Autoregressive Spectral Estimate in Fourier Spectroscopy Applied to Remote Sensing of the Atmosphere

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1. Introduction

Nowadays it is generally recognized as very important the ability of measuring the infrared emission spectrum of the earth with infrared Fourier spectrometers for retrieving temperature, humidity and other parameters of atmosphere and surface. The multiplex and throughput advantages of interferometers make it possible to perform radiometrically precise observations at a much higher spectral resolution than that of current filter radiometers. As a net result, the use of interferometers would make it possible to improve the vertical resolution in troposphere and lower stratosphere by at least a factor 2 over that of current temperature profiling radiometers (Revercomb et al. 1988).

Although the radiance spectrum is obtained in principle by a Fourier transform of the interferogram (i.e., the output of an interferometer), various factors intervene to make the recovered spectrum an imperfect representation of the true spectrum. The most important ones are: a) aperture effect; b) tilt and aberrations; c) phase and compensation; d) truncation; e) noise.

Generally the first two sources of error can be corrected by a suitable design of the hardware, whereas phase and compensation errors can be eliminated, in principle, by measuring two-sided interferograms. Finally, truncation errors and noise are usually handled by software: apodization (truncation error) and filtering (noise). This paper is mostly devoted to the latter two types of error.

As it is well known, the techniques presently used for reconstructing the spectrum are in the large majority of cases purely digital, and operate from sampled interferograms. Only a finite number of samples corresponding to a given maximum path difference can be used for the interferogram. As a consequence, the information beyond the truncation point goes lost and the recovered spectrum (Fourier transform of the inteferogram) exhibits spurious side lobes which can seriously affect its quality. This is the truncation error. One method for overcoming this problem is to assume that all data beyond the end point of the finite-length interferogram are zero, then choose an appropriate window function (apodization operation) which would improve the Fourier transform. However, with each window function the frequency resolution of one frequency component from neighboring frequency components is poor, since the spectral density is corrupted by spurious oscillations due to side lobes, and the covariance of the spectral estimates is large. This is not a serious problem

if the underlying spectrum is a smooth function of the frequency or wavenumber, but the problem becomes acute for spectra which are the superposition of sharp, discrete lines. Such characteristics are found in the infrared emission spectrum of the earth.

As far as noise is concerned, we note that the multiplex gain is the salient feature of Fourier spectroscopy, so that it is expected that measurement errors play a minor role. Anyway, the interferogram of any stationary process must tend to zero as the path difference or lag becomes large. Thus also a negligible measurement error can give place to a large noise-to-signal ratio on the last part of the sampled interferogram. Apodization also permits to reduce the effect of measurement errors: one usually uses weighting functions with weights decreasing to zero as the path difference becomes large. However in the context of the mathematical theory of the Fourier transform there is no quite a general tool which allows one to perform a quality-control of experimental data.

The main objective of this paper is to implement a scheme based on autoregressive (AR) models, and therefore alternative to the Fourier transform, in order to:

a) recover radiance spectra from interferometric measurements without any intervening window or apodizing function;

b) perform a quality-control of experimental data.

The paper mostly deals with the fundamentals of the technique. They rely upon the Wiener-Khinchine theorem, the linear prediction theory and the information theory. Furthermore, the potential advantages of the procedure in the context of remote sensing of the atmosphere are also discussed. Examples of applications of the technique are shown using HIS data.

This paper is so organized: in section 2 we show the basic equations and relations of the technique; section 3 deals with the potential advantages of the procedure over the usual Fourier transform; in section 4 an application of the technique is shown using HIS data; conclusions are taken in section 5.

2. Parametric Autoregressive Modeling Approach

2.1 BASIC RELATIONS IN FOURIER SPECTROSCOPY

Before presenting the autoregressive approach (AR-approach), we premit a brief summary of the basic relations between interferogram and radiance spectrum. As it is well known, for an ideal interferometer the relation between interferogram and radiance spectrum is a Fourier transform:

$$I(x) = \int_{-\infty}^{\infty} B(\sigma) \exp(-2\pi i\sigma x) d\sigma \tag{1}$$

where $I(x)$ denotes the interferogram (x is the optical path difference) and $B(\sigma)$ the radiance spectrum (σ is the wavenumber). Thus usually the recovery of the spectrum is achieved by taking the inverse Fourier Transform.

In practice, the spectrum is limited to a given band:

$$B(\sigma) = \begin{cases} \text{arbitrary} & \text{for} \quad \sigma_1 \leq \sigma \leq \sigma_2 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

and if the limits of the band (i.e., σ_1 and σ_2) satisfy the condition expressed by the sampling theorem:

$$\sigma_2 = h \cdot W; \quad W(\text{bandwidth}) = \sigma_2 - \sigma_1; \quad h \quad \text{integer} \tag{3}$$

and noting that the spectrum is an even function:

$$B(\sigma) = B(-\sigma) \tag{4}$$

the relation between spectrum and interferogram can be written as a cosine Fourier integral:

$$I(x) = 2 \int_0^W B(\sigma) \cos(2\pi\sigma x) d\sigma \tag{5}$$

where we have implicitly assumed $h = 2$. Furthermore, all information about the spectrum is given by a set of discrete samples of the interferogram:

$$I(0), I(\Delta x), \ldots, I(k\Delta x), \ldots \tag{6}$$

provided that the sampling interval Δx satisfies the condition:

$$\Delta x \leq \frac{1}{2(\sigma_2 - \sigma_1)} \tag{7}$$

Eq. (1) (or Eq. 5) is only a particular case of a general theorem: the Wiener-Khinchine theorem which states that the relation between the covariance function and the spectrum of any process is a Fourier transform, i.e.:

$$C(\tau) = \int_{-\infty}^{\infty} S(\sigma) \exp(-2\pi i\sigma\tau) d\sigma \tag{8}$$

or for a band-limited spectrum:

$$C(\tau) = 2 \int_0^W S(\sigma) \cos(2\pi\sigma\tau) d\sigma \tag{9}$$

In (8) and (9) $C(\tau)$ denotes the covariance function (τ is the time or spatial lag) and $S(\sigma)$ the spectrum (σ stands indifferently for frequency or wavenumber). Always in (9) W is the bandwidth.

The Wiener-Khinchine theorem provides the necessary link between the interferogram and the spectrum, for an interferogram is the covariance or autocorrelation of the incident wave amplitude. Furthermore, it enables us to use modern statistical tools which permit to recover spectra from covariance functions (i.e., interferograms in our case).

In this paper we will consider an approach motivated by probalistic arguments. The approach goes under several names: all-poles model, maximum entropy method (MEM), autoregressive (AR) model. The method is a non-linear technique for estimating power spectra with improved resolution from the covariance function. The procedure appears to have been developed independently by Burg (1967) in some unpublished work and by Parzen (1968). Following Parzen we will use the name "AR-approach" or AR-model and so on. In our opinion the maximum entropy property has caused MEM to acquire a certain "cult" of popularity. One sometimes hears or reads that it gives an intrinsecally better estimate than other methods. It is not true. In the context of the maximum entropy formalism, it is a very difficult task to understand how and where the technique recovers spectra with improved resolution. On the other hand, such a problem is easily handled using the linear prediction theory which is mostly based on autoregressive processes (see section 3).

2.2 AR-SPECTRAL ESTIMATE

In force of the Wiener-Khinchine theorem, in the following we use the terms interferogram and covariance function indifferently; both these functions will be denoted by the symbol $I(x)$. Furthermore, $R(\sigma)$ will denote the spectrum.

An autoregressive process of order p is a stochastic process whose covariance function satisfies a difference equation of order p (Box and Jenkins, 1976):

$$I(k) = \alpha_1 I(k-1) + \alpha_2 I(k-2) + \ldots + \alpha_p I(k-p); \quad k > 0 \tag{10}$$

where for simplicity we wrote $I(k\Delta x) = I(k)$, with Δx the sampling interval. The spectrum is:

$$R(\sigma) = \frac{P_{p+1}/W}{\| 1 - \sum_{j=1}^{p} \alpha_j \exp(-2\pi i j \sigma \Delta x) \|^2} \tag{11}$$

where W denotes the Nyquist frequency (bandwidth), i the imaginary unit. The unknown P_{p+1} in (11) and the coefficients $\{\alpha_1, \ldots, \alpha_p\}$ appearing both in (10) and (11) can be computed by solving the following set of linear equations:

$$\mathbf{A} \cdot \alpha = \mathbf{P} \tag{12}$$

where the matrix $\mathbf{A}$ is the covariance matrix (it is a Toeplitz matrix):

$$\mathbf{A} = \begin{pmatrix} I(0) & I(1) & I(2) & \ldots & I(p) \\ I(1) & I(0) & I(1) & \ldots & I(p-1) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ I(p) & I(p-1) & I(p-2) & \ldots & I(1) \end{pmatrix} \tag{13}$$

and

$$\begin{aligned} \alpha &= (1, \alpha_1, \ldots, \alpha_p)^T \\ \mathbf{P} &= (P_{p+1}, 0, \ldots, 0)^T \end{aligned} \tag{14}$$

In practice, if we have an interferogram sampled up to a maximum delay $N\Delta x$ we can compute the radiance spectrum by using the above equations. Thus the technique will consist of fitting to the measured interferogram the covariance function of an AR-model or AR-process.

However if we have a number N of data ($k\Delta x = k$):

$$I(0), I(1), \ldots, I(k), \ldots, I(N) \tag{15}$$

in principle we can fit to the data a number N of AR-models, that is a difference equation or an AR-model of order 1, an AR-model of order 2, and so on up to an order N which uses all the data. If the data are not affected by noise we can choose without any problems the order N. However in practice the data are always affected by measurement errors so that we have the problem of finding the AR-model which best fits to the data.

To handle such a problem we will take a parametric AR-modeling approach. This approach involves two basic tasks. First, the appropriate model (i.e., the order p of the autoregressive process) to be fitted to the data is identified. Second, based on the model chosen, the radiance spectrum is obtained using the above equations. As it will be shown in the next section, such a procedure also permits to perform a quality-control of the experimental data.

2.3 QUALITY-CONTROL OF THE DATA

The procedure requires that all possible orders p, $p = 0, 1, \ldots, N - 1$, are fitted to the data. Then the optimal order, p_{opt}, is selected that minimizes the quantity:

$$SIC(p) = N \log(S^2(p)) + 2p \tag{16}$$

Here N is the number of samples of the measured interferogram. The quantity $S^2(p)$ will be defined in the following. The statistic (16) belongs to a quite general class of indexes used in the context of model identification theory (Akaike, 1974). However, we like to note that the statistic (16) is a new, quite original, statistic among the indexes belonging to the Akaike's class.

In order to illustrate the procedure, we start from the step of order 0. This is the most trivial step. In fact it consists of fitting the covariance function of a white noise to the measured interferogram. Denoting by I^* the fitted covariance function and by I the measured values we have:

$$I^*(0) = I(0); \quad I^*(1) = 0, \ldots, I^*(N) = 0 \tag{17}$$

The recovered spectrum is then the flat spectrum which has the constant value P_{10}/W at each wavenunmber; here $P_{10} = I(0)$. Also the goodness of the fit is "measured" by means of the square of the standard error:

$$S^2(0) = \frac{1}{N-1} \sum_{k=1}^{N} (I^*(k) - I(k))^2 \tag{18}$$

which begins to explain the meaning of the quantity $S^2(p)$

As a less trivial step, we come to order 1. In such a step we fit to the data a model of order 1:

$$I^*(k) = \alpha_{11} I^*(k-1); \quad k > 0 \tag{19}$$

where the unknown α_{11} is computed solving the set of linear equations (12) with $p = 1$, i.e.:

$$\begin{pmatrix} I(0) & I(1) \\ I(1) & I(0) \end{pmatrix} \begin{pmatrix} 1 \\ \alpha_{11} \end{pmatrix} = \begin{pmatrix} P_{21} \\ 0 \end{pmatrix} \tag{20}$$

After that, starting the difference equation (19) with $I^*(1) = I(1)$, the predicted values of the interferogram beyond the lag 1 up to the lag N are computed on the basis of the model (19). Finally, the square of the standard error is computed according to:

$$S^2(1) = \frac{1}{N-2} \sum_{k=2}^{N} (I^*(k) - I(k))^2 \tag{21}$$

For an arbitrary step of order p, $p = 1, \ldots, N - 1$, we fit to the data the difference equation of order p:

$$I^*(k) = \alpha_{1p} I^*(k-1) + \alpha_{2p} I^*(k-2) + \ldots + \alpha_{pp} I^*(k-p), \quad k > 0 \tag{22}$$

where the coefficients $\{\alpha_{11}, \ldots, \alpha_{pp}\}$ are computed by solving the set of linear equations (12), namely:

$$\begin{pmatrix} I(0) & I(1) & I(2) & \cdots & I(p) \\ I(1) & I(0) & I(1) & \cdots & I(p-1) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ I(p) & I(p-1) & I(p-2) & \cdots & I(1) \end{pmatrix} \begin{pmatrix} 1 \\ \alpha_{1p} \\ \vdots \\ \alpha_{pp} \end{pmatrix} = \begin{pmatrix} P_{p+1,p} \\ 0 \\ \vdots \\ 0 \end{pmatrix} \tag{23}$$

Starting the difference equation (22) with:

$$I^*(1) = I(1), I^*(2) = I(2), \ldots, I^*(p) = I(p) \tag{24}$$

we compute the predicted values of the interferogram beyond the lag p up to the lag N and calculate the square of the standard error according to:

$$S^2(p) = \frac{1}{N - p - 1} \sum_{k=p+1}^{N} (I^*(k) - I(k))^2 \tag{25}$$

which ends off to explain the meaning of the quantity $S^2(p)$ appearing in the expression of the statistic SIC(p) (Eq. 16).

At this point of the analisys we want to stress that the above procedure can be implemented in a recursive fashion. Towards this objective it is possible to use the Durbin algorithm or the Levinson algorithm. The recursive procedure that we have implemented uses the Levinson algorithm.

Finally, we note that data are processed in a sequential way: at the step of order 0 we consider only the sample at 0 path difference or lag, at the step of order 1 we add the information coming from the next data in the data series of the interferogram and so on. Thus if the optimal order is p we can conclude that the data from the lag $p + 1$ up to the lag N do not add any information to the spectrum. In other words the technique can be seen as a mere procedure which permits to perform a quality-control of the experimental data.

3 About the potential advantages of the AR-spectral estimate

As it was already pointed out, the AR-spectral estimate has the maximum entropy property. However such a property does not add anything towards a better understanding of the capability of the technique. Maybe a more appealing feature of the technique is that the MEM or AR estimation (see Eq. 11) is a function of continously varying wavenumber σ. There is no special significance to specify equally spaced wavenumbers as in the Fast Fourier Transform case. However there are many other reasons which make the technique very interesting, expecially in the context of the remote sensing of the atmosphere. We will discuss about such a topic in the next sections.

3.1 ABOUT THE SPECTRAL RESOLUTION

We have seen that the AR-approach consists of fitting to the measured inteferogram a model which is a difference equation of some suitable order p. In practice two general situations can occur:

1. the "true" interferogram satisfies a difference equation of order p. In such a case, we need only p samples of the inteferogram and the value of the integral over the spectrum (i.e., I(0)) in order to have an accurate representation of the spectrum. On the other hand using the Fourier transform we need, at least theoretically, the full knwoledge of the interferogram, i.e., from $x = 0$ up to $x = \infty$;

2. the "true" interferogram does not satisfy any difference equation. In such a case the AR-spectral estimate does not offer any advantage upon the Fourier transform; at parity of data both the techniques have the same resolution. Still both the techniques converge to the true spectrum when the number of samples tends to ∞. However, with data affected by measurement errors, the parametric AR-approach we have discussed in the section 2.3 still permits to perform a quality-control of the experimental data.

At this stage of the discussion we note that there exists a very large class of physical phenomena with covariance functions which admit a representation in terms of a difference equation (i.e.. in terms of an autoregressive model). First of all we quote the class of periodic signals. Such signals have a covariance function which reads:

$$I(x) = \frac{A^2}{2} \cos(2\pi\sigma_0 x) \tag{26}$$

where A is the amplitude of the wave.

In optics Eq. (26) describes the ideal interferogram of a monochromatic wave of wavenunmber σ_0. If we sample such an interferogram at discrete points then samples satisfy a difference equation of order 2:

$$I(k) = \alpha_1 I(k-1) + \alpha_2 I(k-2); \quad k > 0 \tag{27}$$

Furthermore, the power spectrum of such signals is a δ-function peaked at σ_0.

Another example is offered by the superposition of M monochromatic waves. The covariance function is:

$$I(x) = \sum_{j=1}^{M} \frac{A_j^2}{2} \cos(2\pi\sigma_j x) \tag{28}$$

where M is the number of independent wavenumbers. The spectrum of this system has δ-functions at these wavenumbers. It can be demonstrated (Serio 1989) that its discrete interferogram is a difference equation of order $2 \cdot M$. In optics such systems describe the interferogram of M monochromatic sources.

To illustrate the very cute property of the AR-approach to fit sharp spectral features, we consider the theoretical example of two cosine waves with wavenumbers $\sigma_1 = 0.1$ and $\sigma_2 = 0.11$ respectively. The ideal interferogram is:

$$I(x) = \frac{A_1^2}{2} \cos(2\pi\sigma_1 x) + \frac{A_2^2}{2} \cos(2\pi\sigma_2 x) \tag{29}$$

Such an interferogram was sampled at a rate $\Delta x = 1$. The samples then satisfy a difference equation of order 4:

$$I(k) = \sum_{j=1}^{4} \alpha_j I(k-j); \quad k > 0 \tag{30}$$

where, as usual, we have written $k\Delta x = k$. We note that the coefficients $\alpha_1, \ldots, \alpha_4$ depend on the sampling interval but they do not depend on A_1^2 and A_2^2. In principle the AR-approach would be able to recover the correct spectrum only on the basis of four samples (and $I(0)$ of course). Fig. 1 (on the top) shows the AR-spectral estimate obtained using the values $I(0), I(1), I(2), I(3), I(4)$, while the Fourier spectrum (Fourier transform), computed using the same data, is shown on the bottom. The AR-method resolves the two spectral components completely, while the Fourier transform fails completely in detecting the presence of two cosinusoidal components.

Furthermore, we do not need to limit ourself to periodic signals. There is a very large class of aperiodic phenomena (that is systems whose covariance functions go to zero as the lag or the path difference tends to ∞). Among many others here we quote the cases described by damped cosines:

$$I(x) = \exp(-\frac{x}{\alpha}) \cos(2\pi\sigma_0 x) \tag{31}$$

Such an interferogram admits a representation in terms of a difference equation of order 2 when sampled at a finite rate. In optics Eq. (31) describes the interferogram of a Lorentzian line.

In general we can say that the AR-spectral estimate provides an accurate representation for underlying spectra which have sharp, discrete lines or δ-functions. Such characteristics are proper of the infrared emission spectrum of the earth or in general of emission spectra of gases. Thus the technique could potentially be very useful in the context of remote sensing of the atmosphere.
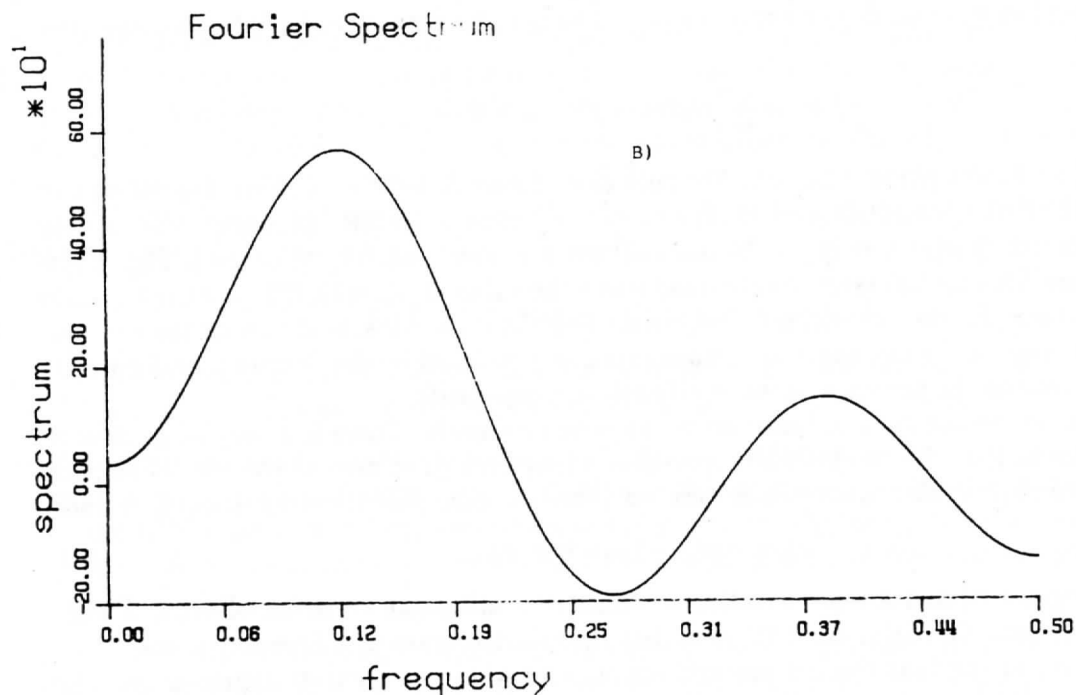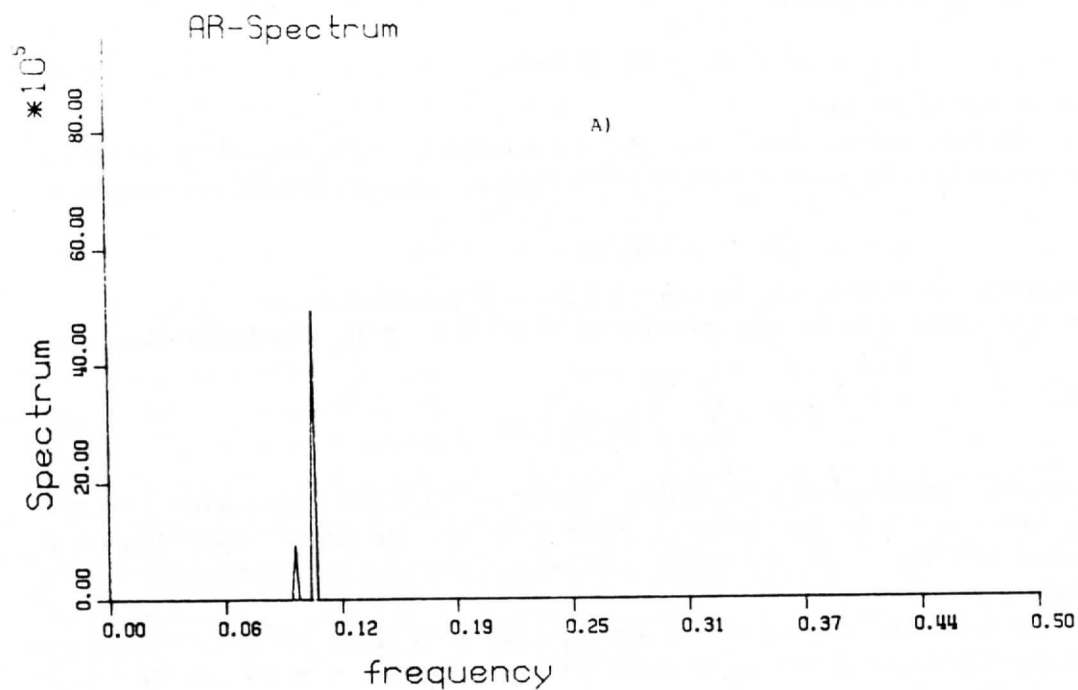
Fig. 1 - Example of two cosinus waves with frequencies 0.1 and 0.11 respectively. The figure shows the spectrum recovered using only 4 samples of the interferogram. A): AR-spectrum. B): Fourier spectrum.

3.2 About the truncation error

It was already pointed out in the introduction that in practice the interferogram is truncated at some finite value of the path difference, and therefore the loss of the information beyond the maximum delay will introduce some distortion in the spectrum. Such a problem becomes acute if the underlying spectrum exhibits sharp features, since in the interferogram periodic signatures will predominate and the convergence to zero is very slow.

In the context of the Fourier transform the tool to handle such a problem is apodization. i.e., the use of window functions. However the use of window functions violates assumptions of statistical inference; that is they assume characteristics of the data which are not known and corrupt available data by smoothing. Furthermore apodization introduces linear dependence among the spectral components.

On the other hand we have already seen that the AR-approach attempts to fit to the data a difference equation of some suitable order p:

$$I(k) = \alpha_1 I(k-1) + \ldots + \alpha_p I(k-p); \quad k > 0 \tag{32}$$

Now whatever the chosen value of p may be, the equation (32) determines a certain sort of extrapolation of the interferogram to the lags larger than N, i.e. larger than the number of measured data. Thus the AR-spectrum is obtained using an interferogram which goes from lag 0 up to lag ∞; that is, we do not need to apply any window function.

From a statistical point of view, the AR-method is a parametric approach to the problem of recovering the spectrum from samples of the covariance function, whereas the Fourier transform takes a non-paramatric approach. The parametric approach makes it possible to identify a dependence model of the data and such a model determines by itself a sort of apodization of the spectrum. However this kind of apodization uses only the available data and does not corrupt them with exogenous mathematical functions, i.e., the window functions. As a result the technique introduces linear dependence among the spectral components at a lower degree than procedures which make use of the Fourier transform.
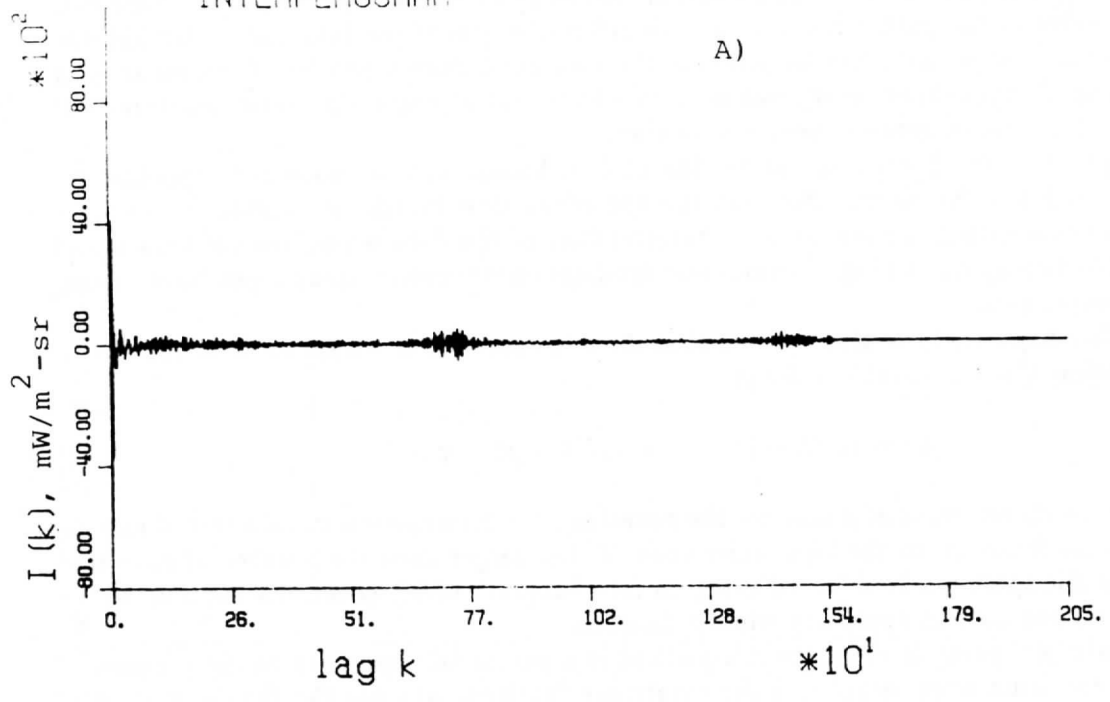
As a final remark we note that this particular extrapolation can be shown to have, among all possible extrapolations, the maximum "entropy" in a definable information theoretic sense. Hence the other name of the technique: maximum entropy method.

4. Application of the AR-approach to HIS data

In this section we discuss the application of the AR-procedure to HIS data (Revercomb et al. 1988) (HIS is a shortening of High-resolution Interferometer Sounder; it is a calibrated Fourier transform spectrometer). Fig. 2 (on the upper side) shows an HIS-interferogram in the band III (from 600 to 1100 cm^{-1}) recorded during a flight on board ER-2 research aircraft. The interferogram consists of 2048 samples from the lag 0 up to the maximum delay $2048 \cdot \Delta x = 1.815$ cm. For convenience the x-axis in Fig. 2 was drawn using $\Delta x =$ one unit; the actual value of the sampling interval is $\Delta x = 1.815/2048$ cm. Due to scale problems, the plot $I(k)$ in Fig. 2 does not show very well all the features of the measured interferogram. Anyway the interferogram exhibits its maximum variability near the origin, i.e., in the region which goes from $k = 0$ to about $k = 100$. After that there are two marked patterns in the intervals $600 \leq k \leq 780$ and $1300 \leq k \leq 1550$ respectively.

As a result of the quality-control analysis of such data, performed using the above discussed parametric AR-approach, in Fig. 2 (on the lower side) we show a plot of the index SIC vs. the lag k
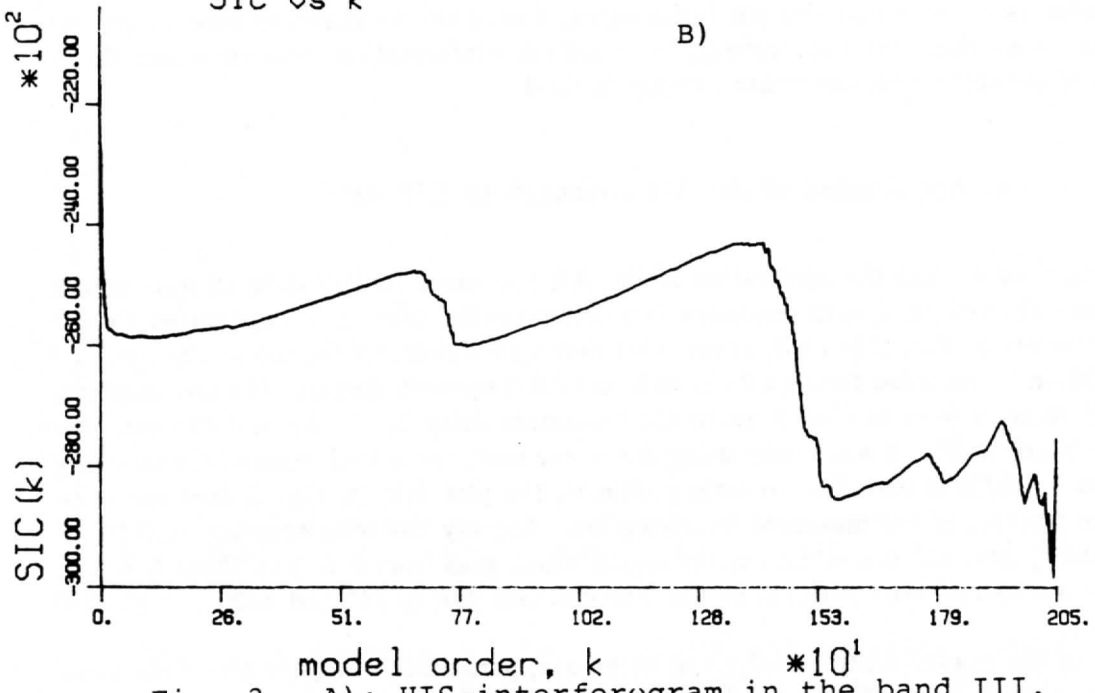
Fig. 2 - A): HIS-interferogram in the band III.
B): Results of the data quality-control
analysis performed using the AR-approach;
the figure shows a plot of the index SIC
vs the order k of the model fitted to the
data.

or, equivalently, vs the order of the model fitted to the data. Note that there is a full correspondence between the x-axes of the two plots shown in Fig. 2.

The curve $SIC(k)$ exhibits a first minimum at $k \approx 100$, where the interferogram ends off its maximum variability. A deeper minimum is located at the end of the next marked pattern ($k \approx 770$). Another deep minimum is located at the end of the last pattern visible in Fig. 2 and finally the deepest minimum appears at the end of the interferogram. Thus we can conclude that all the samples of the interferogram provide useful information about the underlying spectrum.

Fig. 3a shows the AR-spectrum obtained using all the data, while Fig. 3b shows the Fourier spectrum. The strong line structure is quite visible. As a comparison the next Fig. 4 shows the percentage difference between the AR and Fourier spectrum:

$$DIFF\% = \frac{R_{AR} - R_F}{R_F} \cdot 100 \tag{33}$$

where R_{AR} and R_F denote the AR-spectrum and the Fourier spectrum respectively. Also the Fourier spectrum was obtained without any intervening window function. The two spectra agree very well except in the region characterized by a strong line structure.

However we feel obliged to warn the reader that the example above does not permit to infer anything about the superiority of the AR-approach. The problem is that the interferogram we used was obtained (see Revercomb et al., 1988): first by taking the Fourier transform of the uncalibrated interferogram (i.e., the direct output of the HIS ER-2 instrument) to produce the uncalibrated spectrum; second by using the procedure implemented by Revercomb et al. (1988) to produce the calibrated spectrum; third by taking the Fourier transform of the calibrated spectrum to finally produce the interferogram (calibrated) shown in Fig. 2. The double Fourier transform involved in such operations corrupts inevitably the original information in the interferogram. Thus we do not expect that the interferogram we actually possess is able to provide an useful test to check the superiority of the AR-approach. It is only possible to conclude that the technique works; how well it works is a problem that we are at present analysing by using simulated interferograms generated by a line-by-line radiative code (HARTcode, Miskolczi et al, 1988). Moreover, we are going to apply to interferometric data a non parametric technique already developed (Amato and Serio, 1989), which allows one to obtain maximum entropy solutions when data are affected by measurement errors.

5. Conclusions

The authors have implemented a procedure based on AR-models which permits:

a) to recover radiance spectra from interferometric measurements without any exogenous window or apodizing function;

b) to perform a quality-control of the experimental data.

The technique relies on the Winer-Khinchine theorem, on the linear prediction theory and on the information theory. Based on the fundamentals of the procedure, we conclude that AR-models can play a relevant role to improve the spectral quality of spectra recovered from measured interferograms. However much work must still be done in order to show if the potential advantages of the technique may become real advantages in the context of remote sensing of the atmosphere.
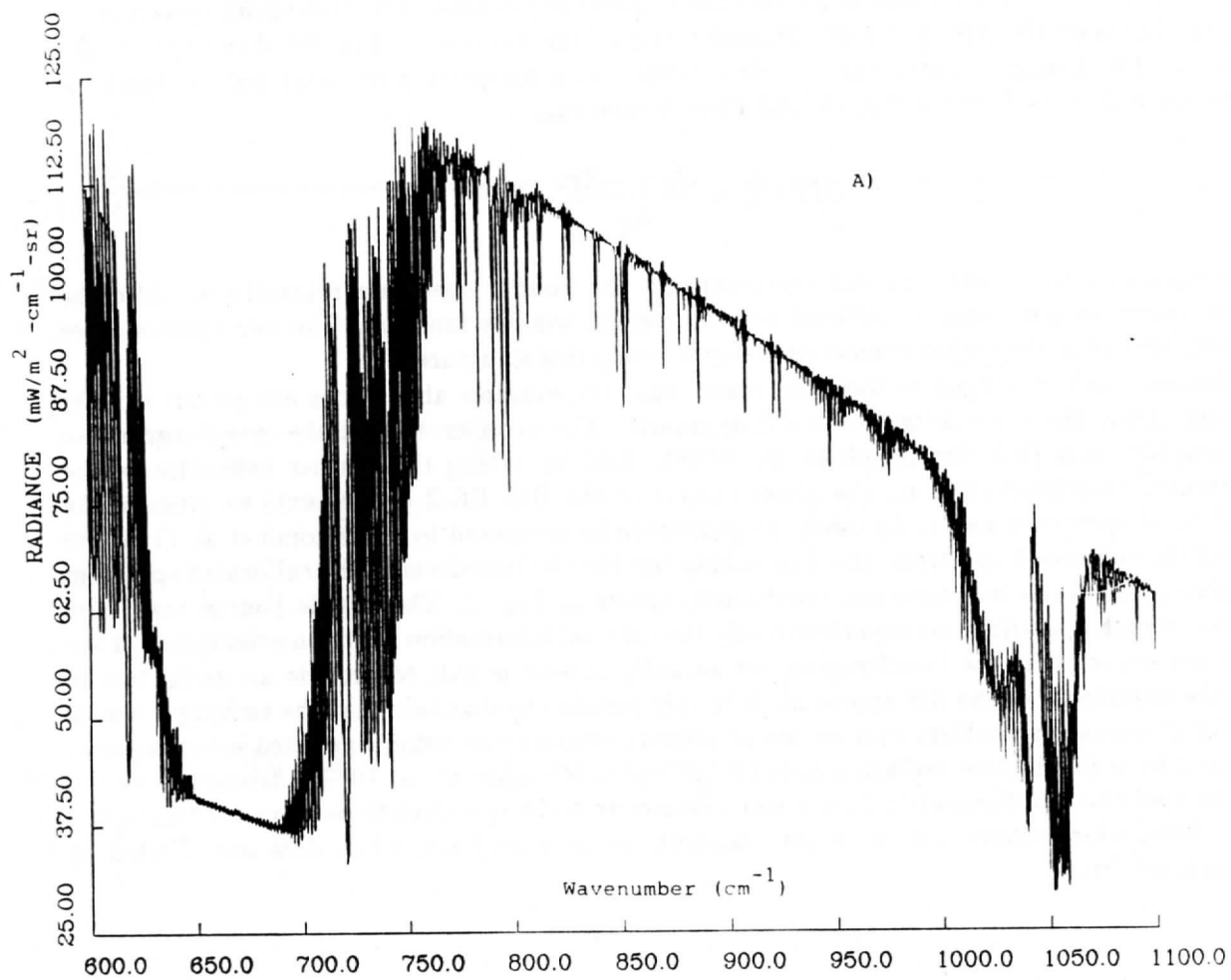
Fig. 3a – AR-spectrum computed by using the interferogram
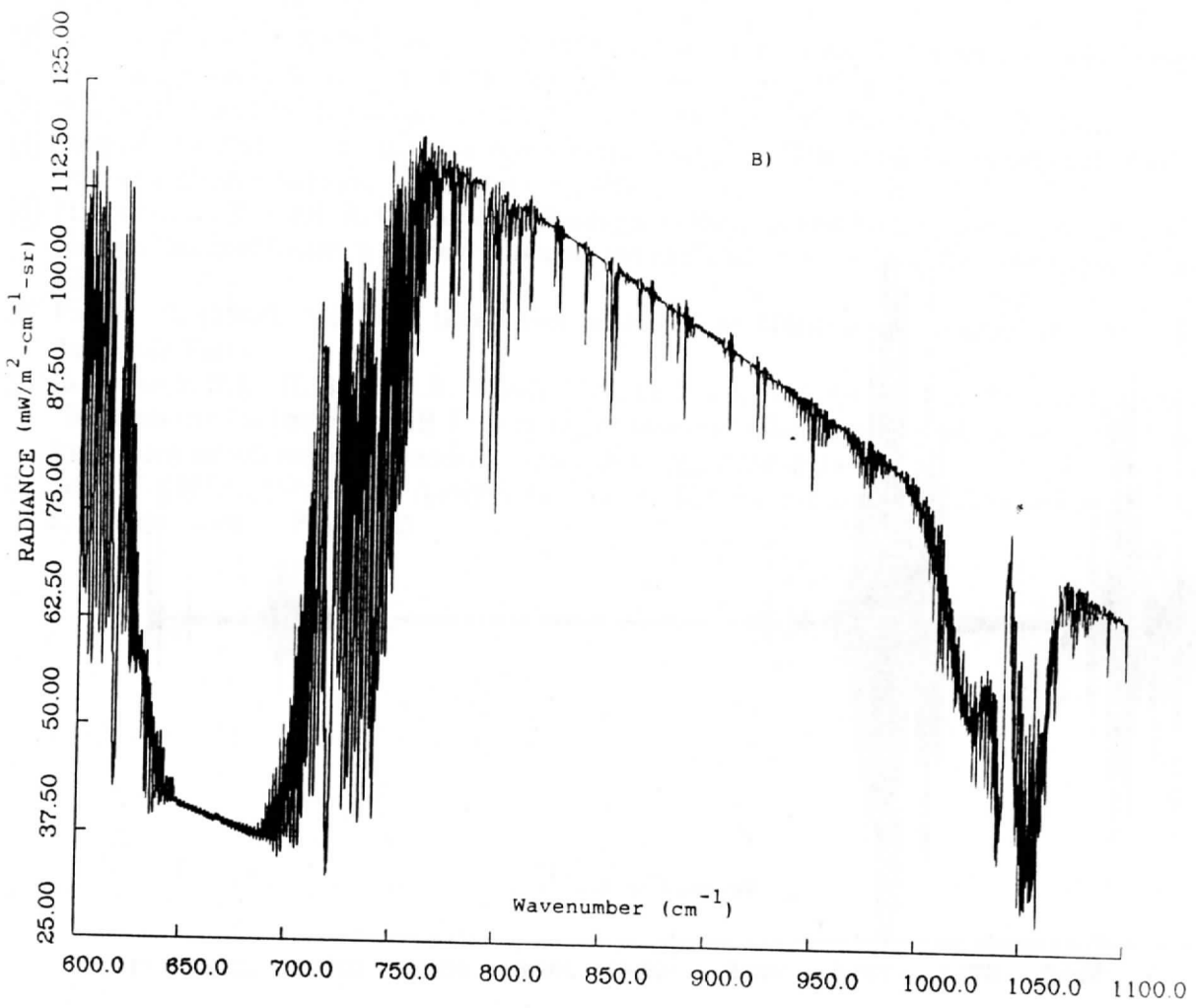of Fig. 2.

Fig. 3b – As Fig. 3a but taking the Fourier transform of the interferogram in Fig. 2.
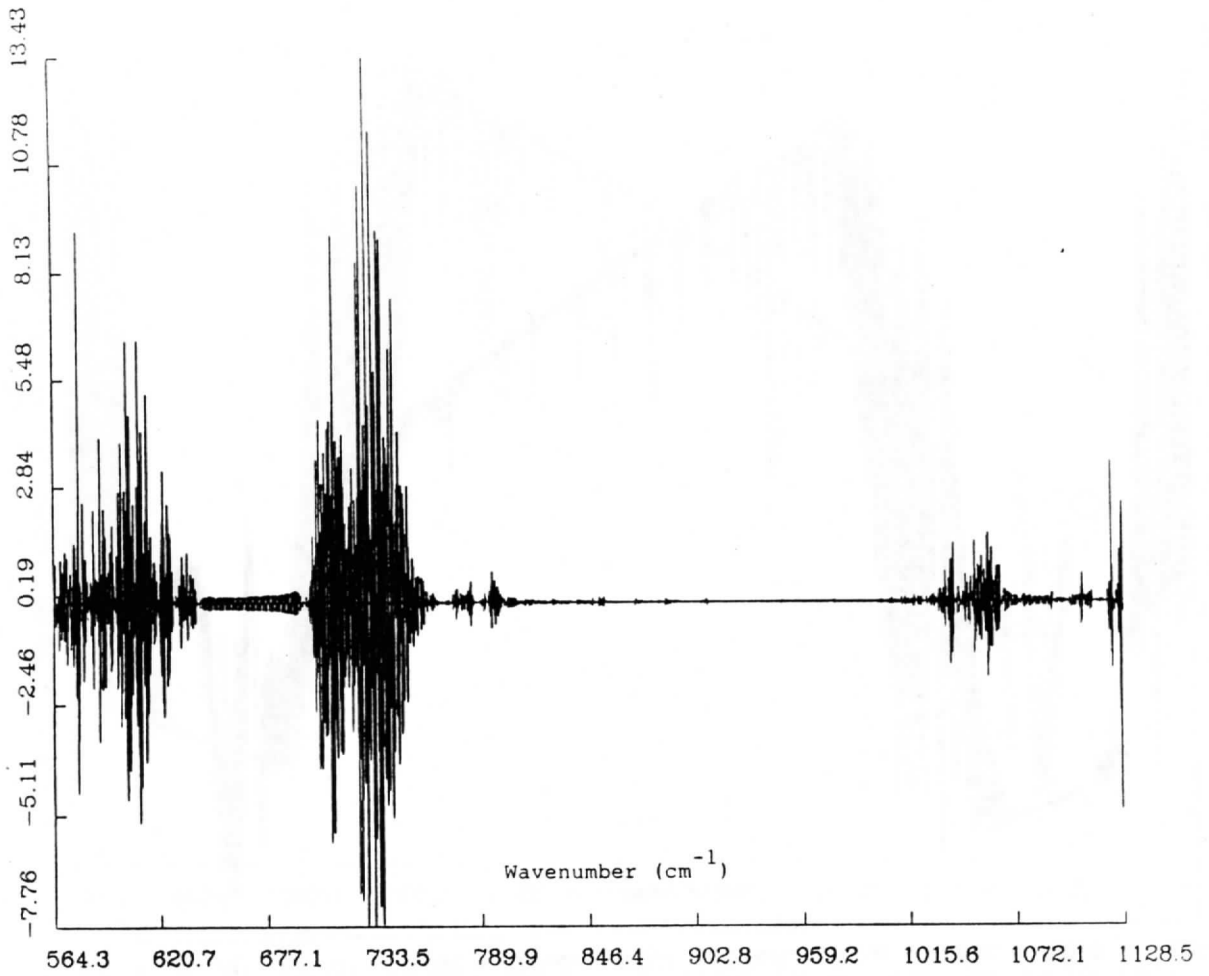
Fig. 4 - Percentage differences between the AR-spectrum
(Fig. 3a) and the Fourier spectrum (Fig. 3b).

Anyway we hope that this paper will open a fruitful discussion about data handling techniques alternate to Fourier transform.

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THE TECHNICAL PROCEEDINGS OF THE FIFTH INTERNATIONAL

TOVS STUDY CONFERENCE

Toulouse, France

July 24-28, 1989

Edited by A. CHEDIN

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January 1990