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THUNDERSTORM TRACKING SYSTEM USING NEURAL NETWORKS AND MEASURED ELECTRIC FIELDS FROM A FEW FIELD MILLS

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This paper presents a novel system to quickly asses the direction of thunderstorm by using a few field mills on the ground. As opposed to the traditional methods of using expensive radar systems to detect the thundercloud movement, the method presented in this paper simply uses the electric waveforms detected by the field mills and using a neural network of suitable complexity and can determine the thunderclouds direction with reasonable accuracy. The neural system is trained with data from the simulation of thundercloud movement using parameters obtained through experiments. Through extensive testing, it is found that the system presented in this paper can track the direction of the thunderstorm as it randomly propagates while dynamically changing its parameters, and thus, offers the possibility of using the system for practical purposes. In this paper, two types of neural networks are developed and their efficiencies are compared.

K e y w o r d s: thundercloud, lightning, dipole, electric charge in cloud, electric charge on ground, field mill, neural network

1 INTRODUCTION

Thunderstorm is a highly destructive force of nature and the timely tracking of the thundercloud direction is of paramount importance to reduce the property damages and human casualties. Annually, it is estimated that thunderstorm related phenomenon causes billion dollars of damages world wide through forest fires, shutdown of electrical plants and industries, property damages, *etc.* Although there are storm tracking mechanisms already in place, often such systems deploy complicated radar systems, the cost of which can only be afforded by bigger institutions. To the best of our knowledge no serious work or attempt has been made to look into the possibility of using field mills to track down the thunderstorm. There are, however, papers already published with regard to using field mills in identifying the lightning location and the charge polarity. X. Qie *et al*[2] have conducted a research to find out the lightning polarity in the Tibet region of China using field mills. W.J. Koshak [3] and his colleagues have developed a system that can retrieve the VHS source of lightning using the time of arrival distance of electric field signal at different field mill stations. K. Masugata [4] has developed a unique system comprising five field mills scattered around Toyama city to evaluate the electrostatic structure of thundercloud. Numerical simulation to estimate the charge distribution using the electrical field measured on the ground is carried out by K. Honda [5]. However, almost all the research activities related to field mills have been static analyses of thunderstorm such as the charge distribution for a particular time snapshot. The lack of dynamic analysis of thunderstorm has been largely due to the dynamic nature of thunderstorm, where its parameters are constantly changing. The method presented in this paper offers an integrated approach where all the dynamic parameters of the thundercloud, as it propagates are carefully considered. Additionally, this system uses only three field mills and uses the measured electric fields to analyze the direction of the developing storm. The neural network of appropriate complexity is trained to recognize the underlying directional pattern of the storm, without having to formulate complex equations which are quite often restrained by the model limitations. The rest of the paper is organized as follows: Section 2 outlines the development of the system. Section 3 talks briefly about the electrical nature of the storm. In Section 4, dynamic cloud model and the neural network design is explained, while Section 5 demonstrates the simulation result of the system and Section 6 concludes the paper.

2 OUTLINE OF THE SYSTEM

2.1 Motivations

The development of the system presented in this paper is motivated by the need to monitor the direction of thunderstorm as reliably and as cheaply as possible, while carefully considering the highly dynamic characteristics of the actual thunderstorm. This system relies only

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on a few field mills, and therefore provides a cheaper alternative for anybody interested in tracking the proper direction of the developing storm. Additionally, this system does not depend on the formulation of complex equations, and instead uses electric fields measured at three field stations.

2.2 Concept

The concept behind the system proposed in this paper is to use electric fields measured by field detectors from the dynamically changing parameters of thunderstorm. Through extensive simulation of dynamic thundercloud development, the neural network of suitable complexity is then trained to read the directional pattern of the thunderstorm as it propagates. The parameters chosen in the simulation are the actual values of the true thunderstorm observed through various experiments over the years.

3 ELECTRICAL NATURE OF THUNDERSTORM

3.1 Charge formation

Thundercloud is a dynamic collection of water vapours, ice, snow particles, hailstones, etc, which are constantly in motion due to gravity and convective forces. A typical thunderstorm extends to the height of 8–16 kilometres, at which the temperature is usually in the range −25 to −40 degree Celsius. At this freezing temperature, all the water moistures are frozen. Through a process not fully known yet, the positive and negative charges get separated within the cloud, with positive charges sitting on the top region and negatives usually in the bottom region of the cloud.

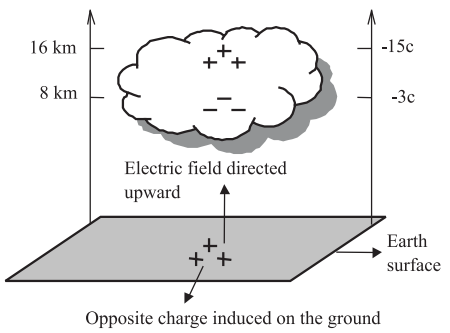

Fig. 1. Typical thunderstorm characteristics.

The bottom negative charges then induce equal and opposite positive charges on the earth surface, hence developing a potential gradient between the earth and the thunderstorm. During the developing of severe thunderstorm, this potential rises as high as 10 kV/m and when the air insulation between earth and cloud breaks down, a lightning is generated, releasing tremendous amount of energy to the ground.

3.2 Charge measurement

The electric filed existing between the storm and the ground can be measured by equipments such as electric meters or field mills. The concept behind the field mill or electric meter is to detect the change of the charge induced on the sensor electrode. At our lab, a unique type of electric meter is developed as shown in Fig. 2.

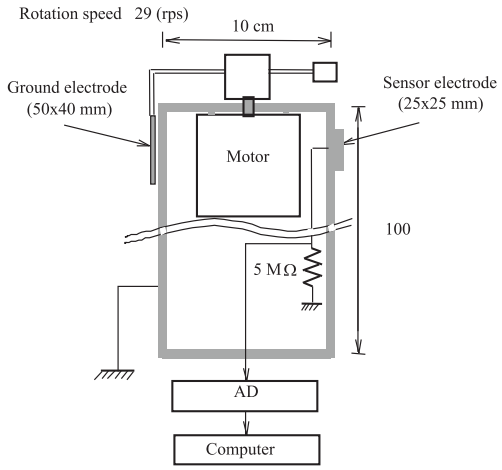

Fig. 2. Field mill developed at our lab.

The ground electrode is a rotating electrode, alternately shielding and exposing the sensor electrode, which is fixed. The opposite charge is induced on the sensor plate when it is not covered by the ground plates proportional to the thundercloud charges as given below by the formula:

$$\vec{E} = \frac{Q}{4\pi\varepsilon_0 r^2}\vec{a}_r \tag{1}$$

where r is the distance of the induced charge from the field mill. When the sensor plate is shielded by the rotating ground plate, the charge induced on it then flows to the earth. Shown below is the graphical illustration of current flow in the sensor electrode.

4 SIMULATION

4.1 Simulation setup for obtaining training data set

In theory, for a dipole charge configuration, its location and charge can be found using the formula shown below:

$$E = \frac{Qd}{4\pi\varepsilon_0 r^3}(2\cos\theta a_r + \sin\theta a_\theta\,. \tag{2}$$

Since in the above formula, there are six unknown variables (x, y, z, Q, d, θ), effectively six equations are needed to solve each variable. Therefore, it would take at least

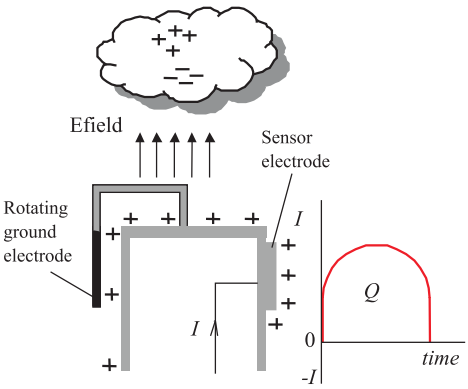

Fig. 3. Direction of current flow when the sensor electrode is exposed to electric field from the storm.

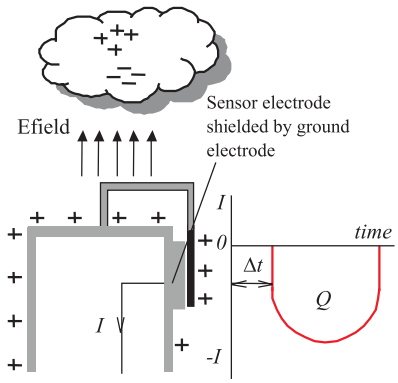

Fig. 4. Direction of current flow when the sensor electrode is shielded from the electric field.

Table 1. Simulation Parameters

$+Q$	2–50 Coulombs
$-Q$	2–50 Coulombs
Distance between $+Q$ and $-Q$	3–10 km
Cloud Height	8–15 km

six field mill stations to measure the electric fields. However, in real thunderstorm, Eq. 2 cannot be used since the magnitudes of the negative and positive charges are not only different, but their relative positions vary too with time. This dynamic nature of thunderstorm parameters has been the significant factor behind the failure of standard statistical methodology to determine the direction, as the equations variables are constantly changing.

A neural network on the other hand is an excellent pattern recognizer, and is notably suitable in reading the underlying feature of nonlinear data. However, since a neural network is only as good as input data, proper data selection is extremely critical. As a result, in order to truly represent the dynamic nature of the thundercloud, we

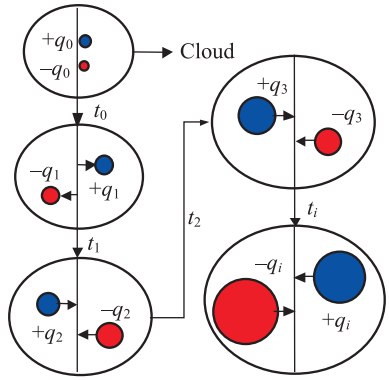

Fig. 5. Dynamic cloud model: The relative positions and magnitudes of the positive and negative charges change randomly with time (t_i) as the thundercloud propagates.

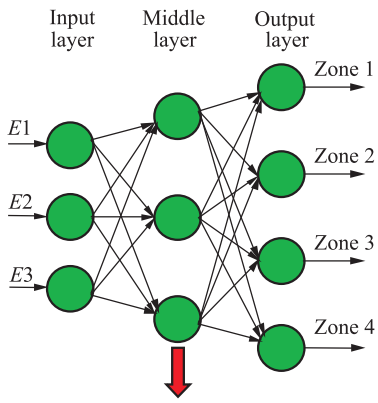

Fig. 6. Neural Network 1: Zone classification topology.

have developed a program that can seamlessly simulate the dynamic characteristics of the storm.

Figure 5 is a simple illustration of the simulation of the cloud movement. The positive charge is represented by the blue circle and the negatives by the red one. Their random positions are represented by the black arrow pointers, and their magnitudes by the size of the circle. For each random distribution of the charge and its position, the program calculates the electric fields for that particular time interval. Hence, the training data is obtained through such extensive simulation with neural network trained on these data to predict or classify storm location.

4.2 Simulation parameters

The simulation parameters used are the actual thundercloud parameters observed through various experiments. The distance between positive and negative charges is chosen to be between 3 km to 10 km, with the height of the cloud ranging from 8 km to 16 km from the earth surface. The magnitude of the dipole charge within the storm ranges from 2 coulombs to 50 coulombs.

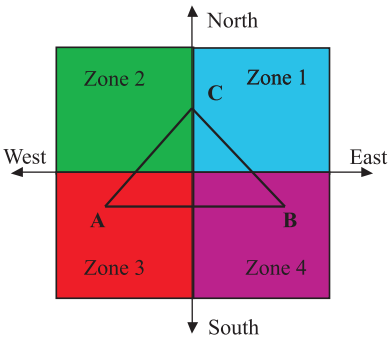

Fig. 7. Zone classification based on the coordinate system of field mill stations A, B, and C.

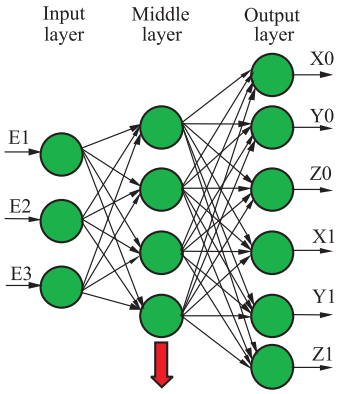

Fig. 8. Neural Network 2: Coordinate prediction topology

4.3 Calculation

The waveforms at different locations are calculated using the simple superposition formula as shown below:

$$E = \frac{+qz_+}{4\pi\varepsilon_0 r_{A0}^3} + \frac{-qz_-}{4\pi\varepsilon_0 r_{A1}^3} \tag{3}$$

where z_+ is the height of the positive charge from the ground and z_- is for the negative charge. ε_0 is the permittivity of the free space and r_{A0}, r_{A1} are the distances of positive and negative charges from the field mill at location A. Similarly, the electric field values at different locations as storm moves forward are calculated and saved.

4.4 Network selection and training

To suitably solve the problems that are unique to the thundercloud dynamics, the proper selection and design of network is vital to correctly read and learn such characteristics. Initially, two design approaches were taken in order to compare which network correctly learns, through least computational cost, the directional pattern from the given electric fields data.

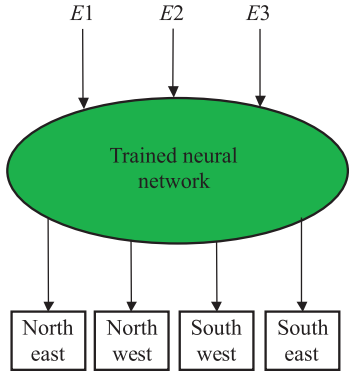

Fig. 9. Trained network. It takes three measured electric fields and then predicts the zone.

4.4.1. Network 1

The above network 1 classifies the direction of the developing storm into four fixed zones. The principle behind this network selection is that instead of trying to correctly predict the exact locations of the positive and negative charges, the network is trained to classify the direction into certain zones.

The disadvantage of such a classification neural system is that the direction is approximate. However, through simulation it is found that the training rate and accuracy level are a lot greater than those of the network trying to precisely identify the storm locations. This network has three inputs for the three measured electric fields, and four outputs for the four zones.

4.4.2 Network 2

The network 2 is designed to read the coordinate points of dipole charges from the waveform input. It has three inputs for the three measured electric fields, and six outputs for the coordinate points for positive and negative charges. Through training, it is found that 3 layers topology is found sufficient enough to train both the network 1 and network 2 to produce results of reasonable accuracy. The parameters for both the networks are summarized below:

4.5 Data and training

For the zone classification network 1, the middle layer nodes use unipolar sigmoid activation function (Eq. 4) and at the output layer, softmax activation is used (Eq. 5).

$$f(x) = \frac{1}{1 + e^{(-x)}}\,, \tag{4}$$

$$\sigma_i = \frac{e^i}{\sum_j e_j} \tag{5}$$

where σ_i is the output of a zone.

Table 2. Comparison of accuracy for zone classification against the number of hidden layers and number of samples

Network 1. Zone Classification					
No. of sample points	Accuracy for zone1	Accuracy for zone2	Accuracy for zone3	Accuracy for zone4	No. of hidden layers neurons
100	60.36%	59.11%	66.32%	49.90%	3
300	61.85%	64.45%	71.83%	50.19%	6
900	85.78%	79.20%	87.74%	75.99%	11
1000	90.65%	91.70%	93.78%	90.32%	15
2000	95.34%	94.89%	96.90%	95.01%	17

Table 3. Comparison of accuracy for coordinate points for positive and negative charge against the number of hidden layers and number of samples

Network 2. Coordinate prediction							
No. of sample points	Accuracy for X–Coordinate	Accuracy for Y–Coordinate	Accuracy for Z–Coordinate	Accuracy for X1–Coordinate	Accuracy for Y1–Coordinate	Accuracy for Z1–Coordinate	No. of hidden layers neurons
100	30.36%	39.11%	36.32%	39.90%	34.87%	31.03%	3
300	41.85%	44.45%	41.83%	40.19%	43.70%	44.45%	6
900	55.78%	49.20%	47.74%	50.99%	52.46%	54.01%	11
1000	59.65%	51.70%	53.78%	56.32%	54.64%	57.29%	15
2000	65.34%	60.89%	56.90%	62.01%	63.67%	64.20%	17

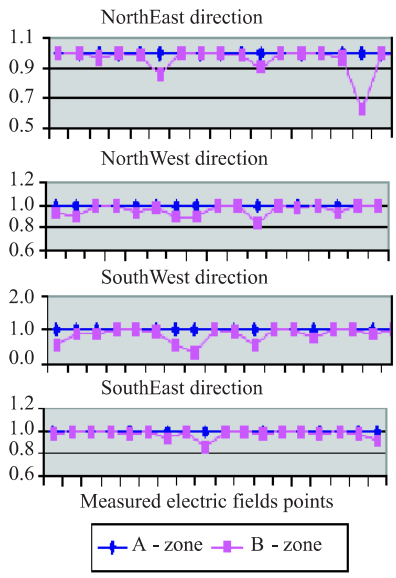

Fig. 10. Prediction of zone when thunderstorm was simulated to be moving in different directions.

The cost function used is the cross entropy for the weight updates, which is shown below:

$$S = \sum t_i \log \frac{t_i}{O_i} \tag{6}$$

where t_i and O_i are the values of the target and the actual output, respectively. For network 2, both the middle and output layer nodes use bipolar sigmoid activations (Eq. 7).

$$f(x) = -1 + \frac{2}{1 + e^{(-x)}} \,. \tag{7}$$

The error function used is the sum of square errors (Eq. 8).

$$S = \frac{1}{2} \sum_p \sum_I \left(t_i^{(p)} - O_i^{(p)}\right)^2 . \tag{8}$$

For both networks, the error is back propagated using the delta error methodology.

5 RESULTS

For the trained network, random samples of new training data are chosen and then tested. Results are displayed only for the zone classification network.

Although the training of the network is exhaustive, once it is trained properly, the network performs satisfactorily as can be seen from the simulation result above. The zone classification accuracy is more than 95 percent for all the zones as shown in Table 2.

5.1 Discussion

When the network 2 was trained to predict the actual coordinate points of the positive and negative charges, it was observed that it was relatively computationally more expensive than the simpler classification network 1. Additionally, it was found that the zone classification network far outperformed the coordinate prediction network with regard to output accuracy. Therefore, the zone classification network offers a quick mechanism to predict the

approximate direction of a storm, which would act as a warning device or simply monitor the region where the storm is developing. Accuracy comparisons between the two networks with respect to the number of hidden layers and training samples are tabulated in Table 2 and Table 3.

6 CONCLUSION

¿From the simulation results displayed above, we can state that a neural network of suitable complexity can be successfully trained to read the highly dynamic characteristics of the developing storm, and then correctly predict the location of a thunderstorm zone from the measured electric fields at three field stations. Additionally, the system presented in the paper can be built using only few field mills, and does not require a complicated formula, but instead learns through training. In conclusion, this paper attempts to find cheaper alternative for thunderstorm tracking based on zone classification using only three field mills. The philosophy behind this approach is to provide affordable mechanism for smaller institutions or individuals for quick monitoring of the developing storms or offer possibility to conduct other thundercloud related researches such as the dynamic charge distribution within the cloud, the work of which is currently underway, without the need for expensive system. For practical utility in meteorology, our system can offer cheaper option besides sophisticated radar system, although with the latter undoubtedly having superior pin pointing storm tracking effectiveness as against our zone classification approach.

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