ATMOSPHERE - Automatic Track Mining and Objective Satellite Pattern Hunting system using Enhanced RBF and EGDLM

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Abstract

Severe weather prediction, such as tropical cyclone (TC) forecast is a typical data mining and forecasting problem that involves high level data manipulation and interpretation of meteorological information such as satellite pictures and other meteorological observation data. In this paper, we present a fully automatic and integrated system known as "ATOMOSPHER" - Automatic Track Mining and Object Satellite Pattern Hunting system using Enhanced RBF and EGDLM - to provide a neural network based TC identification and tracking system. The proposed system consists of two main modules: 1) Object Dvorak technique for TC satellite pattern identification based on an Elastic Graph Dynamic Link Model (EGDLM) and 2) TC tracking system based on an Enhanced Radial Basis Function (RBF) network model.

For system evaluation, 120 TC cases appeared in the period from 1985 to 1998 (provided by National Oceanic and Atmospheric Administration (NOAA)) are adopted. Promising results of over 87% of TC pattern segmentation and 97% of correct classification rate are attained respectively. For TC tracking, an overall of over 86% correct prediction result is achieved.

Keywords: EGDLM, Enhanced RBF, Track mining, TC identification, time series prediction.

1. Introduction

Time series prediction so far is one of the most vital research topics, not only because of its significant practical values, ranging from stock prediction (Liu and Lee 1997; Liu and Tang 1996) to general weather forecast such as rainfall prediction (Li et. al. 1998; Lee and Liu 1999c; Liu and Lee 1999) in meteorology, but also of its academic values.

In a typical weather prediction scenario, factors that affect the coming weather depend not only on local weather elements such as temperatures, relative humidity, air pressure, wind speed and directions, but also regional weather elements such as the effect from global weather pattern, for example El Nino effect (Bao and Xiang, 1991). This constitutes to the handling of a huge amount of information including "extraction", "filtering", "interpretation", "discrimination" and "processing", and also a sophisticate data mining and knowledge discovery process as well. Especially in the case of severe weather prediction such as topical cyclone (TC) forecast, an additional level of complexity with the usage and interpretation of satellite and radar images is being imposed. Unlike those weather elements such as temperature and pressure which can be predicted by classical numerical modeling (Liu 1988) or contemporary neural network models (Liu and Lee 1999), these imagery data are highly variant in the sense that so far only subjective human interpretations by the Dvorak technique is adopted (Dvorak 1973, 1975).

This paper presents an integrated model that provides an effective and fully automatic system for the tropical cyclone (TC) identification and track prediction called ATMOSPHERE (Automatic Track Mining and Satellite Pattern Hunting system using Enhanced RBF and EGDLM). The proposed model consists of two main modules: 1) TC pattern recognition system from satellite pictures known as Elastic Graph Dynamic Link Model (EGDLM), a neural network based model that involves the automatic TC pattern segmentation and elastic pattern matching from the pre-defined TC templates, a process that simulates human TC identification technique called Dvorak analysis (Dvorak 1973, 1975); 2) A time series TC intensity and track mining system using Enhanced Radial Basis Function network, a time series recurrent neural network prediction model that integrates the conventional RBF network with Time Difference and Structural Learning (TDSL) technique.

The paper is organized as follows. Section 2 will present the EGDLM for automatic TC pattern identification. Section 3 will discuss the Enhanced RBF model for TC intensity and track mining. In section 4, an overview of system implementation using 120 TC cases appeared between 1985 to 1998 (information provided by National Oceanic and Atmospheric Administration (NOAA)) will be presented. Comparisons of the proposed system with other contemporary TC tracking system will be conducted as well, together with the conclusion discussed in Section 5.

2. Objective Satellite Pattern Identification of Tropical Cyclone using EGDLM

2.1 Dvorak Technique for TC Identification

In view of the various meteorological phenomena interpreted from satellite images, one of the most valuable contributions is the identification of tropical cyclones - including storms, extra-tropical cyclones, typhoon and hurricanes that threaten numerous human lives and properties.

One of the worldwide accepted methods for TC identification and interpretation was developed by Dvorak (1973; 1975) known as Dvorak technique. From his theory, each TC may go through a life cycle that can be classified into eight categories ranging from TC1 to TC8 (Figure 1). In addition to classifying the tropical cyclones, Dvorak analysis also provides an effective scheme to determine the current strength of the cyclones from the satellite images which are based on the "T-number" (T1-T8) determined from Dvorak technique.

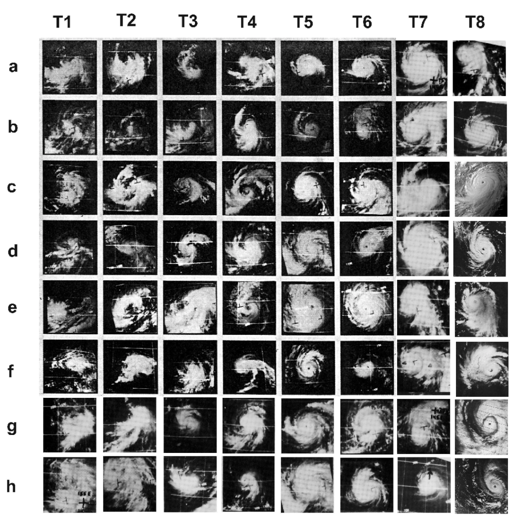

Figure 1 - Dvorak TC templates from T1 to T8 (Each T-number with eight sub-categories corresponds to eight different possible appearance of the TC patterns)

Nowadays, Dvorak technique is still the worldwide agreed official tool for the determination of TC intensity. But due to the highly variation of TC patterns that can appear in satellite pictures, the Dvorak technique is highly subjective which depends on the human justification done by the weather forecasters and meteorologists.

2.2 A Perspective of EGDLM for Invariant TC Pattern Recognition

In this paper, an elastic attribute graph recognition model known as Elastic Graph Dynamic Link Model (EGDLM) is proposed to provide a fully automatic and objective solution for Dvorak technique on TC pattern identification.

In short, object recognition using EGDLM is based on the framework of Dynamic Link Architecture (DLA) (Malsburg 1981) which describes the recognition problem as an elastic graph matching mechanism between the attribute graphs of the image vectors (input layer) with the set of model graphs in the "memory layer". The neural interactions are governed by the onset/offset of the dynamic links between the layers which simulate the functionality of the dynamic memory association in the Short-term memory. Active researches in this area have been done including handwritten character recognition (Liu and Lee 1997, 1998; Lee and Liu 1999e), human face recognition (Lee et. al. 1999, Lee and Liu 1999d) and TC pattern recognition with the integration of Active Snake model for object segmentation based on elastic templates (Lee and Liu 1999a, 2000).

Different from the traditional DLA model, EGDLM makes use of the Composite Neural Oscillatory model to facilitate a fully automatic object segmentation scheme. Recent research of such also involves scene analysis (Lee and Liu 1999b). A schematic diagram of EGDLM for TC pattern matching is shown in Figure 2.

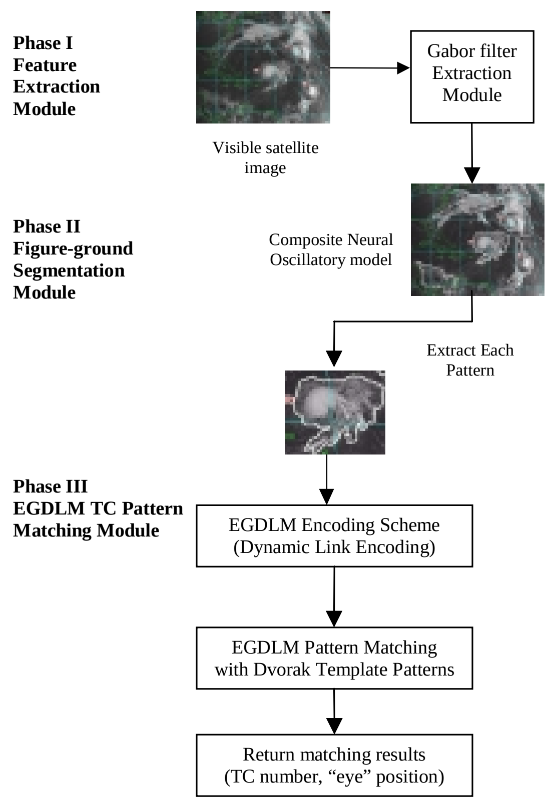

Figure 2 - EGDLM for TC Pattern Identification

2.3 Invariant Properties

One of the most striking features of the EGDLM is the "invariant" property. In the network model, only the topological relations between the composite neural oscillators (ie. dynamic links) are encoded into the network. The pattern matching process is resembled to the "Elastic Graph Matching" which is invariant under various transformations such as translation, rotation, reflection, dilation and occlusion. This occurs commonly in natural scenes (Lee and Liu 1999b).

3. Enhanced Radial Basis Function (RBF) Network for TC Track Mining

3.1 Enhanced RBF Network - System Overview

The proposed Enhanced RBF Network (ERBFN) incorporates with two main technologies into the conventional RBF network for temporal time series prediction problem: 1) Structural learning technique that integrates the "forgetting" factor into the RBF BP algorithm; 2) A Time Difference with Decay (TDD) method is corporated into the network to strengthen the temporal time series relation of the input data sequence for network training. A schematic diagram of the proposed network is shown in Figure 3.

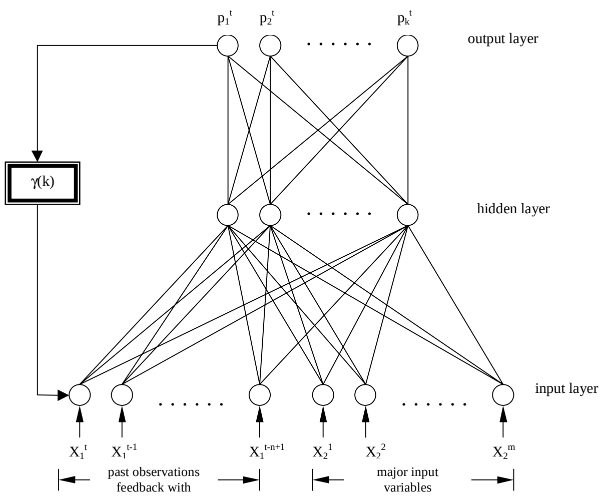

Figure 3 - Schematic diagram of the Enhanced RBF Network

The ERBFN shown in Figure 3 consists of three layers. The first layer is the input layer which consists of two portions: 1) Past network outputs that feedback into the network; 2) Major co-relative variables are concerned with the prediction problem. Past network outputs enter into the network by time-delay unit as the first inputs. These outputs are also affected by a decay factor γ that is governed by the following equation.

$$\gamma = \alpha\, e^{-\lambda k} \qquad (1)$$

where λ is the decay constant, α is the normalization constant and k is the forecast horizon.

In general, the time series prediction of the proposed network is to predict the outcome of the sequence x_1^{t+k} at the time of t+k that is based on the past observation sequence of size n, i.e. x_1^t, x_1^{t-1}, x_1^{t-2}, x_1^{t-3}, …, x_1^{t-n+1} and the major variables that influence the outcome of the time series at time t. For convenience, the following notations are used throughout the following network description: The numbers of input nodes in the first and second portions are set to n and m respectively. The number of hidden nodes is set to p. The predictive steps are set to k, so the number of output nodes is k. At time t, the inputs will be [x_1^t, x_1^{t-1}, x_1^{t-2}, x_1^{t-3},…,x_1^{t-n+1}] and [x_2^1,x_2^2,…,x_2^m] respectively. The output is given by x^{t+k}, denoted by p_k^t for simplicity, w_{ij}^t denotes the connection weight between the i-th node and the j-th node at time t.

3.2 Enhanced RBF Network - Structural Learning Algorithms

The main idea of RBF learning algorithm with a "forgetting" factor is to introduce a constant decay to connected weights that make the redundancy weight(s) fade out quickly. The cost function of the structural learning algorithm is given by equation (2).

$$E^t = E_1^t + \varepsilon' \sum_{i,j} \left| w_{ij}^t \right| \qquad (2)$$

where E_1^t denotes the error square in traditional RBF learning, the second term is the penalty criteria.

If delta rule is used, the learning rule of the weights is given by:

$$\Delta w_{ij}^{t+1} = -\eta \frac{\partial E^t}{\partial w_{ij}^t} + \alpha \Delta w_{ij}^t = \Delta w1_{ij}^t + \alpha \Delta w_{ij}^t - \varepsilon\, \mathrm{sgn}(w_{ij}^t) \qquad (3)$$

where the first term in the first line is the weight change obtained by the traditional RBF network, η is the learning rate and α is the momentum. Besides, ε = ηε' is the "forgetting" factor.

By using this structural learning method, the main "skeleton" of the network can be constructed with weight adapting over a time series of training.

3.3 Enhanced RBF Network – TDD Method

The structural learning algorithm discussed above does provide a "dynamic" structure building of the neural network, but it cannot adapt the temporal time series relations of the input and output feedback data sequences into the model. In order to code with this problem, a temporal difference method with decay feedback is hybridized into the learning algorithm of the proposed model. The basic concepts are presented as follows.

In a typical time series prediction problem, given a series of past observations of time-step n at time t, i.e. [x_1^t, x_1^{t-1}, x_1^{t-2}, x_1^{t-3},…,x_1^{t-n+1}], with the predictive time-step of k, we not only obtain the predicted output at time t+k, i.e. p_k^t , but more importantly is the sequence of future events starting from time t, i.e. [p_1^t, p_2^t, p_3^t …, p_k^t]. In other words, the network can provide an overlapping and inter-related event sequence as an additional "hint" for network learning, which can be implemented by using Temporal Difference technique (Sutton 1983). Besides, by considering a sequence of temporal difference operations from time t+1 to t+k, the prediction from a "nearer" future normally has a higher level of confidence than a "far" future, so a decay operator is integrated into the learning algorithm in order to reflect the situation.

With the integration of TDD methodology, the learning algorithm discussed in equation (3) will be modified into:

$$\Delta w_{ij}^{t+1} = \eta\left(\sum_{h=2}^{k} \gamma(h) \cdot \left(p_{h-1}^{t+1} - p_h^t\right) \sum_{l=1}^{t} \lambda^{t-1} \frac{\partial p_h^l}{\partial w_{ij}^t} + \right.$$
$$(p_1^t - p_0^t) \cdot \sum_{l=1}^{t} \left[\gamma(l) \cdot \lambda^{t-1} \frac{\partial p_1^l}{\partial w_{ij}^t} \right] + \alpha \Delta w_{ij}^t - \varepsilon'' \mathrm{sgn}(w_{ij}^t) \quad (4)$$

where ε" is defined as:

$$\varepsilon'' = \begin{cases} \varepsilon & \left|w_{ij}^t\right| =< \theta \\ 0 & otherwise \end{cases} \quad (5)$$

From equation (4), the learning algorithm consists of three basic components, the first two terms refer to the error adjustment based on the temporal differences between the output event sequences between the two consecutive time steps, which is "weighted" by the decay functions $\gamma(l)$, $\gamma(h)$ given by equation (1). The third and fourth terms refer to the structural learning operations, which is explained in equation (4). Also, λ denotes the exponential scale for a connection weight that determines the effective length of the history windows.

4. ATMOSHPERE - System Implementation

4.1 Introduction

In sampling data for simulation, 120 tropical cyclones cases appeared in the period between 1985 and 1998 were identified. All the time series (3-hourly) satellite images and grid point meteorological data are provided by National Oceanic and Atmospheric Administration (NOAA). For the grid point meteorological data being used in the time series prediction, meteorological data including: mean sea level air pressure (MSLP), surface and upper-air (700mb, 500mb, 300mb) wind speed and direction, dry bulb and wet bulb temperature, that is, all the data that will affect the "steering" motion and development of TC are considered.

System implementation tests of ATMOSHPEREE are mainly divided into two phases: 1) TC identification tests based on the TC pattern recognition using EGDLM; 2) TC intensity and track mining tests using Enhanced RBFN Network (ERBFN). Comparisons on system performance with other neural network models and bureau TC tracking system such as OCTM and TKS will be conducted as well. The whole system implementation and performance evaluations were carried out on Sun Sparc 20 workstation.

4.2 TC Pattern Recognition Tests

In the tests, for each of the 120 TC cases, 5 satellite images were randomly chosen for the test, so totally 600 satellite pictures were being used. Two set of tests were conducted for TC pattern recognition using EGDLM:

1) TC patterns segmentation tests

TC patterns segmentation done by EGDLM model using Composite Neural Oscillating technique verse that using Active Contour Model (Lee and Liu 1999a) is shown in Table I. A snapshot of the segmented TC patterns from a satellite image that contains four TCs in 1997 is shown in Figure 4.

TABLE I
TC PATTERNS SEGMENTATION COMPARED WITH ACM MODEL

Segmentation Models	Segmentation Rate			Av. Speed* (sec)
	TC 1-3	TC 4-6	TC 7-8	
EGDLM	92%	96%	99.5%	50 sec
Hybrid ACM	80%	88.2%	97%	195 sec

2) TC patterns recognition tests

In the test, 600 satellite images were undergone TC segmentation and they were matched with the Dvorak templates (Figure 1) using the elastic graph matching technique of EGDLM. Two sets of tests were conducted: They were "TC Pattern Classification Test of the 600 satellite images" and "TC "Eye" Position Identification Test". Results are presented in Tables II and III.

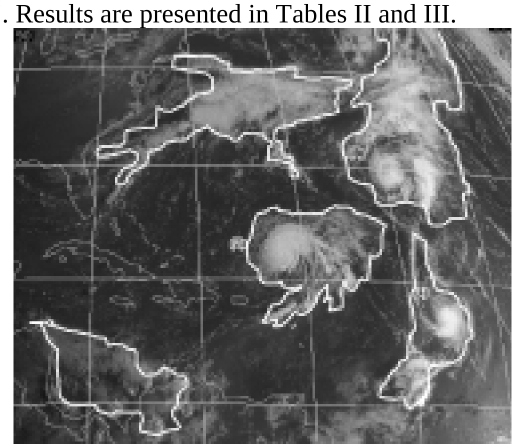

Figure 4 – Segmented TC patterns from satellite image

TABLE II
TC PATTERN CLASSIFICATION RESULTS

	No. of matches for each category			
	TC cat. 1-3 Total no.: 245	TC cat. 4-6 Total no. : 276	TC cat. 7-8 Total no. 231	Overall Total no.:752
EGDLM	229 (93%)	271 (98%)	231 (100%)	731 (97%)
Hybrid ACM	178 (73%)	223 (81%)	211 (91%)	612 (81%)

TABLE III
TC "EYE" POSITION IDENTIFICATION RESULTS

	No. of TC	No. of matches	Recognit-ion rate (%)	"eye" position deviation*
EGDLM	281	278	99%	2.3 km
Hybrid ACM		250	89%	3.0 km

Remark :TC "Eye" position deviation amounts are calculated by the deviation from the TC "eye" location reported by reconnaissance aircraft

4.3 TC Intensity and Track Mining Tests

Using the Enhanced RBF network (ERBFN) for time series TC tracking mining, the 120 TC cases were randomly divided into two sets. The first 60 TC cases were used for network training while the rest used for system testing.

For system evaluation, two types of tests were conducted: 1) Evaluation for the system performance of the Enhanced RBF Network (ERBFN) against two different time series neural network prediction models: conventional RBF network and BBPT (Williams and Zipser, 1995) recurrent network; 2) Comparisons of the TC track mining performance of the proposed ERBFN with the bureau TC tracking systems: OCTM and TKS systems.

In order to provide a systematic performance measure of the proposed model against other neural network prediction tools and the enhancement achieved as compared with the conventional RBF model, the comparison with two other time series prediction models was taken. This included: 1) Conventional RBF network; 2) Backpropagation Time Series Recurrent Network (BBTT). Network training and testing results are shown in Table IV. Storm tracks being successfully mined by all the models for TC Bonnie (1998) against the "Actual" TC track are shown in Figure 5.

TABLE IV
NETWORKS TRAINING AND TESTING RESULTS

Network Models	TC Intensity Prediction		TC Track Prediction	
	MSE training	MSE testing	MSE training	MSE testing
ERBFN	0.014	0.061	0.013	0.079
RBF model	0.412	0.513	0.493	0.581
BPTT model	0.082	0.103	0.093	0.112

Compared with the conventional RBF model, the proposed Enhanced RBF model has achieved a significant enhancement by over 20 and 10 times in mean square error (MSE) in TC intensity and track mining. Even when compared with the BPTT recurrent network, an overall 40% and 30% improvement in these dimensions have been attained respectively.

A quantitative evaluation of the proposed model was performed and tested for its applicability in real time TC track mining as compared with that of the bureau TC Track mining systems: 1) One-way interactive Tropical Cyclone Model (OTCM) used by the JTWC in Guam; 2) Track Forecast System (TKS) – Enhanced numerical prediction forecast used in Central Weather Bureau in Taiwan.

In the experiment, 55 TCs appearing during the period between 1989 to 1992 were used. Track mining accuracy is determined by the great circle distance between the forecast position and the best track position provided by the Central Weather Bureau of Taiwan. Table V shows the comparison results of the Enhanced RBF model with OTCM and TKS models based on the 48-hour TC position forecast during the year 1989-90, detailed TC track mining accuracy figures (in km) for each TC were given for illustration.

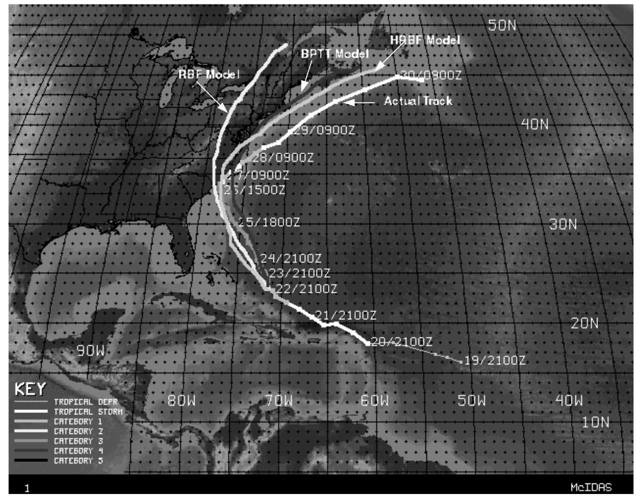

Figure 5 – TC tracks predicted by different models Vs. actual TC track for TC Bonnie (1998)

TABLE V
COMPARISON OF THE HRBF MODEL WITH BUREAU TC TRAC4KING SYSTEMS AT 48-HOUR POSITION FORECAST (1989-1990)

TC/ year	No. of cases	Enhanced RBF	OTCM	TFS
1989	52	296	486	425
1990	41	309	305	322
Overall	93	301	406	379

As shown in Table V, for the 18 TCs appeared in the period between 1989 and 1990, the average 48-hour forecast error reported by Enhanced RBF, OTCM and TFS are 301 km, 406 km and 379 km respectively. The overall improvement comparing with the two models are respectively OTCM (25.8%) and TFS (25.9%), corresponding to less than 3° error. This represents a significant improvement to predict the landfall of TC for warning and precaution measures.

Comparing with the TC track mining results between 1989 and 1990, it can be seen that the errors are somewhat correlated. The track forecasts also depend on the capability in predicting the large scale flow, which is believed to be related to the type of flow regimes. When interpreting Table V, it is worthwhile to realize that 1989 is one of the worst years for OTCM performance. However, the HRBF model still maintains promising track mining capability, giving a good prediction of cyclone movement.

5. Conclusion

This paper proposed a fully integrated and automatic system called ATMOSPHERE (Automatic Track Mining and Objective Satellite Pattern Hunting system using Enhanced RBF and EGDLM) for TC identification and time series intensity and track prediction. Such a task is historically highly dependent on human subjective justification on vast supply of information.

The main contributions of the ATMOSPHERE is two folds: 1) Automate the Dvorak technique for TC identification from satellite images, a process that highly depends on human intervention. With the adoption of EGDLM, the system provides a fully automatic, accurate (over 97% accuracy) solution in a reasonable speed; 2) The adaptability and real time learning track learning technique, which is particularly important for TC Track mining problem due to the rapid development of TC in severe weather conditions. This is also the major weakness of numerical prediction models in forecasting these severe and locally developed weather phenomena.

Acknowledgement

We are grateful to NOAA for the provision of meteorological data and satellite pictures for TC between 1985 to 1998. The authors are also grateful to the partial supports of the Central Research Grants G-S484 of Hong Kong Polytechnic University.

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