FIRST ATTEMPTS AT MEASURING WIDESPREAD SMOKE WITH A MOBILE LIDAR SYSTEM

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Keywords—Lidar, Wild fires, Widespread smoke, Support Vector Regression

Abstract

In the last years, the LIDAR technique has been successfully applied to the detection of the smoke plume emitted by wild fires. Up to now, the attention has been devoted to early detection of quite concentrated smoke plumes to reveal the first stage of fires as soon as possible. In this paper, it is shown how the LIDAR technique can also cope with widespread smoke, which can be the consequence of strong wind dispersion or non-concentrated sources. To this end, innovative signal processing techniques are required. The proposed approach is able to detect, in a reliable way, the presence of widespread smoke in the backscattered signals of compact LIDAR systems. The first experimental evidence is encouraging and the potential of the proposed method is presented.

1 The signature of widespread smoke in Lidar signals

Wild fires have become a very serious problem in various parts of the world. The LIDAR technique has been successfully applied to the detection of the smoke plume emitted by wild fires, allowing the reliable survey of large areas [1, 2, 3, 15 ,16,19]. Recently, mobile compact systems have been successfully deployed in various environments. Up to now, the attention has been devoted to early detection of quite concentrated smoke plumes, characterising the first stage of fires, as soon as possible[4, 5, 6]. The main operational approach envisages the continuous monitoring of the area to be surveyed with a suitable laser [9, 11]. When a significant peak in the backscattered signal is detected, an alarm is triggered. In these applications, the backscattered signal presents strong peaks, which are detected with various techniques. In other applications, it would be interesting also to detect the non concentrated, widespread smoke, which can be the consequence of strong wind dispersion or non concentrated sources. In this case, the signature of the presence of the smoke is not a strong peak but a different slope in the tail of the backscattered signal. Typical examples of backscattered signals for the alternatives of no smoke, strong smoke plume and widespread smoke are shown in Figure 1.

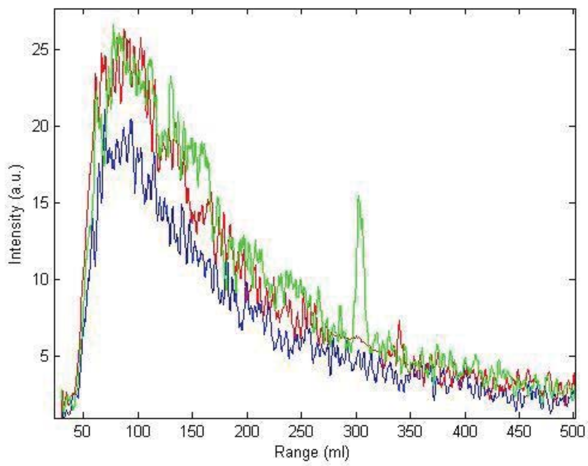

Figure 1 – Examples of LIDAR back scattered signals: a) No smoke (blue line) b) strong smoke plume (green line) c) widespread smoke (red line).

As can be seen from the experimental signals shown in Figure 1, the signature of non concentrated, widespread smoke is not a strong, concentrated peak in the decay phase of the detected power but an overall increase of the curve. This can be ascribed to an increase in the backscattering coefficient, as discussed in more detail in Section 4. The mechanism for the increased signal is therefore quite clear but, from a practical point of view, the discrimination between the two curves is quite challenging. To this end, innovative signal processing techniques have been deployed to filter the backscattered signal. The proposed approach is based on Support Vector Regression (SVR), a nonparametric technique to filter the data without any assumption about the nature of the noise. SVR is used as a way to clean the backscattered signals in order to allow reliable fitting. These methods should be able to detect, in a reliable and automatic way, the presence of widespread smoke in the backscattered signals of a compact LIDAR system. They can therefore be deployed for the automatic survey of large areas of vegetation.

2 The Lidar station

The measurements described in the paper have been performed with the mobile Lidar unit of Industrial Engineering Department, University of Rome "Tor Vergata" [8, 14]. The system consists of an easily transportable compact Lidar system. The transmitter is a Nd:YAG laser that can operate at three wavelengths: 1064, 532 and 355nm. The 532 nm wavelength is not really suited for environmental surveying, since it is not eye safe and therefore requires specific authorizations to be deployed. The other two lines have been both used for particulate detection and there is not overwhelming reason to prefer one. On the other hand, the detectors in the UV are generally more performing than in the IR and therefore the 355 nm wavelength has been chosen for the experiments reported in this paper. It is worth mentioning that there is no reason to expect the 1096 to present any particular difference, as also confirmed by preliminary tests already performed.

The laser is anchored at the receiver system, a Newtonian telescope, and both can move to direct the beam and receive the backscattered radiation over a whole hemisphere. The system is completely auto-powered and the structure is designed to be transportable and steerable. It is easily hooked to azimuth mount for supporting and rotating about two mutually perpendicular axes; one vertical, from -10° to 90°, and one horizontal, from 0° to 220°. By means of two step-motors, it has a global angular resolution of 1.8°. Since the laser source is operating in the UV region, the detector chosen is a Hamamatsu's photomultiplier tube (PMT), R3235 model. These technologies have become relatively standard and therefore they can be procured at reasonable costs [18]. The main characteristics of the mobile unit are reported in Table 1. The entire apparatus is controlled by a software package, written in Labview and Matlab, explicitly developed for this application. The laser activation and the wavelength selection, together with the rotation of the telescope and data acquisition, is controlled by a Labview series of routines. The signal processing algorithms and the visualization of the results have been implemented using Matlab. The signal processing routines calculate the distance of the fire from the station and also show the fire topographic coordinates (essential for the coordination of timely intervention).

The signals analysed in this paper have been collected during an extensive experimental campaign, which has been carried out in Calabria, in the south of Italy.

Transmitter:	
Laser	Q-switch Nd:Yag
Energy pulse at 355 nm	100 mJ
Pulse time width	5 ns
Divergence angle	0,5 mrad
Pulse Frequency	10 Hz
Receiver:	
Telescope type	Newtonian
Nominal focal length	1030 mm
Primary mirror diameter	210 mm
Detector	Photomultiplier (PMT)
Photocathode sensibility	72 mA/W
Response time	30 ns

Table 1. Parameters of Nd:Yag Lidar system [13].

3 Support vector regression for the first signal processing

Support Vector Machines [14] are a very specific class of machine learning tools, whose characteristics are use of kernels, absence of local minima, sparseness of the solution and capacity control obtained by acting on the margins, or on the number of support vectors. They were invented by Vladimir Vapnik and his co-workers, and first introduced at the Computational Learning Theory (COLT) 1992 conference. All these nice features however were already present in machine learning since 1960's. However it was not until 1992 that all these features were combined to form the maximal margin classifier, the basic *Support Vector Machine* (SVM).

SVM can be applied not only to classification problems but also to the case of regression [17]. Still they contain all the main features that characterize maximum margin algorithm: a non-linear function is learned by mapping into a high dimensional kernel induced feature space. In analogy with classification, there is an advantage in optimizing the generalization of the regression margins. This is achieved by defining a loss function that ignores errors, which are situated within a certain distance of the true value. This type of function is often called – epsilon intensive – loss function. Figure 2 shows an example of one-dimensional linear regression function with – epsilon intensive – band.

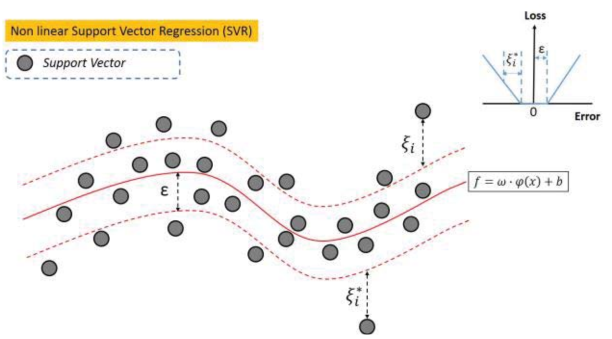

Figure 2 – Example of an epsilon intensive loss function.

The variables measure the cost of the errors at the training points. The errors are considered zero for all points that are inside the insensitive band. In SVM regression, the input x is first mapped onto a m-dimensional feature space, using some fixed (nonlinear) mapping, and then a linear model is constructed in this feature space. Mathematically, the linear model (in the feature space) $f(x, \omega)$ is given by

$$f(x,\omega)=\sum_{j=1}^{m}\omega_j g_j(x)+b \quad (1)$$

where $g_j(x)$, $j=1,\dots,m$ denotes a set of nonlinear transformations, and b is the "bias" term. Often the data are assumed to be zero mean (this can be achieved by preprocessing), so the bias term is dropped. The quality of the estimation is measured by the loss function $L(y, f(x,\omega))$. SVM regression uses a new type of loss function, called ε-insensitive loss function, introduced by Vapnik:

$$L_\varepsilon(y,f(x,\omega))=\begin{cases}0 & \text{if } |y-f(x,\omega)|\le\varepsilon\\ |y-f(x,\omega)|-\varepsilon & \text{otherwise}\end{cases} \quad (2)$$

The so called empirical risk can be calculated as:

$$R_{emp}(\omega)=\frac{1}{n}\sum_{i=1}^{n}L_\varepsilon(y_i,f(x_i,\omega)) \quad (3)$$

SVM regression performs linear regression in the high-dimension feature space using ε-insensitive loss and, at the same time, tries to reduce model complexity by minimizing $\|\omega\|^2$. This can be implemented by introducing slack variables ξ_i,ξ_i^* $i=1,\dots n$, to measure the deviation of training samples outside ε-insensitive zone. Thus SVM regression is formulated as minimization of the functional:

$$\min \quad \frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}(\xi_i+\xi_i^*) \quad (4)$$

$$\begin{cases}y_i-f(x_i,\omega)\le\varepsilon+\xi_i^*\\ f(x_i,\omega)-y_i\le\varepsilon+\xi_i\\ \xi_i,\xi_i^*\ge 0,\ i=1,\dots,n\end{cases} \quad (5)$$

This optimization problem can translated into the dual problem and its solution is given by

$$f(x)=\sum_{i=1}^{n_{SV}}(\alpha_i-\alpha_i^*)K(x_i,x) \quad (6)$$
$$0\le\alpha_i^*\le C \quad 0\le\alpha_i\le C$$

where n_{SV} is the number of Support Vectors (SVs) and the kernel function

$$K(x,x_i)=\sum_{j=1}^{m}g_j(x)g_j(x_i) \quad (7)$$

It is well known that SVM generalization performance depends on the choice of meta-parameters parameters C, ε and the kernel parameters. Selecting a particular kernel type and kernel function parameters is usually based on application-specific knowledge and also should reflect distribution of the training data. Parameter C determines the trade off between the model complexity (smoothness) and the degree to which deviations larger than ε are tolerated. For example, if C is too large, then the objective is reduced to minimizing the empirical risk only, without regard to model complexity. Parameter ε controls the width of the ε -insensitive zone, used to fit the training data. The value of ε can affect the number of support vectors used to construct the regression function. The bigger ε, the fewer support vectors are selected. On the other hand, bigger ε-values results in smother estimates. Hence, both C and ε-values affect model complexity [18].

4 First analysis of Lidar experimental data

One of the advantages of Support Vector Regression consists of the fact that its parameters can be chosen without detailed knowledge of the noise superimposed on the signal. Only the amplitude of the noise really matters, because typically it affects the choice of parameter ε. Moreover, this filtering technique is quite robust to variations in the details of the noise as has already been demonstrated in other applications of LIDAR detection. [10,12,13]. The quality of the signals after filtering can be appreciated in Figure 3. At this point, it is relatively easy to perform a fitting of the signals and, when the maximum of the signal is above a certain threshold, a warning of widespread smoke can be issued.

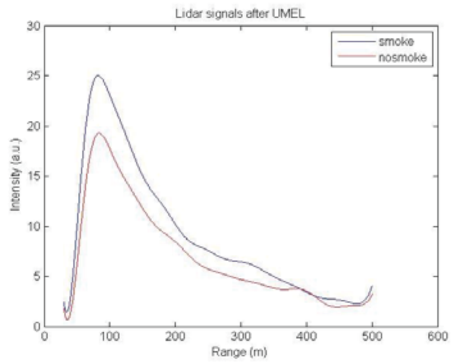

Figure 3 – The experimental signals after filtering with SVR. The case without smoke is in red. The signal for the case with widespread smoke is in blue.

Starting from the typical Lidar equation [8], it has been decided to fit the decaying part of the backscattered signal intensity with a mathematical expression of the form:

$$P = \frac{K_1}{R^2}\exp(-2K_2 R) \qquad (8)$$

where K_1 and K_2 are constants and R is the range. The data of Figure 3 have been fitted with this formula. The results of the non –linear fit are:

- In case of widespread smoke:

$$P = \frac{2.648 \cdot 10^{-1}}{R^2} \cdot \exp(-1.259 \cdot 10^{-3} \cdot R) \qquad (9)$$

- No smoke:

$$P = \frac{1.734 \cdot 10^{-1}}{R^2} \cdot \exp(-1.171 \cdot 10^{-3} \cdot R) \qquad (10)$$

The results of the fit, equations (9) and (10), indicate quite clearly that the parameter K_2 is practically the same for both the case of widespread smoke and clear atmosphere. On the other hand, there is a clear difference, of the order of 25% in the constants K_1. This is expected since K_1 includes the effect of the coefficient β, which indeed quantifies the backscattering properties of the atmosphere [5].

5 Conclusions and further developments

As shown in the previous section, SVR is a sophisticated technique to filter the backscattered signals of LIDAR systems. If this filtering step is successful, it is relatively easy to fit the signals and calculate their maximum. On the basis of the value of this maximum, a decision can be made about the presence of widespread smoke. The effectiveness of the approach will therefore depend on the accuracy and reliability of the first filtering step. The first results are encouraging but a wider statistical study is necessary. In this perspective more examples of widespread smoke will have to be collected. Also, in practical applications, the power output of the laser will have to be monitored to make sure that the changes in the amplitude of the received signals are really due to variations in the atmosphere and not drifts in the system.

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