Automatic recognition of smoke-plume signatures in lidar signal

Andrei B. Utkin\textsuperscript{a}, Alexander Lavrov\textsuperscript{a}, Rui Vilar\textsuperscript{b}

\textsuperscript{a}INOV - INESC Inovação, Rua Alves Redol 9, 1000-029 Lisbon, Portugal
\textsuperscript{b}DEMAT, Instituto Superior Técnico, Universidade Técnica de Lisboa, Av. Rovisco Pais 1, 1049-001 Lisbon, Portugal

ABSTRACT

A simple and robust algorithm for lidar-signal classification based on the fast extraction of sufficiently pronounced peaks and their recognition with a perceptron, whose efficiency is enhanced by a fast nonlinear preprocessing that increases the signal dimension, is reported. The method allows smoke-plume recognition with an error rate as small as 0.31\% (19 misdetections and 4 false alarms in analyzing a test set of 7409 peaks).

Keywords: lidar, target recognition, sensing, fire

1. INTRODUCTION

Detection of smoke plumes using lidar (light detection and ranging) methods provides many advantages with respect to passive fire surveillance. However, increasing the sensitivity of the method involves detecting many spurious peaks in the retroreflected radiation power - time curves — due to electronic noise, atmospheric phenomena and echo from irrelevant targets \cite{1}. As a result, the lidar fire detection must be supported by effective algorithms of separation of the smoke-plume signatures from irrelevant peaks in the lidar curves.

Extending the principles of radar to the optical range, lidar presents significant advantages in comparison to passive surveillance methods, in particular, higher sensitivity and low dependency on the atmospheric light and weather conditions. Lidar detectors provide a large surveillance range, restricted only by the laser-pulse energy and — for distances exceeding \~10 km — by the beam jitter resulting from atmospheric turbulence. Good directionality and precision of distance measurements enable lidar to locate accurately the smoke plumes, without necessitating direct observation of the flames, which is of paramount importance for fire surveillance in mountainous regions.

For efficient early forest-fire detection, the smoke-plume pattern in the lidar signal must be promptly recognized by adequate automatic procedures, despite the presence of spurious peaks due to noise and light scattering agents. The present paper reports the investigation of one such procedure based on the fast localization of peaks potentially corresponding to smoke-plume signatures followed by feature extraction and highly nonlinear binarization transformation in order to increase the number of signal components. The binarized patterns are then classified with a single-layer perceptron.

2. BASICS OF LIDAR DETECTION

A lidar apparatus (Fig. 1) consists of a radiation emitter (a pulsed laser and beam-formation optics) and a radiation receiver (usually consisting of a light gathering optical train, photodetector and preamplifier). The emitter produces short intense radiation pulses. A part of the emitted radiation that is backscattered is collected by the receiver, where its power is converted into an electric signal, which is amplified and directed to the data-acquisition unit, to be recorded in digital form as a function of time.

In order to provide automated surveillance, lidar detectors must be supplemented with a signal recognition system, performing classification of target signatures and issuing, if needed, an alarm signal containing information about the target that caused the alarm situation and its location.

\textsuperscript{*} andrei.utkin@inov.pt; phone 351 213100426; fax 351 213100445; www.inov.pt
2.1 Raw lidar signal

The distance from the lidar to the target $R$ may be calculated from the time delay $t$ between the laser-pulse emission and the reception of the backscattered signal, $t = 2R/c$, where $c$ is the velocity of light. The raw lidar signal $S$ is the receiver-unit output voltage recorded during some period of time immediately after the laser-pulse emission ($t=0$). As far as 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 $S$ versus the distance $R$ rather than the time $t$:

$$S(t) \Rightarrow S(R) = GI_{ubph}(R) + S_0, \quad R = ct/2,$$

where $G$ is the total electronic gain, $I_{ubph}(R) = \xi ph P_f(R)$ the unbiased photodetector current, $\xi ph$ the photodetector responsivity and $S_0$ the background, which represents the electric displacement and low-frequency noise that can be assumed to be constant during the relatively short measurement time: about 67 $\mu s$ for a range of 10 km, according to relation (1).

A theoretical estimation of $P_f$ is given by the lidar equation:

$$P_f(R) = E_i \frac{c\beta(R)}{2} \frac{A_{rec}}{R^2} \tau_tr\tau_rec \exp\left(-2\int_0^R \alpha(R')dR'\right),$$

where $E_i$ is the output laser pulse energy, $\beta$ the backscattering coefficient of the medium, $A_{rec}$ the effective receiver area, $\tau_tr$ and $\tau_rec$ the transmitter and receiver efficiencies, and $\alpha$ the extinction coefficient.

At the early stage of a fire, the characteristic spread of the smoke plume in the direction of laser-beam propagation $\Delta R_{sp}$ (Fig. 2) is about 10 m. However, to be able to reveal the specific structures that make the smoke-plume signatures different from other signal peaks, the data-acquisition unit must measure the photodetector output with a sampling interval $\delta R \geq 1.5$ m, eventually yielding the discrete-time lidar signal in the form

Fig. 1. Lidar equipment and detection principles.
According to Eqs. (1) and (2), smoke plumes manifest themselves in raw lidar signals as peaks whose amplitude and shape vary due to the stochastic changes in the particle distribution within the smoke plume under the action of gasdynamic forces, buoyancy and wind. The smoke-plume signatures are observed against a background contaminated by electronic and atmospheric noise (Fig. 3). The electronic noise of a well constructed receiver usually demonstrates no dependence on the distance and can be estimated from a signal segment recorded far beyond the range of the instrument, where no retroreflection is expected.
Apart from this unstructured noise, the lidar signal may contain peaks due to retroreflection from aerosol, dust clouds, hills, trees, buildings, birds, etc. Solid-target signatures are narrow pulse-like waveforms, since the backscattering occurs at almost a single distance. The shape of these peaks is mainly defined by the bandwidth of the detection channel and the rate of the analog-to-digital conversion.

3. RECOGNITION STRATEGY

3.1 Characterization

As seen from Eq. (3), the shape of the smoke-plume signatures in the lidar signal depends in a complicated way on the profiles of the extinction and backscattering coefficients along the beam propagation direction. Although important for the prediction of the lidar range \( R \), gas-dynamic smoke-plume models do not provide a solid basis for the extraction of the characteristic features of the smoke-plume signature. Due to this lack of reliable parametric models, automated fire surveillance is mainly based on artificial-intelligence algorithms such as neural network (NN) methods.

In order to be feasible, the lidar-detector data processing must be based on a personal computer. In this situation the smoke-recognition algorithm must be implemented in such a way that all its stages — writing and testing the neural-network emulation code, training and recognition — can be carried out with the relatively limited computational resources of these computers.

In principle, lidar locates targets with the precision of a few meters, thus allowing for a very accurate location of the fire. The angular target position (the azimuth \( \phi \) and elevation \( \vartheta \), see Fig. 2) is given by the laser beam direction, but the calculation of the distance to the smoke plume \( R_{sp} \) is carried out by the signal analysis unit.

NN architectures and algorithms suited for lidar data extraction have been discussed in the literature since the 1990s. It was established that waveforms containing small retroreflection from distributed targets cannot be directly presented to a neural network. A simple and fast preprocessing method was developed for facilitating the recognition, ensuring, at the same time, that the processed waveforms properly reflect subtle variations in the original waveforms. Following the same principles as the radial-basis function algorithms, the recognition efficiency of a perceptron-based NN is enhanced by a special binarization procedure that uses a 2-D grid in the signal-distance plane for the waveform representation and a point-to-node proximity criterion for assigning one or zero to the grid nodes. Each node is treated as a separate input component, increasing the network input dimension, number of adjustable weights and, according to Cover’s theorem, improving pattern separability.

3.2 Problems

The application in question is characterized by the following difficulties:

1. The length of the discrete-time sequence \( \{ S(t_i) \}^{i_{\text{max}}}_{i=0} \) to be processed is much larger than in other lidar applications, such as underwater object detection, typically consisting of 5-10 points. The small signature width and the great variety of possible waveforms do not allow the statistics-based noise reduction and signal compression algorithms, which effectively reduce the computational load in many other applications, to be applied.

2. Smoke-plume signatures are compact. As seen from Eq. (3), the characteristic spread of a smoke-plume signature \( \Delta R_{sp} \), within which the backscattering factor \( \beta \) is sufficiently large to produce the signal above the noise level, is restricted by the spread of the plume \( \Delta R_{sp} \); for a starting fire, \( \Delta R_{ss} \leq \Delta R_{sp} \approx 10 \text{ m} \). Well-developed fires result in much wider plumes, but denser smoke, which increases the laser-beam extinction up to the values \( \alpha \sim 0.2 \text{ m}^{-1} \). In these circumstances, the smoke-plume signature decreases down to the noise level at distances of the order of \( \alpha^{-1} \) from its origin due to the Beer-Lambert absorption of both the laser beam and retroreflected light, resulting in \( \Delta R_{ss} \approx 5 \text{ m} \). Thus, measured as number of points in the digitized signal, \( N_{ss} = \Delta R_{ss} / \alpha \), the signature spread is always much less than that for the cases described by Bhattacharya and Mitra, typically consisting of 5-10 points. The small signature width and the great variety of possible waveforms do not allow the statistics-based noise reduction and signal compression algorithms, which effectively reduce the computational load in many other applications, to be applied.
3. The requirement that the distance to the target $R_{sp}$ must be determined by the NN potentially complicates its structure, as it turns the multiple input - single output classification scheme into one with multiple outputs, in which the additional neurons codify, in some way, the analog or digital value of $R_{sp}$.

4. Due to the fact that a constant background can be represented as a sum of uniformly distributed peaks, the problem of peak recognition is not linearly separable a priori, and cannot be solved without introduction of preprocessing and/or non-linearity.

### 3.3 Knowledge and invariances

To compensate the limitations mentioned in Sec. 3.2, a specialized NN system, where all prior information is used in order to simplify the overall structure and facilitate the smoke-plume signature recognition, must be developed. Depending on its nature, the pre-existing knowledge of the input signal can be represented as a transformation, selection rule and/or invariant and then built into the system via specific design or preprocessing procedures. The analysis of the lidar signal, briefly presented in Secs. 2.1, 2.2 and 3.2, makes it possible to point out the following peculiarities:

1. The smoke-plume signatures manifest themselves in the raw lidar signal as peaks whose characteristic width $\Delta R_{ss}$ (several meters) is much less than the typical distance to the smoke plume $R_{sp}$ (from hundred meters to several kilometers).

2. The position of the smoke-plume peak maximum corresponds to the desired distance to the smoke plume.

3. The local noise level may be estimated as the root-mean-square of the signal immediately before and after the peak and the segment of the lidar signal of the length $\sim 3 \Delta R_{ss}$, containing the smoke-signature maximum in its center, is supposed to provide information of both the smoke-plume peak shape and the local noise. The ratio of the peak amplitude to the mean local noise, called peak-to-noise ratio ($PNR$), represents an important scale-independent characteristic of the peak magnitude, closely linked with the probability of the peak to be a target signature rather than clutter. For this reason it is worthwhile to treat $PNR$ as an invariant characteristic feature to be extracted and presented for recognition in a separate way.

4. Within the range $10 \Delta R_{ss} \leq R \leq R_{\text{max}}$ the shape factor of the smoke-plume peak is invariant with respect to the distance $R$. The latter conclusion follows from Eq. (3): for the coordinate originated from the air/smoke interface, $x = R - R_{sp}$ (Fig. 2), the plume peak profile is given by

\[
\tilde{S}(x) = S(R_{sp} + x) = C_0 \beta(R_{sp} + x) \left( \frac{R_{sp} + x}{R_{sp} + x} \right)^{\alpha(R')} dR' + S_0, \quad 0 \leq x \leq \Delta R_{ss}
\]  

(5)

For $R_{sp} \geq 10 \Delta R_{ss}$ the factor $(R_{sp} + x)^2$ can be approximated by $(R_{sp} + \Delta R_{ss}/2)^2$, yielding

\[
\tilde{S}(x) = C(R_{sp}) \Phi(x) + S_0, \quad C(R_{sp}) = \frac{C_0}{R_{sp} + \Delta R_{ss}/2^{\alpha}} \exp \left( -2 \int_0^{R_{sp}} \alpha(\beta') dR' \right),
\]

\[
\Phi(x) = \bar{\beta}(x) \exp \left( -2 \int_0^{x} \bar{\alpha}(x') dx' \right), \quad \bar{\alpha}(x) = \alpha(R_{sp} + x), \quad \bar{\beta}(x) = \beta(R_{sp} + x)
\]  

(6)

where the factor $C(R_{sp})$ characterizes the radiation attenuation on the atmospheric path $0 \leq R \leq R_{sp}$ with the extinction $\alpha = \alpha_{\text{atm}}$ while $\Phi(x)$ represents the backscattering efficiency. The scale-independent shape factor of the smoke plume peak $\tilde{x}(x)$ is defined by the linear transformation satisfying the two minimax conditions.
\begin{align}
\max_{x \in [0, \Delta x]} \tilde{z}(x) &= \tilde{z}(x_{\text{max}}) = 1, \\
\min_{x \in [0, \Delta x]} \tilde{z}(x) &= \tilde{z}(x_{\text{min}}) = -1
\end{align}

Doing the calculations, the following explicit form can be easily obtained:

\begin{align}
\tilde{z}(x) = \frac{2 \tilde{S}(x) - \tilde{S}(x_{\text{max}}) - \tilde{S}(x_{\text{min}})}{S(x_{\text{max}}) - S(x_{\text{min}})} = \frac{2 \Phi(x) - \Phi(x_{\text{max}}) - \Phi(x_{\text{min}})}{\Phi(x_{\text{max}}) - \Phi(x_{\text{min}})}
\end{align}

which is independent from the distance to the smoke plume $R_s$. Obviously, the noise distorts the smoke-plume peaks increasingly at greater distances, and 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 the same.

### 3.4 Implementation

**Preprocessing.** The knowledge and invariances are built into the system via the following preprocessing procedure: The raw lidar signal, consisting of several thousand points ($i_{\text{max}} = R_{\text{max}} / \partial R$), is viewed by the preprocessing software through a window of several tens of points ($\sim 3\Delta x / \partial R$) that moves along the signal curve. The window motion stops if the local signal maximum coincides with the window center $R_p$ and the corresponding peak-to-noise ratio $PNR(R_p)$ is calculated. If $PNR(R_p) < PNR_{\text{thr}}$, where the threshold value $PNR_{\text{thr}}$ (typically, from 3 to 5) is chosen in accordance with some predefined requirements imposed on the rates of misdetection and false alarm, the peak is considered to be too small for being a smoke-plume signature and the observation window continues its motion along the lidar signal curve. Otherwise the signal pattern within the window is directed to the NN input layer. The feature value $PNR(R_p)$ is also fed to the NN, although through a special input, to be treated in a different way.

Eventual alarm generation is performed on the basis of pattern classification (smoke-signature dichotomy) with a single-layer perceptron, which is structurally equivalent to the adaptive linear filter \(^4\), whose classification efficiency is enhanced by nonlinear threshold binarization procedure, similar to Bhattacharya's processing of lidar signal \(^1\) for the detection of fish in near-shore waters (Fig. 4): The signal pattern 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 to that point; otherwise, a zero is assigned. Each sample point is tested in the same way and the method yields at the end a matrix of zeros and ones, eventually converted into a binary pattern vector, which reflects 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 one, is even easier for hardware implementation (using a batch of threshold detectors with linearly increasing thresholds) and results in less sparse and more compact binarized samples: the bottom line always contains ones and can be discarded.

![Fig. 4. Increasing the pattern dimensionality by point binarization and threshold binarization procedures.](image-url)
Recognition. Borrowing the approach used in the radial-basis function network theory, 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\(^4\) for the desired interconnection weights as a product of the 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). Following Bishop’s recommendations\(^3\), the instability arisen from the sparse nature of the binary-sample matrices and incomplete ranks is overcome by stabilized pseudoinversion on the basis of singular-value decomposition\(^8\). The alarm threshold for the perceptron output is established on the basis of ad hoc Neyman-Pierson criterion and the alarm signal is accompanied by the current position of the moving window center \(R_w \approx R_{sp}\), which provides the distance to detected smoke plume.

4. RESULTS AND DISCUSSION

The typical characteristic of the efficiency of the recognition algorithm, expressed as a number of detection errors, \(n_{err}\) (equal to the totality of the false alarm and misdetection occurrences) versus the binarization grid density \(n_Y\) (number of divisions in the vertical scale), is illustrated in Fig. 5.

![Fig. 5. Number of detection errors, \(n_{err}\), as a function of the binarization grid density \(n_Y\).](image)

Increasing \(n_Y\) leads to an increase in the number of nodes and perceptron connections, allowing the NN to learn the training set with more details. As a free parameter of the algorithm, the binarization grid density plays the same role as the number of training epochs in the iterative learning rules. The low density of the grid results in binary samples with few details and in the poorly trained perceptron. On the other hand, the dense grids generate detailed samples that are recognized by perceptron with a large number of nodes, which causes over-training: the perceptron learns not only the typical pattern characteristics, but the noise as well. For the optimal binarization grid density, \(n_Y = 13\), the application of the proposed procedure enabled a software for automatic smoke recognition with an error rate of 0.31\% (19 misdetections and 4 false alarms in the analysis of a test set of 7409 peaks, 224 of them corresponding to the smoke-plume signatures) to be developed.

Within the inherent uncertainty resulting from statistical nature of the recorded signals, a certain degree of arbitrariness in the choice of the training set and incompleteness of description of the variety of smoke-plume peaks, the threshold binarization algorithm demonstrated an efficiency (8.5\% misdetection rate and 0.056\% false alarm rate) similar to a 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 allows nearly one order of magnitude faster training.
Moreover, since the learning procedure does not depend on the choice of the best classifier, it can be strictly formalized and performed by users without special training. The algorithm does not contain repetitive iterational routines like training epochs in the case of gradient-descent methods and the global minimum of the classification error for given training set is readily achieved by a sequence of matrix operations of guaranteed stability.

At very close distances to the lidar, \( R \leq 10 \Delta R_{pp} \), the shape factor of the smoke-plume peak depends on \( R_{pp} \). However, it was observed that the shape distortion does not affect the recognition capability of the system for this region, mostly due to the very high \( PNR \) value that activates the alarm output even if the input from the binary-sample nodes is not univocal.

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REFERENCES