Forest-fire detection by means of lidar

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ABSTRACT: The fundamentals of smoke sensing based on a single-wavelength lidar technique are discussed and experimental results of forest-fire smoke detection using a Nd:YAG laser lidar reported. The investigations include tracing the smoke-plume evolution, estimating the alarm promptness, smoke-plume location and profiling via azimuth scanning, and detection of fires out of line-of-sight and in extremely unfavorable visibility conditions. The possibility of automated lidar-based fire surveillance is discussed on the basis of the results obtained. Finally, a neural-network technique for the automatic recognition of smoke-plume signatures in lidar signals is considered and several neural-network architectures and learning rules tested and compared. The best neural-network algorithm lead to 22 false alarms and 27 misdetections out of ~1.7×10⁴ patterns containing in 231 complete lidar signals, of which 122 had smoke signatures.

1 INTRODUCTION

Lidar is a promising tool for forest-fire monitoring because, due to its very high sensitivity and spatial resolution, this active detection technique enables efficient location of small smoke plumes during both day and night and over a considerable range. By using suitable scanning methods, very accurate location of the smoke source is also possible. Monitoring of smoke produced by power plants and factories was amongst the first applications of lidar (Hamilton, 1969; Hinkley, 1976). Since those early experiments, interest in lidar has steadily increased and lidar methods, along with sophisticated algorithms for lidar signal processing (Weinman, 1988; Wei et al., 2001), are now widely used for atmospheric research and monitoring (Bösenberg et al., 1997).

The use of lidar as a fire detection tool has yet to receive due attention. The few investigations reported recently are mostly concerned with large phenomena on both the spatial and temporal scales, such as on-ground and airborne probing of smoke clouds resulting from large forest fires (Pershin et al., 1999) and weapon firing exercises (Uthe, 1981), tracking of oil smoke plumes (Eberhard, 1983), measuring forest-fire smoke density in the stratosphere (Muller et al., 2000), and investigating the correlation between smoke and ozone concentration (Longo et al., 1999). Ground-based observations are predominantly focused on plumes emitted by power plants (Bennet et al., 1992). Thus, although smoke detection by lidar is a well-known technique, considerable effort is still required to create effective, reliable, and simple methods for forest fire surveillance. An influence of lidar parameters on the efficiency of forest fire detection using lidar was investigated by Andreucci & Arbolino (1993). Later Vilar & Lavrov (1999, 2000) developed a numerical model for lidar forest-fire detection and used this model to assess the influence of lidar parameters on the
monitoring efficiency. Earlier experiments carried out by the authors testified that small fires with a burning rate of about 0.02 kg of wood per second can be promptly detected from a distance of 6.5 km (Utkin et al., 2002).

The present paper partially addresses the problems arising from the high cost and complexity of common lidar equipment by experimentally investigating the possibility of using a simple single-wavelength direct-detection lidar to locate forest fires. This possibility is closely related to the detection sensitivity of the device. Being an active technique, lidar-assisted detection of forest fires has the potential to reveal forest fires in their earliest stages, when the burning area is small enough for the fire to be easily extinguished. Instead of observing the flames, lidar detects the smoke plume, which is much larger and higher. In Sec. 2 the fundamentals of smoke sensing using lidar are briefly discussed and the SNR related to the lidar and smoke plume parameters and the atmospheric conditions. This relation allows theoretical predictions of the SNR to be made. The results of experiments on forest-fire detection by lidar in a mountain region for different atmospheric and ground profile conditions are reported in Sec. 3. It is shown that an average-resolution lidar can reliably discriminate the signal resulting from a small smoke plume from large signals due to ground reflections. Another important characteristic of a lidar surveillance system is the promptness of the fire alarm. The experiments described in Sec. 4 demonstrate the possibility of detecting smoke plumes as early as 40 seconds after the fire starting. Sec. 5 describes how forest-fire location can be performed by an azimuth-angle sweep, allowing the position, dimensions and even internal structure of the smoke plume to be estimated. Examples of location of a smoke plume whose origin is out of line-of-sight and detection in unfavorable visibility conditions are also demonstrated in Sec. 6. Problems related to the automation of lidar fire surveillance are addressed in Sec. 7. It is shown that the recognition of the smoke signatures in lidar signals can be performed by single-layer networks (perceptrons) using a neural-network structure based on a committee machine composed of three perceptrons is discussed. The results are summarized in Sec. 8.

2 FUNDAMENTALS OF SMOKE SENSING

2.1 Lidar signal

The power $P_r$ received by the lidar is defined by the lidar equation (Measures, 1984)

$$P_r(R) = E_i \frac{c \langle \beta(R) \rangle A}{2 R^2} \tau_r \tau_T \exp \left( -2 \int_0^R \alpha(R') dR' \right)$$  \hspace{1cm} (1)

where $E_i$ is the output laser pulse energy, $c$ the speed of light, $\langle \beta(R) \rangle$ the mean backscattering coefficient of the medium, $A$ the effective receiver area, $\tau_T$ and $\tau_r$ the transmitter and receiver efficiencies (the latter is mostly defined by a special filter confining the bandwidth), and $\alpha$ is the extinction coefficient. The parameters of the lidar equipment used in the present work are shown in Table 1.

The backscattering coefficient $\langle \beta \rangle$ is an average over the area illuminated by the laser beam as well as along the line-of-sight within the range $c t_p / 2$, where $t_p$ is the laser pulse duration. The extinction coefficient $\alpha$ is controlled by the aerosol scattering because Rayleigh scattering at 0.532 $\mu$m wavelength is much smaller ($8 \times 10^{-7}$ and $1.5 \times 10^{-5}$ $\text{m}^{-1}$, respectively). Outside the plume, its value may be estimated using the empirical equation (Measures, 1984)

$$\alpha = \frac{3.91}{V} \left( \frac{0.55}{\lambda} \right)^q, \quad q = \begin{cases} 0.585 V^{1/3} & \text{for } V \leq 6 \text{ km} \\ 1.3 & \text{for } V > 6 \text{ km} \end{cases}$$  \hspace{1cm} (2)
in which \( \alpha \) is given in inverse kilometers, the visibility \( V \) is expressed in kilometers, and the wavelength \( \lambda \) in micrometers.

### Table 1. Characteristics of the lidar set-up and pertinent environmental parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Notation</th>
<th>Units of measure</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Q-switched Nd:YAG laser</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>pulse duration</td>
<td>( t_p )</td>
<td>ns</td>
<td>10</td>
</tr>
<tr>
<td>repetition rate</td>
<td></td>
<td>Hz</td>
<td>12</td>
</tr>
<tr>
<td>beam divergence</td>
<td></td>
<td>mr</td>
<td>about 0.5</td>
</tr>
<tr>
<td>operating wavelengths</td>
<td>( \lambda )</td>
<td>nm</td>
<td>532</td>
</tr>
<tr>
<td>estimation of pulse energy for the flashlamp voltage</td>
<td>( \hat{E}_i )</td>
<td>mJ</td>
<td>up to 10</td>
</tr>
<tr>
<td>total transmitter efficiency</td>
<td>( \tau_T )</td>
<td>%</td>
<td>90</td>
</tr>
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</table>

**Receiver Cassegrian telescope**

<table>
<thead>
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<th>Parameter</th>
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<th>Units of measure</th>
<th>Value</th>
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<tr>
<td>focal length</td>
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<td>cm</td>
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</tr>
<tr>
<td>lens diameter</td>
<td></td>
<td>cm</td>
<td>30</td>
</tr>
<tr>
<td>effective area</td>
<td>( A_r )</td>
<td>m²</td>
<td>0.0678</td>
</tr>
<tr>
<td>full angle of field of view</td>
<td>( \gamma )</td>
<td>mrad</td>
<td>1.45</td>
</tr>
<tr>
<td>efficiency</td>
<td>( \tau_R )</td>
<td>%</td>
<td>64</td>
</tr>
<tr>
<td>filter bandwidth</td>
<td>( B_f )</td>
<td>nm</td>
<td>4.8</td>
</tr>
<tr>
<td>photomultiplier FEU-83 with the Peltier cooling</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>dark current</td>
<td>( I_{dark} )</td>
<td>A</td>
<td>( 4 \times 10^{-7} )</td>
</tr>
<tr>
<td>gain</td>
<td>( G )</td>
<td></td>
<td>(~10^5)</td>
</tr>
<tr>
<td>estimated photocathode responsivity</td>
<td>( R_p )</td>
<td>mA·W(^{-1})</td>
<td>0.7</td>
</tr>
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</table>

**Parameters of the atmosphere**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( \alpha )</th>
<th>Units of measure</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>extinction coefficient</td>
<td>( \alpha )</td>
<td>m(^{-1})</td>
<td>( 10^{-4} )</td>
</tr>
<tr>
<td>background solar radiance</td>
<td>( L_\lambda )</td>
<td>W·m(^{-2})·sr(^{-1})·μm(^{-1})</td>
<td>120</td>
</tr>
</tbody>
</table>

### 2.2 Noise of the detection system

Fluctuations in the return lidar signal are due to atmospheric effects and noise associated with the backscattered light measurement chain. The photomultiplier output signal includes three components (Measures, 1984; Andreucci & Arbolino, 1993)

- the current due to the received laser beam energy,

\[
I_{sig} = P_r R_p G ,
\]

(3)

- the current resulting from background radiation,

\[
I_{bgnd} = P_{bgnd} R_p G ,
\]

(4)

- the dark current \( I_{dark} \).
In the equations presented above $G$ is the photomultiplier gain, $R_p$ the photocathode responsivity and $P_{bgnd}$ is the power of received background solar radiation (Youmans et al., 1994),

$$P_{bgnd} = A_r \tau_p B_f \frac{\pi \gamma^2}{4} L_\lambda,$$

(5)

where $B_f$ is the receiver optical bandwidth confined by an optical filter, $\gamma$ is the full angle of field of view, and $L_\lambda$ is the background solar radiance at the lidar operating wavelength. Values of these parameters are also listed in Table 1. The background solar radiance in Table 1 was obtained by interpolation of data available in the literature (Youmans et al., 1994; Eberhard, 1983; Pratt 1969).

For the case of cumulative data, the signal-to-noise ratio is defined by the relation (Measures, 1984)

$$\text{SNR} = \frac{P R_p G \sqrt{n}}{\sqrt{2eG^2 F B_c (P R_p + P_{bgnd} R_p + I_{dark} / G)}} = P R_p \sqrt{n} \frac{\sqrt{2eF B_c (P R_p + P_{bgnd} R_p + I_{dark} / G)}}{2eF B_c (P R_p + P_{bgnd} R_p + I_{dark} / G)}$$

(6)

where $e$ is the electron charge, $B_c = 1/(2t_p)$ characterizes the laser pulse bandwidth, $n$ is the number of accumulated returns (here return means a signal due to one laser pulse) over which the averaging is carried out, and $F$ represents a noise factor associated with the gain.

3 INVESTIGATION OF THE SMOKE PLUME EVOLUTION

As all methods of direct observation, lidar monitoring requires placing the observation points at elevated positions in order to avoid masking of the surveillance area by foreground objects (hills, trees, buildings, etc.). In Portugal forests are predominantly located in mountain areas, where one can take advantage of the natural relief and put observation stations on the tops of mountains. If a forest fire occurs in a valley, the observation conditions (Fig. 1) are such that:

- only upper (and less dense) part of the smoke plume appears in the field of direct visibility;
- in many cases the plume should be detected against the background of a hillside rather than in against clear sky.

Figure 1. Observation of a forest fire in a mountain region.
In view of these remarks, the first aim was to test the lidar sensitivity and spatial resolution for observation of smoke plume in these conditions in controlled real fire trials. Example of the evolution of a smoke plume detected by lidar is given in Fig. 2. The plume was observed at a height of 25 m, about 100 m aside from the fire, the probing pulse energy, $E_p$, was $\sim 1.9$ mJ, and the number of accumulated returns was $n = 128$. The signal due to the smoke plume after 1 min from the start of the fire, is easily differentiated from the strong signal due to a hillside, located 30-70 m behind the smoke plume. At $t = 6$ min the absorption of laser radiation by the smoke is so large that the signal from the hill becomes 2.5 times weaker than at $t = 0$. The time dependence of the signals from the plume and the hillside in terms of their signal-to-noise ratio is shown in Fig. 3. The noise level was estimated by analyzing the behavior of lidar returns in 400-m areas just before and after the signal peak. In these relatively small areas the signal curve is well approximated by a straight line, standard deviation of each point of the signal to that average line gives us the noise. Time-averaged value of the SNR, estimated theoretically using relations (1) and (6) is 54, which is in a good agreement with experimental values.

It should be noticed that signals due to hillsides might change in amplitude. However, the distance from which we receive a signal remains constant for given direction of scanning, allowing these clutter signals to be disregarded, in particular, by automatic detection systems.

4 PROMPTNESS OF FOREST FIRE ALARM

An important feature of any fire-surveillance system is how fast it can detect a fire. This ability is closely connected with the sensitivity of the detection method. Being an active technique, lidar-should be able to reveal a forest fire at its early stage, when the burning area is small enough for the fire to be easily extinguished. Instead of detecting the high-temperature burning material, lidar detects the smoke plume, which is much larger and can be observed above the ground level. Earlier experiments carried out by the authors (Utkin et al., 2002) showed that a small fire of about 0.02 kg/s can be detected from a distance of 6 km.

Fig. 4 shows the temporal evolution of the lidar signal for an experimental forest fire started at 13:37. Each of the curves plotted corresponds to 128 accumulated returns from 15 mJ laser pulses.
at 15 Hz, so the total time required for signal detection does not exceed 8.54 s. The first signal reflected from the smoke plume was obtained 40 seconds after the fire start. Visual observation indicate that this detection delay mostly corresponds to the time required for the dense initial smoke puff to propagate to the point where it met the probing laser beam, 150 m aside (in the horizontal direction) and 80 m above the fire place.

5 AZIMUTH SCANNING

In the experiments described in previous sections, the lidar was pointed at the smoke plume and kept stationary during signal acquisition. However, real fire-monitoring systems should reveal smoke plumes by automatic scanning within a defined solid angle, corresponding to a prescribed surveillance area. To demonstrate this ability, equidistant azimuth sweeps were performed. Figs. 5 and 6 illustrate an example of a two-pass sweep, from $\varphi = 75^\circ$ to $81^\circ$ with a step of $1^\circ30'$ and
backward from $\varphi = 81^\circ$ to $72^\circ 20'$ with a larger step of $2^\circ 10'$. The azimuth angle $\varphi$ is measured clockwise from the north direction, and the positions of the scanning beam with respect to the fire location are shown in Fig. 5. The laser beam was horizontal about 80 m above the fire level.

The corresponding lidar signals are plotted in Fig. 6. At the beginning of the scanning ($\varphi = 75^\circ$) the laser beam does not cross the plume, and only the strong signal backscattered from the hillside is seen (curve 1). With a one-step increase of $\varphi$, to $76^\circ 30'$ (curve 2), the probing laser beam enters the thinnest, external part of the plume, leading to a peak with a near-threshold $SNR = 2$. Reliable smoke detection is achieved in the next scanning step of $\varphi = 78^\circ$ (curve 3). For $\varphi = 79^\circ 30'$ the laser beam goes above the hillside, so only the signal due to the smoke plume is observed in curve 4. A further increase of $\varphi$ moves the laser beam outside the plume (curve 5). Backward scanning with a larger step leads to similar results. The maximum value of $SNR = 17$ is achieved for $\varphi = 76^\circ 40'$ (curve 7). A rough theoretical estimation of the SNR for the case in which the laser beam crosses the plume axis is 50. These results clearly demonstrate the possibility of fire detection by angular scanning. The method also allows the plume dimensions to be evaluated: about 120 m along the laser beam path and about 3 angular degrees crosswise, which for a detection distance of 2.5 km corresponds to 130 m. The lidar signals were recorded with a repetition rate $\nu = 12$ Hz, so for an automatic system with a two-degree step the limiting time of full-circle scanning is as large as $180 \frac{\nu}{\varphi} = 32$ min. It should be noted that an easily achieved ten-fold increase of $E_i$ or $\nu$ leads to a duration of $\sim 3$ min for a full-circle sweep.

The possibility of relating the lidar returns to the local topographic coordinates $x, y$ enables the smoke-plume profiles to be calculated and, an average two-dimensional distribution of the smoke particles to be plotted on a map as shown in Fig. 7. Here the extinction profiles along the scanning beam direction $\alpha = \alpha(x(R), y(R))$ were restored from the raw lidar signals using Klett's inversion method (Klett, 1981) and the particle concentration distribution $n(x, y)$ was estimated using the standard particle distribution measured by Stith (1981).
6 OBSCURED-FIRE DETECTION AT UNFAVORABLE VISIBILITY

Fig. 8 shows a signal obtained in especially unfavorable weather conditions. Due to rain and dense fog the average visibility did not exceed 100 m. Better visibility of about 1 km existed only within a small ten-minute interval during which the smoke plume resulting from an experimental fire located out of the line-of-sight, at the opposite hillside (square 62 in Fig. 5) was detected. The figure clearly indicates the presence of a hundred-meter-thick smoke plume at a distance of 2.9 km from the lidar (SNR = 4.5), being detected through the pronounced cloud structure, which is present in the range 1-2 km.
7 AUTOMATIC RECOGNITION OF SMOKE SIGNATURES IN LIDAR SIGNAL

7.1 Neural-network structure and signal preprocessing

The successful application of lidar in automatic forest-fire surveillance requires that the smoke signatures in lidar signals are promptly recognized and false alarms rejected. These false alarms frequently result from objects causing intense backscattering, such as fog, trees, birds, hills, high-tension cables, etc. Inhomogeneities of the refraction index caused by atmospheric phenomena may also lead to spurious peaks in the lidar signal. In general, the lack of knowledge of the aerosol distribution in the atmosphere and random changes in atmospheric refraction index make it difficult to use parametric models in the present case. Neural-network techniques have been successfully applied to automatic forest fire detection based on images obtained using ground-based, airborne, or spaceborne infrared or video cameras (Ugarte et al., 2000; Arrue et al., 2000; Rauste, 1997; Benediktsson et al., 1990). They have also been exhaustively applied to the classification of radar (Haykin & Deng, 1991), sonar (Gorman & Sejnowsky, 1988), and sodar (Pal et al., 1999) signals. The present application and previously reported applications are however distinct because in image analysis, two-dimensional scenes are classified, while in the present case the classification deals with a one-dimensional signal, the distribution of backscattered radiation intensity along the laser beam propagation direction (Bhattacharya et al., 1997).

As classification implies a one-directional processing of information, the natural option for the network topology is a feedforward structure, whose simplest implementation is a single-layer perceptron (Haykin, 1999a). While a multilayer perceptron is composed of several layers of neurons and one-directional synaptic links between neighboring layers of neurons, a simple perceptron is composed of a single layer of input nodes connected by synaptic links to an output neuron. The activation function used in the perceptron output neuron is a hyperbolic tangent, with outputs in the bound interval (-1, 1). The use of this type of activation function helps to provide non-zero gradient values for learning algorithms based on backpropagation.

Information processing with a single neuron is linear. The use of a non-linear activation function for the final result cannot prevent data processing from being linearly degenerative, it can only damp oscillations when minimizing the error function. As a result, the application of single-layer perceptrons is confined to the classification of linearly separable patterns. However, using a simple the perceptron results in shorter calculation times for learning and classification, a very important feature for real-time applications.

Smoke plumes manifest themselves in raw lidar signals as peaks whose amplitude depends on changes in the density of particles in the smoke plume, distance and wind. The background is composed of electronics (Durieux & Fiorani, 1997) and atmospheric noise and can be represented by a linear combination of uniformly spaced peaks, making the recognition problem linearly inseparable. However, preliminary tests carried out by the authors have demonstrated the efficiency of perceptron-based algorithms in the classification of segments of signal curves if they present a maximum in the center of the segment. Although the signal-to-noise ratio decreases with distance, the smoke signature holds its shape. Thus, the classification problem is distance-independent in the sense that the recognition conditions for a tenuous smoke plume observed at short distance are equivalent to those for a denser plume at a greater distance, provided that the signal-to-noise ratio is similar. This fact enables a lidar signal of two thousand points (a range of about ten kilometers, measured with six-meter resolution) to be viewed by the neural network through a narrow window of several tens of points, which moves along the signal curve, reducing signal preprocessing to the window motion algorithm. Motion stops only if a local maximum coincides with the window center. When this situation occurs, the signal curve in the region of interest is scaled so that the minimum and maximum values are -0.9 and 0.9, in order to eliminate the background and avoid saturation of the neurons. This technique considerably simplifies data processing because: (i) the number of neural inputs and links is reduced to the window width, decreasing calculation complexity; (ii) recognition becomes scale- and background-independent; (iii) linear separation methods, in particular simple perceptron-based algorithms, become applicable; and (iv) the neural
network is only required for classification, while the problem of calculating the distance to the target is eliminated, this distance being given by the coordinate of the window center.

7.2 Smoke and noise patterns

Two sets of patterns were used for supervised learning: a training set consisting of the lidar patterns to be learnt by the network and corresponding outputs, and a validation set, used to test the network learning efficiency and generalization ability. The patterns in the training and validation sets contain peaks due to atmospheric noise, high-tension cables, hills, and smoke plumes and resulted from the accumulation of a small (1-2), medium (32), and large (≥128) number of lidar returns. As the objective of lidar surveillance is to detect the fire in its earliest possible stage, the curves for the sets were recorded from small campfires, with burning rate as small as 0.02 kg/s.

To capture the smoke-plume structure the signals were recorded with a 6 m distance between sampling points, resulting in approximately 7-point-wide smoke signatures. A width of the sliding window of 21 points were chosen because it provides information about the peak shape and the background noise. In accordance with the preprocessing procedure, all patterns have centered maximums and were normalized to fit in the interval [-0.9, 0.9].

From the thousands of curves recorded in field experiments, 282 representative patterns were chosen for the training and validation sets. The atmospheric-noise patterns were collected from lidar signals of smoke-free atmosphere, resulting from the accumulation of 32 or more lidar returns and 95 patterns with smoke signatures were chosen.

7.3 Learning rules

Among available learning rules for multilayer and simple perceptrons, those based on the error backpropagation (BP) remain one of the most efficient and well-known as they are relatively easy to code and demonstrate good numerical stability (Haykin, 1999a). These methods minimize output errors by the gradient descent over the error surface $E(w)$ in the multidimensional space of the interconnection weights $w$ (transmission coefficients of the synaptic links). The weights are updated according to the rule

$$w_i \rightarrow w_i - \mu \nabla_i E$$

(7)

where $w_i$ is the weight of the link to the $i$-th input node, $\mu$ is the learning rate, and $\nabla_i E = \partial E / \partial w_i$ is the component of the error gradient corresponding to the direction $w_i$.

In the simplest form of backpropagation, the learning rate remains fixed. This results in slow convergence, because the error surface usually presents gentle slopes intersected by narrow steep regions. In steep regions the learning rate has to be small to prevent over-adjustment, while in flat regions it has to be large in order to compensate for the small local gradient values. Taking this fact into consideration, all the learning algorithms used employ use dynamic adaptation of the learning rate function of the error gradient. In the calculation of the optimal learning rate, the BP method with adaptation of a self-determined learning rate (BPSDLR - Magoulas et al., 1999) takes the error and error gradient values into consideration. While accelerating the descent, BPSDLR leads to poor stability, so a special convergence criterion tests each value of the learning rate in order to ensure convergence. For the steepest descent with adaptive step size (SDAS), a Lipschitz continuity condition is imposed on the error gradient, and the optimal learning rate is calculated on the basis of a local estimation of Lipschitz constant (Vrahatis et al., 2000). In the resilient propagation method, (RPROP - Riedmiller & Braun, 1993), the calculation of the weight updates only takes into account the changes of the error-gradient sign because they indicate a jump over error surface minima.

The other BP methods selected perform dynamic learning rate adaptation through the computation of both the first and second derivatives of the error. The computational complexity is higher than for standard BP methods, but the gain in convergence speed fully compensates for it.
The objective of the polynomial approximation (PA - Yu et al., 1995) is to find the smallest learning rate \( \mu = \mu^* \) for which the error function has a minimum. Since \( \nabla E \) indicates the local descent direction, the value of the first derivative of the error with respect to the learning rate is less than zero for \( \mu = 0 \). Starting with zero, \( \mu \) is increased stepwise until the first derivative becomes positive. With two values of the learning rate, one corresponding to positive and the other to negative values of the first derivative of the error, it is possible to estimate \( \mu^* \) using a third-order polynomial interpolation. In the Newton-like method with periodically restarted conjugate gradient (NPRCG - Yu et al., 1995) it is assumed that a convex parabola can approximate the dependence of the error function on the learning rate. The optimal learning rate is calculated from the first and second derivatives of the error function. The momentum factor, which defines the influence of the previous weight update values on the current ones, leading to a more stable and faster convergence, is simultaneously calculated. In the points of the weight space where the second derivative of the error for \( \mu = 0 \) is equal to or less than zero the calculations do not converge. In these points the polynomial approximation is used instead.

Comparison of the efficiency of the selected learning methods (Fernandes et al., 2002) led to derivation of a new Polynomial approximation with Periodically Restarted Conjugate Gradient (PPRCG) algorithm, combining polynomial interpolation with the periodically restarted conjugate gradient method. For the problem under consideration, this approach exhibits the best efficiency (very fast convergence while maintaining good generalization characteristics). All numerical results described in the next subsection were obtained with PPRCG learning rule.

7.4 Numerical results

A perceptron consisting of 22 input nodes (21 for the signal plus one for bias representation), connected by synaptic links with a single output neuron, was first used in the numerical calculations. To find the conditions that provide the best generalization capability, the following learning parameters were varied:

- the range for randomly generating the initial weights of the synaptic links (the intervals \([-0.2, 0.2]\), \([-0.5, 0.5]\) and \([-0.8, 0.8]\) were tested);
- the training set length;
- the number of training epochs (weight updates).

Random generation of the initial weights introduces a stochastic character to the perceptron performance. The best classifier constructed using the previously mentioned training and validation sets reached efficiencies of 99% for the validation set (no misdetections and 3 false alarms), and 98% (3 false alarms and 3 misdetections) for both sets. The perceptron classified perfectly 609 additional peaks caused by fog and resulting from the accumulation of 256 or 2048 lidar returns, but the efficiency dropped to 81% when classifying 2514 atmospheric noise patterns resulting from the accumulation of 1 or 2 lidar returns, due to higher noise.

To obtain a classifier capable of distinguishing smoke peaks from hills and high-tension cable peaks, the PPRCG algorithm was used in training sets with 54, 64, 74 and 84 patterns. The best classifier was constructed using a training set with 84 patterns (42 peaks from hills and high-tension-cables and 42 smoke signatures). The validation set contained 92 patterns, 48 from smoke and 44 from hill and high-tension cable signatures. The classifier correctly recognized all patterns of the training set and led to 2 false alarms and 4 misdetections in the validation set, demonstrating a classification efficiency of 93% in the validation set and 97% in both sets.

Further progress in the classifier performance can only be achieved using more complex networks. In order to keep the neural-network algorithms simple and limit the time of learning, the a committee machine (Haykin, 1999b) was chosen. In a committee machine several perceptrons are combined using ordinary logic rather than synaptic links, as is the case in a multilayer perceptron. The classification task is subdivided into simpler tasks, each solved by a specialized perceptron named an expert. Being associated through certain rules, experts bring together their "knowledge" in order to correctly solve the overall problem. The committee machine tested was first composed of two previously described perceptrons. The second perceptron, specialized in distinguishing
smoke plumes from solid targets, analyzed only the patterns that led to alarm output in the first perceptron. The recognition efficiency was assessed for 231 complete lidar signals and led to 32% of false alarms and 19% of misdetections in the 122 lidar signals containing smoke patterns. To increase the classification accuracy, a third perceptron, trained with smoke patterns and atmospheric noise extracted from lidar signals resulting from the accumulation of only one or two lidar returns, was included in the committee machine. Its function is to eliminate the peaks due to atmospheric noise that are classified by the first perceptron as smoke signatures. The addition of the third perceptron reduced false alarms to only 9% but increased misdetections to 22%. However, 50% of the false alarms come from patterns resulting from the accumulation of 32 returns and representing only 11% of the total of 231. This clearly demonstrates that to achieve high recognition efficiency the curves should present low noise level. An increase of the accumulation number or laser pulse energy or decrease electronic noise will improve the recognition efficiency. Automated smoke recognition with software based on the three-perceptron committee machine is illustrated in Fig. 9.

![Lidar Signal Source file: C:\My Documents\Armando\AllLidarSignals16m101061541.tx](image)

Figure 9. Automated recognition of smoke signature in lidar signal with the help of the neural-network algorithm based on a three-neuron committee machine.

8 CONCLUSIONS

The field experiments described demonstrated that simple lidar equipment can promptly detect extremely tenuous smokes plumes and discriminate them from nearby hillsides. The time delay for alarm emission will depend mainly on the scanning algorithm used. Forest-fire detection within a range of 2.5 km can be successfully carried out with uniform azimuth sweep of $\Delta \phi = 2^\circ$, leading to an estimated scanning velocity of about 3 minutes for a full-circle sweep.
The problem of automated smoke signature recognition was addressed and several neural-network algorithms for smoke-plume recognition in the lidar signal derived and tested. Finally, a committee machine composed of 3 perceptrons was created and applied to the classification of complete lidar signals, resulting in 9% false alarms and 22% misdetections. If only signals with 128 or more lidar returns are considered, a false alarm rate of 5% is obtained.

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