SEGMENTATION, CLASSIFICATION AND ANALYSIS OF A SOLAR GRANULATION IMAGE SERIES

Miriam Saldaña Muñoz1,2, Richard Muller1, and Arnold Hanslmeier1

1IGAM-Institute of Physics, University of Graz, 8010 Graz, Austria
2Faculty of Mathematics, University of Vienna, 1090 Vienna, Austria
3Pic du Midi Observatory, 65008 Toulouse Cedex, France

ABSTRACT

A new method for segmenting solar granulation white light images is applied to an image series taken with the same instrument and telescope setup, between 1978 and 1991 by R. Muller at the Pic du Midi Observatory. The area covered by each image lies on the solar disc center and is free of activity (as comparing with its corresponding G-Band image). The segmentation algorithm stands out first by using only one parameter, namely the standard deviation, which is closely related to the contrast of the image, and secondly by being completely unsupervised. The image parameter is only utilised to select initial image intensities and therefore has no influence on the number of regions found. Each region formed in the segmented images is classified as intergranular region or granule. Granular areas as well as some statistical parameters are computed in order to analyse the possible variation of these parameters throughout the solar activity cycle. Here a short preliminary analysis is presented.

Key words: solar granulation; segmentation.

1. INTRODUCTION

Several segmentation algorithms of solar granulation images have been published. Image segmentation by means of image thresholding is a very fast method used mostly between the first investigators in this field, for example by Roudier & Muller (1987). Due to film graininess and low trends like supergranulation, oscillations and large-scale inhomogeneities, a filter had to be applied to the image prior to thresholding. In the present study it is not possible to apply such a method because the parameters of the filter as well as the threshold should be found, for every image, by trial and error and this would give rise to a lack of confidence in the statistical results.

A similar drawback is found in the method of Bovelet & Wiehr (2001), the so called multiple level tracking algorithm (MLT). Although more effective than the one of Roudier and Muller, the selection of the different intensity levels makes the method very difficult to be applied automatically to the present image series.

In order to avoid the use of a threshold, other authors, for instance Schrijver et al. (1997) or Florio & Berrilli (1998), make use of the fact that the intergranular flow shows a well defined network which separates the upflow areas, and thus, edge detection methods are very well suited. For example Schrijver et al. (1997) use a watershed or basins method and Florio and Berrilli (1998) a skeletonizing one.

The present investigation is based on the intergranular network concept, explained above, but the method used to find this network differs from others in the way it is defined. Here, the group of pixels making up the intergranular network do not form surrounding lines but more extended areas. The areas inside the network can be then classified as granular areas or deep intergranular areas (very dark areas). Each granular area composed with more than a single granule, must be further segmented, i.e. the intergranular network inside the granular area has to be computed and added to the general intergranular network found before. The classification process of the areas inside the new network is done again and, as long as there are granular regions with more than one granule, the intergranular network has to be computed again.

The granular area, relative to the total image area, found with this method is smaller than in other investigations due to the way the intergranular network is defined. Nevertheless, we are interested in finding a possible trend of the granulation behaviour throughout the solar cycle, so that fact will not affect the results.

2. ALGORITHM

2.1. Thresholding and Region Growing

The present segmentation method starts applying an image thresholding based on the image histogram. For every
picture in the series, the histogram bin size is chosen to be the half of the standard deviation of the image. Due to the closely relation between the image standard deviation and its contrast, the thresholding algorithm selects pixels in a wider range of intensities for images with higher contrast and viceversa. That is the only method parameter which changes from one image to the next one. The selected intensity bin is defined to be the one with the most counts. The binary image formed by thresholding, shows groups of connected pixels, here called regions, which correspond to intergranular areas on the original image. Next, each of these regions is grown using a standard region growing algorithm, which needs one parameter to be set. In the present case the parameter is the standard deviation multiplier and stays the same through the whole series. In this way, a compact intergranular network is formed.

Figure 1 shows different segmentation stages. Frame 1a represents a cut of one original image. The method just described above corresponds to frame 1b, where the selected bin intensities are marked in light blue and the pixels marked in dark blue are added to those ones by the region growing algorithm.

2.2. Classification

The pixels outside the intergranular network in figure 1b form likewise regions, which have to be classified. The classification algorithm takes into account the intensity information of the regions. First, if the maximum intensity of the region is lower than the initial threshold computed above, the region is classified as intergranule and added to the intergranular network, otherwise the region can be a granule or a group of granules. In order to decide what a region is, two different tests are done. If the region has a low standard deviation, under 25% relative to the whole image standard deviation, it is classified as granule. Next test searches the image histogram bin where the region reaches its maximum and thresholds the region by selecting the intensities of that bin and the one lower. The selected region pixels form one or more sub-regions of local maximal intensities inside the region. If only one subregion is found, the whole region is classified as granule, otherwise the region has a group of granules and therefore it must be further segmented. In figure 1c the regions classified as intergranules are contoured in black. The local maxima regions, granules and group of granules are contoured in lilac, green and pink, respectively.

2.3. Iteration

In order to segment the groups of granules within a region, the region histogram has to be computed in the same fashion as the image histogram. Then, the region histogram bins have a size of half of the region standard deviation and the bins with lowest intensity are selected. The amount of selected bins depends on the number of histogram counts they have, because, in order to make the pixels grow, it is neccessary to have a minimum number of starting pixels. The intergranular subnetwork found inside the region is added to the total intergranular network, and again the regions inside the network have to be classified in the same way it was done before.

Figure 1d shows in pink the regions classified as group of granules and in light and dark blue the intergranular subnetwork computed inside those regions. The subregions formed inside the regions are contoured in green. Figure 1e represents the classification of regions in the second iteration. Regions contoured in dark green are the granules found in the first iteration and in light green and pink the granules and group of granules found in the second iteration, respectively.

As long as there are granular regions which contain more than a single granule, the process is repeated. In the present work the iterations vary between 4 an 7. The final classification is shown in figure 1f. For the present image 7 iterations were needed, although this image cut contains only regions until the sixth iteration. The granules found in the different iterations are contoured in dark green, light green, dark yellow, light yellow, orange and lilac in ascending order. Figure 2 corresponds to the granules found in the whole image.

3. ANALYSIS

Here, it is important to remark that the areas found in the present investigation are slightly smaller than in others but the purpose of relative areas investigation along the solar activity cycle is not affected. The plot shown in figure 3a demonstrates the independence of the granular areas with the image standard deviation, i.e. the image parameter. Thus, the algorithm method can be applied without changes to other kind of solar granulation whitelight images.

In figure 3b the relative granular area is plotted versus the image date. It can be noticed that the granules cover between 15% to 22% of the total area. An interesting trend is found in the ascending part of the solar cycle 22(sep.1986-sep.1991), it seems here that the granular area follows the cycle. On the other hand the solar cycle 21 does not show such a trend, therefore it is still not possible to affirm that the granular area follows the solar cycle.

REFERENCES

Bovelet B., Wiehr E., 2001, SoPh 201, 13
Florio A., Berrilli F., 1998, MmSAI 69, 655
Roudier Th., Muller R., 1987, SoPh 107, 11
Figure 1: different steps of the segmentation algorithm applied to one of the images
Figure 2: granules found in the whole image

(a) granular areas relative to the whole image area plotted versus the image standard deviation

(b) granular areas relative to the whole image area plotted versus the image date

Figure 3: preliminary analysis