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Detection of Sunspot Using Improved Swarm Based Region Growing

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Abstract: The sun spots is the major solar activity which represent the sun's magnetic activity and prominent in the solar feature. This study present a new hybrid model for segmentation and further classification of sunspots from solar images obtained from Michelson Doppler Imager (MDI). Sunspots are regions on the solar surface that look black because they are cooler than the surrounding photosphere. The sunspots are regions where strong magnetic fields emerge from the solar interior and where major eruptive events occur. These energetic events can cause power outages, interrupt telecommunication and navigation services and pose hazards to astronauts. In this study, we present a new hybrid method to detect and extract sunspot features. Based on the efficient classifiers the sunspots classification is done. The input is a sequence of MDI images and the output is detection and classification of solar events. Initially, processing is done to enhance and remove noise from the image. Finally, we analyze the result with the globally accepted solar indices like international sunspot number and different standard data sources are used.

Key words: Sunspots, image enhancement, region growing, ant colony optimization, detection

INTRODUCTION

The significance of solar weather is contributing to life on earth and more on communications and power systems, both of which are vulnerable to solar weather (Hapgood, 2011). The solar is sole source of natural energy in nature. Due to the non-deterministic nature of solar activity and large volume of solar image the need for an automatic detection and analysis of solar data for future to check patterns like sunspot cycle. The analysis of the solar data helps in reliable prediction of solar activity and its impact on the earth (Gray *et al*., 2010). A typical sunspot consists of a dark central region called the umbra and somewhat lighter surrounding region called the penumbra. Sunspots lifetime extend from days or years. Sunspot usually appears as pairs with each sunspot having the opposite magnetic pole to the other. The appearance and disappearance of sunspots is due to the varying magnetic field presence in the sun. This magnetic variation indicates the possibility of large amount of energy release from sun spots. The sun spot may break away from original spot and form another sun spot. The international sunspot number is a quantity that measures the number of sunspots and groups of sunspots present on the surface of the sun. The sunspot activity is cyclical and reaches its maximum around every 9.5-11 years.

In this study, we focus on sunspots detection using swarm based seed selection and region growing. The Solar and Heliospheric Observatory (SOHO) is a spacecraft built by a European industrial consortium led by Matra Marconi Space to study the sun. It is a joint project of international cooperation between the European Space Agency (ESA) and National Aeronautics and Space Administration (NASA). In addition to its scientific mission, it is the main source of near-real-time solar data for space weather prediction. The Michelson Doppler Imager is a instrument attached to SOHO for providing images and taken in the continuum near the Ni I 6768 Angstrom line. The most prominent features of MDI Continuum are the sunspots. The influence of solar activity study is increased due to the increased communication flow in the upper atmosphere. The impact of solar activates on earth and spacecraft can be the evaluate using a measure called solar indices. The magnetosphere and ionosphere has increased influence of solar activity at different latitudes. One of the most widely used solar indices is the Wolf sunspot number that is based on the number of sunspots and sunspot groups (Clette *et al*., 2007). Sunspot number counts are taken at several solar observatories like Zurich Observatory, Ebro Observatory and SIDC, located in the Royal Observatory of Belgium they are used to calculate the relative Wolf sunspot number (Curto *et al*., 2008).

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Fig. 1: SOHO/MDI continuum sample images

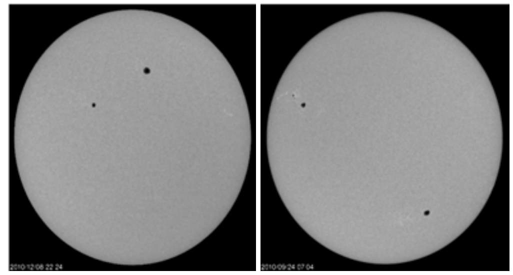

Fig. 2: Solar images after applying median filtering

LETERATURE REVIEW

J.J. Curto developed the automatic identification of sunspots using mathematical morphology tools based on images at Ebro observatory, it focused on the position and area of sunspots (Zharkov *et al*., 2005a). Improved version of sunspot detection having more geometric parameters were introduced by Zharkov *et al.* (2005b) which consist of classification of sunspots groups like umbra and penumbra. Further edge-detection methods are applied to find sunspot candidates followed by local thresholding using statistical properties of the region around sunspots by Zharkov, Zharkova and Ipson (Fuller and Aboudarham, 2004) (Fig. 1).

IMAGE ENHANCEMENTS

Image acquisition: The detection of sunspots can be done from Continuum images provided by Michelson Doppler Imager Instrument at the SOHO. In addition to its scientific mission, it is the main source of near-real-time solar data for space weather prediction. Michelson Doppler Imager (MDI) which measures velocity and magnetic fields in the photosphere to learn about the convection zone which forms the outer layer of the interior of the sun and about the magnetic fields which control the structure of the corona. MDI is the predecessor to the current Helioseismic and Magnetic Imager (HMI) under the Solar Dynamics Observatory. The Solar Dynamics Observatory is the first mission to be launched for NASA's Living with a program designed to understand the causes of solar variability and its impacts on earth. SDO is designed to help us understand the Sun's influence on Earth and Near-Earth space by studying the solar atmosphere on small scales of space and time and in many wavelengths simultaneously.

Image preprocessing: The images acquired from MDI are preprocessed artifacts and noise portion is filtered out. The ground based observatory images are prone to noise and other errors compared to the space-borne satellite images which have low levels of noise and errors. The captured solar images are not suitable because of their orientation, shape and variation of background intensity over the solar disk for the immediate use of segmentation algorithms (Walton *et al*., 1998). These may be due to several causes lead to error like the imaging instrument, slit position, inclination and the time taken to capture an image in particular spectral line, the variations of transparency, turbulence in the terrestrial atmospheric. In the solar images acquired, intensity standardization is done to improve the accuracy of feature recognition near the limb, due to darkening of the solar disk towards the limb. Researchers can apply the method modified median filter to reduce noise and the variations in the intensity over image. The median filter is an excellent removal of shot noise in which individual pixels are corrupted or missing from the image which is dominant in solar images. A window size of 3×3 is used by the median filter. The median filter eliminates the highest and lowest values to give a first approximation of the background fluctuations which can then be subtracted from the original image (Pavlidis and Liow, 1990). Before filtering the image is converted into grayscale for better processing (Fig. 2).

DETECTION OF SUNSPOTS

The region based segmentation is a method for shaping the region directly. The first step in region growing is to select a set of seed points. Seed point selection is based on some user criterion for example, pixels in a certain gray-level range, pixels evenly spaced on a grid, etc. (Murugan, 2013). The initial region begins as the exact location of these seeds. The regions are then grown from these seed points to adjacent points depending on a region membership criterion. The criterion could be for example, pixel intensity, gray level texture or color. Since, the regions are grown on the basis of the criterion, the image information itself is important. For example, if the criterion were a pixel intensity threshold value, knowledge of the histogram of the image would be of use as one could use it to determine a suitable threshold value for the region membership criterion.

Different parameters should be defined for proper working of method like suitable selection of seed points and similarity threshold. The similarity threshold can be identified by the knowing content information about the image. Here, the sunspot images captured earlier will provide the information regarding similarity threshold value. The sunspot will occur randomly on the solar image The seed points can be considered as points nearby the sunspot or within sunspot. Due to the random nature of sunspot automatic selection of seed is required which further require knowledge about the solar image. To retrieve basic information from solar image preprocessing is done.

The ant colony optimization method is used to detect the boundary of sunspot as a standalone technique for segmentation (Comaniciu and Meer, 2002). The ACO output can be considered as an initial map which helps us to initiate seed within the sunspot image. Ant Colony Optimization (ACO) is a population based swarm approach to find approximate solutions to difficult optimization problems. The inspiring source of ACO is the pheromone trail laying behavior of real ants which use pheromone as a communication medium. In analogy to the biological example, ACO is modeled based on the indirect communication of a colony of simple agents, called artificial ants, mediated by artificial pheromone trails. These pheromone trail values are modified at runtime based on a problem-dependent heuristic function and the amount of pheromone deposited by the ants while they traverse between their colony and a food source. The problem-dependent heuristic function in the case of famous ACO algorithms for travelling salesman problem is set to be the inverse of the distance between one city and another city. In ACO, pheromone trail values serve as distributed, numerical information which the ants use to construct solutions probabilistically. There is one solution per ant. The higher the pheromone value (initial edge) the higher the probability of an ant choosing that particular trail will be. The pheromone values on lower quality trails which are not reinforced often enough will progressively evaporate. The Pheromone based evaporation implements a useful form of forgetting: it avoids the algorithm from converging too rapidly toward a suboptimal region therefore mentioned above are repeatedly applied until a termination condition is satisfied. In practice, a termination condition may be the maximum number of solutions generated, the maximum CPU time elapsed or the maximum number of iterations without improvement in solution re-favoring the exploration of new areas in the search space. The Swarm based Region Growing (SRG) Method uses ACO for seed selection for region growing method to identify the sunspot. The region growing methods can correctly separate the regions that have the same properties defined by us. The initial preprocessing will help us to decide the numbers of seed point to be initiated in an image (Fig. 3).

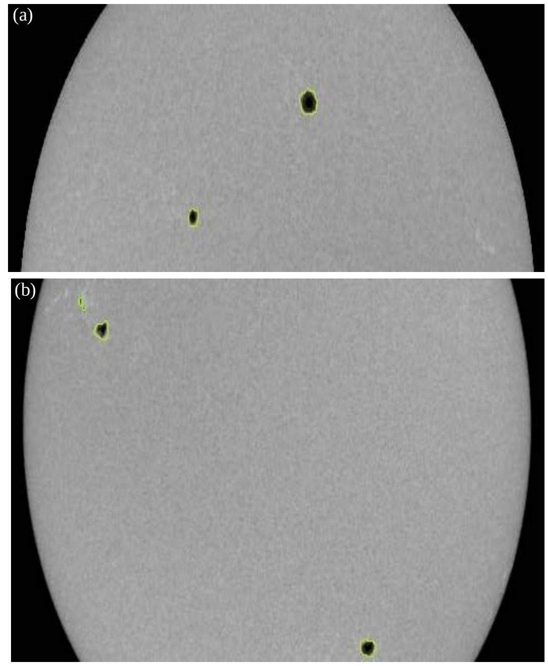

Fig. 3: Solar images after applying SRG method on; a) 2010/12/08 22:24 and b) 2010/09/24 7:04

EXPERIMENTAL ANALYSIS

We applied the sunspot detection and identification procedure to several images, obtained from the data archive of SOHO MDI continuum images. The process for automatic detection of sunspots is done for the year 2010 and collected data from different time intervals. For comparison and evaluation nearly 200 different MDI continuum images are taken. Different segmentation methods like region growing and mean shift segmentation methods are used for comparison in terms of time required for completion and normalized probabilistic rand index (Murugan, 2013; Unnikrishnan *et al*., 2007). The normalized probabilistic rand index can be used to perform a quantitative comparison between image segmentation algorithms using a hand-labeled set of ground-truth segmentations (Unnikrishnan *et al*., 2007).

Table 1: Evaluation of segmentation results in time

Time	Mean shift	Region growing	SRG
Average CPU time (sec)	250	280	300

Table 2: NPR score comparison for solar images in different segmentation methods

Solar images acquired date	Normalized probabilistic rand index			Number of seed points detected by ACO
	Mean shift	Region growing	SRG	
19-09-2010	0.708	0.701	0.715	3
21-09-2010	0.766	0.765	0.786	2
22-09-2010	0.780	0.670	0.806	3
23-09-2010	0.801	0.740	0.815	4
24-09-2010	0.765	0.778	0.807	4

Table 3: Performance chart based on FAR and FRR values of different sources with SRG methods on the test images

Solar images acquired date	No. of sunspots				
	SRG	SIDC	NOAA	FAR	FRR
19-09-2010	32	34	34	4	2
20-09-2010	29	27	27	5	2
22-09-2010	23	25	25	4	2
23-09-2010	25	27	27	3	6
25-09-2010	29	27	27	3	3
26-09-2010	36	34	34	4	2
27-09-2010	45	39	39	5	2
28-09-2010	41	38	38	3	1
30-09-2010	31	33	33	2	1
01-10-2010	24	25	25	3	1
02-10-2010	19	19	19	5	1
Total	427	419	419	49	30

Comparison is done between manually detected solar features from external sources and new hybrid algorithm detection. Solar Influences Data Analysis Center provides the sunspot numbers is world data center for the production, preservation and dissemination of the international sunspot number. National Geophysical Data Center also provides the sunspot number and its associated data. The false acceptance count and false rejection count is calculated to check the performance of method used that is shown in the Table 1-3. The overall false acceptance detection rate of automatically detected sunspots is 7% and overall false rejection rate is nearly 5%.

CONCLUSION

Automatic detection of sunspot in solar images based on new Hybrid Detection Method is implemented. This method can be used for automatic sunspot detection on full disk solar images obtained from MDI images obtained from instrument on SOHO satellite. A new detection algorithm defines the regions of interest possibly containing sunspots. Efficient and automatic sunspots identification leads to the accurate and better identification of sunspots, their variation and impact on earth. The detection result for the selected >100 images shows good outcome with those produced at National Observatory for Astronomy and Astrophysics and Solar Influences Data Analysis Center. The evaluation of the performance of this method specific to solar application shows the sunspot measurement is optimum at smaller number of sunspot.

RECOMMENDATIONS

Detection accuracy can be improved using different combination of neural network, edge detection techniques and self learning algorithms which refers the history of sunspot. By feature identification of sunspots and exact impact on earth and space climate in terms of climatic parametric values can be done as the further research. As a future research the images obtained from HMI can be tested with SRG Method. The change in the radiation, energy, wing also causes the different segmentation method behaves differently due to the effect on the image capture in different time period. So, based on the solar nature a combination of different methods can be implemented.

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