Abstract

Neural networks for supervised classification of lidar signals at forest-fire surveillance

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Keywords: Forest fire; Remote sensing; Lidar; Neural network

Detection of smoke plumes using lidar (light detection and ranging) presents many advantages as compared to passive methods of forest-fire surveillance. However, due to the great sensitivity of the method, false alarms due to interference of spurious targets may occur. To be efficient, automatic lidar fire detection must be supported by effective algorithms that allow the smoke-plume signatures to be distinguished from peaks due to atmospheric phenomena, other targets and electronic noise. This work proposes a new simple and robust algorithm of lidar-signal classification based on the fast extraction of sufficiently pronounced peaks followed by their classification with a perceptron. Within the framework of the radial-basis-function-network ideology, the perceptron capability is enhanced and linear degeneracy overcome by a special fast and highly non-linear transformation that efficiently increases the number of the perceptron nodes and, consequently, the number of adjustable interconnection weights responsible for the memorization capacity. Application of this method made it possible to develop software for automatic smoke recognition with an error rate as small as 0.31% (19 misdetections and 4 false alarms at recognition of a test set of 7409 peaks, from which 224 are the smoke-plume signatures).

Within the inherent uncertainty resulting from the statistical nature of the noised signals used for the training, certain degree of arbitrariness in the choice of the training set and incompleteness of description of all the variety of smoke-plume signatures via a limited number of examples recorded during the field experiments, the threshold-binarization algorithm demonstrated nearly the same efficiency (8.5% misdetection rate and 0.056% false alarm rate) as far more complicated committee machine composed of four single-layer perceptrons (7.4% misdetection rate and 0.041% false alarm rate). At the same time, the proposed algorithm:

- requires nearly one order of magnitude faster training,
- the training procedure is not connected with the choice of the best classifier, so it can be strictly formalized and performed by users without special instruction,
- the training is not connected with repetitive iterational routines like training epochs in the case of gradient-descent methods,
- within the framework of the model the global minimum of the classification error for given training set is readily achieved by a sequence of matrix operations of guaranteed stability.

Further potentialities of this method are linked with more complicated structures (as well as ordinary perceptrons, the perceptrons with threshold-binarization layers can be united into committee machines, yielding much better efficiency) and introduction of additional information connected with the statistical properties of the signal peak that can be obtained during averaging of several lidar signal returns from the same atmospheric path.
Neural networks for supervised classification of lidar signals at forest-fire surveillance

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Abstract: Detection of smoke plumes using lidar (laser radar, light detection and ranging) provides many advantages with respect to passive methods of forest-fire surveillance. However, great sensitivity of the method involves detection of many spurious targets. To be efficient and automated, the lidar-assisted fire detection must be supplemented with effective algorithms of separation of the smoke-plume signatures from the irrelevant peaks due to various atmospheric phenomena and electronic noise as well as from the signals resulted from other targets. This work proposes a new simple and robust algorithm of lidar-signal classification based on the fast extraction of sufficiently pronounced peaks followed by their classification with a perceptron. Within the framework of the radial-basis-function-network ideology, the perceptron capability is enhanced and linear degeneracy overcome by a special fast and highly nonlinear transformation that efficiently increases the number of the perceptron nodes and, consequently, the number of adjustable interconnection weights responsible for the memorization capacity. Application of this method made it possible to develop software for automatic smoke recognition with an error rate as small as 0.31% (19 misdetections and 4 false alarms at recognition of a test set of 7409 peaks).

Keywords: forest fire, remote sensing, lidar, neural network

1. Introduction

Remote detection of forest fires via light detection and ranging (lidar) technique has been developed by the authors since 1998. By extending the principles of radar to the optical range, lidar presents significant advantages over passive surveillance methods. In particular, this technique demonstrated high sensitivity that does not have significant daylight and weather dependence. As a sequence, the lidar detector provides great range of surveillance, restricted only by the laser-pulse energy and — for the distances exceeding ~10 km — by the beam jitter resulting from atmospheric turbulence. Good directionality of the laser beam and a several-meter precision of the distance measurements enable lidar to provide accurate location of the smoke plumes, without the necessity of direct observation of the flames, a matter of extreme importance for fire surveillance in mountaineous regions.

For efficient early detection of forest fires, the smoke-plume pattern in the lidar signal must be promptly recognized and separated from the peaks due to noise and other targets, whose number and intensity inevitably increase with the sensitivity of the method — an issue that can only be solved with some automatic procedure. The present paper is devoted to the investigation of one of these procedures based on the fast extraction of sufficiently pronounced peaks followed by their classification with a perceptron.
2. Targets and Noise in Raw Lidar Signal

2.1. Principles of lidar detection

The main parts of lidar equipment (Fig. 1) are the radiation emitter (pulsed laser) and receiver that collects light and sends it to the photodetector. The emitter emanates short intense radiation pulses through the atmosphere. Part of the radiation backscattered by eventual targets enters the receiver where its power is measured as a function of time.

![Figure 1. Schematics of lidar detection.](image)

The distance from the backscattering center to the lidar $R$ may be calculated from the time delay between the laser-pulse emission and the reception of the backscattered signal $t$

$$ t = \frac{2R}{c} \quad (1) $$

(radar equation, $c$ is the velocity of light).

The raw lidar signal is the photodetector voltage $U_{pd}$ recorded during some period of time immediately after laser-pulse emission (moment $t = 0$). As far as the photodetector voltage is supposed to be a linear function of the retroreflected radiation power $P_r$

$$ U_{pd}^* = A_{pd} P_r, \quad U_{pd}^* = U_{pd} - U_{bg} \quad (2) $$

and the transition from the time to the distance dependence is reduced to a simple rescaling, usually the raw lidar signal is represented as a plot of $P_r$ versus the distance $R$ ($U_{pd}^*$ represents the photodetector voltage free from the background component $U_{bg}$ and $A_{pd}$ is the lidar calibration coefficient). In most cases one can get rid from the background component using relatively simple tail-averaging procedure (Durieux & Fiorani, 1997) while representation of the retroreflected power in absolute units is connected with a complicated calibration procedure that usually includes particle concentration/size-distribution measurements and requires an extraordinary amount of sophisticated equipment and manpower (Ezcurra et al., 1985; Benech et al., 1988).
2.2. Smoke signatures

A theoretical estimation of $P_r$ is

$$P_r(R) = E_t \frac{c \beta(R)}{2 R^2} A_{rec} \tau_r \tau_{rec} \exp\left(-2 \int_0^R \alpha(R')dR'\right)$$

(3)

where $E_t$ is the output laser pulse energy, $\beta$ the backscattering coefficient of the medium, $A_{rec}$ the effective receiver area, $\tau_r$ and $\tau_{rec}$ the transmitter and receiver efficiencies (the latter is mostly defined by a special filter confining the bandwidth), and $\alpha$ the extinction coefficient. To improve the signal-to-noise ratio, returns from several laser pulses are usually accumulated in each signal.

The lidar equation (3) gives us a clue as to how the structure of a distributed target, such as atmospheric aerosol, cloud or smoke plume is related to the profile of its pattern in the raw lidar signal. Supposing that the target front is observed at the distance $R_o$ from the lidar and has

- the characteristic spread in the direction of laser-beam propagation $\delta L$,
- the backscattering-coefficient profile $\beta(L)$ and
- the extinction-coefficient profile $\alpha(L)$,

one can write for the target-pattern profile $S_t$

$$S_t(L) = P_t(R_o + L) = A_o \frac{\beta_t(L)}{(R_o + L)^2} \exp\left(-2 \int_0^L \alpha_t(L')dL'\right), \quad L = R - R_o \in [0, \delta L]$$

(4)

where

$$A_o = E_t \frac{c}{2} A_{rec} \tau_r \tau_{rec} \exp\left(-2 \int_0^R \alpha_{atm}(R')dR'\right)$$

(5)

depends on the observation conditions (the distance $R_o$ and the atmospheric extinction $\alpha_{atm}$) as well as on the lidar characteristics and does not depend on the target parameters.

For typical forest-fire surveillance conditions, the observation distance exceeds more than one order of magnitude the smoke-plume pattern spread, so without significant loss of precision we can replace $(R_o + L)^2$ in Eq. (4) by $R_o^2$, which yields the simpler expression

$$S_t(L) = C_o \beta_t(L) \exp\left(-2 \int_0^L \alpha_t(L')dL'\right)$$

(6)

where $C_o = A_o R_o^2$ is a new target-independent parameter.

As it is seen from this brief theoretical consideration, the shape of the smoke-plume pattern has a sufficiently complicated dependence on the target parameters involving both the backscattering and extinction coefficients of the plume in local and integral forms correspondingly. As the two unknown profiles, $\beta_t(L)$ and $\alpha_t(L)$, are combined by a unique relationship (6), further extraction of the characteristic features is impossible without
establishing an additional relationship between the backscattering and extinction. There are several hypothetical relationships of this kind published in the literature; one of the simplest, $\beta_i = B \alpha_i^k$, where $B$ and $k$ are positive constants, constitutes the basis of a popular algorithm of extinction retrieval known as Klett's lidar signal inversion (Klett, 1981 & 1985).

Notably, the problem under discussion deals only with recognition of the presence of the smoke-plume pattern in the signal, leaving aside assessment of the parameters of smoke distribution. For this reason the description of a compact distributed target, such as a smoke plume in the initial stage of its development, may be constrained to the general relation (6), sufficient for establishing the following important facts:

1). The shape of the smoke-plume patterns (signatures) in the lidar signal depends in a complicated way on the distribution of the extinction and backscattering coefficients in the volume of the smoke plume. Both parameters are closely connected with the distribution of soot particles. Experimental investigations (Utkin et al., 2002, 2003 & 2004) showed that both the soot-particle density and corresponding lidar-retroreflection peaks vary greatly in their shape and amplitude, following complicated, hardly predictable and an inherently stochastic (North & Cahalan, 1981; Arnold, 1998) process of smoke-plume evolution in natural conditions. Although important for the prediction of the range of the lidar instrument, the gasdynamic smoke-plume models cannot provide a solid basis for extraction of characteristic features of the smoke-plume signature, especially for small- and middle-scale fires developing in terrains with complicated relief in the presence of wind. This fact is illustrated by a photo of a wildland fire (Fig. 2) taken during Gestosa experiments (Viegas, 2000 & 2003; Viegas et al., 2002), in which two upward- and downward-propagating smoke flows are observed simultaneously. Due to this lack of reliable parametric models, the automated fire surveillance mainly is based on the artificial-intelligence algorithms like artificial neural networks for both passive (Arrue et al., 2000) and active (Fernandes et al., 2005) detection techniques.

![Figure 2. Wildland fire developing in terrain with complicated relief in the presence of wind. A downward-propagating smoke flow is observed along with conventional buoyancy-dominated plume.](image)
2). Let us introduce a normalized smoke-plume signature \( \tilde{S}_i(L) \), for example, its \([-0.9, 0.9]\)-segment mapping defined as a linear transformation

\[
\tilde{S}_i(L) = a_{0.9} S_i(L) + b_{0.9},
\]

in which the constants \( a_{0.9} \) and \( b_{0.9} \) are defined from the two minimax conditions

\[
\min_{L\in[0.9]} \tilde{S}_i(L) = -0.9, \quad \max_{L\in[0.9]} \tilde{S}_i(L) = 0.9.
\]

Substituting into Eq. (6), one can readily check by direct calculations that \( \tilde{S}_i(L) \) does not depend on the initial scaling factor \( C_o \) and, subsequently, on the range and atmospheric extinction. Thus, the pattern-recognition problem in question can be treated as distance-independent in the sense that the recognition conditions for a tenuous smoke plume are equivalent to those for a dense plume observed at a greater distance provided that the signal-to-noise ratio is similar.

2.3. Noise

In accordance with the theoretical estimation given by formula (6), smoke plumes manifest themselves in the raw lidar signal as peaks whose amplitude and shape vary due to stochastic changes in the particle distribution within the smoke plume under the action of gasdynamic forces, buoyancy and wind. These smoke-plume signatures are observed against the background contaminated by electronic and atmospheric noise (Fig. 3).

Electronic noise of a well constructed receiver usually demonstrates no dependence on the observation distance and can be estimated from the signal segment recorded far beyond the range of sensitivity of the instrument, where no retroreflection is expected.

Apart from this unstructured noise, lidar signal may contain peaks due to retroreflection from irrelevant targets (hills, trees, buildings, birds, low clouds, fog, etc.). As in the case of distributed targets, solid-target signatures do not demonstrate dependence of their shape on the observation distance. Usually they are intense and narrow pulse-like waveforms, similar to each other as for the most part the pulse front and back are defined by the low-pass filtering of the detection channel and the rate of analog-to-digital conversion.

2.4. Recognition Requirements

Computerized recognition of the smoke signatures in the lidar signal is essential for successful application of lidar in automatic forest-fire surveillance. To be competitive in the market, the lidar fire surveillance systems under development are based on cheap, simple and robust one-wavelength direct-detection lidars and ordinary personal computers. In this situation it is mandatory to implement the smoke-recognition algorithm in such a way that all its stages - writing and testing the neural-network emulation code, training and recognition - can be carried out easily and promptly within the framework of relatively limited computational resources of these computers. This means that in order to achieve a reasonable (one hour’s scale) time of interconnection-weight computation during training it is necessary that either (i) the number of weights be small enough (about 100 for the best iterative algorithms like error backpropagation) or (ii) the training procedure be extremely fast and straightforward, yielding the result without variation of the initial weight values.
and iteration loops. Training algorithms of the first type have been investigated by Fernandes et al. (2002, 2003, 2004a, 2004b). The present work is devoted to approach of the second type in which interconnection weights of a single-layer perceptron are calculated by pseudoinversion of the matrix composed of the training-pattern vectors.

3. Signal Preprocessing

3.1. Objectives and Stages

A single-layer perceptron can successfully classify only linearly separable subsets (Utkin et al., 2002). However, even the simplest problem of recognition of peaks against an unknown constant background is not linearly separable and this type of linear non-separability is closely related to another problem resulting from linearity: the capacity of correct memorizing only linearly independent patterns (linear degeneracy), with leads to overdetermined training conditions even for small training sets. Arising difficulties are traditionally overcome using some preprocessing algorithm that breaks the linear dependence between the input signal and the NN output.
In its normal sequence, the lidar signal preprocessing is reduced to a subdivision of the whole lidar curve consisting of several thousands of signal points into much shorter (tens of points) regions of interest, or patterns, intended for classification in a subsequent manner. In the case in question the regions of interest are signal segments containing local maxima (peaks) in the middle point. The second preprocessing stage deals with extracting from the patterns some characteristic feature(s) that facilitate recognition. Here the chosen characteristic feature is a measure of the relative amplitude of the middle peak, so-called peak-to-noise ratio to be discussed in Subsection 3.2. It turned out to be easy to calculate and so descriptive that the procedure of signal preprocessing was reversed: first the feature extraction is made (peak-to-noise ratio calculated) for all the segments containing local maxima and then the regions of interest are chosen among them based on the feature value (whether or not it is greater than some predefined threshold).

3.2. Feature Extraction

As seen from the consideration made in Section 2, the characterization of the signatures to be classified can be made in a distance-independent manner. The authors' previous investigations on different methods of automatic classification (Fernandes et al. 2002, 2003; Utkin et al. 2002) indicated that the smoke recognition efficiency increases if the scaled peak patterns of form (7) are provided for recognition together with a specific feature describing the relative peak amplitude and it is reasonable to characterize this relative amplitude by the peak-to-noise ratio (PNR). This distance-irrelevant parameter extends the conception of the signal-to-noise ratio to the cases in which the nature of the detected peak is not yet known, so the "signal" peak itself may, in fact, originate from the structured noise or even a random fluctuation of the background noise. Having the pattern length $\delta L$ and the admissible center peak width estimated from some preliminary information about dimension of possible targets, the instrument resolution and the signal sampling distance $\delta R$, a line estimating a slowly varying signal background is first defined using the well-known least-squares regression formulas; the points lying within the presumable peak width are not taking into account. Then the peak amplitude $P_p$ and the standard deviation of the out-of-peak signal points with respect to the background line (noise amplitude estimation) are calculated as illustrated in Fig. 4. Finally, the PNR is defined as a ratio of these two values.

3.3. Pattern Extraction and Definition of the Fire Location

During the sample extraction, a lidar signal of several thousands of points is viewed by the preprocessing software through a window of several tens of points that moves along the signal curve. For efficient recognition, the window should be wide enough to contain the smoke-signature peak and some points its vicinity in order to provide information on the noise level. The window motion stops if the local signal maximum coincides with the coordinate window center $R_p$ and the corresponding $PNR = PNR(R_p)$ is calculated. If

$$PNR(R_p) \geq PNR_{thr}$$

(9)

where the threshold value $PNR_{thr}$ (typically, from 3 to 5) is chosen in accordance with some predefined requirements imposed on the rates of misdetections and/or false alarms (see Fernandes et al., 2003), the region is recognized as a region of interest. The
corresponding signal segment is concatenated with $PNR$ and directed as a pattern to the input layer of the perceptron.

As seen from Fig. 5 representing the entire diagram of the smoke-signature recognition, while working in conjunction with this preprocessing algorithm, the perceptron's task is reduced exclusively to the pattern recognition, without any need to define fire location: if the perceptron generates an alarm output, the direction to the forest fire is the current direction of the scanning laser beam while the distance is equal to the segment middle (peak) distance $R_p$.

If $PNR$ is less than $PNR_{thr}$, the peak is believed to be too small to be a smoke-plume signature; the region is discarded and the observation window continues its motion along the lidar signal curve.

4. **Alarm Generation**

4.1. **Pattern binarization**

Eventual alarm generation is performed on the basis of pattern classification (smoke-signature dichotomy) with an adaptive linear filter, which is structurally equivalent to the single-layer perceptron (Haykin, 1999). Within the framework of the single-layer perceptron structure, the only way to enhance the classification efficiency is to increase the number of the input nodes (and, correspondingly, the number of interconnection weights), as was done by Bhattacharya et al. (1997) for the similar case of lidar signal classification at monitoring the spatial distribution of melt in near-shore waters.
Preprocessing, phase 1: PNR calculation

\[ R_p = 1296 \text{ m} \]

\[ \text{PNR} = 2.485 \]

Preprocessing, phase 2: Pattern extraction

\[ R_p = 1584 \text{ m} \]

\[ \text{PNR} = 6.745 \]

Initial input: raw lidar signal

Figure 5. Overall scheme of the smoke-signature recognition.
The initial 1D signal segment (pattern to be recognized) is mapped on a rectangular 2D grid. Each sample point is checked against the grid-crossing points. If a sample point falls within half a grid space on either side in both the horizontal and vertical directions, a one is assigned at that point; otherwise, a zero is assigned. Each sample point is tested in the same way yielding at the end a matrix of 0s and 1s, which is eventually converted into a longer binary pattern vector reflecting all the peculiarities of the pattern provided that a sufficiently fine grid is chosen. When the vertical grid spacing equals the lidar sampling distance so that all the signal points are located on the vertical grid lines, the above algorithm reduces to a simple point binarization of the signal with resolution corresponding to the horizontal grid spacing. The threshold binarization procedure, corresponding to the point binarization in which a one is assigned to each grid point situated below any point already assigned to 1, is even easier for hardware implementation (using a batch of threshold detectors with linearly increasing thresholds) and results in less sparsely binarized samples.

Results of application of both binarization procedures are shown in Fig. 6. The point binarization with a grid of order 10 yields a sparse binary vector with a tenfold increase in dimensionality, which, being represented in a matrix form, reflects peculiarities of the initial pattern. Similar binary vector due to the threshold binarization is less sparse. Although bearing the same information about the initial sample, point- and threshold-binarization patterns cannot be converted into each other by a linear transformation. The latter sample demonstrates explicitly the ambiguity of the binary code: the bottom raw of the matrix representation of the threshold-binarization pattern always consists of 1s and can be discarded without any loss of information, thus resulting in a denser and more compact pattern and more efficient recognition code. For this reason, the classification code was finally constructed on the basis of those reduced threshold-binarization patterns.

4.2. Linear Least-Squares Filtering

Borrowing the approach from the radial-basis function network theory (notably, it can be shown that the binarization processing correspond to a radial-basis function technique with some specific norm), the threshold-binarization patterns are classified using the simplest adaptive linear least-squares filter. For a given training set, the least-squares filtering readily yields a unique deterministic solution (Haykin, 1999): desired interconnection weights as a product of Penrose pseudoinverse of the matrix composed
from the binarized training samples and the vector of corresponding classification tags (e.g., 0.9 for the smoke-signature peaks and –0.9 for the spurious signal peaks).

The straightforward application of the above fast and simple classification scheme demonstrated significant advantages with respect to the statistical and iterative methods: even for one thousand training patterns it takes about ten minutes for the weights to be calculated, the training duration does not depend on the training data, and the solution is guaranteed to provide the global, rather than some local minimum of the error function. At the same time, the algorithm suffered from significant numerical instability, which increased with the binarization grid order and did not disappear even when all the sources of information redundancy causing singularity of the pseudoinversion are tracked and eliminated (e.g., the central column of the binarized pattern corresponds to the central peak of the initial pattern and always consists of 1's).

Analysis of the reasons of this instability enabled the authors to develop another solving scheme with similar efficiency. Being based on a more robust pseudoinversion procedure, the singular-value decomposition (SVD) instead of the Penrose pseudoinversion, this method yields the regularized least-squares filtering solution and needs only one empirically chosen scalar parameter to establish a trade-off between solution accuracy and stability. Application of this method enabled a software for automatic smoke recognition with an error rate of 0.31% (19 misdetections and 4 false alarms at recognition of a test set of 7409 peaks, from which 224 are the smoke-plume signatures) to be developed on the basis of a single least-squares filter (perceptron), see Fig. 7.

**Figure 7.** Software for automatic smoke recognition in raw lidar signal of the basis of the threshold binarization procedure combined with SVD-regularized least-squares filtering.
5. **Conclusion**

Within the inherent uncertainty resulting from statistical nature of the noised signals used for the training, a certain degree of arbitrariness in the choice of the training set and incompleteness of the description of all the varieties of smoke-plume signatures due to a limited number of examples recorded during the field experiments, the threshold binarization algorithm demonstrated nearly the same efficiency (8.5% misdetection rate and 0.056% false alarm rate) as a far more complicated committee machine composed of four single-layer perceptrons (7.4% misdetection rate and 0.041% false alarm rate) that uses patterns twice the size and, apart from the PNR, two more characteristic features — maximum amplitude ratio and average amplitude ratio — which are extracted at preprocessing (Fernandes et al., 2005). At the same time, the proposed algorithm:

- requires nearly one order of magnitude faster training,
- the training procedure is not connected with the choice of the best classifier, so it can be strictly formalized and performed by users without special instruction,
- the training is not connected with repetitive iterative routines like training epochs in the case of gradient-descent methods,
- within the framework of the model the global minimum of the classification error for given training set is readily achieved by a sequence of matrix operations of guaranteed stability.

Further potentialities of this method are linked with more complicated structures (as well as ordinary perceptrons, the perceptrons with threshold-binarization layers can be united into committee machines, yielding much better efficiency) and introduction of additional information connected with the statistical properties of the signal peak that can be obtained during averaging of several lidar signal returns from the same atmospheric path.

**References**


