QoI Symptotics

I. Introduction

Here we will introduce the topic (and possibly include related works?).

II. Symptotics Framework

Here, we provide an overview of the network scalability framework.

III. QoI Examples

The utility of data that is extracted from a sensor or military tactical network is often highly dependent on the context of the data with respect to aspects like the network's goals and the other data being collected from the rest of the network. While this effect is often very qualitative by nature, we introduce metrics here that provide real examples of how QoI can be measured quantitatively. These measures will then be used as examples in the QoI-aware network scalability in Section IV.

As an example scenario, we choose a mobile network in which nodes generate photographs that are to exchanged or collected at one or more data sinks. This example covers surveillance missions of military tactical networks or civilian/social scenarios, one example of which could be smartphone users contributing to an image-sharing application.

Qualities like lightness, contrast, and color are all inherent to a photograph, and many techniques have been studied to compare photographs. We use one such technique called Color and Edge Directivity Descriptor (CEDD) [1]. [DESCRIPTION OF HOW CEDD WORKS?] Using the CEDD vector of each image, we can compare any two images. To achieve a scalar representation of similarity, from comparing two vectors, we use *Tanimoto similarity* [CITATION NEEDED], T_s. Naturally, to describe the dissimilarity, or distance, of two photographs, then, we simply use $T_d = 1 - T_s$.

A. Image Selection Algorithms

With the Tanimoto similarities and distances between all of the images, a chosen algorithm can be applied to select images to provide a desired level of quality of information. We present two such possibilities here along with examples and scenarios.

The first application of selecting images based on content occurs when a user would like to find more images that are similar to one already obtained. For example, if a user observes a picture of an unknown suspicious person entering a building, but the person is not identifiable from that image, it would be useful to collect more images that are similar to that one with the possibility that another picture of the building from another user may have a better view of the person in question that can be used for identification or more context. Called *Top-k*, this algorithm choose the k images with the smallest distance from the given image.

The second application we introduce is called a *spanner*, and it is based on an opposing scenario. Instead of choosing matching images, the goal of a spanner is to select the k images that exhibit the most joint dissimilarity. This algorithm would be useful in a surveillance mission or other setting in which a user would like to get a snapshot of all areas of which photographs were taken that is as complete as possible. In order to choose images with the most dissimilarity, though, we must first define what that means. While the dissimilarity between two images is determined by the Tanimoto distance, creating a measure of the distance between more than two images requires consideration.

B. QoI vs. Throughput

With both the Top-k and Spanner algorithms, initial choices exhibit higher degrees of similarity and dissimilarity, respectively, that naturally decrease. Therefore, if we establish a measure of overall QoI being obtained as k is increased, we witness an effect of diminishing returns. For the Top-k algorithm, we define *Sum Similarity*, which is the sum of the Figures 1 and 2 show the diminishing returns of using similarity and dissimilarity metrics.

This effect is important also because it visually shows how Quality of Information differs from throughput. As these graphs clearly show, transmission of successive images is not linear in terms of gained completeness. Inversely, this relationship shows that obtaining a certain value of QoI or completeness may require a different number of images depending on the set available and their similarities. Specifically, we can denote the number of images required to achieve a level of completeness, S, as $N(S)$. This relationship will be useful later in determining feasible scalability.

If necessary, here, we could also include the toy examples of which pictures are actually selected from the top-k and spanner algorithms, showing that they are useful tools.

IV. QoI Scalability

Put the symptotics scalability equations here, including the scaling factor of the QoI function, and then include discussion.

$$\eta W = \sum_j (1 + \gamma_j)\xi(Q)(1 + T_j) \tag{1}$$

V. Results

Figures 3 and 4 are some example figures that we can use to show the feasible scalability when considering QoI.

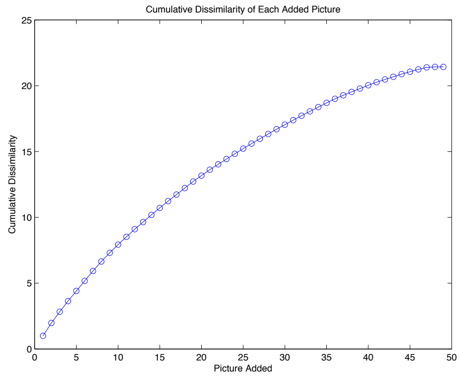

Fig. 1. Cumulative Distances for Spanners of Varying k - Regular

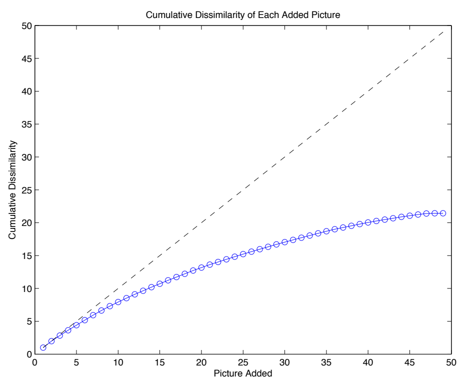

Fig. 2. Cumulative Distances for Spanners of Varying k - Square Axes

VI. Conclusion

Wrap it up with the highlights/takeaways. Maybe also include future work.

References

[1] Savvas A Chatzichristofis and Yiannis S Boutalis. Cedd: color and edge directivity descriptor: a compact descriptor for image indexing and retrieval. In *Computer Vision Systems*, pages 312–322. Springer, 2008.

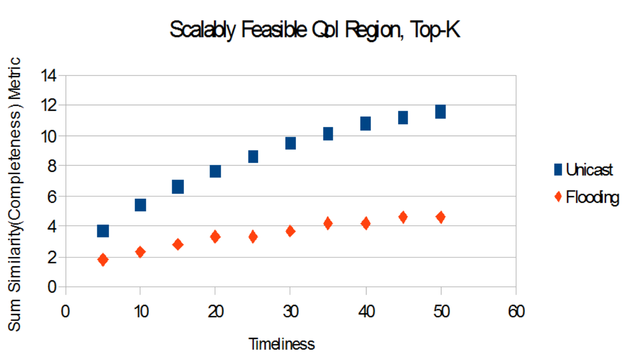

Fig. 3. Feasible Scalability Region of Top-K Algorithm

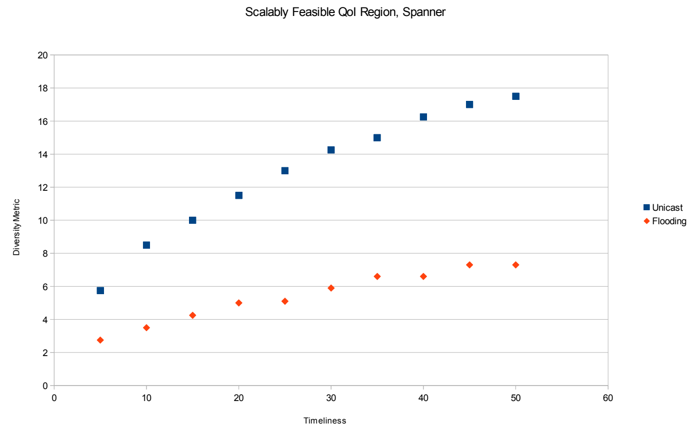

Fig. 4. Feasible Scalability Region of Spanner Algorithm

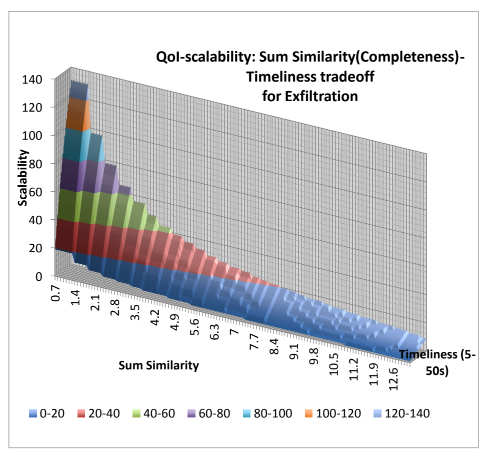

Fig. 5. Sum Similarity vs. Scalability vs. Timeliness