNP
					Median GNP	Midway GNP	GNP	Uncorrected
1	10.60	1.90	14.88	4.38	9.90	2.08	9.53	4.59
2	4.63	1.62	10.79	3.58	4.30	1.13	6.19	4.55
3	13.83	2.20	32.33	5.83	10.41	2.25	8.39	4.91
4	3.69	1.36	10.40	3.84	3.80	1.25	6.26	4.50
5	3.73	1.19	11.35	4.13	4.20	1.87	8.68	3.98
6	22.72	1.65	34.41	6.30	20.59	1.72	12.35	7.02
7	15.57	2.07	21.23	4.17	12.63	2.07	13.33	4.65
8	6.28	1.73	10.77	4.11	6.68	1.82	8.00	4.26
9	2.96	2.10	11.96	4.41	2.93	1.83	10.20	4.71
10	11.73	1.97	20.71	7.54	11.53	1.99	14.03	8.01
11	28.02	3.28	30.86	5.10	15.95	3.83	13.39	5.80
12	15.16	3.68	19.29	4.71	13.95	3.44	14.86	5.03
13	11.92	2.19	17.50	5.95	10.75	4.44	8.16	5.44
14	11.83	2.36	21.07	6.77	10.65	1.75	14.56	7.46
15	11.81	2.94	20.22	5.07	10.41	3.73	13.59	6.48
16	15.53	4.64	19.74	6.98	15.17	3.88	13.71	6.91
17	22.13	2.08	26.12	4.71	18.71	2.25	12.72	5.59
18	16.96	2.79	19.60	5.20	15.43	3.01	10.04	6.40
19	41.89	2.34	44.83	4.95	35.36	2.74	14.10	5.97
20	16.55	1.92	20.20	6.62	17.02	2.42	10.79	6.00
21	6.02	2.40	17.69	6.30	6.34	2.29	12.26	7.02
22	24.36	1.94	27.68	4.77	23.03	2.49	9.57	5.19
23	40.66	1.64	34.76	13.08	30.84	12.55	15.23	5.51
24	11.20	2.30	17.35	5.51	10.43	1.91	12.40	6.52
25	21.38	1.66	26.32	4.66	17.37	2.02	13.31	4.73
26	37.39	2.01	36.01	5.01	27.33	3.16	15.60	5.23
27	8.95	1.56	17.33	5.27	8.53	1.30	9.38	6.64
28	14.19	1.79	22.80	5.22	11.42	1.53	11.92	5.54
29	24.69	1.63	31.26	7.00	19.78	2.18	13.25	7.47
30	17.08	2.94	21.27	7.33	15.70	2.73	10.68	7.47
31	7.92	1.71	12.05	3.32	7.48	1.52	5.49	4.35
32	9.69	1.86	14.54	4.26	9.21	1.69	7.45	4.86
33	6.24	2.26	11.80	3.68	5.31	1.77	6.43	4.86
34	24.99	3.10	20.42	3.84	18.85	2.83	11.55	3.99
35	2.83	1.62	11.62	4.13	2.83	1.31	7.97	5.02
36	11.22	1.48	18.89	3.92	10.99	1.75	6.50	4.72
37	10.43	1.25	13.66	3.70	9.02	1.94	4.58	3.93
38	40.46	1.76	84.94	7.94	19.74	1.94	12.71	6.89
39	18.59	2.04	16.67	3.81	14.96	2.73	11.66	3.95
40	5.42	1.39	11.56	3.58	5.15	1.25	6.83	3.87
41	17.60	2.02	56.15	6.29	9.52	2.61	16.65	7.06
42	12.01	1.70	22.67	5.94	11.67	2.34	12.67	5.57
43	5.11	1.42	10.78	4.13	4.40	1.40	7.47	4.48
44	5.64	1.42	13.02	2.99	5.09	1.52	6.71	5.53
45	2.69	1.13	9.39	2.81	2.97	1.11	4.18	4.25
46	6.70	2.06	13.48	4.78	6.42	1.56	7.45	5.55
47	6.68	1.87	13.42	4.85	6.90	2.06	9.15	5.37
48	16.60	1.60	30.14	5.31	11.90	2.47	12.27	6.02
49	11.86	1.17	19.75	3.50	8.79	1.44	8.00	3.88
50	1.38	1.30	9.52	3.74	1.39	1.15	5.22	4.51
Scene LNNP	Median	Midway	Ratio LNNP	Cluster LNNP	Cluster	Cluster	er Cluster Ratio LNN	
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	LNNP	LNNP			Median	Midway	LNNP	Uncorrected
					LNNP			
1	10.60	1.83	12.47	3.61	9.84	2.21	7.99	3.30
2	4.62	2.01	8.27	2.79	4.26	1.67	5.11	3.38
3	13.78	2.27	36.16	3.28	10.53	1.88	7.52	3.22
4	3.69	1.49	7.77	2.54	3.87	1.73	3.66	3.13
5	3.73	1.24	8.95	3.24	4.15	1.74	4.87	2.82
6	22.72	3.37	36.39	5.53	20.49	3.50	12.12	5.60
7	15.57	2.03	20.80	2.92	12.63	1.95	12.79	3.28
8	6.28	1.81	8.50	3.35	6.65	2.07	6.18	3.16
9	2.96	2.27	9.62	3.43	3.01	1.80	8.20	3.47
10	11.85	4.94	22.73	6.54	11.61	4.39	14.59	7.43
11	28.01	3.77	30.93	4.32	16.08	3.58	13.02	4.31
12	15.15	3.66	18.74	3.64	13.89	3.37	14.45	3.54
13	12.03	2.45	16.53	4.19	10.93	3.75	6.04	3.48
14	11.82	4.26	17.56	6.02	10.74	3.70	12.32	6.57
15	11.72	3.74	17.30	4.59	10.59	3.93	11.06	4.98
16	15.51	5.56	18.55	5.79	15.17	4.95	12.67	5.62
17	22.13	2.36	23.37	3.51	18.72	2.65	10.71	3.89
18	16.92	3.60	18.11	3.72	15.39	2.96	8.90	4.81
19	41 92	2 93	45.82	3.62	35 27	2.57	13.33	4.38
20	16.55	2.58	18.58	7.36	17.01	5.03	9 41	4.34
21	6.01	3 91	13 31	5 21	6 36	3.86	9.47	5 73
22	24 36	2.40	26.94	3.90	23.04	2.67	8 89	4.07
22	40.60	1.89	36 21	12 72	20.04	12.07	14 65	3.87
20	11 16	3.27	16.02	12.72	10.39	2 84	11 24	1 97
24	21.37	1.86	24 02	3 72	17 31	2.04	12.02	3.26
26	27.35	2.26	36.30	J.12 A 15	27.20	3.11	15.02	3.62
20	9 0 <i>1</i>	2.20	17.61	2 12	27.20 9.52	1 00	7.00	5.02
28	1/ 18	2.04	21 77	3.63	0.55 11 / 2	1.00	10.07	3.07
20	24.10	A 12	22.17	5.00	10 56	1.22	11.00	6.52
20	17.09	4.12	10 74	5.33	15.50	4.22	0.09	6.60
21	7.00	4.04	19.74	2.76	15.01	4.41 2 1 0	9.00	2.17
22	7.92	1.04	9.20	2.70	7.47	2.10	4.70	3.17
3Z	9.09	1.95	10.25	2.95	9.00	1.71	0.24	3.10
33	0.24	2.25	10.25	2.00	5.32 10.01	1.58	4.78	3.17
34	25.13	2.99	20.31	2.58	18.91	2.10	11.32	2.53
35	2.83	1.88	8.18	2.62	2.83	1.48	5.21	3.40
30	11.22	1.62	10.69	3.31	10.98	2.00	5.73	3.31
37	10.43	1.39	11.16	3.16	9.06	2.23	4.10	2.78
38	40.31	2.14	86.02	5.48	19.64	1.92	12.59	5.18
39	18.71	2.07	16.49	2.69	14.95	2.30	11.07	2.61
40	5.41	1.66	9.20	2.28	5.16	1.19	5.55	2.68
41	17.27	2.40	63.36	3.87	9.21	2.85	17.10	4.20
42	11.97	2.12	19.97	4.29	11.48	2.96	10.45	3.82
43	5.11	1.60	7.06	3.06	4.43	1.50	5.53	3.06
44	5.64	1.91	10.83	1.96	5.11	1.65	4.08	3.91
45	2.69	1.24	6.58	2.09	2.88	1.12	3.07	2.74
46	6.70	2.31	10.18	3.26	6.50	1.77	5.52	3.77
47	6.68	2.40	11.86	3.88	6.95	2.31	7.64	3.99
48	16.53	2.34	26.57	5.15	12.16	1.60	9.33	4.32
49	11.85	1.27	18.03	2.72	8.95	1.62	4.80	2.58
50	1.38	1.43	6.21	2.38	1.41	1.19	3.17	2.91

Scene LNP	Median LNP	Midway LNP	Ratio LNP	Cluster LNP	Cluster	Cluster	Cluster Ratio	LNP
					Median LNP	Midway LNP	LNP	Uncorrected
1	10.60	1.59	11.73	2.75	9.85	2.16	7.19	2.30
2	4.62	1.47	6.48	1.86	4.26	1.05	4.15	2.14
3	13.78	1.97	33.54	2.63	10.53	1.91	6.41	2.25
4	3.69	1.03	5.89	2.03	3.84	1.39	3.21	2.06
5	3.73	0.75	6.35	2.18	4.15	1.49	4.71	1.82
6	22.72	2.03	32.95	3.47	20.42	2.22	10.68	3.42
7	15.57	1.77	19.96	2.29	12.62	1.76	12.08	2.27
8	6.28	1.45	7.10	2.33	6.61	1.70	5.12	1.95
9	2.95	1.89	6.84	2.40	3.05	1.51	5.67	2.23
10	11.74	2.53	16.94	3.79	11.49	2.21	10.75	3.93
11	27.95	3.11	30.75	3.47	15.98	3.39	12.49	2.71
12	15.11	3.51	17.74	2.99	13.91	3.17	13.76	2.73
13	11.91	2.12	15.07	4.24	10.89	4.00	4.96	2.51
14	11.82	2.80	15.12	3.55	10.70	2.13	10.29	3.72
15	11.70	3.03	15.62	3.62	10.52	3.67	8.87	3.14
16	15.49	4.78	15.92	3.92	15.15	4.22	10.23	3.34
17	22.13	1.97	23.64	2.72	18.76	2.17	10.68	2.63
18	16.91	2.84	16.87	2.98	15.42	2.54	8.26	3.07
19	41.91	2.43	44.98	3.14	35.29	2.83	13.28	2.87
20	16.55	1.98	17.09	4.82	16.97	4.02	8.12	2.93
21	6.01	2.71	9.39	3.34	6.34	2.72	6.19	3.42
22	24.36	1.67	26.21	2.94	23.04	2.32	8.42	2.45
23	40.60	1.39	35.17	12.66	30.59	12.39	14.28	2.64
24	11.13	2.42	13.77	2.66	10.29	1.95	9.57	3.15
25	21.37	1.45	24.84	3.36	17.39	1.92	11.82	2.23
26	37.35	1.94	35.91	3.67	27.25	3.10	15.05	2.57
27	8.94	1.80	13.41	2.11	8.53	1.20	5.86	3.18
28	14.18	1.55	20.63	2.59	11.21	1.49	9.46	2.65
29	24.63	2.06	30.28	4.18	19.71	3.07	10.22	3.64
30	17.08	3.30	16.86	4.38	15.52	3.24	7.26	3.69
31	7.92	1.63	8.34	3.10	7.47	2.06	3.78	2.18
32	9.69	1.61	10.74	2.34	9.23	1.53	5.45	2.27
33	6.24	2.07	8.52	1.65	5.31	1.42	4.03	2.38
34	25.07	2.87	20.03	2.05	19.00	1.88	11.13	1.92
35	2.83	1.35	6.10	1.84	2.82	1.22	3.98	2.36
36	11.22	1.15	15.62	2.64	10.98	2.41	4.82	2.17
37	10.43	1.18	10.88	2.56	9.13	2.06	3.23	1.82
38	40.17	1.56	86.60	3.55	19.28	1.81	11.74	2.97
39	18.60	1.67	16.11	2.13	14.96	2.00	10.87	1.73
40	5.41	1.33	7.85	1.83	5.15	1.28	4.82	1.83
41	17.17	1.97	63.49	2.83	9.15	2.49	15.71	2.72
42	11.97	1.59	18.93	3.26	11.40	2.44	8.79	2.67
43	5.11	1.33	6.03	2.16	4.37	1.13	4.75	2.20
44	5.64	1.39	8.45	1.74	5.09	1.60	3.24	2.62
45	2.69	0.78	5.03	1.01	2.88	0.87	1.42	1.91
46	6.70	2.00	8.52	2.36	6.42	1.39	4.74	2.72
47	6.68	1.62	9.14	2.75	6.92	1.91	6.07	2.52
48	16.53	1.68	26.37	3.92	11.81	2.14	8.56	2.90
49	11.85	0.90	18.02	2.18	9.00	1.35	4.27	1.83
50	1.38	1.01	4.54	1.68	1.45	0.94	2.44	2.05

Scene PBN	Median PBN	Midway PBN	Ratio PBN	Cluster PBN	Cluster	Cluster	Cluster Ratio	PBN
		-			Median PBN	Midway PBN	PBN	Uncorrected
1	10.60	10.56	18.24	9.86	9.91	9.81	13.50	10.56
2	4.62	7.61	15.45	6.05	4.32	5.95	10.38	7.58
3	13.82	11.09	49.39	11.15	7.68	10.65	13.18	11.03
4	3.69	11.11	22.82	9.38	3.82	9.49	13.49	11.18
5	3.73	11.23	24.74	10.97	3.52	10.88	10.70	11.29
6	22.72	10.50	29.08	8.62	20.70	8.39	11.41	10.55
7	15.56	10.66	28.22	9.74	12.65	9.60	20.24	10.63
8	6.28	10.60	21.68	9.82	6.72	9.47	15.63	10.56
9	2.97	10.70	23.44	9.73	3.08	9.70	15.95	10.63
10	11.69	10.68	21.65	9.69	11.56	9.41	16.01	10.77
11	28.35	10.45	31.87	6.69	15.94	6.88	13.09	10.21
12	15.33	10.66	27.38	9.17	13.97	9.31	20.95	10.30
13	11.91	10.65	28.55	9.28	9.60	9.27	16.44	10.61
14	11.87	10.57	33.02	9.04	10.55	8.99	21.15	10.52
15	11.86	10.70	29.53	9.43	10.50	9.37	19.13	10.50
16	15.67	11.28	28.00	9.04	15.14	9.64	18.45	10.41
17	22.13	10.57	25.14	9.04	18.76	9.01	13.49	10.54
18	17.20	10.48	28.22	7.78	15.53	7.85	15.12	10.31
19	41.99	10.56	39.20	10.43	35.91	9.38	13.55	10.41
20	16.59	10.57	26.55	10.28	17.00	10.17	16.16	10.54
21	6.05	10.64	25.22	9.46	6.30	9.47	15.94	10.53
22	24.50	10.50	35.62	9.03	23.25	8.94	15.15	10.49
23	40.66	11.13	32.53	19.76	32.14	19.37	19.74	11.25
24	11.34	10.48	25.33	8.68	10.49	8.90	17.30	10.38
25	21.40	11.21	30.44	10.30	17.50	10.33	19.38	11.27
26	37.39	11.44	33.97	10.06	29.14	9.93	16.31	11.46
27	8.96	10.50	26.19	8.89	8.52	8.70	15.32	10.55
28	14.17	10.62	27.16	9.33	11.51	9.26	15.14	10.64
29	24.61	10.62	24.84	9.83	20.42	9.67	13.04	10.74
30	17.11	10.71	21.79	9.37	15.71	9.22	14.32	10.53
31	7.93	11.24	24.51	9.59	7.52	9.57	13.94	11.25
32	9.69	10.67	16.51	10.02	9.47	10.30	13.61	10.65
33	6.54	10.65	27.51	8.96	5.51	8.84	15.64	10.55
34	25.82	10.17	26.95	8.39	19.07	8.43	16.45	9.91
35	2.83	10.51	21.77	9.43	2.82	9.38	15.43	10.55
36	11.22	10.63	24.64	10.74	10.95	10.67	14.17	10.67
37	10.43	10.94	26.93	9.59	9.78	9.52	13.44	10.99
38	40.41	10.40	86.56	10.05	20.69	9.82	39.77	10.49
39	18.85	9.86	17.56	8.87	15.20	8.69	12.14	9.86
40	5.44	6.97	17.78	6.27	5.21	6.23	10.95	7.02
41	17.34	9.65	55.40	10.61	13.40	10.43	17.00	9.67
42	12.87	10.12	34.42	9.56	12.29	9.85	17.65	10.13
43	5.11	7.62	18.47	6.45	4.40	6.39	11.00	7.65
44	5.65	11.16	23.26	9.62	4.96	9.51	13.05	11.40
45	2.69	7.48	16.30	5.40	2.87	5.35	6.77	7.53
46	6.70	10.61	20.30	9.39	6.52	9.53	13.51	10.55
47	6.75	10.53	21.86	8.82	7.03	8.75	14.71	10.53
48	16.58	9.71	26.95	9.26	13.40	9.33	12.43	9.69
49	11.85	7.67	27.01	6.96	8.41	6.92	10.71	7.70
50	1.38	10.94	23.61	10.03	1.52	10.01	12.30	11.00

Scene SN	Median SN	Midway SN	Ratio SN	Cluster SN	Cluster Median SN	Cluster Midway SN	Cluster Ratio SN	SN Uncorrected
1	10.60	1.25	11.87	1.98	9.85	1.96	6.84	0.93
2	4.62	1.27	4.83	0.98	4.30	1.04	3.28	0.46
3	13.78	1.81	31.05	2.07	10.62	2.04	4.95	0.70
4	3.69	0.75	3.97	1.22	3.84	1.16	2.12	0.44
5	3.73	0.43	4.37	1.37	4.20	1.41	2.42	0.55
6	22.72	1.65	31.02	1.68	20.42	1.66	9.25	0.75
7	15.56	1.47	19.41	1.66	12.62	1.73	11.18	0.47
8	6.28	1.26	6.21	1.45	6.61	1.50	4.20	0.43
9	2.94	1.69	4.30	1.44	3.12	1.54	3.04	0.48
10	11.69	1.98	13.30	1.94	11.51	1.95	7.87	1.16
11	27.90	2.89	30.13	3.06	16.05	3.23	11.83	0.83
12	15.09	3.37	16.88	2.32	13.90	3.08	12.85	1.45
13	11.83	1.81	13.68	4.37	10.92	4.30	4.59	0.79
14	11.82	2.36	14.29	1.67	10.63	1.75	9.33	1.31
15	11.70	2.81	14.93	2.92	10.33	3.17	7.49	0.68
16	15.47	4.63	14.30	2.47	15.23	4.13	8.57	0.70
17	22.13	1.74	24.00	1.74	18.66	1.89	10.59	0.57
18	16.89	2.58	15.94	2.28	15.33	2.47	7.85	0.67
19	41.90	2.19	43.62	2.74	35.31	2.84	13.03	0.63
20	16.55	1.69	16.07	4.36	17.04	4.43	7.00	0.63
21	6.01	2.43	7.42	1.58	6.31	2.33	3.84	0.72
22	24.36	1.43	25.97	2.28	23.05	2.36	7.75	0.52
23	40.60	1.04	34.50	12.55	30.59	12.46	14.05	0.58
24	11.12	2.13	12.01	1.40	10.32	1.59	8.26	0.95
25	21.37	1.18	24.66	3.10	17.49	1.97	11.64	0.49
26	37.31	1.88	35.67	3.17	27.01	3.11	14.72	0.53
27	8.94	1.39	9.65	1.43	8.53	1.39	5.12	0.96
28	14 18	1 22	18.96	1.32	11 43	1 21	8.55	0.58
29	24.60	1.59	29.07	2 51	19.58	2.39	9.05	1.09
30	17.08	2.94	15.25	2.27	15.58	2.58	5.90	1.09
31	7.92	1.29	7.83	2.77	7.51	2.67	2.97	0.45
32	9.69	1 42	10.41	1 26	9.23	1 25	4 91	0.86
33	6 24	1.83	6.48	1 24	5.31	1 28	3 73	0.86
34	25.17	2.70	19.73	1.40	18.96	1.69	10.87	0.67
35	2 83	1.06	3 29	0.89	2 82	1.00	2 28	0.52
36	11 22	0.89	15.02	1 61	11 04	1.58	3.88	0.65
37	10.43	0.66	11.05	2.00	9.02	1.95	2.53	0.79
38	40.05	1 21	87 42	2.08	19 10	1.88	10.87	0.91
39	18 49	1 44	15 77	1 79	15.06	1.83	10.71	0.40
40	5 41	1 17	6.81	0.94	5 14	1 13	3 79	0.39
41	17.07	1 70	63.87	2 36	9.15	2 46	14 84	0.83
42	11.07	1 31	17 75	2.00	11 39	2.40	7 39	0.97
43	5 11	0.95	5 42	1 27	4 41	1 20	4 07	0.78
44	5.64	1.03	6.09	1 56	5.09	1.57	2.85	0.56
45	2.69	0.40	2 92	0.88	2.88	0.88	1.00	0.42
46	6.70	1 70	7.04	0.75	6 42	1 11	3.78	0.56
47	6.68	1 37	7.06	1.67	6.98	1 75	4.83	0.54
48	16.48	1.40	27.00	2.56	11 46	2 36	8 19	1 37
49	11.85	0.62	17.89	1 19	8 79	1.07	3 75	0.39
50	1.38	0.72	1.82	0.88	1.45	0.73	1.30	0.44

1     10.60     1.21     11.57     1.52	Scene Base	Median Base	Midway Base	Ratio Base	Cluster Base		
2       4.62       1.26       4.74       0.90	1	10.60	1.21	11.57	1.82		
3 : 13.78 $1.80$ $31.01$ $1.85$ $1.44$ $3 : 69$ $0.73$ $3.90$ $1.14$ $1.46$ $5$ $3.73$ $0.38$ $4.02$ $1.31$ $1.61$ $6$ $22.72$ $1.63$ $30.77$ $1580$ $1.61$ $7$ $15.56$ $1.46$ $1.44$ $1.58$ $1.61$ $8$ $6.28$ $1.25$ $6.19$ $1.39$ $1.61$ $9$ $2.94$ $1.68$ $4.07$ $1.36$ $1.61$ $10$ $11.69$ $1.92$ $13.00$ $1.69$ $1.61$ $112$ $77.90$ $2.86$ $3.013$ $2.98$ $1.61$ $1.61$ $112$ $77.90$ $2.86$ $3.53$ $1.61$ $1.61$ $1.61$ $114$ $11.82$ $2.31$ $1.4.01$ $1.06$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ $1.61$ <td< td=""><td>2</td><td>4.62</td><td>1.26</td><td>4.74</td><td>0.90</td><td></td><td></td></td<>	2	4.62	1.26	4.74	0.90		
4       3.69       0.73       3.90       1.14       Image: state sta	3	13.78	1.80	31.01	1.85		
5       3.73       0.38       4.02       1.31	4	3.69	0.73	3.90	1.14		
6 $22.72$ $1.63$ $30.77$ $1.58$ $                                    $	5	3.73	0.38	4.02	1.31		
7       15.56       1.46       19.41       1.88	6	22.72	1.63	30.77	1.58		
8       6.28       1.25       6.19       1.39	7	15.56	1.46	19.41	1.58		
9         2.94         1.68         4.07         1.38         1.08         1.01           10         11.69         1.92         13.00         1.69         1         1           11         27.90         2.46         30.13         2.93         1         1           12         15.05         3.35         16.78         2.25         1         1           13         11.83         1.79         13.63         4.30         1         1           14         11.82         2.31         14.01         1.06         1         1         1           15         11.70         2.80         15.66         3.11         1	8	6.28	1.25	6.19	1.39		
10 $11.69$ $1.92$ $13.00$ $169$ $(1)$ 11 $27.90$ $2.86$ $30.13$ $2.98$ $(1)$ 11 $15.05$ $3.35$ $16.78$ $2.25$ $(1)$ 13 $11.83$ $1.79$ $13.63$ $4.30$ $(1)$ 14 $11.82$ $2.31$ $14.01$ $106$ $(1)$ $(1)$ 15 $11.70$ $2.80$ $15.06$ $3.11$ $(1)$ $(1)$ 16 $15.47$ $4.62$ $14.15$ $2.33$ $(1)$ $(1)$ 17 $22.13$ $1.72$ $23.93$ $1660$ $(1)$ $(2)$	9	2.94	1.68	4.07	1.36		
11 $27,90$ $286$ $30.13$ $2.98$ $                                    $	10	11.69	1.92	13.00	1.69		
12       15.05       3.35       16.78       2.25	11	27.90	2.86	30.13	2.98		
13       11.83       1.79       13.63       4.30             14       11.82       2.31       14.01       1.06             15       11.70       2.80       15.06       3.11               16       15.47       4.62       14.15       2.33	12	15.05	3.35	16.78	2.25		
1411.822.3114.011.06 $                                    $	13	11.83	1.79	13.63	4.30		
15       11.70       2.80       15.06       3.11       Image: constraint of the state of the stat	14	11.82	2.31	14.01	1.06		
16       15.47       4.62       14.15       2.33       Image: constraint of the second	15	11.70	2.80	15.06	3.11		
17 $22.13$ $1.72$ $23.93$ $1.68$ Image: constraint of the state o	16	15.47	4.62	14.15	2.33		
18       16.89       2.56       15.96       2.19       Image: constraint of the second	17	22.13	1.72	23.93	1.68		
19       41.90       2.18       43.61       2.71 $(1, 1, 2, 2)$ 20       16.55       1.68       16.01       4.33 $(1, 2, 2)$ $(1, 2, 2)$ 21       6.01       2.42       7.21       1.46 $(1, 2, 2)$ $(1, 2, 2)$ 22       24.36       1.42       25.93       2.23 $(1, 2, 2)$ $(1, 2, 2)$ 23       40.60       1.01       34.50       12.53 $(1, 2, 2)$ $(1, 2, 2)$ 24       11.12       2.10       11.96       1.16 $(1, 2, 2)$ $(1, 2, 2)$ 25       21.37       1.17       24.65       3.08 $(1, 2, 2)$ $(1, 2, 2)$ 26       37.31       1.88       35.67       3.16 $(1, 2, 2)$ $(1, 2, 2)$ 28       14.18       1.21       18.87       1.22 $(1, 2, 2)$ $(1, 2, 2)$ $(1, 2, 2)$ 29       24.60       1.54       29.45       2.26 $(1, 2, 2)$ $(1, 2, 2)$ 30       17.08       2.91       15.01       2.75 $(1, 2, 2)$ $(1, 2, 2)$ 31       7.92       1.28       1.94 $(1, 2, 2)$ $(1,$	18	16.89	2.56	15.96	2.19		
20       16.55       1.68       16.01       4.33                                 21       6.01       2.42       7.21       1.46                                 22       24.36       1.42       25.93       2.23   23       40.60       1.01       34.50       1.253   24       11.12       2.10       11.96       1.16	19	41.90	2.18	43.61	2.71		
21       6.01       2.42       7.21       1.46       Image: constraint of the second se	20	16.55	1.68	16.01	4.33		
22       24.36       1.42       25.93       2.23       Image: Constraint of the second	21	6.01	2 42	7 21	1 46		
23       40.60       1.01       34.50       12.53       Image: Constraint of the second	22	24.36	1 42	25.93	2 23		
24       11.12       21.0       11.96       1.16       Image: constraint of the second	23	40.60	1.01	34.50	12.53		
25       21.37       1.17       24.65       3.08       Image: constraint of the second	24	11 12	2 10	11 96	1 16		
26       37.31       1.88       35.67       3.16       Image: constraint of the state	25	21.37	1 17	24.65	3.08		
27       8.94       1.35       9.53       1.20       Image: constraint of the second se	26	37.31	1.88	35.67	3.16		
28       14.18       1.21       18.87       1.22       1       1         29       24.60       1.54       29.45       2.26       1       1       1         30       17.08       2.91       15.01       2.06       1       1       1         31       7.92       1.28       7.96       2.75       1       1       1         32       9.69       1.39       10.22       1.01       1       1       1         33       6.24       1.80       6.25       1.10       1 <td< td=""><td>27</td><td>8 94</td><td>1.35</td><td>9.53</td><td>1 20</td><td></td><td></td></td<>	27	8 94	1.35	9.53	1 20		
29       24.60       1.54       29.45       2.26       Image: constraint of the second	28	14 18	1 21	18 87	1 22		
30       17.08       2.91       15.01       2.06	29	24.60	1.54	29.45	2.26		
31       7.92       1.28       7.96       2.75       Image: Constraint of the second se	30	17.08	2.91	15.01	2.06		
32       9.69       1.39       10.02       1.01       Image: state s	31	7 92	1 28	7 96	2 75		
33       6.24       1.80       6.25       1.10	32	9.69	1.39	10.22	1 01		
34       25.16       2.68       19.71       1.27       Image: constraint of the state	33	6.24	1.80	6.25	1.10		
35       2.83       1.04       3.08       0.79         36       11.22       0.86       14.87       1.53	34	25.16	2.68	19.71	1.27		
36       11.22       0.86       14.87       1.53       Image: constraint of the state	35	2 83	1 04	3.08	0.79		
37       10.43       0.60       10.82       1.94	36	11 22	0.86	14 87	1.53		
38       40.05       1.17       87.38       1.83         39       18.49       1.43       15.75       1.76         40       5.41       1.16       6.73       0.87         41       17.07       1.66       63.70       2.27         42       11.97       1.26       17.56       2.22         43       5.11       0.91       5.26       1.09         44       5.64       1.02       5.92       1.56         45       2.69       0.37       2.80       0.85         46       6.70       1.69       6.85       0.71         47       6.68       1.36       6.97       1.59         48       16.48       1.32       26.63       2.31         49       11.85       0.61       17.79       1.17         50       1.38       0.70       1.56       0.81	37	10.43	0.60	10.82	1.94		
39       18.49       1.43       15.75       1.76	38	40.05	1.17	87.38	1.83		
40       5.41       1.16       6.73       0.87	39	18.49	1 43	15 75	1 76		
41       17.07       1.66       63.70       2.27         42       11.97       1.26       17.56       2.22         43       5.11       0.91       5.26       1.09         44       5.64       1.02       5.92       1.56         45       2.69       0.37       2.80       0.85         46       6.70       1.69       6.85       0.71         47       6.68       1.36       6.97       1.59         48       16.48       1.32       26.63       2.31         49       11.85       0.61       17.79       1.17         50       1.38       0.70       1.56       0.81	40	5.41	1.16	6.73	0.87		
11.07       1.00       17.50       2.22       11.97       1.26       17.56       2.22         43       5.11       0.91       5.26       1.09       11.97       1.26       17.56         44       5.64       1.02       5.92       1.56       11.97       1.26       1.09         45       2.69       0.37       2.80       0.85       11.00       11.00       11.00         46       6.70       1.69       6.85       0.71       11.00       11.00       11.00         47       6.68       1.36       6.97       1.59       11.00       11.00       11.00         48       16.48       1.32       26.63       2.31       11.00       11.00       11.00         50       1.38       0.70       1.56       0.81       11.77       11.77       11.77	41	17.07	1 66	63 70	2 27		
43       5.11       0.91       5.26       1.09	42	11 97	1 26	17 56	2 22		
44       5.64       1.02       5.92       1.56   <	43	5 11	0.91	5 26	1 09		
45       2.69       0.37       2.80       0.85   <	44	5.64	1.02	5.92	1.56		
46       6.70       1.69       6.85       0.71   <	45	2.69	0.37	2.80	0.85		
47     6.68     1.36     6.97     1.59       48     16.48     1.32     26.63     2.31       49     11.85     0.61     17.79     1.17       50     1.38     0.70     1.56     0.81	46	6.70	1.69	6.85	0.71		
48     16.48     1.32     26.63     2.31       49     11.85     0.61     17.79     1.17       50     1.38     0.70     1.56     0.81	47	6.68	1.36	6.97	1.59		
49         11.85         0.61         17.79         1.17           50         1.38         0.70         1.56         0.81	48	16.48	1.32	26.63	2.31		
50 1.38 0.70 1.56 0.81	49	11.85	0.61	17.79	1.17		
	50	1.38	0.70	1.56	0.81		

## A.4 Row Bias RMSE Metric

Scene	Median	Midway	Ratio	Cluster	Cluster Median AN	Cluster Midway AN	Cluster Ratio AN	AN Uncorrected
1	10.61	1 33	8 86	2.51		1 10	6 22	4 33
2	163	8 28	17.03	7 22	3.03 4 31	4.10 7.26	11 68	9.22
2	4.03	10.63	22 72	11.20	11 93	10.73	10.88	10.60
3	3 60	10.03	10 35	9.56	3 80	0.75 0.78	12.23	10.03
5	3.05	12.13	21 /6	12.06	5.09	9.40 12.05	15.75	12.10
5	22 72	9 79	10 76	7 10	20.02	6.85	13.73 9.07	0.04
7	15 55	0.70	10.12	8.03	12 00	0.00 9.01	14 51	0.94
8	6.28	6.53	13.12	6.05	12.99 6.62	6.01 6.18	14.31	9.37 6.59
0 0	2 9/	9.55	10.24	0.21	3 12	0.10 0 /2	14.86	0.56
10	11 70	7 58	21.02	7 75	5.42 11 //7	5.42 7.54	14.00	7 75
11	26.07	854	30.05	6.44	1/ 96	6.49	13 55	9.20
12	14 72	7.64	21 /3	7.08	13 / 8	0.43 7 3/	17.86	7 40
12	11 97	6.02	10 10	6.12	11 12	6 11	12.00	7.45
14	11.07	8.66	20.24	7.52	10.61	7.54	15.50	0.00
15	11.00	7.60	20.34	7.52	10.01	7.54 9.05	17 27	0.00
16	15.72	0.88	23.00	9.79	15.02	0.05	16.40	0.47
17	22.07	9.00	25.22	6.16	19.14	9.30 6 17	14.26	9.47
10	17.01	9.79	26.04	6.24	15.00	6.20	12 12	0.03
10	11.01	9.52	27.52	6.49	25.00	6.28	12.05	8 50
20	16 53	8.68	15 /1	11 00	17.05	11 10	11.78	0.35 9 71
20	6 01	0.00	18 21	9.41	6 30	9 <i>1</i> 7	14.60	0.71
22	24.41	9.07 8.47	27.31	7 57	23 11	7 53	14.00	9.03 8.52
22	24.41	8 37	36.79	15/18	20.11	15 30	15.04	9.55
23	11 16	8.96	24 37	7 90	10.22	7.83	17 31	0.55
24 25	21.25	10.35	24.37	7.50	17.51	8.40	16.38	10.26
25	21.33	10.35	23.12	9.06	28.06	8.40 8.94	17.50	10.20
20	8 96	6.01	10/18	5.00	20.00 8 5/	5.83 5.83	11.55	7.02
28	1/ 15	8.47	28.45	7.63	11 10	7 69	1/ 39	9.61
20	24.37	9.17	20.40	9.07	20.34	7.03	11 21	0.01
30	17 07	9.25	16.42	8 57	15.82	8 49	9.92	9.34
31	7 92	10.93	20.22	10.42	7 86	10 36	14 50	11 01
32	9.69	9 33	16.25	8.83	9.42	8 82	12 34	9.36
33	6.39	8 99	16.78	7 67	5 20	7 59	13.03	9.00
34	24 16	8 38	15.92	8 53	17 19	8.62	10.24	8.46
35	2 83	6.87	15.39	5.98	2 82	5 96	11 23	6 90
36	11 22	8 98	22 15	8.57	11 15	8 53	11 72	9.03
37	10.43	9.09	16 47	8 14	9 91	8 07	10.85	9 1 7
38	34.71	8.53	60.73	8.99	17.36	8.08	9.41	8.68
39	17.93	6.23	14.14	4.83	14.23	4.72	9.70	6.39
40	5 41	4 51	9 79	4 18	5 13	4 20	7 57	4 52
41	15.17	5.41	43.87	5.99	9.16	5.95	15.01	5 74
42	11.82	7.89	18.28	8.49	11.10	8.52	12.86	7 97
43	5.10	6.66	13.97	6.26	4.45	6.17	9.38	6.74
44	5.64	10.02	22.04	8.23	4.87	8.12	12.39	10.18
45	2.69	8.59	17.38	7.99	2.82	7.96	9.11	8.62
46	6.69	6.65	12.57	6.25	6.52	6.19	9.13	6.76
47	6.68	10.39	21.41	9.56	7.03	9.51	15.50	10.45
48	15.84	6.43	26.88	5.49	11.86	5.66	12.11	6.61
49	11.86	10.09	28.21	9.53	8.75	9.41	12.57	10.17
50	1.38	8.98	18.29	8.32	1.45	8.28	11.34	9.11

Scene GNNP	Median GNNP	Midway GNNP	Ratio GNNP	Cluster GNNP	Cluster Median GNNP	Cluster Midway GNNP	Cluster Ratio GNNP	GNNP Uncorrected
1	10.60	2.05	17.55	6.35	9.90	2.66	11.89	6.86
2	4.63	2.02	15.80	5.68	4.29	1.81	9.22	7.12
3	13.87	1.93	30.02	7.31	10.51	2.75	10.74	7.34
4	3.69	1.83	14.71	5.34	3.84	1.83	8.63	6.65
5	3.73	1.73	16.22	5.84	4.24	1.88	9.80	5.82
6	22.72	2.86	35.92	10.94	20.74	2.95	15.15	11.78
7	15.56	2.11	22.04	5.89	12.72	2.39	15.42	6.78
8	6.28	1.89	13.99	5.60	6.61	2.01	10.55	5.94
9	2.95	2.10	17.45	6.76	3.22	2.24	14.15	7.05
10	11.69	3.54	28.62	12.27	11.46	3.66	20.31	13.18
11	25.60	2.88	27.53	5.73	15.37	3.30	13.54	8.28
12	14.67	2.80	19.32	6.20	13.39	3.28	16.36	6.77
13	11.92	2.34	20.06	7.55	11.06	4.72	12.24	8.28
14	11.83	3.15	27.19	10.35	10.68	2.80	20.01	12.01
15	11.73	2.82	24.93	7.89	10.49	3.70	18.91	10.13
16	15.47	4.41	24.99	11.09	15.21	4.63	18.27	11.55
17	22.09	2.51	26.26	6.93	18.71	2.66	14.99	8.50
18	16.63	2.66	22.20	7.39	15.13	3.01	12.81	9.78
19	41.55	2.20	42.13	7.48	34.98	4.02	14.29	8.81
20	16.50	2.09	23.34	8.51	16.98	2.79	13.79	8.92
21	6.02	3.61	28.11	10.85	6.30	3.61	18.57	11.95
22	24.36	2.24	28.70	7.16	23.04	2.92	11.68	8.10
23	38.54	2.28	33.70	14.72	30.24	12.35	16.12	8.29
24	11.13	2.76	22.26	8.73	10.20	2.65	16.65	10.34
25	21.35	1.98	26.15	6.48	17.41	3.54	14.83	6.95
26	37.28	2.29	34.22	6.59	27.26	3.39	16.63	7.94
27	8.95	2.60	25.03	8.78	8.53	2.34	14.51	10.83
28	14.20	2.23	25.67	8.43	11.45	2.15	14.52	8.65
29	24.62	2.86	32.23	10.46	19.54	2.59	16.97	11.94
30	17.07	3.27	26.49	10.51	15.72	3.73	15.03	12.03
31	7.92	1.82	15.66	4.29	7.49	2.01	6.72	6.47
32	9.69	2.03	17.74	6.18	9.20	2.07	9.63	6.95
33	6.24	1.98	15.62	5.41	5.26	2.09	9.24	6.94
34	23.35	1.96	17.94	4.44	17.52	2.79	11.80	4.76
35	2.83	2.08	16.96	5.63	2.83	1.93	10.51	7.41
36	11.22	1.96	22.19	5.63	11.07	2.23	8.36	7.02
37	10.43	1.60	16.31	5.29	9.08	2.24	7.17	5.74
38	35.41	2.26	63.65	9.70	16.97	2.36	11.69	9.38
39	17.49	1.76	15.60	4.69	13.98	2.15	11.95	5.14
40	5.41	1.72	15.77	5.34	5.16	1.75	9.41	5.95
41	16.64	1.97	43.15	9.08	8.68	2.80	16.69	9.25
42	11.93	2.26	24.94	8.47	11.57	2.60	16.70	8.42
43	5.11	1.77	15.63	6.01	4.41	1.80	9.74	6.78
44	5.64	1.81	17.61	6.36	5.12	2.15	9.11	7.96
45	2.69	1.56	12.97	5.41	2.88	1.53	6.30	6.04
46	6.70	2.28	19.06	6.96	6.42	2.23	9.96	8.48
47	6.68	2.52	19.20	7.37	6.97	2.83	12.53	8.39
48	16.35	2.25	29.98	8.23	11.62	2.49	15.10	9.00
49	11.86	1.46	20.86	5.24	8.91	1.78	9.85	5.56
50	1.38	1.67	13.67	5.45	1.42	1.54	7.20	6.38

Scene GNP	Median GNP	Midway GNP	Ratio GNP	Cluster GNP	Cluster	Cluster	Cluster Ratio	GNP
					Median GNP	Midway GNP	GNP	Uncorrected
1	10.60	1.55	14.55	4.38	9.90	2.08	9.52	4.59
2	4.62	1.11	10.72	3.58	4.29	1.13	6.19	4.55
3	13.82	1.36	29.61	5.83	10.40	2.25	8.39	4.91
4	3.69	1.15	10.37	3.84	3.80	1.25	6.26	4.50
5	3.73	1.11	11.10	4.13	4.20	1.87	8.68	3.98
6	22.72	0.63	31.83	6.30	20.59	1.72	12.34	7.02
7	15.56	1.60	19.48	4.16	12.62	2.05	13.31	4.64
8	6.28	1.30	10.60	4.10	6.67	1.81	7.99	4.25
9	2.94	1.42	11.68	4.40	2.91	1.81	10.16	4.70
10	11.68	0.86	20.08	7.48	11.48	1.74	13.90	7.96
11	25.68	1.72	26.80	4.69	15.10	3.25	12.23	5.46
12	14.66	2.44	16.63	4.32	13.48	2.86	14.32	4.67
13	11.89	1.36	16.11	5.89	10.72	4.36	8.11	5.38
14	11.81	1.51	19.74	6.75	10.62	1.70	14.52	7.45
15	11.68	1.58	18.40	4.91	10.26	3.50	13.32	6.36
16	15.44	3.28	18.59	6.91	15.07	3.73	13.53	6.83
17	22.09	1.49	23.94	4.71	18.68	2.25	12.71	5.58
18	16.64	1.39	18.39	4.97	15.15	2.55	9.82	6.22
19	41.57	1.22	41.28	4.91	34.99	2.68	13.64	5.95
20	16.52	1.15	19.16	6.62	16.99	2.42	10.77	5.99
21	6.01	1.88	17.34	6.30	6.33	2.27	12.24	7.01
22	24.36	1.48	26.68	4.77	23.02	2.49	9.54	5.19
23	38.28	1.23	32.90	12.94	30.04	12.21	15.13	5.50
24	11.08	1.36	16.40	5.41	10.28	1.59	12.22	6.44
25	21.36	1.24	24.24	4.65	17.35	2.00	13.29	4.72
26	37.18	1.30	33.19	4.99	27.24	3.13	15.58	5.22
27	8.94	0.98	17.03	5.27	8.53	1.30	9.38	6.64
28	14.19	1.38	21.41	5.22	11.42	1.53	11.92	5.54
29	24.46	0.90	29.42	7.00	19.57	2.17	13.24	7.47
30	17.07	1.74	20.44	7.32	15.69	2.72	10.67	7.46
31	7.92	1.16	11.94	3.32	7.48	1.52	5.49	4.35
32	9.69	1.42	14.30	4.26	9.20	1.69	7.44	4.86
33	6.23	1.54	11.61	3.67	5.30	1.76	6.42	4.85
34	23.52	1.74	17.51	3.28	17.65	1.94	10.73	3.45
35	2.83	1.33	11.52	4.13	2.83	1.31	7.97	5.02
36	11.22	1.23	18.54	3.92	10.99	1.75	6.50	4.72
37	10.43	1.09	13.48	3.70	9.01	1.94	4.58	3.93
38	34.95	1.35	61.99	7.91	17.08	1.88	10.70	6.89
39	17.50	1.14	14.75	3.33	14.21	1.90	11.03	3.49
40	5.40	0.99	10.98	3.58	5.14	1.25	6.82	3.87
41	16.19	1.23	41.53	6.22	8.62	2.35	14.87	7.02
42	11.80	1.18	19.43	5.90	11.52	2.28	12.35	5.56
43	5.11	1.16	10.62	4.13	4.40	1.40	7.47	4.48
44	5.64	1.01	12.91	2.99	5.09	1.52	6.71	5.53
45	2.69	1.04	9.38	2.81	2.97	1.11	4.18	4.25
46	6.70	1.43	13.43	4.78	6.42	1.56	7.45	5.55
47	6.68	1.43	13.17	4.85	6.90	2.06	9.15	5.37
48	16.09	1.02	25.85	5.31	11.55	2.46	12.03	6.02
49	11.85	0.98	18.91	3.50	8.79	1.44	8.00	3.88
50	1.38	1.11	9.50	3.74	1.39	1.15	5.22	4.51

Scene LNNP	Median	Midway	Ratio LNNP	Cluster LNNP	Cluster	Cluster	er Cluster Ratio LNI	
	LNNP	LNNP			Median	Midway	LNNP	Uncorrected
					LNNP			
1	10.60	1.47	12.13	3.61	9.84	2.20	7.99	3.30
2	4.62	1.63	8.21	2.79	4.26	1.67	5.11	3.38
3	13.76	1.48	33.29	3.28	10.53	1.88	7.52	3.22
4	3.69	1.30	7.74	2.54	3.87	1.73	3.66	3.13
5	3.73	1.17	8.71	3.24	4.15	1.74	4.87	2.82
6	22.72	3.01	33.70	5.53	20.49	3.50	12.11	5.60
7	15.56	1.54	18.99	2.91	12.63	1.92	12.76	3.26
8	6.28	1.41	8.31	3.35	6.65	2.07	6.17	3.16
9	2.95	1.66	9.31	3.42	3.00	1.78	8.15	3.46
10	11.77	4.53	21.85	6.41	11.53	4.18	14.35	7.31
11	25.75	2.58	26.85	3.98	15.19	3.15	11.73	3.97
12	14.68	2.48	16.05	3.26	13.46	2.94	13.94	3.16
13	11.97	1.69	14.70	4.05	10.87	3.58	5.75	3.30
14	11.79	3.83	16.18	6.00	10.72	3.67	12.29	6.56
15	11.63	2.81	15.48	4.50	10.49	3.82	10.90	4.90
16	15.42	4.46	17.35	5.71	15.08	4.84	12.51	5.54
17	22.09	1.87	21.09	3.51	18.69	2.64	10.69	3.89
18	16.61	2.63	16.96	3.44	15.14	2.59	8.71	4.61
19	41.60	2.13	42.19	3.57	34.91	2.50	12.89	4.35
20	16.52	2.07	17.46	7.36	16.98	5.03	9.39	4.34
21	6.01	3.61	13.02	5 21	6 36	3 85	9.46	5 73
22	24 36	2.04	25.02	3.90	23.04	2.67	8.87	4.07
22	29.00	1.62	34.40	12 52	20.04	12.13	14 54	3.87
24	11.05	2 70	15.08	1 03	10.27	2 73	11.09	/ 91
25	21 35	1.50	22 73	3 71	17 30	3 10	12.02	3 25
26	37.14	1.68	33 49	4 15	27.12	3 1 3	15.45	3.61
27	8 9/	2.56	17 32	3 13	8 53	1.88	7 00	5.07
28	1/ 18	1.81	20.32	3.63	11 /2	1.00	10.07	3.83
20	2/ 38	3.76	30.07	5.00	19 35	1 19	11 97	6 51
20	17.07	2.05	19.92	6.28	15.55	4.13	0.08	6.60
21	7.02	1.26	0.15	2 76	7 47	4.40 2.19	4.70	2.17
22	0.60	1.50	9.10	2.70	7.47 0.0E	2.10	4.70	3.17 2.10
ວ∠ วว	9.09	1.55	11.23	2.95	9.05	1.71	0.23	3.10 2.17
33 24	0.23	1.55	17.40	2.05	5.31 17.90	1.57	4.77	3.17 2.16
34 2F	23.73	1.03	17.49	2.23	17.00	1.70	10.01 F 21	2.10
35	2.83	1.04	8.09	2.02	2.83	1.48	5.21	3.40
30	11.22	1.40	10.33	3.31	10.97	2.00	5.73	3.31
37	10.43	1.25	10.96	3.10	9.06	2.23	4.10	2.78
38	34.49	1.83	62.86	5.44	16.98	1.84	10.65	5.18
39	17.66	1.17	14.58	2.21	14.27	1.71	10.44	2.13
40	5.39	1.34	8.59	2.28	5.14	1.19	5.54	2.68
41	15.31	1.79	47.78	3.72	8.31	2.66	15.58	4.15
42	11.73	1.75	16.43	4.26	11.29	2.91	10.13	3.82
43	5.11	1.38	6.91	3.06	4.43	1.50	5.53	3.06
44	5.64	1.63	10.72	1.96	5.11	1.65	4.08	3.91
45	2.69	1.18	6.56	2.09	2.88	1.12	3.07	2.74
46	6.70	1.77	10.13	3.26	6.50	1.77	5.52	3.77
47	6.68	2.07	11.61	3.88	6.95	2.31	7.64	3.99
48	15.95	1.99	21.99	5.15	11.83	1.60	9.11	4.32
49	11.85	1.12	17.10	2.72	8.95	1.62	4.80	2.58
50	1.38	1.26	6.19	2.38	1.41	1.19	3.17	2.91

Scene LNP	Median LNP	Midway LNP	Ratio LNP	Cluster LNP	Cluster	Cluster	Cluster Ratio	LNP
					Median LNP	Midway LNP	LNP	Uncorrected
1	10.60	1.16	11.38	2.75	9.85	2.16	7.19	2.30
2	4.62	0.88	6.41	1.86	4.26	1.05	4.15	2.14
3	13.76	0.96	30.48	2.63	10.53	1.91	6.40	2.25
4	3.69	0.75	5.86	2.03	3.84	1.39	3.21	2.06
5	3.73	0.64	6.13	2.18	4.15	1.49	4.70	1.82
6	22.72	1.36	30.10	3.47	20.42	2.22	10.67	3.42
7	15.55	1.22	18.13	2.28	12.62	1.75	12.07	2.26
8	6.28	0.90	6.90	2.33	6.61	1.70	5.11	1.95
9	2.94	1.08	6.53	2.39	3.05	1.49	5.64	2.23
10	11.71	1.82	16.25	3.74	11.47	2.13	10.61	3.88
11	25.72	1.75	26.68	3.33	15.16	3.23	11.29	2.54
12	14.66	2.28	15.03	2.58	13.50	2.77	13.29	2.29
13	11.89	1.29	13.47	4.18	10.87	3.94	4.88	2.41
14	11.79	2.13	13.57	3.55	10.68	2.12	10.28	3.71
15	11.63	1.79	13.70	3.59	10.45	3.63	8.76	3.10
16	15.42	3.48	14.72	3.89	15.09	4.18	10.12	3.30
17	22.09	1.35	21.32	2.72	18.73	2.17	10.67	2.63
18	16.63	1.60	15.80	2.85	15.20	2.38	8.12	2.95
19	41.59	1.39	41.34	3.11	34.93	2.78	12.73	2.85
20	16.52	1.26	15.90	4.82	16.94	4.02	8.10	2.93
21	6.01	2.26	9.05	3.34	6.34	2.72	6.19	3.42
22	24.36	1.10	25.15	2.94	23.04	2.32	8.39	2.45
23	38.15	1.00	33.34	12.44	29.85	12.08	14.15	2.64
24	11.04	1.62	12.83	2.62	10.20	1.90	9.44	3.12
25	21.36	0.95	22.67	3.36	17.38	1.91	11.81	2.23
26	37.14	1.24	33.10	3.67	27.17	3.10	15.03	2.57
27	8.94	1.32	13.08	2.11	8.53	1.20	5.86	3.18
28	14.17	1.05	19.10	2.59	11.21	1.49	9.46	2.65
29	24.37	1.53	28.21	4.18	19.50	3.06	10.21	3.64
30	17.07	2.29	15.89	4.38	15.51	3.23	7.26	3.69
31	7.92	1.05	8.20	3.10	7.47	2.06	3.78	2.18
32	9.69	1.07	10.47	2.34	9.23	1.53	5.44	2.27
33	6.23	1.25	8.33	1.65	5.30	1.41	4.02	2.37
34	23.68	1.53	17.28	1.83	17.93	1.61	10.45	1.66
35	2.83	0.98	6.02	1.84	2.82	1.22	3.98	2.36
36	11.22	0.81	15.25	2.64	10.97	2.41	4.82	2.17
37	10.43	1.02	10.68	2.56	9.13	2.06	3.23	1.82
38	34.02	1.10	63.05	3.49	16.70	1.71	9.91	2.97
39	17.58	0.73	14.30	1.86	14.32	1.71	10.33	1.42
40	5.39	0.91	7.20	1.83	5.14	1.28	4.81	1.83
41	15.07	1.21	46.88	2.67	8.26	2.30	14.05	2.69
42	11.73	1.04	15.26	3.21	11.19	2.37	8.38	2.67
43	5.11	1.05	5.86	2.16	4.37	1.13	4.75	2.20
44	5.64	0.98	8.34	1.74	5.09	1.60	3.24	2.62
45	2.69	0.68	5.01	1.01	2.88	0.87	1.42	1.91
46	6.70	1.35	8.47	2.36	6.42	1.39	4.74	2.72
47	6.68	1.08	8.87	2.74	6.92	1.91	6.07	2.52
48	15.95	1.15	21.57	3.91	11.51	2.13	8.28	2.90
49	11.85	0.66	17.09	2.18	9.00	1.35	4.27	1.83
50	1.38	0.76	4.52	1.68	1.45	0.94	2.44	2.05

Scene PBN	Median PBN	Midway PBN	Ratio PBN	Cluster PBN	Cluster	Cluster	Cluster Ratio	PBN
		-			Median PBN	Midway PBN	PBN	Uncorrected
1	10.59	10.50	18.05	9.86	9.91	9.81	13.50	10.56
2	4.61	7.50	15.36	6.05	4.30	5.94	10.37	7.57
3	13.80	10.95	46.30	11.14	7.67	10.65	13.15	11.03
4	3.69	11.09	22.77	9.38	3.82	9.49	13.49	11.18
5	3.73	11.22	24.29	10.97	3.52	10.88	10.70	11.29
6	22.72	10.39	26.37	8.62	20.70	8.39	11.38	10.55
7	15.54	10.58	26.38	9.73	12.64	9.59	20.22	10.62
8	6.28	10.53	21.52	9.82	6.72	9.47	15.62	10.56
9	2.95	10.58	22.89	9.73	3.06	9.70	15.93	10.62
10	11.67	10.53	21.12	9.68	11.55	9.40	15.98	10.76
11	26.42	9.88	28.08	6.33	14.96	6.45	11.68	9.97
12	14.82	10.12	24.28	8.87	13.47	8.99	20.24	10.05
13	11.89	10.51	27.16	9.27	9.58	9.26	16.42	10.60
14	11.82	10.39	31.07	9.02	10.49	8.96	21.02	10.50
15	11.75	10.33	27.41	9.34	10.37	9.28	18.88	10.42
16	15.56	10.66	26.61	8.95	15.02	9.53	18.13	10.33
17	22.08	10.47	22.96	9.04	18.73	9.01	13.47	10.54
18	16.91	10.01	26.84	7.60	15.24	7.64	14.87	10.17
19	41.67	10.22	35.72	10.32	35.60	9.24	13.03	10.32
20	16.56	10.45	25.49	10.27	16.97	10.16	16.12	10.53
21	6.03	10.52	24.64	9.45	6.28	9.46	15.92	10.53
22	24.48	10.38	34.40	8.99	23.23	8.89	15.06	10.45
23	38.36	11.07	29.97	19.24	31.10	18.56	19.22	11.25
24	11.16	10.14	24.13	8.55	10.30	8.74	16.97	10.28
25	21.38	11.15	28.48	10.29	17.48	10.31	19.30	11.26
26	37.18	11.34	31.02	10.06	29.05	9.93	16.28	11.46
27	8.95	10.43	25.72	8.89	8.51	8.69	15.30	10.55
28	14.16	10.56	25.59	9.33	11.50	9.26	15.13	10.64
29	24.32	10.51	23.01	9.80	20.20	9.65	12.99	10.72
30	17.09	10.43	20.78	9.36	15.70	9.21	14.26	10.52
31	7.93	11.16	24.40	9.59	7.52	9.57	13.94	11.25
32	9.68	10.58	16.36	10.01	9.45	10.29	13.59	10.64
33	6.39	10.37	27.10	8.87	5.25	8.70	15.42	10.47
34	24.40	9.40	24.09	7.93	17.91	7.96	15.17	9.52
35	2.83	10.47	21.57	9.43	2.82	9.38	15.43	10.55
36	11.21	10.60	24.26	10.74	10.95	10.67	14.17	10.67
37	10.43	10.92	26.76	9.59	9.78	9.52	13.44	10.99
38	34.52	9.66	58.95	9.20	17.79	8.64	33.35	9.89
39	18.00	9.29	15.79	8.45	14.30	7.95	11.00	9.48
40	5.32	6.81	16.77	6.19	5.02	6.12	10.77	6.95
41	15.26	8.83	38.88	9.81	11.84	9.32	15.37	9.05
42	12.32	9.73	29.74	9.20	11.73	9.32	16.65	9.83
43	5.10	7.58	18.29	6.45	4.39	6.39	11.00	7.65
44	5.65	11.10	23.10	9.62	4.95	9.50	13.04	11.40
45	2.69	7.47	16.29	5.40	2.87	5.35	6.77	7.53
46	6.70	10.51	20.24	9.39	6.51	9.53	13.51	10.55
47	6.72	10.43	21.46	8.80	7.00	8.73	14.67	10.51
48	15.74	9.01	23.08	8.79	12.70	8.73	11.27	9.24
49	11.85	7.64	26.34	6.96	8.41	6.92	10.71	7.69
50	1.38	10.92	23.58	10.03	1.52	10.01	12.30	11.00

Scene SN	Median SN	Midway SN	Ratio SN	Cluster SN	Cluster	Cluster	Cluster Ratio	SN
	10.00	0.01	11.10	1.00	Median SN	Midway SN	SN	Uncorrected
1	10.60	0.61	11.49	1.98	9.85	1.96	6.83	0.93
2	4.62	0.47	4.74	0.98	4.29	1.04	3.28	0.46
3	13.76	0.58	27.78	2.07	10.62	2.04	4.95	0.70
4	3.69	0.24	3.93	1.22	3.84	1.16	2.12	0.44
5	3.73	0.20	4.16	1.37	4.20	1.41	2.42	0.55
6	22.72	0.66	28.11	1.68	20.42	1.66	9.24	0.75
1	15.55	0.71	17.56	1.66	12.62	1.73	11.17	0.47
8	6.28	0.55	5.98	1.45	6.61	1.50	4.20	0.43
9	2.94	0.69	3.97	1.44	3.12	1.54	3.04	0.48
10	11.67	0.95	12.71	1.94	11.49	1.94	7.82	1.16
11	25.69	1.44	26.03	3.04	15.23	3.20	10.69	0.79
12	14.65	2.06	14.17	1.84	13.50	2.73	12.45	0.47
13	11.83	0.81	12.23	4.37	10.92	4.30	4.58	0.79
14	11.79	1.51	12.63	1.67	10.61	1.75	9.32	1.31
15	11.64	1.42	12.86	2.92	10.28	3.16	7.41	0.66
16	15.41	3.28	13.07	2.46	15.17	4.12	8.50	0.70
17	22.09	0.97	21.64	1.74	18.63	1.89	10.57	0.57
18	16.63	1.17	14.91	2.27	15.14	2.45	7.74	0.65
19	41.59	0.92	39.94	2.72	34.95	2.80	12.47	0.62
20	16.53	0.72	14.82	4.35	17.02	4.43	6.98	0.63
21	6.01	1.92	6.99	1.58	6.31	2.32	3.83	0.72
22	24.36	0.68	24.92	2.28	23.05	2.36	7.72	0.52
23	38.15	0.37	32.68	12.27	29.85	12.12	13.92	0.58
24	11.03	1.18	11.04	1.39	10.24	1.58	8.15	0.95
25	21.36	0.47	22.48	3.10	17.48	1.97	11.64	0.49
26	37.09	1.15	32.83	3.17	26.94	3.10	14.70	0.53
27	8.94	0.67	9.29	1.43	8.53	1.39	5.12	0.96
28	14.17	0.46	17.39	1.32	11.43	1.21	8.55	0.58
29	24.32	0.81	26.87	2.51	19.37	2.39	9.04	1.09
30	17.07	1.73	14.23	2.27	15.57	2.57	5.89	1.09
31	7.92	0.34	7.69	2.77	7.50	2.67	2.97	0.45
32	9.69	0.75	10.14	1.26	9.23	1.25	4.90	0.86
33	6.23	0.78	6.26	1.24	5.30	1.28	3.72	0.86
34	23.84	1.21	17.00	1.35	17.92	1.64	10.13	0.56
35	2.83	0.52	3.18	0.89	2.82	1.00	2.28	0.52
36	11.22	0.37	14.64	1.61	11.04	1.58	3.88	0.65
37	10.43	0.32	10.86	2.00	9.01	1.95	2.53	0.79
38	33.55	0.49	63.66	1.98	16.58	1.76	9.21	0.91
39	17.50	0.47	14.05	1.76	14.41	1.79	10.23	0.34
40	5.39	0.66	6.12	0.94	5.12	1.13	3.78	0.39
41	14.81	0.72	46.46	2.19	8.26	2.28	13.11	0.83
42	11.73	0.50	13.87	2.32	11.19	2.16	6.92	0.97
43	5.11	0.48	5.21	1.27	4.41	1.20	4.07	0.78
44	5.64	0.31	5.98	1.56	5.09	1.57	2.85	0.56
45	2.69	0.17	2.88	0.88	2.88	0.88	1.00	0.42
46	6.70	0.84	6.98	0.75	6.42	1.11	3.78	0.56
47	6.68	0.65	6.74	1.67	6.98	1.75	4.83	0.54
48	15.81	0.68	21.96	2.55	11.15	2.35	7.97	1.37
49	11.85	0.18	16.95	1.19	8.79	1.07	3.75	0.39
50	1.38	0.28	1.78	0.88	1.45	0.73	1.30	0.44

Scene Base	Median Base	Midway Base	Ratio Base	Cluster Base		
1	10.60	0.52	11.20	1.82		
2	4.62	0.44	4.65	0.90		
3	13.76	0.52	27.73	1.85		
4	3.69	0.18	3.86	1.14		
5	3.73	0.08	3.81	1.31		
6	22.72	0.60	27.84	1.58		
7	15.55	0.69	17.55	1.58		
8	6.28	0.53	5.97	1.39		
9	2.94	0.67	3.73	1.36		
10	11.67	0.85	12.42	1.69		
11	25.69	1.40	26.02	2.97		
12	14.64	2.05	14.10	1.78		
13	11.83	0.76	12.17	4.30		
14	11.79	1.44	12.33	1.06		
15	11 64	1 41	13.00	3 10		
16	15 41	3 28	12 92	2.33		
17	22.09	0.95	21 57	1.68		
18	16.63	1 13	14.93	2.00		
19	41 59	0.90	39.92	2.10		
20	16 53	0.69	14 75	4 33		
20	6.01	1 90	6 78	1.46		
22	24.36	0.66	24.87	2.23		
22	24.00	0.00	32.68	12.25		
20	11 03	1 13	10.00	1 15		
24 25	21.36	0.44	22 17	3.08		
25	27.00	0.44	22.41	2.16		
20	0 0 A	1.13	0.16	1 20		
20	0.54	0.30	17 20	1.20		
20	24.22	0.42	27.30	2.26		
20	17.07	1.60	12 00	2.20		
21	7 02	0.21	7 92	2.00		
32	0.60	0.51	0.05	1.01		
32 22	9.09 6.22	0.03	5.55 6.04	1.01		
33	22.84	1 10	16.02	1.10		
25	23.04	0.48	2 06	0.70		
26	2.03	0.40	2.90	1 52		
27	10.42	0.29	14.30	1.00		
38	22 55	0.13	63.58	1 72		
20	17 50	0.30	14.02	1.72		
39	5 20	0.45	14.03 6.04	0.97		
40	1/ 91	0.04	0.04 16.22	2.00		
41	14.01	0.04	40.23	2.09		
42	11.73 E 11	0.37	13.05 E 06	2.14		
43	5.11	0.40	5.00	1 56		
44	2.04	0.24	3.00 2.77	1.50		
45	2.09	0.07	2.11 6.70	0.05		
40	6.69	0.62	0.79	1.50		
47	15.00	0.03	0.00	7.29		
40	13.81	0.50	21.33 16.94	2.30		
49	1 20	0.13	10.84	1.1/		
50	1.30	0.23	1.51	0.8T		