AUTOMATED DETECTION OF EARLY TROPICAL CYCLONES FORMATION IN SATELLITE IMAGES

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ABSTRACT: The satellite imagery based weather predictions especially identification and classification of pressure zones that leads to formation of tropical cyclones was the objective of this paper. The presented approach was based on Principal Component Analysis (PCA) algorithm and Markov Logic Networks (MLN) for identification of pressure zones where PCA was used to extract features and Markov Logic for classification purposes. The system worked in two phases: Firstly, National Oceanic and Atmospheric Administration (NOAA) satellite images which were used to train the system and in training phase, an image space was generated on the basis of the spatial features of the input images. The results of the experiments showed that Markov Logic improved the accuracy of low level clouds by 8% and for high level clouds 12% classification of pressure zones in NOAA satellite images.

Keywords: Image Classification, Principal Component Analysis, Markov Logic, Satellite Images and Tropical Cyclones.

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INTRODUCTION

The formation of low and high pressure zones play an important role in rainy weather. A typical process of formation of clouds is heave of moisture and its condensation caused by the coldness of air (Folmer *et al.,* 2012). The condensed substance constitutes a variety of elements such as water drops, dust, or smoke particles in the air. It is a natural attribute of air particles that start condensing when the temperature gets colder in the air. Hence, when the air rises higher in altitude, the moisture in air forms the clouds (Wong *et al.,* 2015). Conversely, due to increase in temperature the rise of air creates a partial vacuum that leads to an area of low pressure in the air. The entire climate is affected by development and twisting of such (low or high) pressure zones (González-Alemán *et al.,* 2015). Recognizing such pressure zones in terms of low and high areas in satellite imagery is one of the significant issues involved in weather forecasting. The available approaches are not highly accurate due to its discrete nature of data in satellite images.

A tropical cyclone is formed by anticlockwise rotation in the Northern Hemisphere in Pacific Ocean, and Indian Ocean. Typically, a tropical cyclone is the combination of heavy clouds and storms formed over tropical and sub-tropical waters (Hennon *et al.,* 2011).

Present study proposes an improvement of PCA (Principal Component Analysis) algorithm reported by the authors (Yousif and Ban, 2013). This approach utilized Markov Logic to automate the classification of satellite images in low and high pressure zones (Kunte and Aswini, 2015 and Thomas *et al.,* 2011).

A typical process of detecting the pressure zones in terms of low and high areas, one has to look for clockwise or anticlockwise arrangements in the satellite imagery found by the authors (Licciardi *et al.,* 2012). Hence, present study proposes an improved version of PCA algorithm to demonstrate the basic concept of Eigenvectors.

MATERIALS AND METHODS

The proposed approach introduced a new modified and enhanced version of PCA algorithm used for classification of satellite images. To validate the working and performance of the improved PCA algorithm and its comparison with other variants of PCA, the proposed approach was tested with a dataset of satellite images. The details of the experiments settings, used apparatus and input dataset are discussed in details in the following sub-sections.

Data Set:A set of sample satellite images having various types of clock-wise and anti-clockwise patterns is required to train the PCA algorithm (Licciardi *et al.,* 2012; Yousif *et al.,* 2013). Sample images (see Figure 1) were retrieved from NOAA HRPT (High Rate Picture Transmission) receiving station that was maintained at the Institute of Geography. The 70% selected images were used as training data set and the remaining 30% was used as testing set.

In the training stage of the proposed PCA algorithm, an image space was produced that was further used for the classification purpose. The sample input satellite image data was used to train the proposed system in thetraining phase. Here, light intensity, image resolution, color intensity and some other factors (Piñeros *et al.*, 2010) attribute quality of the training image dataset. The training images given in Figure 2 used in designed software system were coloured images with various coordinates.

The images required by designed system should be gray scale 8-bit bitmap images and have 50 x 50 pixel ratio. Following are some examples of training satellite images used to evaluate the ratio of success or failure of the designed system.

Normalizing Satellite Images: In this phase, the input images were converted to 256-bit gray color bitmap image. All image types were converted into bitmap image format. Input images were scaled to size 50 x 50 pixels. As the greater number of pixels can immensely affect the memory usage so array of smaller range was preferred. This was the complimentary processing requirement of the system. But this ratio can be tuned from 30 x 30 to 50 x 50. This pre-processing of the input satellite images helped in improving the accuracy of the results.

RESULTS AND DISCUSSIONS

After the zone identification (explained in previous section), a set of testing images were used to test the accuracy of the designed system. There were three types of images such as images with (a) clear sky, (b) with low pressure zones and (c) with high pressure zones. For accuracy evaluation, the processing results of each class of testing images were compared with other class of images. For testing purpose, 25 images per satellite type were used. While three types of satellite types i.e. clear sky, low-pressure and high-pressure images were taken. The calculated training time per image was 43 seconds.

If a system accurately identifies the type of an image, it was given one point otherwise that image was considered with zero point. The overall score ofconventional PCA classification of satellite images for cyclone detectionis shown in Table 1. The experimental results showed that classification accuracy of low pressure zone is 84 % and for high pressure zone is 76% in NOAA satellite images.

The accuracy of classification results after using Markov Logic of low and high pressure zones is depicted in Table 2. The results showed that classification accuracy of low pressure zone is 92 % and for high pressure zone is 88% in NOAA satellite images with the Markov logic.

The accuracy of classification of each class was compared with the other classes such as images with clear sky were compared with the clear sky, low pressure and high pressure zone. The PCA classification accuracy achieved with the Markov Logic is 8% improved for low pressure zone while 12% for highpressure zone in NOAA satellite images.An overall accuracy of the system has also been shown in Table 2. The results given in Table 2 shows the significant improvement in accuracy of classification by using Markov Logic over the heuristic approach conventionally used with PCA algorithm in the related work (Licciardi *et al.*, 2012;Yousif *et al.*, 2013).

The graph given in Figure 3 shows the comparison of the results of conventional PCA classification of satellite images for cyclone detection with the Markov Logic based PCA classification of satellite images for cyclone detection. The bar-chart results in Figure 3 shows that the Markov Logic based PCA provide major improvement in detection of cyclones.It has been observed that PCA with Markov Logic is 8% improved detection of low level clouds and 12% of high level clouds in the satellite data.Therefore, more accurate results can be helpful in predicting the future weather.

The authors (Heinle *et al.*, 2010) proposed an automatic cloud classification algorithm, which was based on a set of mainly statistical features describingthe color as well as the texture of an image. The researcher used the k-nearest neighbor classifier and achieves about 97% accuracy. These results were taken on seven different sky conditions. However,random sample test yields an overall 87.52% classification accuracy. Moreover the researcher achieved 98% accuracy for the clear condition but our method achieved the 100% accuracy for the clear sky. But the results obtained with Markov logic in present study have significant improvement over the k-nearest neighbor classifier study.

In comparison to a little bit older work of (Hennon *et al.*, 2011) an objective algorithm was discussed to detect and track tropical cloud clusters again the results were used for tropical cyclogenesis prediction. The authors (Roy and Kovordányi, 2012) presented many cyclone track forecasting techniques in this review article. However, the researcher suggested to adopt the modern artificial neural network based techniques to increase the cyclone forecast accuracy, this approach is given in this research paper. In another related study, the authors (Changhui *et al.*, 2013) presented a cloud detection method technique by using the feature extraction for remote sensing images. Firstly, the researchers calculated the different effective features through training pattern. After that useful features are selected to form a feature set through the statistical analysis of all the features. However, the accuracy of this system was in high 80s that is not sufficient for such type of real time weather monitoring systems.

The authors (Zabolotskikh *et al.*, 2014) presented an approach based on satellite passive and active microwave methods to study motion of arctic cyclones. However, in this work very small images with insufficient data information and too-large images that contain insufficient features parameters decreased the feature identification probability. This results in relatively high misclassification. In another relevant work, the researchers (Kimberly *et al.*, 2015) investigated tropical cyclogenesis detection in the North Pacific using the deviation angle variance technique. In this work, the cloud region was separated by the comparison between the actual feature values and the pre-settled thresholds value calculated by the sample training process. By this technique researchers achieved 85% cyclogenesis detection accuracy. Our system also outplays the results of this work in terms of accuracy. However, in year 2015, (González-Alemán *et al.,* 2015) presented a classification system of only sub-tropical cyclones within a specific area of Northeastern Atlantic Ocean and our works is different from this work on the basis of scope as the presented framework covers all types of cyclones. However, the results in both (Hennon *et al.,* 2011) and (González-Alemán *et al.*, 2015) were less accurate than the results presented in this research. Akin to these results, (Kunte and Aswini, 2015) presented a detection and monitoring system of super sandstorm and also studies its impacts on Arabian Sea specifically. This work was closely relevant to the presented work however the results of this work also lack in accuracy in comparison with the results of presented in this article.

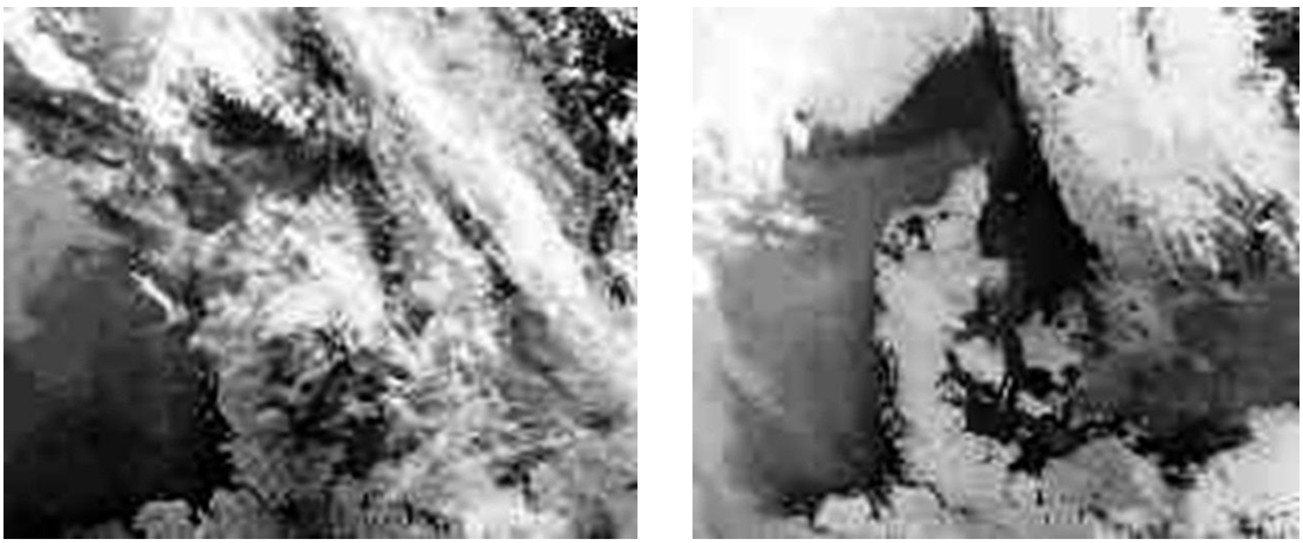

Figure-1: Sample dataset of NOAA imagery used for training

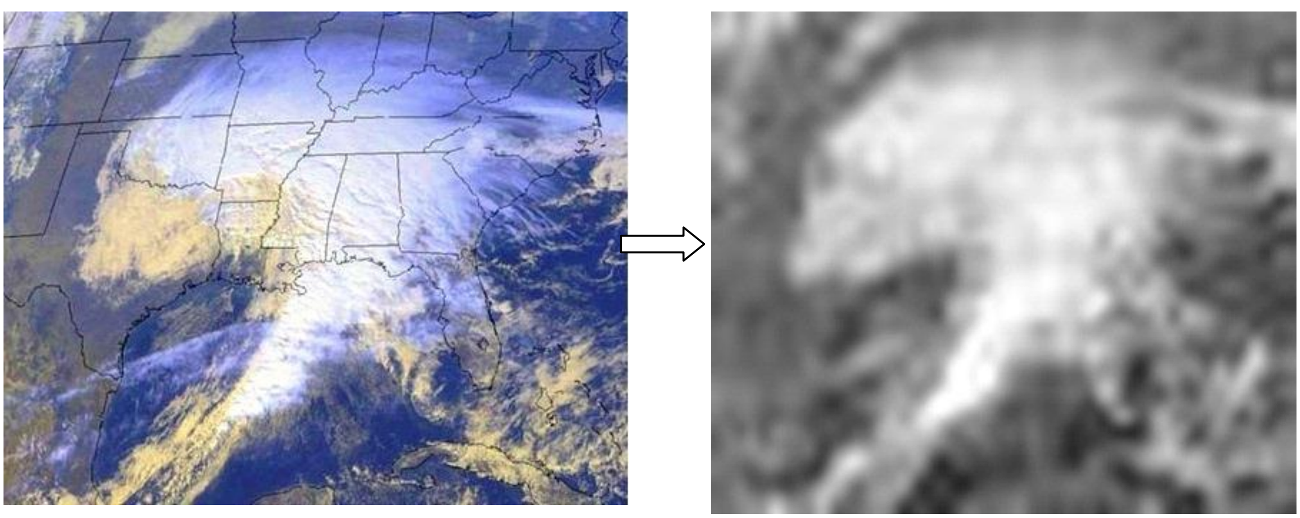

Figure-2: Converting original satellite image into 50 x 50 ratio of 256-bit gray scale image

The authors (Folmer *et al.,* 2015) presented a study to monitor and predict Hurricane using satellite tools. However, the said work depends upon the high quality spatial data generated by satellite tools but lack intelligent classification. Similar to this work, another research was presented (Wong *et al.*, 2015), a multi-scale hybrid neural network retrieval model for dust storm detection, a study in Asia. The extracted features in this work were selected from three domains that were gray, frequency and texture domain. Additionally, classification accuracy was also lower than the accuracy of the presented approach in this research. The researchers (Velden *et al.*, 2016) presented a system for reprocessing the most intense historical tropical cyclones in the satellite era using the Advanced Dvorak technique; however the said system was lacking classification into different types of cyclones.

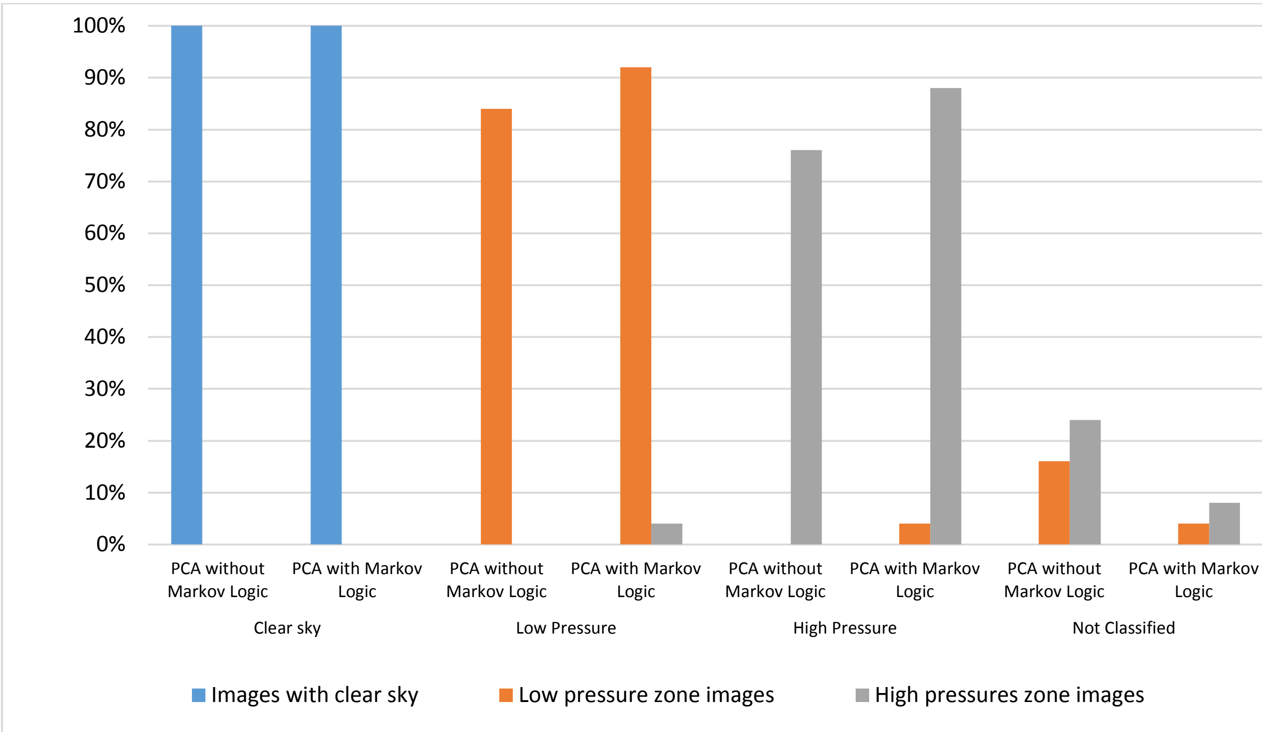

Figure-3: Comparison of PCA based approach with Markov Logic and without Markov Logic

Table-1: Testing results of different Pressure Zone type image classification before using Markov Logic.

Image Class	Clear sky		Low Pressure		High Pressure		Not Classified	
	Total	**%**	**Total**	**%**	**Total**	**%**	**Total**	**%**
Images with clear sky	25	100%	0	0%	0	0%	0	0%
Low pressure zone images	0	0%	21	84%	0	0%	4	16%
High pressures zone images	0	0%	0	0%	19	76%	6	24%

Table-2: Testing results of different Pressure Zone type image classification after using Markov Logic.

Image Class	Clear sky		Low Pressure		High Pressure		Not Classified	
	Total	**%**	**Total**	**%**	**Total**	**%**	**Total**	**%**
Images with clear sky	25	100%	0	0%	0	0%	0	0%
Low pressure zone images	0	0%	23	92%	1	4%	1	4%
High pressure zone images	0	0%	1	4%	23	88%	2	8%

Conclusion: The results have shown that PCA is an effective classifier with respect to processing time and accuracy of results. PCA has been successfully used to handle complex special information of the satellite images. It had also been observed that PCA with Markov Logic is a better approach for classification of pressure zones in term of high and low in the satellite data.

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