Elliptic Fourier Descriptors in the Study of Cyclone Cloud Intensity Patterns

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Abstract

Cyclone cloud intensity analysis is conducted to study the evolution of a cyclone storm mainly using two approaches, namely: wind field analysis and pattern recognition. Of the pattern recognition based approaches , the Dvorak technique has been a pioneering effort which is widely used today. However, the Dvorak technique is subjective, as it relies on human judgment and is, therefore, error prone. Efforts have been described in the literature to automate the classification process. In this paper, we describe our efforts to perform a semi-automatic computer analysis of the cyclone cloud intensity evolution pattern which compares preprocessed visible (VIS) and enhanced infra-red (EIR) satellite images with the corresponding prototype Dvorak patterns using Elliptic Fourier Descriptors (EFD) and Principal Component Analysis (PCA) techniques. This novel approach is simple and intuitive and is robust to noise, and at the same time provides classification in cases where the cyclone exhibits fluctuations during its evolutionary cycle.

Keywords: Cyclone Cloud Intensity, Dvorak Technique, Elliptic Fourier Descriptors, PCA, Spiral Band.

1. INTRODUCTION

A Tropical Cyclone (also known as hurricane / typhoon) is an area of low atmospheric pressure characterized by rotating and converging winds and ascending air, with the central core being warmer than the surrounding atmosphere. The evolution of the cyclone is manifest as changing cloud intensity patterns, with the development of a central eye at an early stage of its evolution surrounded by spiraling cloud bands of varying intensity. The cyclone then intensifies, matures and finally dissipates. At each stage of its evolutionary sequence, the cyclone is characterized by a set of physical parameters related to wind intensity, as well as characteristic cloud intensity patterns obtained from Visible (VIS) and Enhanced Infra-Red (EIR) images obtained using satellite technology. Hence, there are two approaches to TC intensity determination: namely pattern matching and wind field analysis [1,2]. In this note we will describe our attempts in the study of cyclone cloud intensity patterns from VIS and EIR images. A pioneering effort in comprehensive pattern recognition based analysis for estimating tropical cyclone intensity from satellite imagery can be attributed to Dvorak [3] for visible and, later EIR [4] images. The latter set of images wears the additional advantage that intensity estimates can be made at night. Dvorak describes the evolution of the cyclone through the various stages of evolution, viz., formation from a disorganized cloud structure through intensification, maturity and finally dissipation using different cloud intensity templates, as depicted in Figure 1. Satellite images are matched by visual inspection with these templates to obtain a classification using a characteristic number referred to as T-number. There are eight different T-numbers for the different stages.

However, Dvorak's technique [5] is based on human judgement, requires expert training and is thus, subjective. Hence, there have been a number of attempts to automate this analysis procedure over the past three decades. This paper presents a semi-automated approach to classify cyclone images based on Dvorak's technique.

2. PREVIOUS WORK

The pattern recognition based approaches can be broadly classified into three categories. The earlier approaches focussed on the location of the cyclone eye. These include Griffin et. al. [6] who have defined the geometric centre of the TC eye wall. Wood [7] used an axi-symmetric hurricane vertex flow model to locate the ideal TC. Using Doppler velocity data, a TC is identified by locating areas with cyclonic shear, and its center is then located by the identification of extreme Doppler velocity value duplex. However, this method only works well for an ideal TC. Later approaches in this category include those of Tsang et. al. [8] and Pao and Yeh [9]. Tsang et al. [8] suggested morphology operations like erosion and region growing to automatically locate the TC center but their approach is limited to TCs whose main bodies are the most significant characteristics of circle regions. Using infrared and visible time series satellite images, Pao and Yeh [9] have attempted to locate the center of the typhoon and segment it from the background using morphology operations and statistical image classification methods. Some other distinctive features from slices of typhoon satellite cloud images, especially the rotation feature of wind movement vector were also found.

Another set of approaches involved the extraction of the contours of the dominant cyclone and compared with templates either generated from modeling based on the spiral helix equation or from prototype images. The works of Lee et. al. [10], Lee et. al. [11], Lui et. al. [12], Zhang et. al. [13] and Pineros et. al. [14], fall into the category of matching with prototype images. Lee et.al.[10] proposed a neural oscillatory elastic graph matching (NOEGM) model, for automatic TC pattern identification and track mining. The procedure is comprised of three steps, feature extraction, segmentation of cyclone contours using neural oscillators and elastic graph matching. This procedure could not develop a high level data mining and pattern prediction model by the generation of the time dependent relationship of the TC templates based on the past TC cases. Therefore they (Lee et. al.[11]) have proposed another elastic graph dynamic link model (EGDLM) based on the elastic contour matching to automate Dvorak technique. Lui et al. [12] proposed the use of angle features and time warping for TC forecast. The Gradient Vector Flow (GVF) snake model is applied to extract the contour points a tropical cyclone from the satellite image. Similarity among Dvorak templates and the candidate cyclone were retrieved using angle features found among the successive contour points. Zhang et. al. [13] extended the model of artificial ant colony (AAC) to continuous space by aid of multi-kernel Gaussian functions. The whirling shapes of real unclear typhoon eyes are simulated by snake contour boundaries. However, the stability of calculation, the selection of an effective initial Gaussian kernel and its deviation need to be improved. In addition, the performance of Gaussian parameter calculations may limit the number of selected kernels. Pineros et. al. [14] propose a technique using gradient vectors for obtaining features associated with shape and dynamics of cloud structures in cyclones. This method was not able to characterize intensity curves of some systems which exhibit extremely strong oscillations on time frames of 18–20 hours that overwhelm the intensity trend.

The third category, which is an extension of the second category, uses gradient vectors along the contours of the cyclone pattern. Contour matching based on the mathematical modeling of the spiral band of the cyclone is also performed. Wong et. al. [15] modelled the spiral rain-band of a TC by a polar equation given below, in which all vectors are tangents to the logarithmic spiral

$$R = ae^{\theta \cot(\alpha)} \qquad (1)$$

where (R, θ) are the polar co-ordinates at any point R is radial coordinate and θ the angular coordinate, *a* determines the rate of growth of the spiral, and α (pitch angle) is the angle between the radial line and the tangent to the spiral at (R, θ). Cot (α) is the rate of change of R w.r.t. θ per unit R. Templates generated by the estimated parameters are then used to match against radar images at plausible latitude– longitude positions. By using a genetic algorithm suggested by Yip and Wong [16] this method is automated by Wong et. al. [17]. Such a model may be unsuitable if images are sampled infrequently, or when TCs are rapidly moving. In another paper Wong et. al. [18] introduced a method of finding the centers of circulating and spiraling vector field patterns that can handle vector fields with multiple centers and is robust against noise. However, some vector field parameters must be defined beforehand, which limits the method’s applicability. Wei and Jing [19] have also performed optimization of the spiral band model. Also, a novel Spiral Band Model (SBM) is designed to extract and describe the spiral pattern of a spiral band which spirals out from a TC's center.

Although Fourier descriptors have been used extensively for boundary description, matching and recognition, no work appears to have been done in using Fourier Descriptors or Elliptic Fourier Descriptors (EFD) for decomposing cyclone cloud intensity shapes. Abidi and Gonzalez [20] have decomposed time varying shapes associated with cells of tornadic thunderstorms using EFD. These time varying shapes evolve rapidly, in a matter of a few seconds. In this work we only use primary, EIR and VIS patterns. The next sections outline the Methodology, followed by Results and Discussion and finally some Concluding Remarks and Future Work.

3. METHODOLOGY

Satellite images of several cyclones /hurricanes/typhoons spanning over two decades have been used for the study. Of these 252 images, 227 are EIR images and 15 are visible images. As depicted in the flowchart of Figure 2, the input images are first pre-processed followed by shape analysis in the post-processing stage.

3.1 Pre-processing

In the pre-processing step, image enhancement and filtering is applied to obtain high quality images.A median filter is used to remove additive noises. In order to separate the target image (dominant cyclone) from the background, segmentation is performed. The segmentation, binarization, opening and hole filling operations are carried out subsequently, following Guo et. al.'s [21] methodology for galaxy image segmentation. This is done using Otsu's [22] thresholding which separates the predominant cyclone from the background. Otsu's algorithm for automated thresholding is a popular choice in 2D scenes because it is simple to implement, easy to use and gives satisfactory results in 2D when number of pixels in each class are close to each other. A small offset ranging from -0.2 to 0.3 was given in some cases to improve the visual quality of the results. After binarization, an opening operation was performed to remove neighboring cloud disturbances from the dominant cyclone (to be referred to as the region of interest or ROI). A hole filling operation was then performed for boundary extraction. The boundary can then be chain coded using the Freeman code [23] for segmentation purposes. This chain coding procedure is implemented as part of the SHAPE package to be described below.

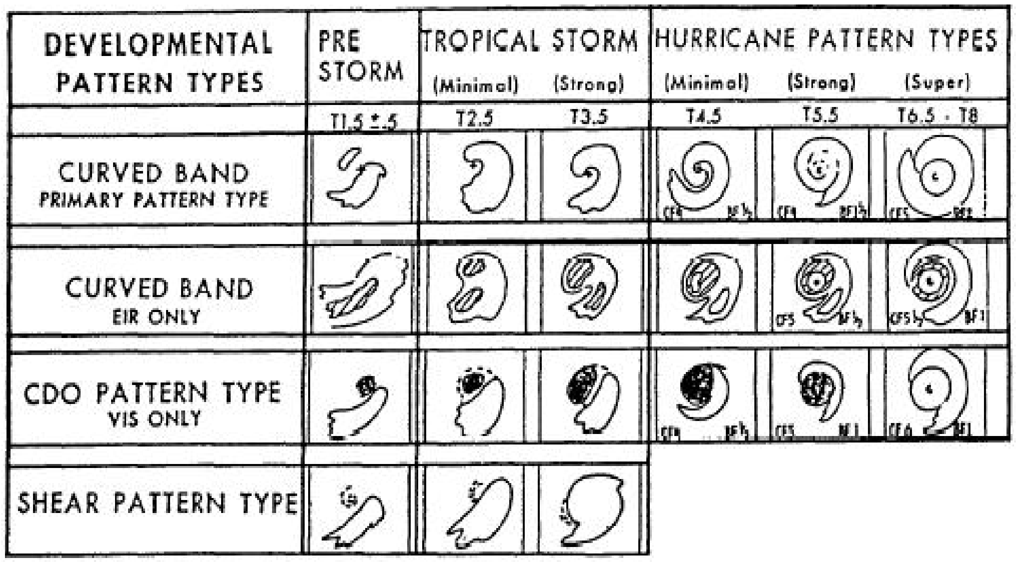


FIGURE 1: Typical Dvorak templates for cyclone cloud intensity patterns (from [35]).

3.2 Post Processing

The second part of our procedure is the post-processing part which involves shape analysis. For this purpose we use the SHAPE software package developed by Iwata ans Ukai [24]. SHAPE is an open-source software that was originally used for the analysis of biological shapes. This package extracts the contour shape from a full color bitmap image, delineates the contour shape with Elliptic Fourier Descriptors and finally performs the Principal Component Analysis (PCA) of the EFDs for summarizing the shape information. The package, SHAPE is open source and easy to use as a researcher can analyze 2 D shapes on a personal computer without special knowledge about procedures related to the method. However, in the following, details of the processes involved will be described below, for completeness. It may also be noted in passing that, SHAPE is characterized by the following features: (1) the packaged programs are easily operated with the aid of a graphical user interface (GUI); (2) No special computer devices for image processing are required; (3) A large number of samples (say 1,000) can be treated; (4) The scores of principal components are stored in tabbed text format files and can be easily exported for analysis by other software; and (5) The variations in shape accounted for by the principal components can be visualized and printed out.

SHAPE essentially performs the following operations on our images: After noise reduction, the closed contour is extracted by edge detection. The contours of the cyclone cloud shapes (candidate images) are then encoded in the Freeman chain code form and then approximated with the coefficients of Elliptic Fourier Descriptors. (EFD). The coefficients of the EFDs are normalized to be invariant with respect to size, rotation and starting point.

Principal Component Analysis (PCA) is then performed to reduce dimensionality, based on the variance-covariance matrix of scores. He scores of derived principal components are also calculated and stored in text format files which were used for quantitative analysis. SHAPE also visualizes shape variations accounted for by each principal component. Reconstructed contours can be printed. The classification is performed with the help of PCA. There are 6 classes of prototype images images used for the classification of both for EIR and VIS images, corresponding to T-numbers T1.5, T2.5 etc., increasing in steps of unit T numbers. There are 252 candidate images of which 227 are EIR images which were classified. Since there are at most three to five spiral turns due to the banding effect of the cyclones, we have used five harmonics, although for our results, results converged for three harmonics.

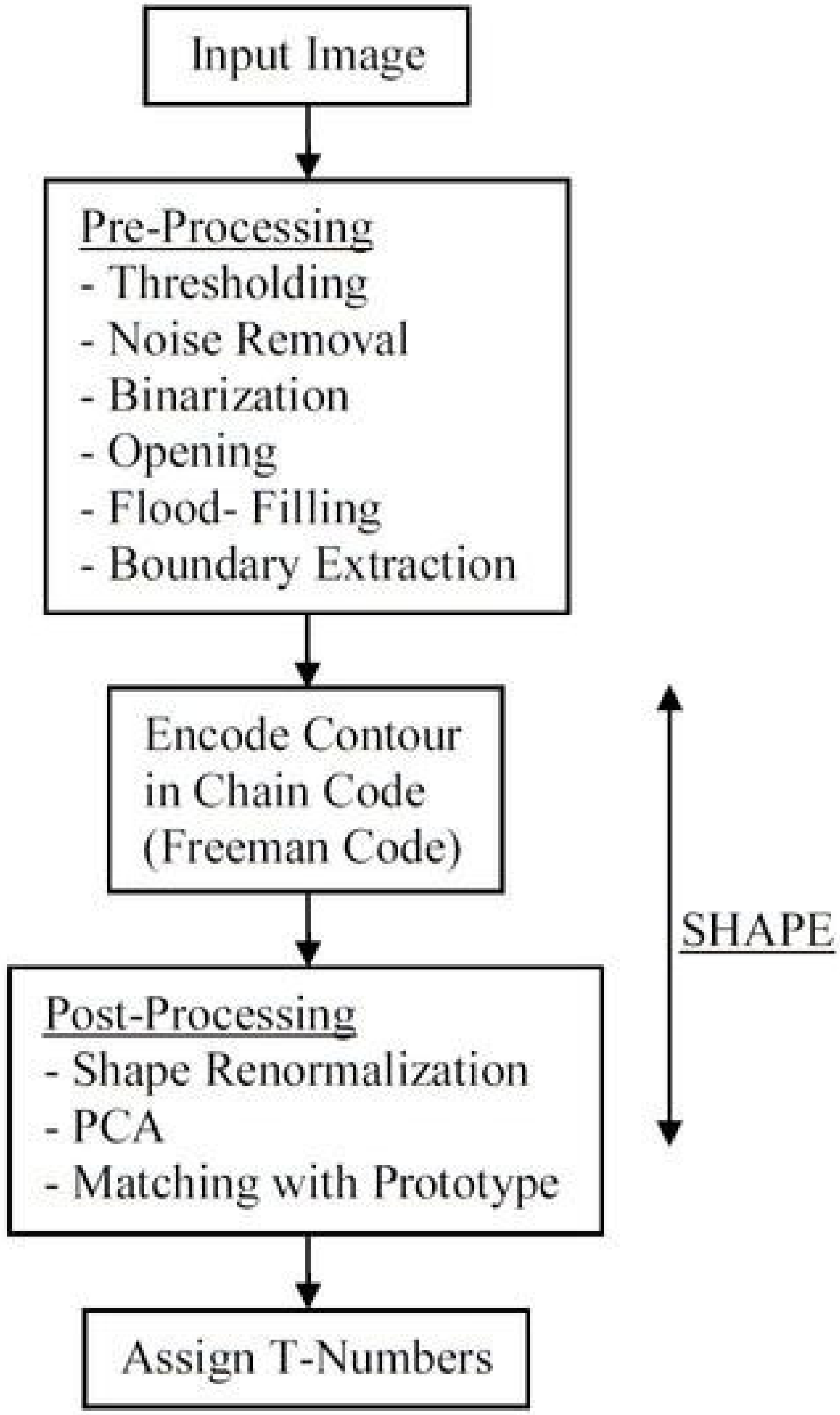


FIGURE 2: Flowchart for the Proposed Algorithm.

Cyclone Name	Number of Images	Number of Images Whose Computed T-numbers are in Agreement with Indian Meteorological Department (IMD)	Percentage (%) Agreement	Comments
Aila	29	28	96.55	Excellent
Bijli	50	35	70	Fairly Good
Phyan	24	19	79.2	Fairly Good
Rashmi	14	10	71.42	Fairly Good
Ward	4	4	100	Excellent

TABLE 1: Comparison of calculated table numbers with IMD T-numbers.

Cyclone Name	Number of Images	Number of Images Whose Computed T-numbers are in Agreement with Cyclone Evolution Trend	Percentage (%) Agreement	Comments
Emily	9	8	89	Very Good
Andrew	4	3	75	Fairly Good
Roxanne	10	7	70	Fairly Good
Nargis	7	6	86	Very Good
Irene	9	8	88	Very Good
Others (Elida, Jeanne, Darby, Flossie)	4	3	75	Fairly Good

TABLE 2: Comparison of Calculated T-numbers with Cyclone Evolution Trend.

A similar procedure is repeated for prototype images corresponding to the Dvorak [3,4] templates. The Euclidean distances between the score value of candidate images we have used and the prototype images are then computed. The best match corresponds to the minimum Euclidean distance between the candidate and prototype image, and the T-number obtained from the prototype image is taken to be the T-number of the candidate image.

After chain coding using the Freeman code [23] , SHAPE then approximates the cyclone contours using Elliptic Fourier Descriptors (EFD) proposed by Kuhl and Giardina [25] , who claim that there are several advantages of EFDs over standard Fourier descriptors. Firstly, integration and Fast Fourier transforms are not required. Moreover, bounds on the accuracy of image contour reconstruction are easy to specify. In addition, EFDs provide a convenient and intuitively pleasing procedure of normalizing a Fourier contour representation. The steps that have been followed for obtaining EFDs in SHAPE have been outlined below (Yoshioka et.al. [26]).

Each contour is represented as a sequence of x and y coordinates of ordered points that are measured counter-clockwise from an arbitrary starting point. Assume that the contour between the (i-1)-th and the i-th chain coded points is linearly interpolated, and that the length of the contour from the starting point to the p-th point and the perimeter of the contour are denoted by tp and L, respectively. The quantity tp is defined as:

$$t_p = \sum_{i=1}^{p} \Delta t_i \qquad (2)$$

and L = t_K.

Here Δt_i and K are the distances between the (i - 1)-th and the i-th points and the total number of the chain-coded points on the contour, respectively. One point to note is that the K-th point is equivalent to the starting point. The x and y coordinates of the p-th point are

$$x_p = \sum_{i=1}^{p} \Delta x_i \qquad (3)$$

And

$$y_p = \sum_{i=1}^{p} \Delta y_i \qquad (4)$$

where Δx_i and Δy_i are the distances along the x and y axes between the (i - 1)-th and the i-th point. Thus, the elliptic Fourier expansions of the coordinates on the contour are

and

$$y_p = C_0 + \sum_{n=1}^{\infty} \left(c_n \cos\frac{2n\pi t_p}{P} + d_n \sin\frac{2n\pi t_p}{P} \right) \qquad (6)$$

with summation n=1, …, ∞, and a_n, b_n, c_n, and d_n being the Elliptic Fourier coefficients of the n-th harmonic and P being the period. As said earlier the coefficients of an elliptic Fourier descriptor [20],[25], are not invariant in size, rotation, shift and starting point of chain-coding about a contour, the Fourier coefficients are standardized (Yoshioka et al. 2008). Let the standardized coefficients of the n-th harmonic be a_n^{**}, b_n^{**}, c_n^{**} and d_n^{**}. Then,

$$\begin{bmatrix} a_n^{**} & b_n^{**} \\ c_n^{**} & d_n^{**} \end{bmatrix} = \frac{1}{E^*} \begin{bmatrix} \cos\psi & \sin\psi \\ -\sin\psi & \cos\psi \end{bmatrix} \begin{bmatrix} a_n & b_n \\ c_n & d_n \end{bmatrix} \begin{bmatrix} \cos n\theta & -\sin n\theta \\ \sin n\theta & \cos n\theta \end{bmatrix} \qquad (7)$$

Where $E^* = [(A_0 - x_q)^2 + (C_0 - y_q)^2]^{1/2}$,

$$\psi = \arctan\left[\frac{y_q - C_0}{x_q - A_0}\right] (0 \leq \psi < 2\pi)$$

and

$$\theta = \frac{2\pi t_q}{T} (0 \leq \theta < 2\pi)$$

In the above equations, E* is the distance between the centre point (A_0, C_0) and a specific point (x_q, y_q), and ψ is the spatial rotation angle. These two parameters are for the size invariance and the rotation invariance. θ is a parameter for chain-code starting point invariance. This standardization makes a_n**, b_n**, c_n** and d_n** independent of the size, rotation, shift and chain-code starting point of a contour. The coefficients of the EFDs are thus, subsequently normalized to be invariant with respect to the size, rotation, and starting point, with the procedure based on the ellipse of the first harmonic. The normalized coefficients of the EFDs can still not be used directly as shape characteristics because the number of coefficients is generally very large and the morphological meaning of each coefficient is difficult to interpret separately and so, Principal Component Analysis (PCA) is to be performed.

Principal component analysis is effective for summarizing the information of the variations contained in the coefficients. The scores of the derived principal components are also calculated and stored in text format files, which can be provided as input files for the various subsequent analysis. Then scores of the derived principal components are calculated. Then, score values for the Principal component for candidate images and model images are calculated. Then the Euclidean distance between a particular candidate image and all the model images are calculated and the best match is chosen.. This process was performed both for candidate and prototype images.

4. RESULTS

The images that we have used in our study include image sequences (i.e. images depicting successive stages of evolution of the cyclone) of cyclone Ward , cyclone Aila, cyclone Phyan , as well as images of hurricane Emily, hurricane Andrew, hurricane Roxanne, Nargis and individual images of hurricanes Elida, Jeanne, Darby and Flossie. Some images of the recent hurricane, Irene have also been been included in our study.

Input images are first digitized and subsequently Otsu's method is applied with a small offset ranging from -0.2 to 0.3 to threshold the images. Then morphological opening operation is applied with the structuring element of disk shaped with a radius of 60 pixels. This is followed by a hole filling operation to enable boundary extraction. Figure 3 depicts images of cyclone Ward, hurricanes Emily, Andrew and Roxanne (first column) and the images after Otsu thresholding (column 2), morphological opening (column 3) and hole filling (column 4), respectively.

During the post-precessing stage, the software package SHAPE extracts contours and assigns chain codes to the contours. Then EFDs are extracted followed by PCA. PCA results of candidate images are compared with PCA results of prototype images corresponding to the Dvorak templates. Best matches correspond to the minimum Euclidean distance between candidate and prototype images. Figure 4 gives principal components for Andrew (EIR T1.5) and Emily (VIS T1.5) with the template images with which they are matched.

Results obtained will be discussed under two categories. In the first category, our results will be compared with the T-numbers estimated by meteorological experts. In the second category, we correlate our results with reports of cyclone evolution trends. In the second set of experiments, T numbers of the cyclones were determined with the algorithm described above and compared with the description of the cyclone evolution given in the reports, since some cyclones have been described with the help of the Saffir Simpson Hurricane Scale (SSHS) a gradation scheme for hurricanes, based on wind field analysis. This set of experiments have been conducted on hurricanes Emily, Andrew, Roxanne, Irene and Nargis image sequences, as well as as individual images of Darbie, Elida, Flossie and Jeanne.

Cyclone Ward [27] formed and intensified to storm status and further intensified to cyclone status before finally weakening due to wind shear and eventually dissipating. Cyclone Nargis [28] formed and quickly intensified to severe storm status before weakening and dissipating. Table 1 gives the comparisons of the T-numbers obtained using our methodology with the data for the cyclones obtained from the Indian Meterological Department (IMD). Hurricane Emily [29] formed and intensified to cyclone status and again fluctuated from moderate to severe cyclone storm status before weakening and finally dissipating. Our analysis indicates an increase of T number from 1.5 to 4.5, followed by a subsequent decrease to 3.5, an increase to 6.5 and finally a fairly stable period with T number of 5.5, followed by another increase to 6.5 and finally, a gradual decrease. This fluctuation corroborates with the report [29]. Hurricane Andrew [30] also followed a similar pattern of fluctuations after formation and intensification to storm status and eventually dissipating. Hurricane Roxanne had a confusing formation [31] and fluctuated frequently between low intensity and severe cyclone storm status before finally dissipating. Such behaviour patterns of cyclone storms indicate irregularities and deviations from a model cyclone evolution pattern, as is true of any natural phenomena. The cyclones had been assigned categories based on the SSHS scheme at different stages. The T-numbers corresponding to each of these categories can be obtained from conversion tables and the T-numbers thus obtained give an indication of the cyclone evolution trend. We compared our results with the T-numbers obtained from these conversion values. In Table 2, we compare our results with the values obtained from this cyclone evolution trend (obtained from reports on the Internet [32]) . Table 3 provides calculations for obtaining the Receiver Operating Characteristics (ROC) and Table 4 provides the Confusion Matrix for the T-numbers that we have classified versus the T-numbers manually assigned. This table gives an indication of the true and false classification rates. Figure 8 shows the ROC curve with TP indicating True Positive and FP indicating False Positive. The Area Under the Curve of the ROC curve (Figure 5) was 0.8278 indicating an 82.78% agreement with predicted values.

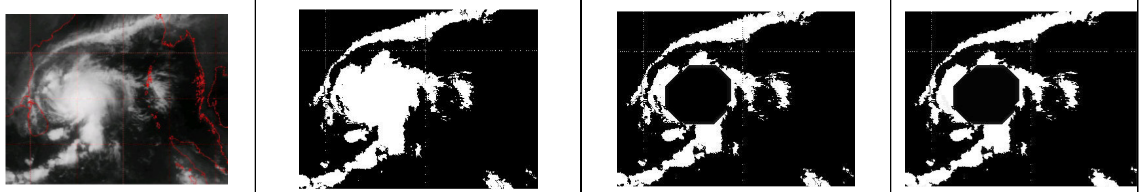
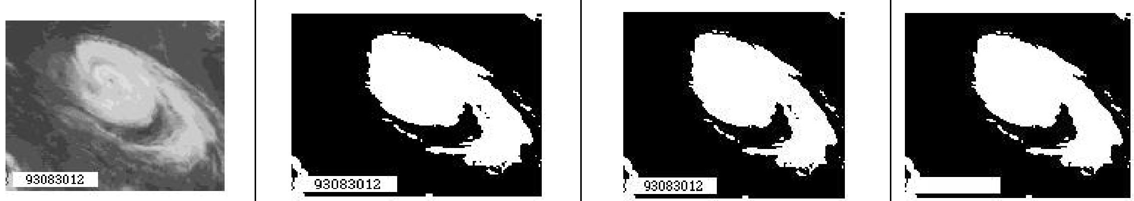
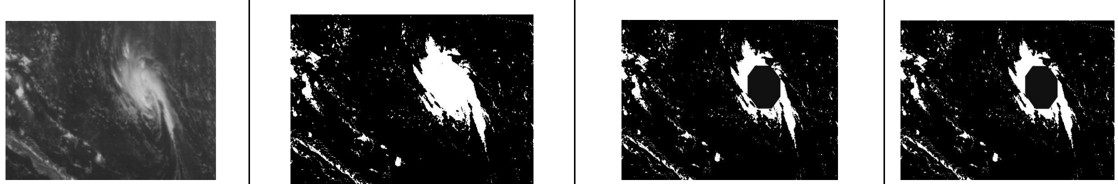
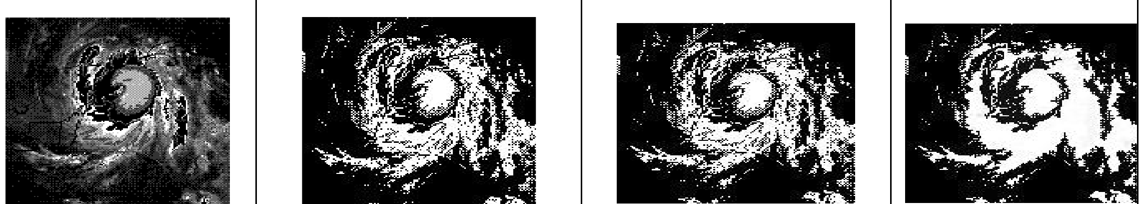
Fig.3 (a)	
Fig.3 (b)	
Fig.3 (c)	
Fig.3 (d)	

FIGURE 3: Images of Ward, Emily, Andrew and Roxanne after image preprocessing in rows 1-4, respec -tively.

Our proposed methodology falls under the second category. As with other approaches under this category, we preprocess the images using noise removal, Otsu thresholding, morphological operations like opening and filling, as appropriate. After preprocessing we use the SHAPE package for boundary extraction, chain coding, use of the EFD and PCA analysis, after which comparisons are made between the candidate and prototype (Dvorak template) images. Hence our matching procedure is based on shape descriptors. It may be mentioned here that, SHAPE can convert a color image to a binary image, remove noise and perform thresholding before boundary extraction and subsequent operations that we have used the package for.

T-number	Total number of images matched with the original T-number (TP)	Total number of images mismatched with the original T-number (FP)	Cumulative Rate	
			TP	FP
T1.5	11	1	0.0558	0.0256
T2.5	110	22	0.614	0.564
T3.5	35	9	0.792	0.821
T4.5	18	2	0.883	0.872
T5.5	13	4	0.949	0.974
T6.5	11	1	1.0	1.0
Total	197	39		

TABLE 3: Calculation of Receiver Operating Characteristic (ROC).

Predicted Class							
Actual Class		T1.5	T2.5	T3.5	T4.5	T5.5	T6.5
	T1.5	11	1	0	0	0	0
	T2.5	12	107	5	3	0	0
	T3.5	0	3	35	5	1	0
	T4.5	0	0	1	15	1	0
	T5.5	0	0	2	2	13	1
	T6.5	0	1	0	0	0	9

TABLE 4: Confusion Matrix for the Algorithm.

5. DISCUSSIONS AND FUTURE WORK

This paper describes a novel approach to study the evolution of cyclones using both VIS and EIR satellite images of cyclone cloud intensity patterns. As discussed earlier, there are broadly three categories of pattern matching analysis of cyclones. The first approach focuses on the extraction of the eye. Most of the earlier approaches and also some later approaches fall under this category. The second and third categories involve a segmentation procedure after image pre-processing to extract cyclone cloud intensity contours. Subsequently, efforts in the second category attempt to match these images with Dvorak prototypes using soft computing techniques like neural networks, genetic algorithms, ant colony optimization, etc.,. Another set of approaches under this category involve generating gradient vectors or angle features at different points along the contour and matching these features with prototypes. The third category involves fitting the contours to curves generated from mathematical models (e.g. logarithmic helix, spiral band, etc.,).

5.1 Comparison with Other Work

The location of the cyclone "eye" is important as the very existence and metamorphosis of the cyclone is dependent on its presence, and hence, the detection of the eye does play an important role in cyclone evolution analysis. However, the typical cyclone contour is "comma" shaped and so the degree of spiralling of the curved band is indicative of the different stages of evolution of the cyclone and thus, the approaches of the second and third categories provide a clearer picture of the cyclone evolution. Mathematical models provide exact shapes, but cyclones being natural phenomena do not always correspond to regular curves. So an empirical image matching scheme with prototypes could give a good estimate of cyclone evolution trends. Our correct classification rate of 83% percent compares favorably with the other techniques in all these categories. Lee and Liu [11] have claimed an overall accuracy of 82% and found that EIR images give better results because of a better spiral pattern. Their earlier effort [10] yield an overall value 86% for track intensity mining but their efficiency depended on the inter-relationship of successive pictures. Pao and Yeh [9] claimed a correct classification rate of 82% while locating the center and contour of the typhoon. Pineros et. al. [14] achieved correlation rates ranging between 82-86% with the highest being for instances where the maximum hurricane strength was achieved. Liu et. al. [12] achieved a 10% (72.41%) improvement of human visual justification (62.86%).

The methodology that we have proposed has not been used previously, to the best of our knowledge. In an earlier attempt [33] we have used a different preprocessing technique involved a classical edge extraction template followed by erosion and dilation. However, edge detectors produce broken contours and so we have replaced [34] this earlier methodology with a filling algorithm to produce closed contours before performing boundary extraction followed by Freeman chain code implementation that is available in SHAPE. This has improved the results by 16%. The use of Elliptic Fourier Descriptors has several advantages over Fourier descriptors. Integration or use of fast Fourier techniques are not required and bounds on the accuracy of the image contour representation are easy to specify.

EFDs are convenient and Fourier contour representations can be conveniently normalized and is thus useful for the analysis of well defined 2D contours. Dvorak templates are widely used and we have also used them as they capture the essence of the intensity patterns effectively. As EFDs involve the use of many coefficients, PCA is used to reduce the dimensionality. In the earlier attempt [33] we had used 20 harmonics in the PCAbased classification , but because there are at most three to five spiral turns, we have used five harmonics, although our results converged after three harmonics. The degree of banding and thus the evolutionary stage of the cyclone can thus be described.

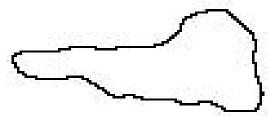
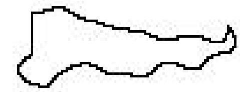
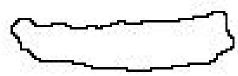
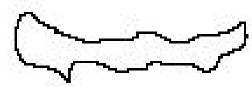
Particular of Candidate and Model image	PCA of Candidate image	PCA of model image
The principal component of the candidate image Andrew 2 and the model image EIR(T 1.5) with 5 harmonics.		
The principal component of the candidate image Emily and the model image VIS (T1.5) with 5 harmonics.		

FIGURE 4: Principal component of candidate images of Hurricanes Andrew and Emily and template images with which they are matched.

EFDs are convenient and Fourier contour representations can be conveniently normalized and is thus useful for the analysis of well defined 2D contours. Dvorak templates are widely used and we have also used them as they capture the essence of the intensity patterns effectively. As EFDs involve the use of many coefficients, PCA is used to reduce the dimensionality. In the earlier attempt [33] we had used 20 harmonics in the PCAbased classification , but because there are at most three to five spiral turns, we have used five harmonics, although our results converged after three harmonics. The degree of banding and thus the evolutionary stage of the cyclone can thus be described.

5.2 Future Work

Future work will heve to focus on a clear extraction of the eye and also try to integrate the preprocessing stage with boundary extraction, chain coding, etc. and to automate the whole process. This work will have to be extended to larger datasets in order to standardise the technique for cyclone intensity prediction. Also, a more accurate registration scheme between the SSHS scheme and Dvorak technique needs to be formulated and designed, in order to provide a more accurate prediction technique. The methodology will also have to be improved to cater to situations where the storm interacts with unfavourable environments such as land or wind shear. The database to be used should also include complicated situations where there are several cloud structures located within the disturbance, or when the shape of the cloud structures are elongated.

One of the most challenging problems is to predict the cyclone formation at an early stage of development, and hence, another long term goal is to incorporate cyclogenesis in this study.

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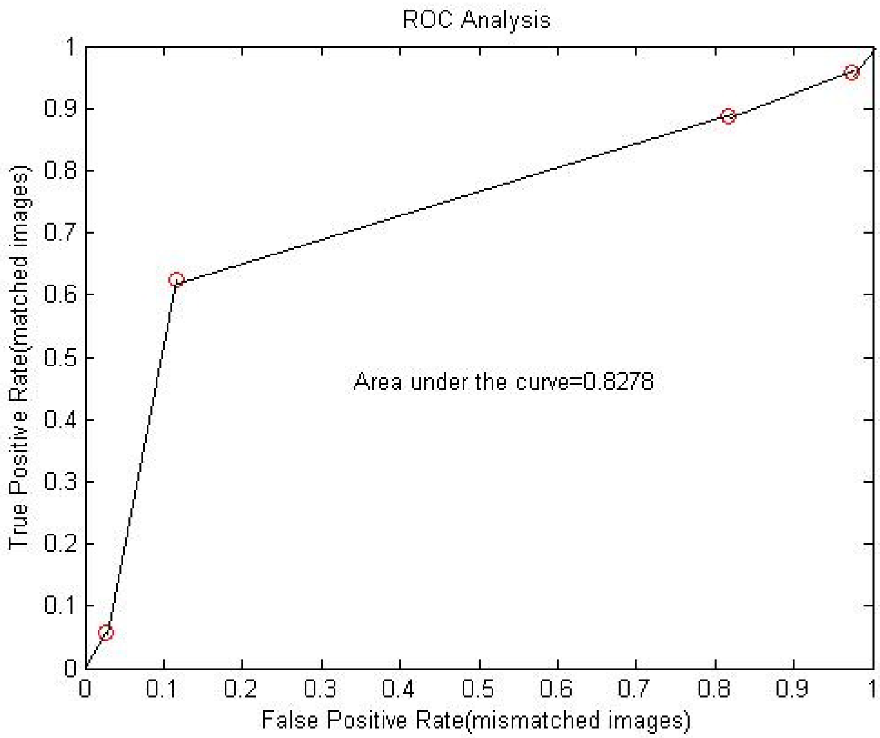

FIGURE 5: Data fitted with Receiver Operating Characteristic Curve.

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