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Automatic quality assessment of planetary images

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Abstract

A significant fraction of planetary images are corrupted beyond the point that much scientific meaning can be extracted. For example, transmission errors result in missing data which is unrecoverable. The available planetary image datasets include many such "bad data", which both occupy valuable scientific storage resources and create false impressions about planetary image availability for specific planetary objects or target areas. In this work, we demonstrate a pipeline that we have developed to automatically assess the quality of planetary images. Additionally, this method discriminates between different types of image degradation, such as low-quality originating from camera flaws or low-quality triggered by atmospheric conditions, etc. Examples of quality assessment results for Viking Orbiter imagery will be also presented.

1. Introduction

The quality assessment of multimedia content began at the same time as the television broadcasting of pictures. Ever since, a large number of objective image quality measures have been introduced. Recently, research interest has shifted towards no-reference image quality assessment, in which the image quality is assessed without any a priori information about the authentic image. No-reference image quality assessment can be performed only if it is based on assumptions regarding the relationship of image quality with pixel-level image appearance. For a thorough presentation of automatic image quality assessment (IQA) domain, the reader is referred to [1].

Image quality assessment techniques that focus on planetary images should take into account the characteristics of these type of images, especially the multitude of causes that can trigger content degradation. The nine types of image degradation that are included in this work are summarized in Table 1. The low-quality types are further discriminated into those originating from system failure (internal) and those originating from imaging conditions (external). Currently, no metadata is included in any of the PDS/PSA archives for such low quality.

Table 1: Degradation mechanisms triggering low-quality planetary images.

Id	Degradation	Group
1	Burst Noise	Internal
2	DN Quantisation	Internal
3	Horisontal Stripes	Internal
4	Verticall Stripes	Internal
5	Salt & Pepper Noise	Internal
6	Low contrast	Internal
7	Dust	External
8	Clouds	External
9	Near Terminator Image	External

2. Methods

The automatic image quality assessment that has been developed combines 6 quality assessment measures, 3 selected from the (generic) image quality assessment literature and 3 novel ones, tailored to the planetary image requirements. More specifically, the literature measures included image anisotropy [2], which is a generic image quality measure based on the assumption that high-quality images have richer information content than low-quality images, power spectrum slope [3], which gauge image blur at the local level, and edge profile kurtosis [4], which is a computationally efficient measure of global image blur based on image edge appearance. In addition, we developed three more image quality measures, a novel self-similarity measure to gauge distortion types that create symmetrical image patches, such as gravity waves, a measure that aims to detect images suffering from low contrast and, finally, an impulse noise measure.

The above 6 features comprise the image quality vector of a planetary image. The image quality assessment is performed through a Support Vector Machine

(SVM) classifier [5]. The SVM classifier includes a training step, which is conducted through the extraction of the image quality vectors from a set of manually annotated (regarding their quality) planetary images, and the estimation of the hyperplane that best separates the two classes of image quality vectors (i.e. vectors extracted from low-quality images and vectors extracted from high-quality images) by a Support Vector Machine (SVM). After estimating the class boundary, for each input planetary image it's quality vector is extracted and the sub-space that it belongs to determines the quality label that is assigned, i.e. high-quality or low-quality image. Finally, a group of (trained in a similar way) SVM classifiers is used to identify different types of planetary image degradations.

3. Results

We have tested our technique on planetary visual spectrum images that were acquired from Viking Orbiter missions. These missions were active between 1976 and 1980, during which approximately 47 thousand visual spectrum images were acquired. Due to relatively primitive technology, images were degraded through a number of types of data corruption, which in total can reach up to several thousand images. The preliminary tests included only a small part of the available data (Figure 1), while currently we have started the evaluation of the complete Viking Orbiter dataset. Results and statistics of this on-going work are going to be presented during EPSC.

4. Conclusions and future work

In this work we have presented a method, which we have developed to perform fully automatic planetary image quality assessment. Preliminary results have been shown that automatic quality assessment is feasible to be conducted in a systematic approach. In the future we plan to make our system both faster and more accurate, while the ultimate goal is to develop a hardware prototype, which can be used on future space missions.

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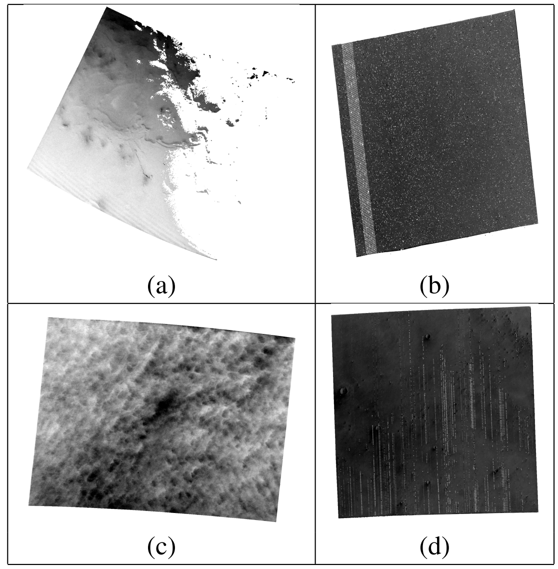
Figure 1: Examples of Viking Orbiter low-quality images, caused by (a) DN Quantisation (b) Salt and pepper noise (c) Atmospheric dust (d) Vertical stripes.



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