ASTRONOMY & ASTROPHYSICS
SUPPLEMENT SERIES

NOVEMBER II **2000**, PAGE 1

Astron. Astrophys. Suppl. Ser. **147**, 1–4 (2000)

How to determine the quality of solar granulation images: The optimal window method

C. Giammanco[1,2]

[1] Università degli studi di Roma Tor Vergata, Roma, Italy
[2] Instituto de Astrofísica de Canarias, Via Lactea, E-38200 La Laguna, Tenerife, Spain

Received January 21; accepted June 9, 2000

Abstract. An optimal window for image analysis is determined by means of information theory. The size of the window is then used as a good estimator of image quality. The method is sensitive to the size of the structures present in the image (contrary to the contrast method, widely used to select the best images of a series) and can provide a quality map, indicating the zones more or less degraded in the image. In this letter I describe the optimal window method (OWM) and compare it with the contrast method, showing a first application to a series of images taken at Themis IPM.

Key words: the Sun: granulation — methods: data analysis

1. Introduction

All astronomical images observed from the ground are subject to degradations of various kinds, instrumental or atmospheric, that cancel out part of the information. In recent years many methods of image restoration have been elaborated. However, such methods are very expensive in computing time and allow only a partial recovery of the information. Therefore it is convenient, before any numerical treatment of a series of images, to select the best ones (Bonet 1999). In solar astronomy a good indicator of image quality is granular contrast, given by the standard deviation of the image normalized to the average (Ricort et al. 1981; Collados & Vázquez 1987). Such an indicator allows rapid estimates, but it is not very sensitive to the presence of structures of small dimensions (a result known as Parseval's theorem), while we are often interested in the study and analysis of flux-tubes or other small magnetic structures (del Toro et al. 1990).

In this letter I propose a new method for the analysis of image quality that is sensitive to the dimensions of the structures present. The method is applicable to images of solar granulation but could, in principle, be applied in other astronomical contexts. One of the principal characteristics of this method is that it allows us to select the most meaningful zones of the image to provide a quality map: i.e. it allows us to distinguish, within the same image, zones that are more or less degraded. This might allow us, when searching for details in the image, to restrict the use of the segmentation algorithms that trace the contours of these structures only to good-quality zones. Besides, when we are interested in the reconstruction of the image, the quality map helps us to find the most suitable restoring strategy for each image zone given its quality.

2. The method

Given an image $I_{i,j}$ (corrected for flat-field and dark-current), we say that it is of good quality if it contains numerous structures of small dimension. The relationship between the number of structures at the different scales defines the optimal analysis scale for the image. The fundamental hypothesis of the whole method is that such a scale, which we will call $p_{\rm o}$, is a good estimator of image quality. We observe that, given an image, it is easy to decide if it is blank (uniformly illuminated) or contains structures (detailed). I define an image to be blank if:

$$\overline{n} - \sqrt{\overline{n}} < n_{i,j} < \overline{n} + \sqrt{\overline{n}} \qquad (1)$$

for a fraction α of the pairs (i,j); here $n_{i,j}$ is the number of counts recorded in the pixel i,j and $\overline{n}$ is the mean number of counts in the image. If all the image is detailed, after dividing it into $N_{\rm p}$ windows of dimensions $p \times p$, we expect that a good number of them continue to contain structures. I define $r_{\rm p} \equiv n_{\rm p}/N_{\rm p}$ as the ratio between the number of detailed windows and the total number of windows. Information theory will provide (as we will see shortly) a criterion for determining the optimum sampling dimension, $p_{\rm o}$.

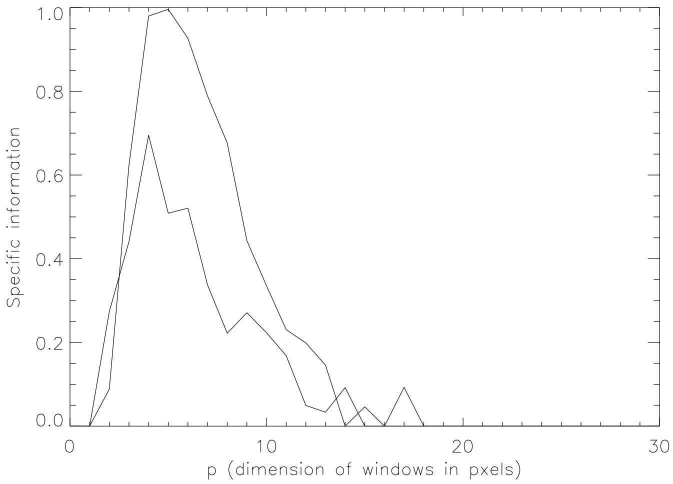


Fig. 1. Specific information as a function of the scale, p, for an image of solar granulation and a numerical simulation of a uniformly illuminated image (the lowest amplitude curve). Although the latter presents a peak, it is much smaller than unity; therefore the measurement is not reliable

2.1. The criterion of maximum specific information

Dividing the image into $N_{\rm p}$ windows, we can ask what the probability, P, is that a given window is detailed: to a first approximation $P_{\rm p} = r_{\rm p}$.

In other terms, we have $N_{\rm p}$ measurements, each of which can give a positive or negative result with probability $P_{\rm p}$ or $(1 - P_{\rm p})$, respectively. Following information theory (Bijaoui 1981), the specific information we obtain for one of such a series of measurements is given by the expression:

$$S_{\rm p} = -r_{\rm p} \cdot \ln_2(r_{\rm p}) - (1 - r_{\rm p}) \cdot \ln_2(1 - r_{\rm p}). \quad (2)$$

The "best" ratio, $r_{p_{\rm o}}$, can now be defined as the ratio that provides the largest specific information; then $p_{\rm o}$ (i.e. the step which provides the best ratio) is the best sampling scale. Therefore, $p_{\rm o}$ directly provides an estimate of the image quality: the smaller its value, the better the image. The reliability of the estimate is measured by the peak value itself, which stays between 0 ($r_{\rm p} = 0$, $r_{\rm p} = 1$) and 1 ($r_{\rm p} = 1/2$). In general, reliable estimates are obtained for $S_{p_{\rm o}} \simeq 1$. This is illustrated by Fig. 1, in which $S_{\rm p}$ is plotted as a function of p for the image of solar granulation shown in Fig. 2 and for a numerical simulation of a blank image. The value adopted for α is 68%. The results, for the image of the solar granulation and the blank one, are $S_{p_{\rm o}} \simeq 1$ and $S_{p_{\rm o}} < 0.7$, respectively.

These values support the choice made for α and, at the same time, also provide an answer to a possible criticism to the method, based on the fact that statistics in Eq. (1) ave not valid for small values of p. In fact, when errors due to a wrong choice of the statistics are large, as in the blank image, then the estimate of $p_{\rm o}$ loses its significance, which allows one to work with the same statistical function for any p, provided that $S_{p_{\rm o}} > 0.7$.

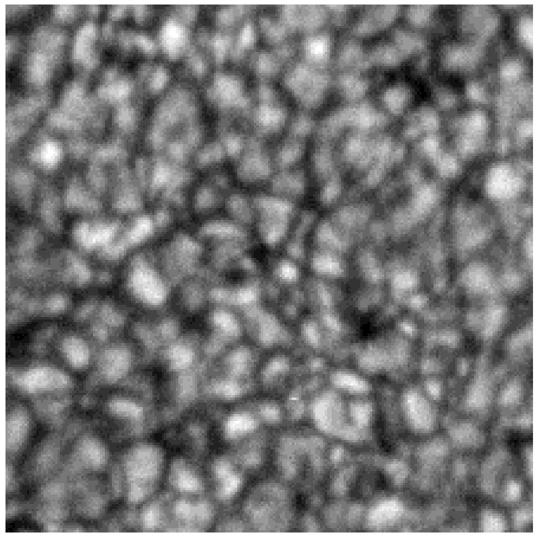


Fig. 2. Image of solar granulation (223 × 223 pixels) obtained on 1999 July 1 with the Themis IPM. Image scale: 29″ × 29″

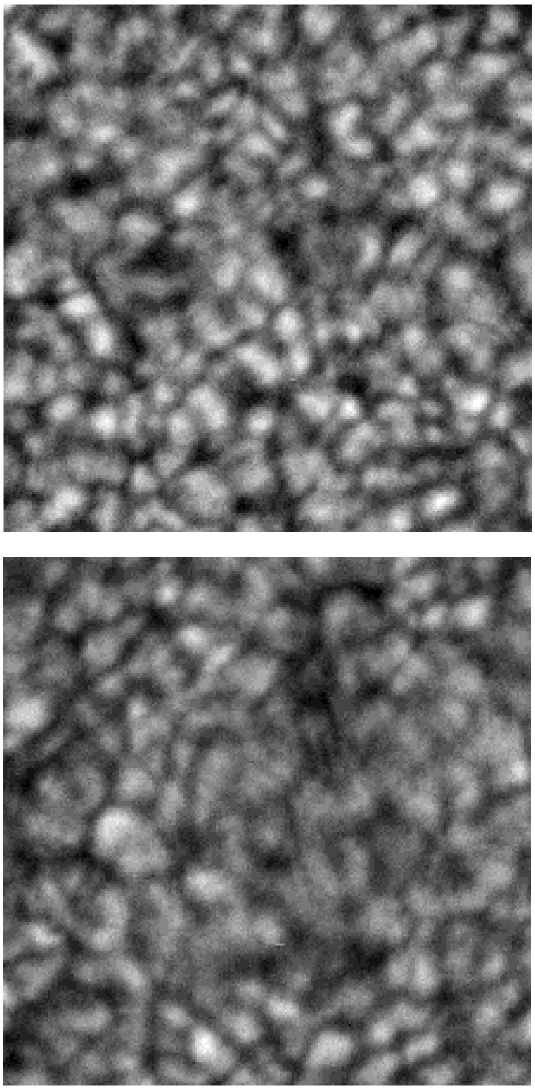
3. Discussion

First of all I show the principal characteristic that differentiates the OWM from the contrast method. As already mentioned in the introduction, the contrast is sensitive, above all, to the variations of intensity on a large scale. This is made clear by writing the contrast as:

$$\sigma = \sqrt{\sum_i P_i}, \quad (3)$$

where P_i is the power of i-th Fourier frequency and remembering that, in the case of granulation, the power falls drastically for spatial frequencies of the order of 8 $\rm Mm^{-1}$ (Schmidt et al. 1981). Such a limit makes the method effective when we compare two similar images captured with a short time difference from each other, but the method is less reliable when we want to choose the best images in a long series. To quantify the above, I show, in Fig. 3, two images of granulation recorded with $\sim$ 7 min difference. The contrast shows image b) to be better than a) contradicting simple visual analysis. The OWM, on the contrary, correctly classifies the two images, providing for a) the parameter $p_{\rm o} = 6$ and for b) $p_{\rm o} = 8$ (remember that good images correspond to small parameters). Besides, the method gives the quality map of the aforesaid images, in which the more degraded zones can be identified. In other words, the OWM is sensitive directly to the size of the structures present in the image, while the contrast method is determined only by the percentage of white or black pixels present in it. To clarify this idea, we consider two chessboards of black and white squares of 4 × 4 and 8 × 8 pixels: evidently both chessboards have the same contrast, while my method provides as quality parameter 3 for the first one and 6 for the second.

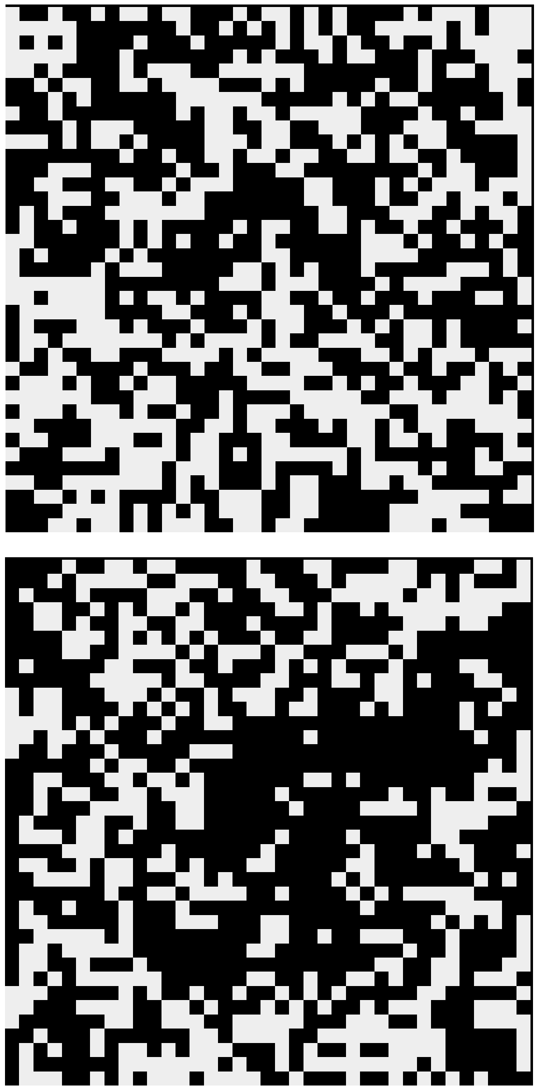
One of the main properties of the method is that it provides reliable results even for *small* images. To clarify



a.

b.

Fig. 3. The images of different quality class, from the same series as that in Fig. 2: **a)** contrast = 4.4%, $p_{\rm o} = 6$, **b)** contrast = 5%, $p_{\rm o} = 8$. The indication given by the two quality parameters are opposite. The contrast give image **b)** as the best one, while it is apparent by eye that image **b)** as a better resolution



a.

b.

Fig. 4. Quality maps of the images shown in Fig. 3. The images were divided in 6×6 windows, corresponding to the optimum width for image **a)**. The detailed windows are givn in white, "flat" windows in black. Note the presence in **b)** of a large black region which, nevertheless, contributes significantly to the higher contrast of **b)** with respect to **a)**

the meaning of the term "small", consider Fig. 5, which shows an artificial image with uniform quality over its entire area. We estimate $p_{\rm o}$ considering at first the whole image, then only 1/4, 1/8 of it, and so on. The estimates are essentially constant as a function of the size of the sub-image which is considered ($p_{\rm o} = 4$ in the interval size = 256, size = 12). The OWM gives coherent results down to a minimum size of 12×12 pixel, i.e. for images as small as 3 times the estimated $p_{\rm o}$ (equal to 4 in this case).
Consider now the convolution of the image of Fig. 2 with Gaussians of $FWHM = 2$ pixel, 3 pixel, etc. The values of $p_{\rm o}$ as a function of the adopted $FWHM$ are plotted in Fig. 6, which shows that the method is sensitive even to the smallest degradation factors. Finally I have analysed a series of 608 images taken at Themis IPM during about one hour of observation on 1999 July 1. In Fig. 7 the results obtained with the OWM are compared with the contrast method. The plot shows that there are many intervals of contrast which do not identify a unique class of quality. In other words, there is a danger of the situation described in Figs. 3 and 4 occurring.

4. Conclusions

I have presented a method to determine the quality of granulation images that associates uniquely with every image a quality class. The discrete character of quality classes and the fact that very different images (e.g. those

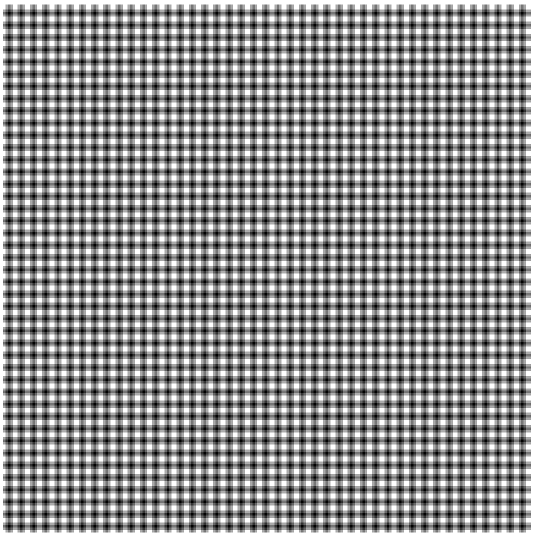


Fig. 5. Artificial image with uniform quality. White spots represent the peak of Gaussians with a full width at half maximum ($FWHM$) of 6 pix; the maximum is 1000 ADU. Nearby peaks are separated by 5 pix

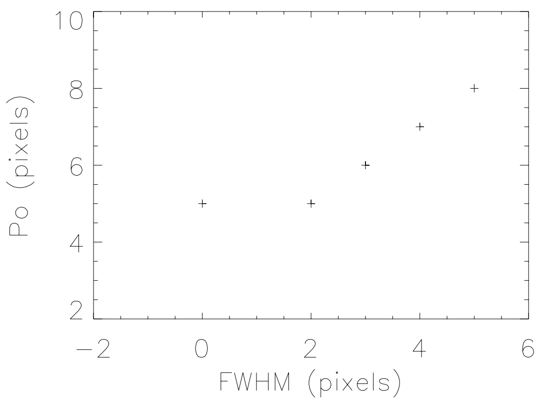


Fig. 6. p_o as a function of the $FWHM$ of the Gaussian which has been used to degrade the image in Fig. 2

acquired after a long time interval) can be compared with them, make this method useful for characterizing the performance of instruments such as Themis IPM. The main advantages of the OWM are that it is easy to implement, it needs little computing and it also gives reliable results for small images, so that we can distinguish zones of different quality within the same image. This last characteristic makes it useful for a preliminary study when we want to use segmentation or restoration programs. In the first case, the quality map determines the zones of the image where it is more probable to find structures of small dimensions. In the second, it would allow us to restore in a different

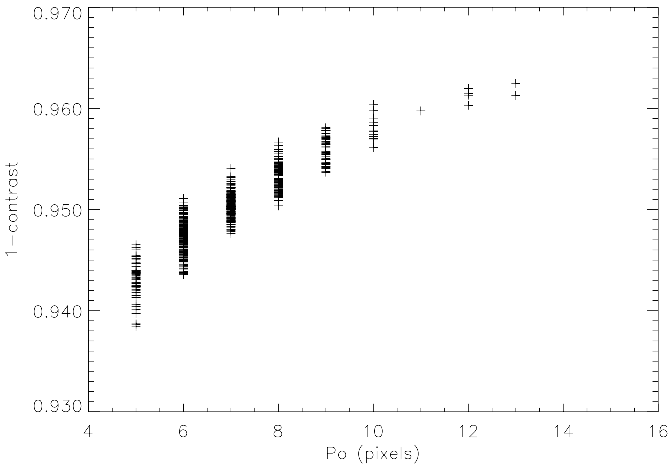


Fig. 7. Analysis of the images obtained at Themis IPM during one hour of observation. Note how images of different quality classes can have the same contrast

manner the zones more or less degraded. In both cases it would save computing time, thereby improving the results.

I wish to stress that image quality, as defined here, does not directly represent the spatial resolution, although it is clear that better quality also means higher resolution. In a forthcoming study, the precise relationship between the two quantities will be clarified. One possible development will be to distinguish within the same image regions with different resolutions in order to correct the image locally.

Acknowledgements. This work is based on observations obtained with the IPM mounted at the THEMIS-CNRS/INSU-CNR telescope at the Spanish Observatorio del Teide (Tenerife) of the Instituto de Astrofísica de Canarias. I thank also C. Briand, F. Berrilli, J.A. Bonet, B. Caccin, G. Ceppatelli, M. Collados, R. Corradi, G. Molodij and T. Roudier for their encouragement and useful suggestions. I thank T. Mahoney for the english supervision.

References

Bijaoui A., 1981, Image et Information. Masson, Paris, p. 82

Bonet J.A., 1999, in Motions in the Solar Atmosphere, Hanslmeier A., Messerotti M. (eds.). Kluwer, Astrophys. Space Sci. Library, 239, pp. 1-34

Collados M., Vázquez M., 1987, A&A 180, 223

del Toro Iniesta J.C., Collados M., Sánchez Almeida J., Martinez Pillet V., Ruiz Cobo B., 1990, A&A 233, 570

Ricort G., Aime C., Roddier C., Borgnino J., 1981, Solar Phys. 69, 223

Schmidt W., Knölker M., Schröter E.H., 1981, Solar Phys. 73, 217