A NEW HYBRID ALGORITHM FOR FIRE VISION RECOGNITION

*Magy Kandil ** May Salama
*Authority of Atomic Energy-Egypt
**Shobra Faculty of Engineering - Banha university

Abstract: **This paper proposes a novel method to detect fire and/or smoke in real-time by processing the video data generated by an 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 new hybrid algorithm that depends on optimizing the back-propagation algorithm, after canny edge detection, for determining the smoke and fire boundaries. Another clue is used in the fire detection algorithm that detects smoke and fire flicker by analyzing the video in the wavelet domain. Color variations in flame regions are detected by computing the spatial wavelet transform of moving fire-colored regions. Experimental results show that the proposed algorithm is very successful in detecting fire and/or smoke.**

***Index Terms*:** **Fire recognition, neural network, back-propagation, canny edge, wavelet.**

I. INTRODUCTION

Conventional point smoke and fire detectors are widely used in buildings. They typically detect the presence of certain particles generated by smoke and fire by ionization or photometry. Alarm is not issued unless particles reach the sensors to activate them. Therefore, they cannot be used in open spaces and large covered areas. Video based fire detection systems can be useful to detect fire in large auditoriums, tunnels, atriums, etc. The strength of using video in fire detection makes it possible to serve large and open spaces. In addition, closed circuit television (CCTV) surveillance systems are currently installed in various public places monitoring indoors and outdoors. Such systems may gain an early fire detection capability with the use of fire detection software processing the outputs of CCTV cameras in real time.

Image and video content understanding and analysis methods have been studied by many researchers including [1,2,3,4]. Content based understanding methods have to be designed according to the specific application. Fire detection in video is such an application that needs specific methods. There are several video based fire and flame detection algorithms in the literature [5,6,7,8,9]. These algorithms make use of various visual signatures including color, motion and geometry of fire regions. Healey et al.[7] use only color clues for fire detection. Phillips et al.[9] use pixel colors and their temporal variations. Chen et al.[5] utilize a change detection scheme to detect flicker in fire regions. In Fastcom Technology [6], Fast Fourier Transforms (FFT) of temporal object boundary pixels are computed to detect peaks in Fourier domain. Liu and Ahuja [8] also represent the shapes of fire regions in Fourier domain. An important weakness of Fourier domain methods is that flame flicker is not purely sinusoidal but random. Therefore, it is hard to detect peaks in FFT plots. In addition, Fourier Transform does not carry any time information. In order to make FFTs also carry time information, they have to be computed in windows of data. Hence, temporal window size is very important for detection. If the window size is too long, then one may not observe peakness in the FFT data. If it is too short, then one may completely miss cycles and therefore no peaks can be observed in the Fourier domain.

The fire recognition algorithm described in this work, includes recognition of evolving region shapes. A survey about static shape analysis methods can be found in [10]. These methods implicitly assume all shapes have to be observed before learning the subspace or the manifold. Thus, they are very likely to fail to recognize objects with stochastic appearances, such as fire. The shapes of fires with different burning materials could be of a large degree of variability. These methods also do not have good representation of shapes, evolution and their learning. Our method is more relevant to works on modeling and recognition of deformable shapes/objects [11,12].

Neural networks (NNs) have advantage to any other artificial learning methods, since they are able to deal with several data types. The back-propagation (BP) algorithm [13] 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. Back-propagation 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 suboptimal solutions since it converges to local minima [10].

Attempts to speed up training and reduce convergence to local minima have been made in many context of gradient descent such as [14,15,16,17]. The major algorithms 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 (for example, Yao [16]), as well as methodology studies [17, 18].

One of the fundamental drawbacks of learning by Back-propagation gradient descent techniques is the

 978-1-4244-3861-7/09/$25.00 ©2009 IEEE

susceptibility to local minima during training. Recently, some authors have independently introduced new learning algorithms that are based on the properties of terminal attractors and repellers. These algorithms were claimed to perform global optimization of the cost in finite time, provided that a null solution exists.

In this paper, the parameters of the terminal attractor algorithm [19] are adapted to guarantee that the optimal solution is reached in a number of steps that is independent of the cost function using a wavelet based fire detection method in video. Our method 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. High-frequency analysis of moving pixels is carried out in wavelet domain. There is an analogy between our motion analysis in wavelet domain and the temporal templates of Davis and Bobick [1] and the motion recurrence images of Javed and Shah [3].

Wavelet transform is a time frequency analysis tool. One can examine an entire frequency band in the wavelet domain without completely losing the time information, Cetin and Ansari [20]; Mallat and Zhong [21]. Since the wavelet transform is computed using a sub-band decomposition filter bank, it does not require any batch processing. It is ideally suited to determine an increase in high-frequency activity in fire and flame colored moving objects by detecting zero crossings of the wavelet transform coefficients. Turbulent high-frequency behaviors exist not only on the boundary but also inside a fire region. Another novelty of the proposed method is the analysis of the spatial variations inside fire and flame colored regions. The method described in Fastcom Technology [6] does not take advantage of such color variations. 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.

The paper is organized as follows: Section II represents issues of designing the new hybrid algorithm. Section III discusses the experimental results. Section IV concludes the paper with discussion.

II. THE NEW HYBRID ALGORITHM

The proposed video-based fire detection algorithm consists of four steps:(i) Canny edge detection for determining moving pixels or regions in the current frame of a video, (ii) The optimized BP algorithm for learning the moving pixels in training part or for checking to see if they match the pre-specified fire colors that were learning in the testing part. (iii) Using the wavelet analysis in spatial domains to determine high-frequency activity within these moving regions. In the following sub-sections, each step of the proposed algorithm is explained in details.

A. Canny edge detection

Moving pixels and regions in the video are determined by using canny edge detection for the previous estimate of the background intensity value at all pixel positions. Other more sophisticated methods, including the ones developed by Bagci.[22] and Stau and Grimson [23] can also be used for moving pixel estimation. In our application, accurate detection of moving regions is not as critical as in other object tracking and estimation problems. We are mainly concerned with real-time detection of moving regions as an initial step in the fire and flame detection system. We choose to implement this suggested method because of its computational efficiency.

A fire in motion has a relatively static general shape (determined by the shape of burning materials) and rapidly changing local shape in the unobstructed part of the border. The lower frequency components of fire region boundary are relatively steady over time, and the higher frequency components change in a stochastic fashion. Accordingly, we use a stochastic model to capture the characteristic random motion of fire boundaries over time.

In our algorithm, the shape of a fire region is represented in terms of the content of the region edges using canny edge detection [24] 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, (Evolutionary and terminal attractor for improving the generalization of the BP algorithm, Gradient-descent training algorithms) to reach the global minimum.

B. Canny edge detection

In the first stage of the new algorithm, Canny operator [24] is applied (as showing figure1) to be an optimal edge detector, according to particular criteria (there are other detectors around that also claim to be optimal with respect to slightly different criteria). It takes as input a gray scale image, and produces as output an image showing the positions of tracked intensity discontinuities. The Canny operator works in a multi-stage process. First, the image is smoothed by Gaussian convolution. Then a simple 2-D first derivative operator (somewhat like the Roberts Cross) is applied to the smoothed image to highlight regions of the image with high first spatial derivatives. Edges give rise to ridges in the gradient magnitude image. The algorithm then tracks along the top of these ridges and sets to zero all pixels that are not actually on the ridge top so as to give a thin line in the output, a process known as *non-maximal suppression*. The tracking process exhibits hysteresis controlled by two thresholds: *T1* and *T2*, with *T1* > *T2*. Tracking can only begin at a point on a ridge higher than *T1*. Tracking then continues in both directions out from that point until the height of the ridge falls below *T2*. This hysteresis helps to ensure that noisy edges are not broken up into multiple edge fragments.

Figure 1 Different fire patterns

C. The optimized Back Propagation algorithm

The training algorithm in the BP can be viewed as the optimization of the error with respect to the weights. A local optimization technique is almost always employed for training and as a consequence our training algorithm usually reaches a local minimum. Furthermore, the particular local minimum will determine the quality of the neural network solution. On one hand, if the minimum is close to the global one, the performance will be acceptable and the training will be successful. On the other hand, there are minima that result in poorly trained networks and unsuccessful convergence.

The factors that determine the final local minimum are mainly the particular weight initialization and the training algorithm. Furthermore, the weight initialization influences the speed of convergence, the probability of convergence and the generalization.

Under the point of speed of convergence, a particular initialization value can be closer or farther than another different value to the same final local minimum. So, the number of iterations of the training algorithm and the convergence time will vary depending on the weight initialization. Considering the probability of successful convergence, it is clear that a particular weight initialization value can lead the training algorithm to an acceptable local minimum or to a false local minimum. In one case, we will consider that the neural network converged successfully, and in the other, that the neural network did not converge. The probability of successful convergence depends on the weight initialization scheme.

Finally, the third effect is the generalization performance of the neural network. Consider the case of two successful convergences, but two different local minima were reached. In this case, we have considered that the performance of both local minima is acceptable, but it can be different and therefore the generalization performance will also be different.

Alternatively, the detection of more than one minimiser can be achieved by modifying the objective function, so as to contain information concerning the position of the previously detected minimisers in its new form. In this context, Goldstein and Price proposed an efficient algorithm for the minimization of algebraic functions, which exploits higher order derivatives of the involved polynomials [25]. The technique was later generalized for non-polynomial problems using a transformation, which involves the Hessian of the objective function. However, the numerical, computation of the Hessian is not always feasible and in any case, it is computationally expensive. Thus, in its general form, this approach is not widely applicable. Similar algorithms were proposed by Laurence [26], but, after the detection of a few minimisers, the objective function becomes very flat and, thus, minimization is becoming increasingly difficult. An interesting approach is the *tunneling* technique, proposed by Hamacher *et al.* [27] for one-dimensional (1-D) functions, and generalized or the multidimensional case by Wenzel [28], and Zhijun Wu. [29]. However, the hyper surface constructed by the tunneling algorithm becomes very flat as the number of the detected minimisers increases, hindering further exploration of the search space, after the detection of a few minimisers. A different technique for avoiding local minimisers is *simulated annealing* that combines local search with Monte Carlo techniques and simulates the annealing processes which are used to reveal the low temperature state of materials [19].

From the above discussion, we can conclude that the weight initialization is a very important issue. However, the usual way to initialize the weights is at random. This fact seems to be paradoxical because we leave an important topic at random. In the bibliography, we can find several papers on weight initialization for the Multilayer Feedforward. In some of them a new weight initialization scheme is proposed.

Therefore, the first stage, in the new hybrid structural to form an optimizing BP, is initializing the weights using the Evolutionary Algorithm [30]. ENN enables the parallel evolution of a population of ENN models which exhibit estimated optimality with respect to multiple functions of errors by using terminal attractor. This stage is very important to speed up the training, reduce convergence to local minima and improving the non-linear generalization approach of BP. The hybrid structural optimizes and adapts the weights, and biases to dynamically adapt BP algorithm during its training cycle. The new hybrid algorithm adapts by implementing the Evolutionary Neural Networks domain for initializing the weights to recognize the different fire patterns, with little or no a priori knowledge of the form [32].

The second stage of the optimized BP algorithm is adapting the terminal attractor method and applying it for optimizing the weights of the BP to skip from the local minimum and enforce them to global minimum. Each pixel $x_n[k,l]$ of the binary mask fire is fed to a two stage-filter bank as shown in Fig. 2. The signal $x_n[k,l]$ is a one-dimensional signal representing the temporal variations in color values at location $[k,l]$ in the nth frame. The two-channel sub-band decomposition filter bank is composed of half-band high-pass and low-pass filters with filter coefficients {_0.25, 0.5,_0.25} and {0.25, 0.5, 0.25}, respectively, as shown in Fig. 2. The filter bank produces wavelet sub-signalsd$_n[k,l]$ and e$_n[k,l]$. Absolute values of low–high, high–low and high–high wavelet sub-images are added to obtain these images. A decision parameter v_4 is defined for this step, according to the energy of the wavelet sub-images:

$$v_4 = \frac{1}{MxN}\sum_{K,l}|x_{lh}[k,l]|^2 + |x_{hl}[k,l]|^2 + |x_{hh}[k,l]|^2$$

Where: $x_{lh}[k,l]$ is the low–high subimage, $x_{hl}[k,l]$ is the high– low subimage, and $x_{hh}[k,l]$ is the high–high subimage of the wavelet transform, respectively, and $M \times N$ is the number of pixels in the fire-colored moving region. If the decision parameter of the fourth step of the algorithm, v4, exceeds a threshold, then it is likely that this moving and fire-colored region under investigation is a fire region.

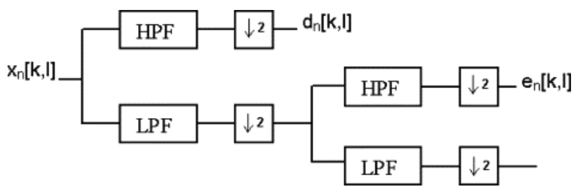

Fig. 2: A two-stage filter bank. HPF and LPF with filter coefficients {-0.25, 0.5, -0.25} and {0.25, 0.5, 0.25}.

The images in figs. 4 and 5 are obtained after a single stage two dimensional wavelet transform that is implemented for the original images shown in fig. 3.

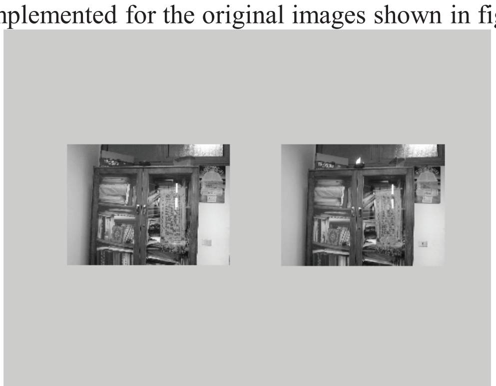

Fig.. 3 The original images.

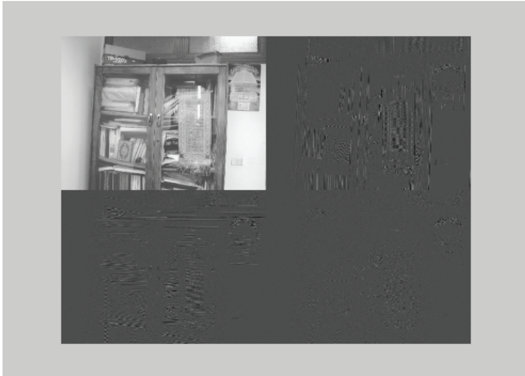

Fig. 4 the spatial wavelet for image 1

Fig. 5 The spatial wavelet for image 2

The spatial wavelet analysis is computationally an efficient scheme because a multiplier less filter bank is used for both 1-D and 2-D wavelet transforms computation. Low-pass and high-pass filters have respectively {_0.25, 0.5,_0.25} and {0.25, 0.5, 0.25}. They can be implemented by register shifts without performing any multiplications. 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. EXPERMNTAL RESULTS

The proposed 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.

Three NNs (BP) are trained using the new hybrid, the Gradient- descent and Evolutionary algorithms for 500 epochs (learning rate = 0.05, momentum = 0.5), in order to compare the points in decision space. (one hidden layer with 5 hidden logistic sigmoid activation functions). 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 new hybrid algorithm (optimized BackPropagation algorithm)

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

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

Three NNs (BP) are trained using the new hybrid, the Gradient-decent and Differential Evolutionary algorithms for 500 epochs using (learning rate = 0.05, momentum = 0.5), in order to comparison point in decision space. (one hidden layer with 5 hidden logistic sigmoid activation functions). The training set was 300 fire patterns (or 200/100 with train/test) for the test function.

Fig. 6 represents the training performance for the Gradient-decent only. Fig. 7 represents the training performance for the Evolutionary algorithms only. Fig. 8 represents the training performance for Gradient-decent and the Evolutionary algorithms. Fig. 9 represents the training performance for the new hybrid algorithm, after training it with 200 samplings of fire patterns.

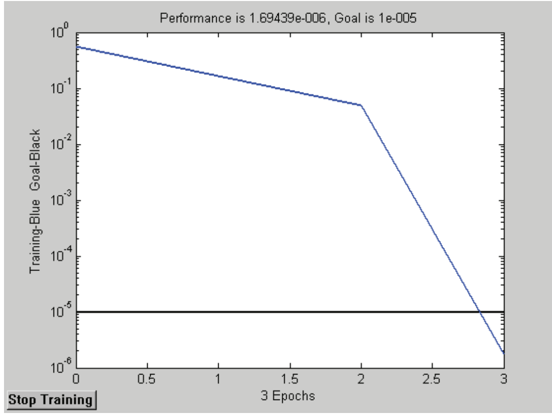

Fig. 6 The training performance for Gradient-descent algorithm only.

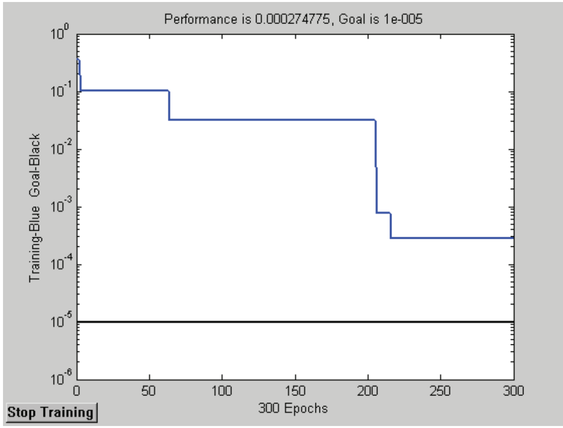

Fig. 7 the training performance of the Evolutionary algorithm only.

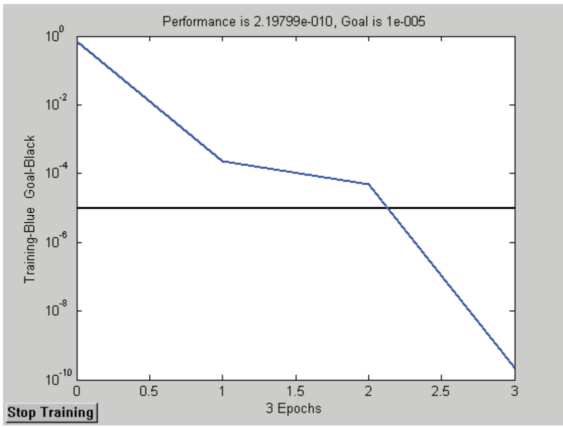

Fig. 8 the training performance for the Gradient- descent + the Evolutionary algorithms.

Table 1 represents the comparison between the new hybrid algorithm, the Gradient-descent and Evolutionary algorithms

Algorithm name	Gradient	Mean Error	Standard Deviation	Success
Gradient Descent	2.81758e-005	1.69439e-006	5.0766e-009	84%
Differential Evolutionary	2.1465e-004	0.000274775	7.786e-006	77%
Gradient Descent +Differential Evolutionary	1.6547-010	2.19799e-010	2.456e-010	90%
The new hybrid algorithm	7.6746e-012	2.19855 e-019	6.9683e-0012	96%

Table 1: Comparison between the training performance for four algorithms

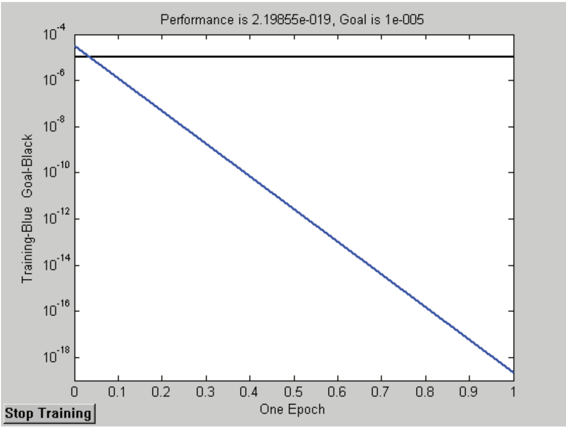

Figure 9 the training performance of the new hybrid algorithm.

Figure 10 represents the comparison of the training performance between the new hybrid algorithm, the Gradient-descent and Evolutionary algorithms where the solid line represents the target recognition, the dashed line represents the performance (output) after training by BP only and the dot represents the performance after training by Evolutionary only. The dashed with dots represent the performance after training with the new hybrid algorithm. As shown in figure 10, the performance of the new hybrid algorithm is almost fiddle with the target

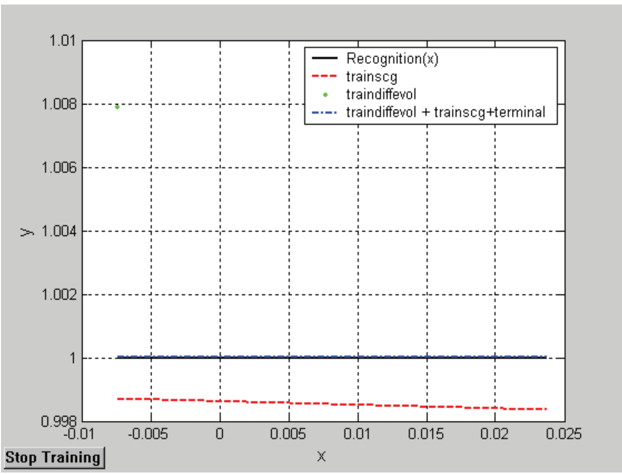

Figure 10 Comparison between the new hybrid algorithm,, the Gradient- descent and Evolutionary algorithms.

.

From Figure 6, 7, 8, 9 and 10 and table 1, the new hybrid algorithm has the best (less) Gradient, MSE and standard deviation. In addition, it is faster and it has best success 96% to reach the goal. Thus, the new hybrid algorithm reduces the training time since it converges very fast (one epoch) and reaches to the global minimum.

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 2 represents the validation performance for the new hybrid algorithm, the Gradient-descent and Evolutionary algorithms after testing them with 100 sampling of fire patterns.

Table 2. The performance CPU execution time and Hit rate parameters

Algorithm name	Average CPU time	Hit rate
Gradient-descent	0.160	84%
Differential Evolutionary	0.430	76%
Gradient Descent + Differential Evolutionary	0.05	88%
The new hybrid algorithm	0.002	97%

From table 2 the new optimized BackPropagation has the best recognition accuracy (Hit rate) 97%. The new hybrid algorithm increases the generalization of the NNs and reduces the recognition time.

The new hybrid structural optimized BackPropagation algorithm 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 and adapts the *objective error function* to dynamically adapt BP algorithm 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 and Terminal attractor algorithms for recognizing the different fire patterns, with little or no *a priori* knowledge of the form.

IV. CONCLUSION

The new structural forms a new hybrid real time fire recognition algorithm by optimizing BP algorithm for speeding up the training, reducing convergence to local minima and improving the non-linear generalization approach. The hybrid structural optimizes and adapts the parameters of the terminal attractor algorithm for optimizing the objective function of the BP algorithm during its training cycle. The new hybrid algorithm optimizes the BP by combining global and local searches algorithms to determine the local minimum of the Gradient–descent within the Evolutionary Neural Networks domain for recognizing the fire or smoke patterns.

In addition, the new hybrid algorithm uses the spatial wavelet algorithm for the analysis of moving regions containing fire mask pixels to capture color variations in pixel values to determine the fire patterns in the images.

REFRENCES

[1] Davis, J.W., Bobick, A.F., 1997. "The representation and recognition of action using temporal templates", In: Proc. IEEE Computer Vision and Pattern Recognition Conference (CVPR_97), pp. 928–934.

[2] Haering, N., Qian, R.J., Sezan, M.I., 2000. "A semantic event-detection approach and its application to detecting hunts in wildlife video". IEEE Trans Circ. Syst. Video Technol. 10 (6), 857–868.

[3] Javed, O., Shah, M., 2002. "Tracking and object classification for automated surveillance". In: Proc. European Conf. on Computer Vision (ECCV_02), pp. 343–357.

[4] Naphade, M.R., Kristjansson, T., Frey B., Huang, T. S., 1998. "Probabilistic multimedia objects (multijects): A novel approach to video indexing and retrieval in multimedia systems". In: Proc. IEEE Internat. Conf. on Image Processing, ICIP _98, pp. 536–540.

[5] Chen, T., Wu, P., Chiou, Y., 2004. "An early fire-detection method based on image processing". In: Proc. IEEE Internat. Conf. on Image Processing, ICIP _04, pp. 1707–1710.

[6] Fastcom Technology SA., 2002. Boulevard de Grancy 19A, CH-1006

[7] Healey, G., Slater, D., Lin, T., Drda, B., Goedeke, A.D., 1993. "A system for real-time fire detection". In: Proc. IEEE Computer Vision and

[8] Liu, C.B., Ahuja, N., 2004. "Vision based fire detection". In: Proc. Internat. Conf. on Pattern Recognition (ICPR_04), vol. 4, pp. 134–137.

[9] Phillips III, W., Shah, M., Lobo, N.V., 2002. "Flame recognition in video. Pattern Recognition" Lett. 23 (1–3), 319–327.

[10] H. Lutkepohl. "*Introduction to Multiple Time Series Analysi*s" ,Springer Verlag, 1991.

[11] S. Mori, H. Nishida, and H. Yamada, "*Optical Character Recognitio*n", John Wiley & Sons, 1999.

[12] W. Phillips, III, M. Shah, and N. Lobo. "Flame recognition in video". In *Fifth IEEE Workshop on Applications of Computer Visio*n, pages 224–229, December 2000.

[13] G. Schwarz. "Estimating the dimension of a model". *Annals of Statistic*s, 6:461–464, 1978.

[14] V. N. Vapnik. "*The Nature of Statistical Learning Theor*y. Springer", second edition, 1999.

[15] M.-H. Yang and N. Ahuja. "Gaussian mixture model for human skin color and its application in image and video databases". In *Conference on Storage and Retrieval for Image and Video Databases (SPIE 99*), volume 3656, pages 458–466, 1999.

[16] X. Yao, "Evolution of connectionist networks," in *Preprints Int. Symp. AI, Reasoning & Creativit*y, Queensland, Australia, Griffith Univ., 1991, pp. 49–52.

[17] *Int. J* ,"A review of evolutionary artificial neural networks," *Intell. Syst*., vol. 8, no. 4, pp. 539–567, 1993.

[18] J. *Int.*, "Evolutionary artificial neural networks," *Neural Syst*., vol. 4, no. 3, pp. 203–222, 1993.

[19] M. Binachini, S. Fanelli, M. Gori "Optimal algorithm for well-conditioned nonlinear systems of equation", www: http://www-dsi.ing.unifi.it/~marco.

[20] Cetin, A.E., Ansari, R., "Signal recovery from wavelet transform maxima". IEEE Trans. Signal Process. 42, 194–196. 1994.

[21] Mallat, S., Zhong, S., 1992. "Characterization of signals from multiscale edges". IEEE Trans. Pattern Anal. Machine Intell. 14 (7), 710–732.

[22] Bagci, M., Yardimci, Y., Cetin, A.E., 2002. "Moving object detection using adaptive subband decomposition and fractional lower order statistics in video sequences". Signal Process., 1941–1947.

[23] Stauffer, C., Grimson, W.E.L., 1999. "Adaptive background mixture models for real-time tracking". In: Proc. IEEE Computer Society Conf. on Computer Vision and Pattern Recognition, vol. 2, pp. 246–Pattern Recognition Conference (CVPR_93), pp. 605–606.

[24] M. Sonka, V. Hlavac, and R. Boyle, "Image Processing, Analysis and Machine Vision" , PWS - an Imprint of Brooks and Cole , 2002.

[25] J. Sprave, "Linear neighborhood evolution strategies", In Proc. of the 3-rd Annual Conf. on Evolutionary Programming, San Diego, CA, World Scientific 1994.

[26] Laurene F., "Fundamentals of Neural Network" New York: Thomas Publishing Co., 1999.

[27] K. Hamacher, "Adaptation in Stochastic Tunneling Global Optimization of Complex Potential Energy" Landscapes, Europhys.Lett. 74(6):944, 2006.

[28] K. Hamacher and W. Wenzel. "The Scaling Behaviour of Stochastic Minimization Algorithms in a Perfect Funnel Landscape". Phys. Rev. E, 59(1):938-941, 1999.

[29] Zhijun Wu. "The effective energy transformation scheme as a special continuation approach to global optimization with application to molecular conformation". Technical Report, Argonne National Lab., IL (United States), November 1996.

[30] X. Yao and Y. Lin A new evolutionary system for evolving artificial neural networks, Transactions on Neural Networks, 8(3): 694-713, 1997.

[31] R. Storn, "Differential Evolution-A simple and efficient adaptive scheme for global optimization overt continuous spaces", 2005.