Fire Detection Using a Dynamically Developed Neural Network

Magy Kandil [1], May Salama [2], Samia Rashad [3]
[1] Authority of Atomic Energy-Egypt Cairo, Egypt
[2] Shoubra faculty of Engineering, Cairo, Egypt
msalama@megacom-int.com

Abstract— **Early warning systems are critical in providing emergency response in the event of unexpected hazards. Cheap cameras and improvements in memory and computing power have enabled the design of fire detectors using video surveillance systems. This is critical in scenarios where traditional smoke detectors cannot be installed. In such scenarios, it has been observed that the smoke is visible well before flames can be sighted. This paper proposes a method to detect fire flame and/or smoke in real-time by processing the video data generated by ordinary camera monitoring a scene. The objective of this work is recognizing and modeling fire shape evolution in stochastic visual phenomenon. It focuses on detection of fire in image sequences by applying a hybrid algorithm that depends on optimizing the structure of a feed forward neural network. Fire detection experiments using various algorithms were carried. Results show that the proposed algorithm is very successful in detecting fire and/or smoke.**

Keywords- Fire detection, neural network, back-propagation, canny edge, wavelet .

I. INTRODUCTION

Automatic fire detection systems play a major role in the early detection and response of unexpected fire hazard scenarios. Various researches have been carried out in this scope. For example, three commercially available video based fire detection systems were tested against conventional spot systems in a ship board scenario and found that the video based systems were far more effective than flame detection [1]. Most of the flame detection systems are either based on pixel intensity recognition or on motion detection. A comprehensive work on flame detection using wavelets and intensity based approaches was carried out in [2]. A new method of flame detection was presented in [3] using a general color model to develop a rule based approach. These methods are targeted for flame detection and in general made use of the pixel color properties of the flame. A non-linear classification method using support vector machines and luminescence maps was presented showing that the method is robust in several scenarios [4]. A rule based system to detect smoke based on pixel intensity was proposed in [5]. Another method for smoke detection used a single stage wavelet energy and a back propagation neural network on a small dataset. The system required high processing power, which is unavailable in CCD camera networks [6]. A Bayesian framework was presented in [7] for smoke motion detection using the wavelet energy of an 8 _ 8 pixel block and intensity of the pixels. While in [8] a support vector machine based approach using motion detection as the feature to detect the smoke contour was proposed, a block by block approach based on chrominance and motion orientation was reported in [9]. The chrominance based methods have a disadvantage in their dependence on the color of smoke. Also, the motion estimation algorithm is very time consuming in the context of smoke detection.

Three commercially available video based fire detection systems were tested against conventional spot systems in a ship board scenario and found that the video based systems were far more effective than flame detection [9]. These systems are economically viable as CCD cameras are already available for traffic monitoring and surveillance applications. Importantly, it is often observed that in in- and out-door scenarios, smoke is visible before the fire itself. This motivates us to build a system which detects smoke in the absence or presence of flame from a single frame of video. The work in this paper is based on the characterization and detection of smoke observable from low quality fixed video surveillance. The method is independent of atmospheric conditions at the time of filming: temperature, wind speed, wind direction and the time of the day. Artificial Neural Networks (ANNs) have advantage to any other artificial learning methods, since they are able to deal with several data types. The back-propagation (BP) algorithm is one of the most common supervised training methods. The main attribute, which distinguishes BP from traditional econometric methods, is its ability to generate non-linear relationships between a vector of input variables and a dependent. BP also has the ability to model any complex system. Although BP training has proven to be efficient in many applications, its convergence tends to be slow, and yields to sub-optimal solutions since it might converge to local minima.

The major algorithms to speed up training and reduce convergence to local minima are based on adapting the weights, learning rate, step size and bias to dynamically adapt BP algorithm during its training cycle. There are a number of review papers in this area ([10], [11], [12]). Optimizing the number of hidden layers/neurons for BP contributes to reducing the learning time.

In this paper, fire detection algorithm is based on combining the work in [13] and [14]. It not only detects fire and smoke colored moving regions in video but also analyzes the motion of such regions in wavelet domain for object estimation. Spatial wavelet analysis makes it possible to detect high-frequency behavior inside fire regions. Variation in energy of wavelet coefficients is an indicator of activity within the region. On the other hand, a fire-colored moving object will not exhibit any change in values of wavelet coefficients because there will not be any variation in fire-colored pixel values. A neural network is defined by means of hybrid algorithm [14] that optimizes the number of hidden layers and their neurons. The initial weights are determined by an evolutionary algorithm. This NN is used for training and testing.

The paper is organized as follows: Section II represents issues of fire detection. Section III discusses the experimental results. Section IV concludes the paper with discussion.

II. NEURAL NETWORK DEVELOPMENT

The shape of a fire region is represented in terms of the content of the region edges using canny edge detection [15] applied at the sequences of images for verifying the edges of the fire patterns. The temporal changes in these edges are used for learning the temporal signatures of the fire region. The learning is a framework for global and local searches algorithms to reach the global minimum.

Figure 1. Different fire patterns

A. The optimized Back Propagation algorithm

The typical performance function that is used for training BP feed forward neural networks is the mean sum of squares of the network errors. It is possible to improve generalization if we determine the number of neurons in the hidden layer N according to the performance function. Using this function will cause the network to have smaller weights and biases, and this will force the network response to be smoother and less likely to overfit. The issue of determining the number of the neurons in the hidden layers and determining the initial weights, for adjusting the ANN architectures, is difficult to achieve for the performance parameter. If we make this parameter too large, we may get overfitting. If the ratio is too small, the network will not adequately fit the training data.

The applied algorithm adapts the number of the hidden layers and their neurons in the combination of global and local searches algorithms then, exhibits the optimality of EANN's weights with respect to minimum errors. It usually has many local minima, but which of these local minima indicates the occurrence of overfitting? It is desired to have a quantitative measure of overfitting based on the training error so that we decide if the learning can be improved by adding hidden neurons or not. When error is smaller than the threshold, computing the error signal and the learning process is stopped.

The applied algorithm initiates with one hidden layer and 2 neurons then layers/neurons are added according to certain calculation. Weights are then evaluated using evolutionary algorithm.

Each chromosome is constructed from the weights of ANN and the fitness of the chromosome is the performance of the neural network on a selected training dataset. The fitness/cost function is considered as:

$$f(x) = (1/Q)(\Sigma y_{real} - \Sigma y_{net}) \qquad (1)$$

It is used to evaluate the MSE (Minimum Squared Error) that would be minimized by the proposed algorithm. Q denotes the number of samples, while y_{real} is the real output for each input x and y_{net} is the desired network output. In this approach, in order to overcome the problem of local minima and fast convergence, the fitness/cost function has been minimized for number of the hidden layer/neurons selection.

The performance of a function approximation is measured by training error and testing error. Once the testing performance stops improving with further increase of the number of hidden neurons, it is possible that overfitting occurs. Therefore, the stopping criterion is set so that, when the testing set error starts to increase, or equivalently when training error and testing error start to diverge, the optimal value of the number of hidden neurons is reached.

The applied algorithm improves the generalization of the BP algorithm since it is trained using EA's to initialize the initial weights in the BP network with optimized number of the hidden layers and their neurons. This avoids repeatedly determining unpromising local minima, and avoids computationally expensive descent algorithms from random starting points.

In the third stage, the spatial wavelet is applied according to the criteria stated in [13]. The wavelet analysis based steps of the algorithm are very important in fire and smoke detection because they distinguish ordinary motion in the video from motion due to turbulent smoke and fire.

III. EXPERIMENTAL RESULTS

The applied new hybrid algorithm is implemented on a PC with an Intel Pentium 4.2, 40 GHz processor. It is tested for a large variety of conditions.

ANNs BP are trained using the new hybrid, the Gradient-descent and Evolutionary algorithms for 150 epochs (learning rate = 0.05, momentum = 0.5), in order to compare the points in decision space. Hidden logistic sigmoid activation functions are used The training set was 300 fire patterns (or 200/100 with train/test) for the test function.

The video clips used in the experiments are real-world image sequences. They were taken from a random selection of commercial / training video clips. They include different types of fires such as residential fire, warehouse fire, and wild fire. We used images captured at daytime, dusk and nighttime to evaluate system performance under different lighting conditions. We also used other image sequences containing objects with fire-like appearances such as sun and light bulbs as negative examples. Most image sequences involve camera motion. The video clips that were used contain a total of the image frames in sequences. Figure 1 shows some selected fire images used in our experiments. The contours depicted in the images are the detected fire region contours. As seen in some images, fire sometimes complements with smoke nearby. Canny edges models of fire regions define boundaries between fire and smoke.

Our potential region extraction algorithm extracts almost all the true fire regions. It also extracts other fire like objects. What it does not extract are mainly spark like, small fire regions emanating from the main fire regions. In the test data, the algorithm extracted the total of fire like region contours, from true fire region contours. These contours are used for testing of the most fire region.

A. The learning in the applied algorithm (optimized BP algorithm)

The typical performance function that is used for training BP feed forward neural networks is the mean sum of squares of the network errors.

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad (2)$$

Figure 2 represents the training performance for the Gradient-decent only while figure 3 depicts the training performance for the Evolutionary algorithm alone and figure 4 represents the training performance of [13]. Figure 5 represents the training performance for the applied new hybrid algorithm.

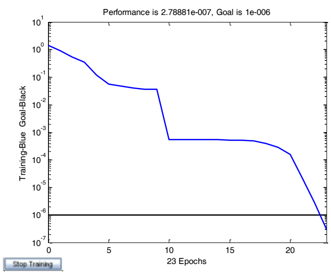

Figure 2. Training performance for Gradient-descent algorithm.

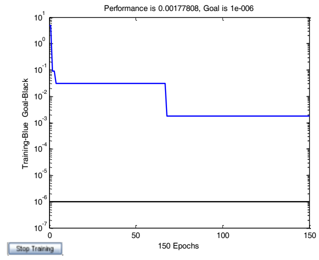

Figure 3. The training performance of the Evolutionary algorithm only.

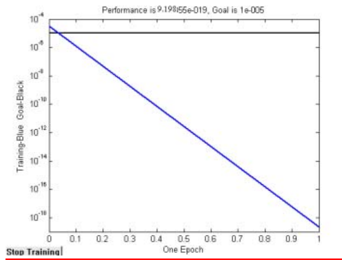

Figure 4. Training performance of the hybrid algorithm in [13].

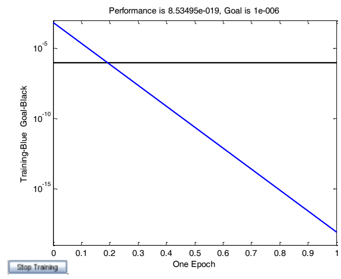

Figure 5. Training performance of the applied hybrid algorithm.

B. The testing in the new hybrid algorithm

The optimized Back-Propagation algorithm running the testing of proposed neural network on the moving fire pattern is applied then the spatial wavelet is applied for providing the final fire detection.

Table 1 represents the validation performance for the applied hybrid algorithm [14], the Gradient-descent, the Evolutionary algorithm and the proposed algorithm stated in [13] after testing them with 100 sampling of fire patterns.

TABLE I. THE PERFORMANCE CPU EXECUTION TIME AND HIT RATE PARAMETERS

Algorithm name	Average CPU time	Hit rate
Gradient-descent	0.160	84%
Differential Evolutionary	0.230	76%
The first hybrid algorithm [13]	0.002	97%
The new hybrid algorithm [14]	0.001	98%

From table 1, the new optimized BP network has the best recognition accuracy with Hit rate= 98%. The applied hybrid algorithm [14] increases the generalization of the BP and reduces the recognition time.

The applied hybrid structural Back Propagation algorithm [14] and the spatial wavelet algorithm form a new hybrid fire recognition algorithm for speeding up the training, reducing convergence to local minima and improving the non-linear generalization approach of BP. The hybrid structural optimizes BP by adapting the number of the hidden layers and their initial weights to dynamically adapt BP algorithm according the input and output data during its training cycle. The hybrid algorithm adapts the Back-Propagation by combining global and local searches algorithms to determine the local minimum of the Gradient–descent within the Differential Evolutionary Neural Networks domain within the optimum hidden layers for recognizing the different fire patterns, with little or no a priori knowledge of the form.

IV. CONCLUSION

Real time fire recognition is achieved by applying a dynamically developing a feed forward neural network with optimized structure. It was shown that the developed network algorithm experimental results outperformed the 3 above mentioned algorithms.

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