Semi-supervised learning in quality metrics for Electron Microscope data

Anon

Anon
anon@anon.edu,
WWW home page: http://anon.com/

Abstract. Modern electron microscopes can acquire image volumes at very high rate with nano scale resolution. Physical constraints of the machines as well as variation in sample quality result in very variable image quality in-plane and between image sections. Scientists assess the acquired image data qualitatively by using simple quality measures. They rescan data which appears to not be useful. Nevertheless, qualitatively poor data might be quantitatively sufficient for analysis and a high percentage of rescans could be avoided. In addition, manual assessment of images is extremely time consuming and not feasible for the large amount of generated data. This results in a reduced throughput of the electron microscope and ultimately creates a gap between theoretical and practical acquisition speed.
We studied the image quality assessment process performed by scientists after acquisition of electron microscope data. Our research shows that even though scientists perceive data as not useful, XX percent of this data would be sufficient for analysis. Therefor, we propose a novel objective image quality metric which takes post-processing such as contrast normalization, deblurring and segmentation into account. Our metric is based on a classifier trained using semi-supervised learning and delivers a stable assessment of acquired data for analysis. We implemented our metric as part of a demand driven visualization framework for a modern multibeam electron microscope.
We evaluate our metric on multiple Connectome datasets of different quality. Our results show an overall decrease in required rescanning attempts.

Keywords: Demand-driven rendering, electron microscopy, image server.

1 Introduction

- modern electron microscopes produce a ton of data
- scientists judge the quality of the data using their experience or simple quality metrics
- we think that a lot of data has sufficient quality for automatic analysis even though the scientists' perception thinks it is bad data

- a lot of research has been performed on image quality metrics to simulate the human visual system
- subjective metrics
- objective metrics
- we think that in Connectomics, the human visual system is not the right classifier for deciding if images can be used or not
- therefor, previous research does not yield good results

we show variable quality

we show the current approach of quality assessment and segmentation results for good and bad cases based on it

we describe our metric

we evaluate our metric

1.1 Related Work

see other document

2 Image Quality of EM data

2.1 Acquisition process of a multibeam microscope

Briefly describe how the acquisition works (sections on wafer, focus sampling, different mFoVs etc.)

2.2 Variable Image Quality

Show subjective image quality discrepancies a) in-plane and b) per image section which result from mechanical constraints and other reasons

We should probably have some quantitative measures for this based on several datasets.

Fig. 1. *Left:* In-plane. *Right:* Per section.

2.3 Traditional Quality Assessment

Talk about how scientists measure image quality using their experience and also simple metrics.

Maybe describe Josh's metric which is implemented in Matlab.

Show examples of good data and bad data and the results of the segmentation of both. Also, maybe show Josh's metric result. Maybe compare VI against a small manually labeled sub-set?

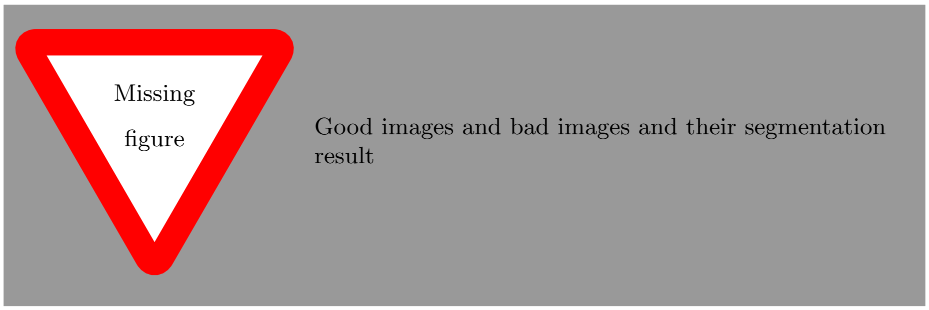

Fig. 2. *Left:* Good image and the segmentation/analysis result. *Right:* Bad image and the segmentation/analysis result.

3 Our Metric

3.1 Preprocessing

- contrast normalization based on lookup table from microscope
- deblurring using dark channel prior (Jinshan's work)
- segmentation using rhoana or something faster

3.2 Feature Collection

- compare VI in-plane and across sections (but against what?) - maybe use segmentation quality assessment?

3.3 Learning

- learn from each classification but how?

3.4 Classification

3.5 The System

- the mbeam viewer / butterfly server

4 Evaluation and Results

- we test our metric against the traditional quality assessment process - and maybe against other previously published methods???
- we hopefully find that a lot of data does not need to be rescanned when using our processing and hopefully the metric shows that

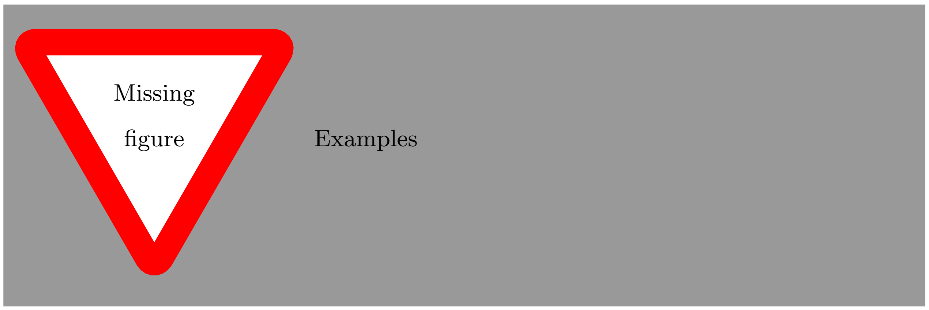

Fig. 3. *Left:* System in use with a cool dataset. *Right:* System in use with another cool dataset. Wow.

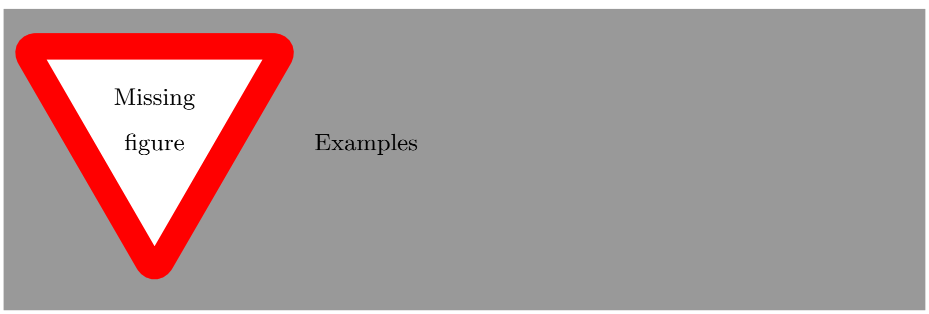

Table 1. Quantitative performance results. So good.

5 Discussion

Limitations of current approach

References

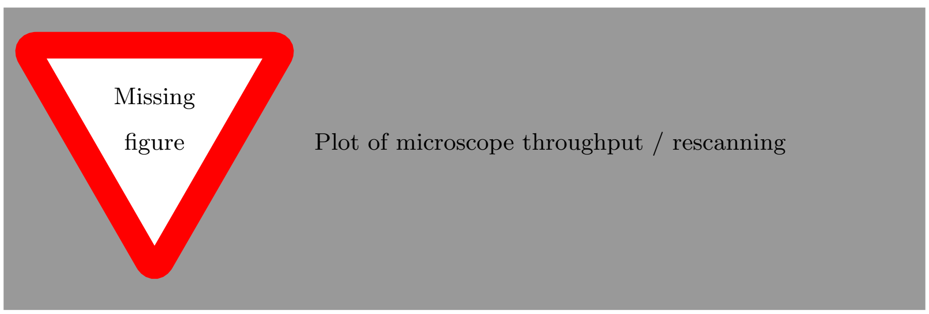

Fig. 4. *Shows hopefully that a zickzack curve gets smoothed out*