Semi-supervised learning in quality metrics for Electron Microscope data

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Abstract. Modern electron microscopes acquire image volumes very quickly with nanometer-scale resolution. However, the physical constraints of the machines and the variations in samples produce variable image quality in-plane and between planes of the volume. After capture, domain-expert scientists often assess the acquired image data qualitatively with simple visual inspection. Images which do not reach an undefined quality threshold are rescanned, which takes time and sets back the EM workflow. This manual assessment and rescanning is time consuming, is infeasible for large samples, and significantly reduces the practical throughput of the microscope. Automatic reviewing and attemped image restoration methods are needed to maximize throughput.
Often, the goal of image acquisition is cell segmentation and classification. Yet, the quality assessment process performed by domain scientists is one step removed from this goal, as are existing automatic metrics to describe image quality, as they typically attempt to measure image contrast, blah blah. We propose to display a novel image quality assessment to domain scientists which considers 1) the application of image restoration techniques such as contrast normalization, deblurring, and denoising, to show immediately what quality is possible without a rescan, and 2) a lower bound on the achievable final segmentation and classification quality. Our assessment is based on a classifier trained using semi-supervised learningand 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 - even though scientists intially perceived data to be not useful, XX percent of this data would be sufficient for analysis.

Where did the semi-supervised learning come in?

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
- the real goal is segmentation and classification, so let's try and build this in as early as possible as a quality metric, even if it provides only a lower bound

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.

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

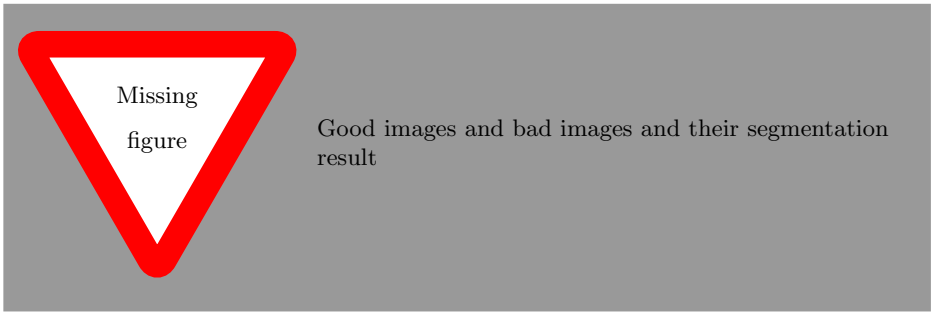

Fig. 2. *Left:* Good image and the segmentation/analysis result. *Right:* Bad image and the segmentation/analysis result.

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?

Across section measures are basically not possible without Adi's alignment, no?

3.3 Learning

Daniel, what do you mean here? My understanding is that we already had a classifier that was trained.

- 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

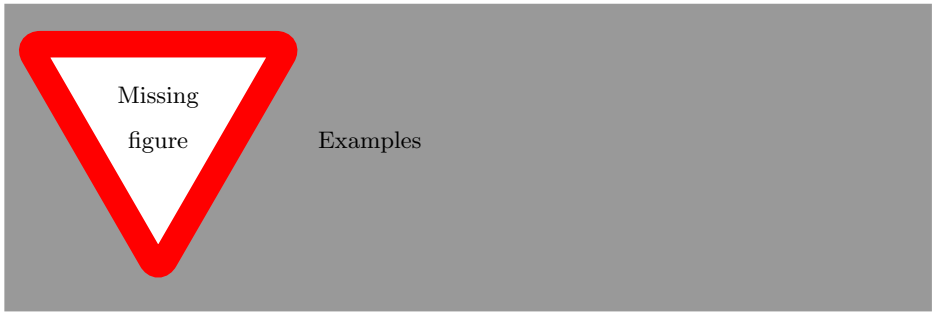

Fig. 3. *Left:* System in use with a cool dataset. *Right:* System in use with another cool dataset. Wow.

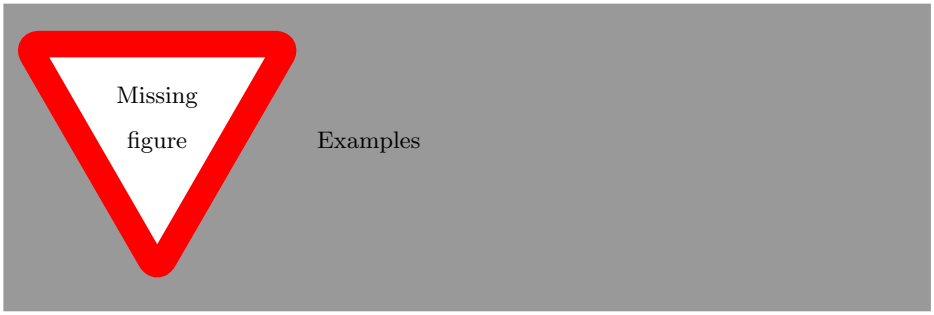

Table 1. Quantitative performance results. So good.

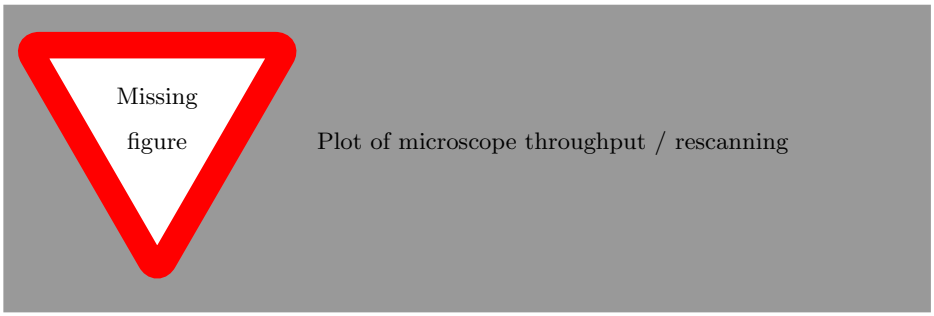

Fig. 4. *Shows hopefully that a zickzack curve gets smoothed out*

5 Discussion

Limitations of current approach

References