Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 5, Issue. 2, February 2016, pg.199 – 205

Evaluating the Performance of Automatic Sunspot Detection Algorithms using Full-Disk Solar Images

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Abstract -Sunspots are Solar features located in active regions of the Sun, whose number is an indicator of the Sun's magnetic activity. The Objective of this work is to study two automatic Sunspot detection algorithms such as Watershed transformation and K-means Clustering. In this paper, Sunspot is obtained by above stated methods from the full-disk solar images. This work presents a performance comparison of Sunspot detection algorithms based on performance metrics MSE and PSNR. From the evaluated results, K-means Clustering method performs better than Watershed transformation method.

Index Terms – Sunspot Detection, K-means Clustering, Watershed transformation, Full-disk solar image

I. INTRODUCTION

Sunspots are dark areas that grow and decay on the photosphere, the lowest layer of the Sun visible from the Earth. Sunspots are darker than their surrounding area because they are cooler than the average temperature of the solar surface [1]. The presence and disappearance of sunspots is because of changes in the magnetic fields throughout the Sun. The strong magnetic fields present in the sunspots reveals existence of enormous energy that potentially can be released. Generally, sunspots are first observed as tiny dark spots named pores. From hours to days some of the sunspots developed into fully-fledged sunspot regions, evolving over time scales. When a spot becomes darker and larger, portions of it may break away from the original spot; hence, the reason for a total sunspot count and a group classification. Sunspot region of preferred size can be observed to form a double-ended group, and with an instrument known as a solar magnetograph it can be determined that spots at opposite ends of the group have opposite magnetic polarity. A sunspot group is thus defined as the collection of sunspots that belong to the same magnetic flux tube.

In accordance with the solar-terrestrial physics, and especially in geophysics, solar indices are of vital importance for evaluating the potential impact of solar activity on the Earth [5], as measured by indices of the geomagnetic field and/or ionospheric parameters [10]. One of the most widely used solar indices is the Wolf sunspot number that is based on the number of sunspots and sunspot groups. SIDC acts as data analysis service of the FAGS (Federation of Astronomical and Geophysical Data Analysis Services) broadcasting the daily, monthly, and yearly international sunspot numbers, with middle range predictions of vital importance for space weather services [9]. With that, they were reconstructed to 300 years back in time, and various periodicities facts have been found in these data. The most important usable things are the 11-year solar cycle and the 27-day Bartels solar rotation [3].

One of the main tasks of its solar section for the sunspot detection was a daily routine involving manual detection of faculae and sunspots. Manually, the task of detection was undertaken by skilled observers visually inspecting the plates. Then, using templates and the mathematical term abacus, position and the area of each sunspot group were determined...

For Automatic detection, availability of digital cameras with CCD sensors and digital image processing techniques opened new possibilities for processing. In 2001 a new telescope with a Zeiss lens equipped with a solar filter and with a calibrated CCD camera was installed at Ebro Observatory to obtain a daily photograph of the solar photosphere (see an example in Figure 1) [1]. The pictures have a resolution of 1024 × 1024 pixels and an intensity range of 256 levels (8 bits per pixel). The automatic detection system described below has been implemented.

In this paper, we will discuss the procedure that we developed for the automatic detection of sunspots. The particular characteristics of solar images are square SE sized 11 × 11 basis of that sunspot detection algorithms used here to detect the sunspots is provided. Section II (a) & Section II (b) explains detailed information of how the solar limb and the sunspots are detected. There also, an explanation of how sunspots are classified in groups can be found too. A comparison of results of two automatic sunspot detection algorithms with metrics MSE and PSNR. Finally, concluding remarks and further work are drawn in Section.

II. METHODOLOGY

A. Watershed Transformation Method

Watershed image segmentation can be regarded as an image in three dimensions (two spatial coordinates versus intensity). We will use three types of point which “minimum”, “catchment basin”, and “watershed line” to express a topographic interpretation. There are two properties of continuous boundaries and over-segmentation in watershed image segmentation. Because watershed image segmentation has the disadvantage of over-segmentation, we use the maker to improve it. Use internal markers to obtain watershed lines of the gradient of the image to be segmented. Use the obtained watershed lines as external markers. Each region defined by the external markers contains a single internal marker and part of the background. The problem is reduced to partitioning each region into two parts: object (Containing internal markers) and a single background (containing external markers).

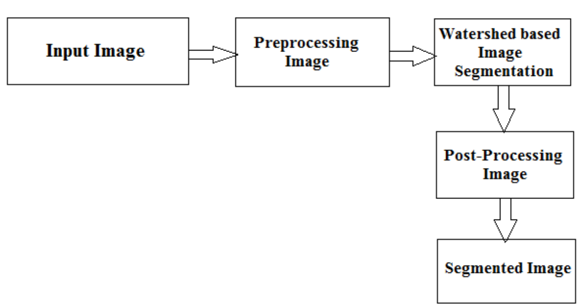


Fig. 1. Methodology of Watershed Transformation method

Internal markers are used to limit the number of regions by specifying the objects of interest like seeds in region growing method and it can be assigned manually or automatically. Regions without markers are allowed to be merged.

External markers those pixels we are confident to belong to the background. Watershed lines are typical external markers and they belong the same (background) region. Distance transform of a binary image is defined by the distance from every pixel to the nearest non-zero valued pixel. Instead of working on an image itself, this technique is often applied on its gradient image. Three types of points are points belonging to a regional minimum, Catchment basin / watershed of a regional minimum, points at which a drop of water will certainly fall to a single minimum Divide lines / Watershed lines Points at which a drop of water will be equally likely to fall to more than one minimum. Crest lines on the topographic surface This technique is to identify all the third type of points for segmentation. This visualization illustrates how the locations of the foreground and background markers affect the result. In a couple of locations, partially occluded darker objects were merged with their brighter neighbor objects because the occluded objects did not have foreground markers. Another useful visualization technique is to display the label matrix as a color image. Label matrices, such as those produced, can be converted to true color images for visualization purposes.

The simulation result of watershed algorithm has an advantage that it is fast speed. At the same time, it has a critical over-segmented problem.

*A.*1 *Algorithm*

1. Read in the color image and convert it to gray scale.
2. Use the gradient magnitude as the segmentation function.
3. Mark the foreground objects.
4. Mark the background objects.
5. Compute the watershed transform of the segmentation function.
6. Visualize the result.

B. K-means Clustering Method

Step 1: First, an image is taken as an input. The input image is in the form of pixels and is transformed into a feature space (RBG).

Step 2: Next similar data points, i.e. the points which have similar colour, are grouped together using any clustering method. A clustering method such as k-means clustering is used to form clusters as shown in the flow chart. The distances are calculated using Euclidean distance problem.

The data points with minimum Euclidean distance are grouped together to form the clusters. Euclidean distance measures are described below. The Euclidean distance is the straight-line distance between two pixels

Euclidean distance= $\sqrt{((x1 - x2)^2 + (y1 - y2)^2)}$ (1)

Where (x1, y1) & (x2, y2) are two pixel points or two data points.

Euclidean distance = $(P – Q) * (P – Q)'$ (2)

Here P is a data point and Q is the centre of a cluster. The image segmentation is done using k-means clustering in 3-D RGB space, so it works perfectly fine with all images. The clarity in the segmented image is very good compared to other segmentation techniques. The clarity of the image also depends on the number of clusters used. One disadvantage of the procedure used is that the number of clusters is to be defined in each iteration.

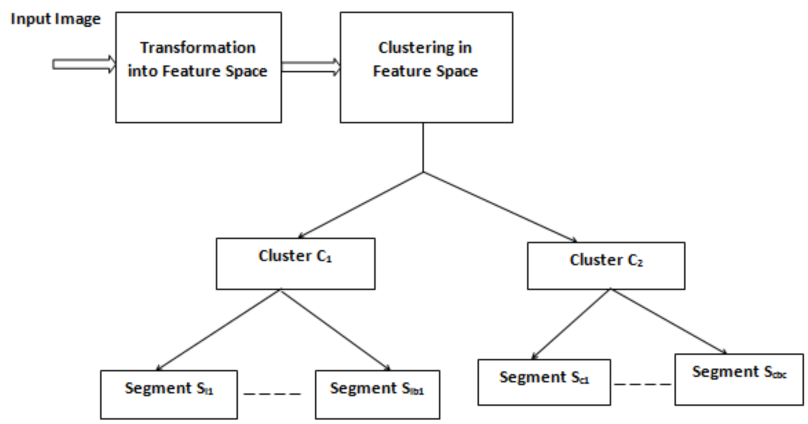


Fig. 2. Methodology of K-means Clustering method

B.1 Algorithm

1. The dataset is partitioned into K clusters and the data points are randomly assigned to the clusters resulting in clusters that have roughly the same number of points.
2. For each data point calculate the Euclidean distance from the data point to each cluster.
3. If the data point is closest to its own cluster, leave it where it is. If the data point is not closest to its own cluster, move it into the closest cluster.
4. Repeat the above step until a complete pass through all the data points results in no data point moving from one cluster to another. At this point the clusters are stable and the clustering process ends.
5. The choice of initial partition can greatly affect the final clusters that result, in terms of inter-cluster and intra-cluster distances and cohesion.
6. K-means algorithm was used in the project and the distances were calculated using Euclidean distances.

III. EXPERIMENTAL RESULTS

A. Performance Metrics

In order to perform the comparative evaluation of two types of Sunspot detection method, in this project consider the following two metrics

A.1 Mean Squared Error (MSE)

Mean squared error is a performance function used to evaluate the restoration performance. It measures the performance according to the mean of squared errors. MSE is defined as

$$\boldsymbol{MSE} = \frac{\sum_{\mathbf{M,N}}[\mathbf{I_1(m,n)-I_2(m,n)}]^2}{\mathbf{M*N}} \qquad (3)$$

A.2 Peak-Signal-To-Noise-Ratio (PSNR)

The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is often used as a quality measurement between the original and a restored image. To compute the PSNR, the block first calculates the mean-squared error (MSE). PSNR is defined as

$$\mathbf{PSNR = 10log10\ (255/MSE)} \qquad (4)$$

B. Data description

Fragment of the original image of the solar photosphere obtained at Ebro Observatory on 16 April 2013 at 11:54 hours.

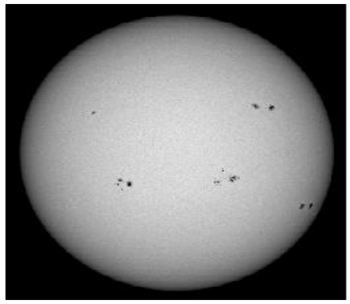
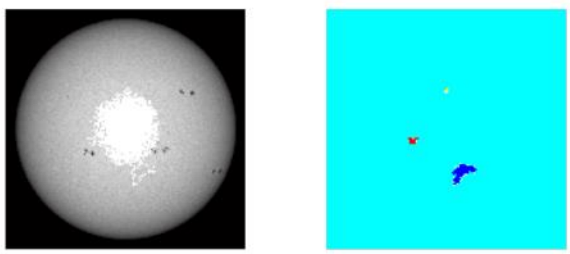


Fig. 3. Input image for sunspot detection

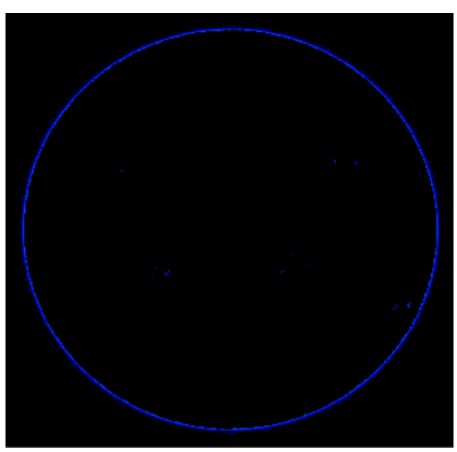
C. Results and Analysis

An input of Ebro Observatory watershed transformation technique worked on the gradient of that image was employed to reduce the over segmentation of the watershed algorithm. But the result is over segmentation image if we use the watershed algorithm with the gradient of raw data image without clustering method above. To get rid over segmentation, merging method based on mean gray values and edge strengths (T1, T2) were used. The watershed algorithm can segment image into several homogeneous regions which have the same or similar gray levels. To perform meaningful segmentation of image, regions of different gray levels should be merged if the regions are from the same object. The watershed segmentation generates spatially homogeneous regions which are over segmented.



(a) (b)

In Fig. 4 the results of watershed transformation method (a) Markers and Object boundaries (b) Colored watershed label matrix



In Fig. 5 the results of K-means Clustering Method

D. Performance Evaluation

The Performance analysis shows in tables and graphs which tells that, the best method. Comparing the two methods with respect to metrics MSE and PSNR gives the better results.

Table 1. Evaluation of MSE

METHODS	MSE	MSE1	MSE2	MSE3
Watershed Transformation	0.165	0.180	0.373	0.400
K-means Clustering	0.67	0.80	0.72	0.500

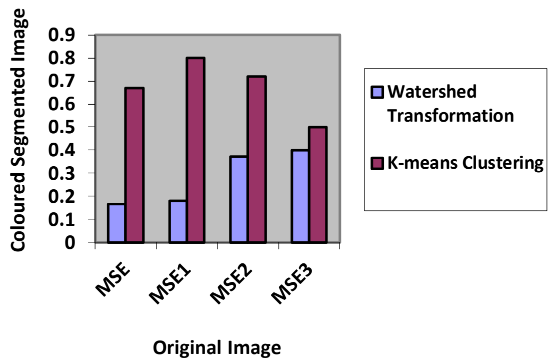


Fig. 6. Change values of MSE using Watershed and K-Means Clustering method

Table 2. Evaluation of PSNR

METHODS	PSNR	PSNR1	PSNR2	PSNR3
Watershed Transformation	3.0027	0.8	3.5691	3.0181
K-means Clustering	3.7000	3.1699	5.7264	3.8551

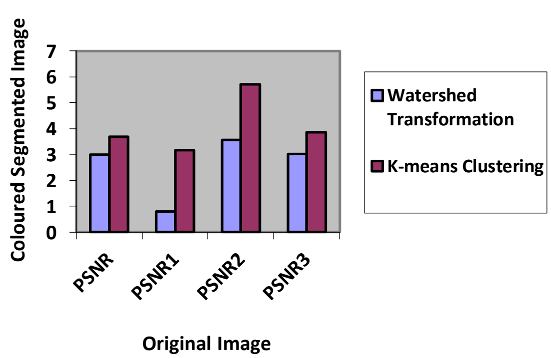


Fig. 7. Change values of PSNR using Watershed and K-Means Clustering method

In table 1,2 & fig 6,7, comparison of two Sunspot detection algorithms are showed. It clearly showing the best among the two methods in terms of metrics like MSE and PSNR. From the Confusion matrix (Bayesian decision error) showing the best among the three methods in terms of false alarm in percentage. The minimal percentage of false alarm is chosen as best one

IV. CONCLUSIONS

In this work, Automatic detection of sunspots in photographic plates is possible with procedures based on mathematical morphological tools. These procedures have been implemented with a robust and simple technique which has been used routinely at Ebro Observatory for automatic detection. The development of our automatic algorithms, a part of saving manpower, is able to provide an immediate evaluation of solar parameters that are very valuable for real-time space weather predictions. New software developments are now in course aiming to the automatic determination of other geometric parameters of the sunspots, which will help improve the classification of the sunspots groups. Trying to be coherent with the former manual method of detection, considers both, umbra and penumbra, as a unity in the sunspot. sunspots are formed in groups that share physical properties such as belonging to the same magnetic flux loops. Both the number of individual sunspots and the number of sunspot groups are needed to determine the Wolf solar activity index. Thus, the future work is to determine the groups as individual entities. This is equivalent to joining the sunspots belonging to the same solar group. The procedure is similar to that used to assign each pixel to its sunspot: here sunspots play the role of the pixels and groups, that of the sunspots. Although a crosscheck with the synchronized solar magneto-gram gives very reliable structure criteria for verification, neighborhood is a simple and good enough criterion to classify groups and only in very few cases, when groups are placed in a very close space, mostly in the maximum of the solar cycle, the operator who supervises

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