CLOUD-CLEARING WITH RADIAL BASIS FUNCTIONS.

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1. INTRODUCTION

Cloud-clearing problems very often involve the three canonical statistical tools of prediction, filtering and smoothing. A typical example is offered by cloud-clearing for satellite temperature inversions. Optimal estimation theory, e.g. Wiener filter or Kalman filter, might be used in this cases, but their application to such problems is not straightforward, since cloud clearing problems involve at least two-dimensional (2-D) settings. Optimal prediction and filtering are strictly connected to the concept of physical realizability or causality, which, in practice, means that the signal or process of interest must be characterised by an evolution parameter which, in turn, permits to distinguish between past and future realizations of the signal itself. In other words, the presence of an evolution parameter make it possible to order the measured values of the signal. Typically, such an evolution parameter is the time and, therefore, prediction and filtering are a natural topic in time series analysis.

However, satellite imagery do not meet the requirements above, since the time is not directly involved. Now, we deal with spatial signals or fields which, as far as cloud-clearing problems are concerned, we can consider to be recorded at a definite time. In 1-D cases this is not a serious shortcoming, since the real axis admits a natural order relation. Such a relation makes it possible to order the mesaurements and, therefore, to use the usual 0-D tools of time series analysis. Conversely, the real plane does not admit any natural order relation, and it is for this that the generalization to the 2-D case of optimal prediction and filtering is quite a difficult task.

As a consequence, when implementing an optimal filter, the 2-D signal, $F(n,m)$, is first mapped into 1-D sequence, $f(k)$, by means a suitable transform and then 1-D filters are used. The most commonly used mapping is the so-called row-sequential scanning

(Ekstrom, 1982), which involves a simple 2-D to 1-D transformation in which the $N \times M$ field or image is raster scanned and converted to a vector given by:

$$f(k) = f(m + nM) = F(n, m); \quad \text{with:} \quad 0 \le n \le N; \quad 0 \le m \le M; \quad k = 1, \ldots, N \times M \tag{1}$$

This mapping involves a simple concatenation of rows (Fig. 1), and totally orders the bisequence $F(n, m)$. Furthermore, from the fundamental causality condition, the filter can process only present and past values of the input sequence. Under the inverse transform, these values of $F(n, m)$ are shown always in Fig. 1.

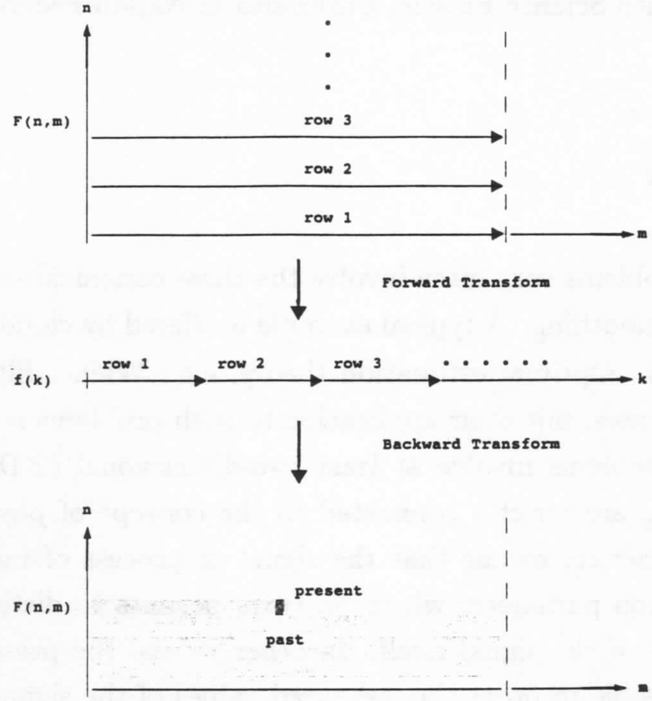

Fig.1 - Row sequential mapping of $F(n, m) \Rightarrow f(k)$.

Although this transformation closely resembles the way in which satellite sounders work, it is inadequate to represent imagery data, since in a 2-D field, e.g. an infrared radiance field, the value at a given field of view (FOV), is highly correlated with its neighbours along the horizontal and vertical directions and other directions, as well. Thus, although such a transform allows one to use optimal estimation theory, the implementation structure itself of the filtering process is not optimal.

Fully 2-D implementations of optimal filters are only possible for the case of smoothing, since smoothing is intrinsecally *noncausal and physically unrealizable.* However, Wiener smoothing is routinely handled with fast Fourier transform which requires the input data to be equally spaced on a regular grid. Conversely, in cloud-clearing problem data are likely to be sparse and non-uniformly distributed across the area of interest.

Furthermore, optimal estimation theory is well developed for cases where the signal and the "noise" are additive and not correlated each other, whereas the "noise" effects of clouds are not a strictly additive or multiplicative process.

In contrast, objective filters can be fully implemented in 2-D without any mathematical complexity and do not depend critically on the assumptions of additive noise. Thus, in some cases, they can be more suitable than the optimal analogues.

Because of applications interests, the problem of designing fully 2-D digital objective filters is addressed in this paper. The mathematical background of digital filtering based on radial basis functions is illustrated. Canonical versions of the filtering process are derived for the cases of smooth interpolation and smoothing. Our derivation will point out the immediate extension of such an objective filtering approach to multidimensional settings (n-D). Applications of the technique are discussed in the context of a new cloud clearing scheme.

2. RADIAL BASIS FUNCTIONS

We now briefly review what is known about radial basis functions; for more information see the review by Powell (Powell, 1985). Powell's review deals mostly with the problem of interpolation; for more information about the filtering process with radial basis functions see Robinson and Silvia (1981).

2.1 INTERPOLATING WITH RADIAL BASIS FUNCTIONS

In the interpolation method with radial basis functions, the interpolated value, $\hat{F}$, at the point $\mathbf{x}_o$ is taken to be:

$$\hat{F}(\mathbf{x}_o) = \sum_{l=1}^{L} \lambda_l \phi(\|\mathbf{x}_l - \mathbf{x}_o\|) + \sum_{j=1}^{J} \mu_j p_j(\mathbf{x}_o) \qquad (2)$$

Here $\phi(\|\mathbf{x}_l - \mathbf{x}_o\|)$ is a function from $\Re^n$ to $\Re$, $\|\cdot\|$ denotes the Euclidean norm on $\Re^n$ and p_j is a polynomial of degree at most J from $\Re^n$ to $\Re$. Always in (2) L indicates the number of points which are used to obtain the interpolated value at $\mathbf{x}_o$. The functions $\phi(\|\mathbf{x}_l - \mathbf{x}_o\|)$ are called *radial basis functions.* They depend only on the radius $r = \|\mathbf{x}_l - \mathbf{x}_o\|$ and, therefore, such functions possess *circular symmetry.*

When in (2) the polynomial term is not included, which is frequently the case, the interpolating coefficients λ_l are computed by imposing the interpolation conditions:

$$\hat{F}(\mathbf{x}_l) = F(\mathbf{x}_l): \quad l = 1, \ldots, L \qquad (3)$$

Adding also the polynomial term, the corresponding coefficients μ_j are determined by the additional constraints:

$$\sum_{l=1}^{L} \lambda_l p_j(\mathbf{x}_l); \quad j = 1, \ldots, J \tag{4}$$

For interpolation problems, $\phi(r)$, with $r = \|\mathbf{x}_l - \mathbf{x}_o\|$, usually has the form $\phi(r) = (r^2 + a^2)^{-\alpha}$ with $\alpha > 1$ and $\alpha \neq 0$. Indeed, such functions have good properties of localization. As far as the 1-D case is concerned, if $\phi(r) = r^3$ and $J = 1$, then the resulting interpolation is identical to the one obtained using cubic splines (Powell, 1985). Moreover, in the case n-D, with n> 1, if $\phi(r) = r^2 \log r$ and $J = 1$, then the resulting interpolant minimizes the *bending energy* of a thin plate constrained to go through the data point (Dyn et al., 1986). Thus some increasing radial basis functions can be considered as the generalizations of splines to higher dimensions, and hence have good localization properties.

We have tested the above procedures in the context of cloud clearing and they do not work. The problem is that the schemes become unstable as soon as the cloudy FOVs are not randomly distributed across the area of interest.

2.2 FILTERING WITH RADIAL BASIS FUNCTIONS

To prevent the interpolation from becoming unstable, we have to design some suitable schemes which incorporate smoothing, too. Towards this objective we consider the following linear integral filter:

$$\hat{F}(x_o, y_o) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F(x,y)\phi(r)dxdy; \quad r = \sqrt{(x - x_o)^2 + (y - y_o)^2} \tag{5}$$

where F indicates the *input* and $\hat{F}$ the *output*. For the sake of simplicity and clearness, here we limit ourself to examine the 2-D case.

Because of the circular symmetry of $\phi(r)$, (5) is a convolution which, in turn, implies that the Fourier taransform of input and output are simply related by:

$$\frac{\mathcal{F}\{\hat{F}\}}{\mathcal{F}\{F\}} = \mathcal{F}\{\phi\} \tag{6}$$

where $\mathcal{F}\{\cdot\}$ indicates 2-D Fourier transform. Thus, the Fourier transform of the function $\phi(r)$ completely determines the filtering properties of the linear operator (5).

Furthermore, it can be demonstrated that the 2-D Fourier transform of a radial basis function can be computed by the one-dimensional integral:

$$\mathcal{F}\{\phi(x,y)\} = \Phi(k) = 2\pi \int_0^{\infty} \phi(r) r J_o(kr) dr \tag{7}$$

where $J_o(kr)$ is a Bessel function of the first kind, zero order. Eq. (7), which defines the Hankel transform, states that the 2-D Fourier transform of a circularly symmetric function is itself a radial basis function and depends only on the radial wavenumber $k = \sqrt{k_x^2 + k_y^2}$, where k_x, k_y indicate angular wavenumbers along the x-axis and y-axis respectively.

From Eq. (6), we see that the Fourier transform of $\phi(r)$ completely determine the frequency response of the filter (5), while from Eq. (7) we learn how to choose $\phi(r)$ so that the filter (5) is a smoother. It suffices to take $\phi(r)$ to be a decreasing function ($\phi(r_1) < \phi(r_2)$ for each $r_2 > r_1$) and ensure that $r^2\phi^2(r)$ is integrable into the interval $[0, +\infty]$.

As an example, such properties are common to the two following radial functions:

$$\begin{aligned} \phi(x,y) &= \frac{1}{2\pi\sigma^2}(\frac{x^2+y^2}{\sigma^2}+1)^{-3/2} \\ \phi(x,y) &= \frac{1}{2\pi\sigma^2}\exp(-\frac{1}{2}\frac{x^2+y^2}{\sigma^2}) \end{aligned} \tag{8}$$

where σ is a scale parameter. The 2-D Fourier transform of these two functions is, respectively:

$$\begin{aligned} \Phi(k_x,k_y) &= \exp(-\sigma\sqrt{k_x^2+k_y^2}) \\ \Phi(k_x,k_y) &= \exp(-\frac{k_x^2+k_y^2}{2}\sigma^2) \end{aligned} \tag{9}$$

The second of (8) is the well-known Gaussian function, while the first of (8) plays a particular role in the frame of relaxation methods, e.g. Laplacian interpolation and Dirichelet's problem.

Both functions in (9) have the low-pass filter characteristic, since they decrease as the radial wavenumber increase and tend to zero as k becomes large. Thus they can be used to design low-pass filters in order to smooth 2-D fields. A plot of these functions for the case $\sigma = 1$ is shown in Fig. 2.

To modify the amount of filtering we have only to change the value of the scale parameter σ which here works as the tuning parameter of the smoothing/filtering process. A *small* value for σ (i.e. a *large* value for $1/\sigma$ must be prescribed if one wishes a slight filtering. On the other hand a *large* value for σ (i.e. a *small* value for $1/\sigma$) must be prescribed if one wishes a strong filtering, that is a strong suppression of noise.

From Eq. (6) we learn how to implement the filtering process in the wavenumber domain. However, for many applications it is more suitable to implement the filtering process in the space domain, directly. After trasforming the filter equation in polar coordinatees one obtains (Robinson and Silvia, 1981; Serio, 1989; Andretta et al., 1990):

$$\hat{F}(i,j) = \frac{1}{2}\left[F(i,j)W_1 + \tilde{F}(a_1)J_2 + \sum_{k=2}^{\infty}\tilde{F}(a_k)(W_{k+1} - W_{k-1})\right] \tag{10}$$

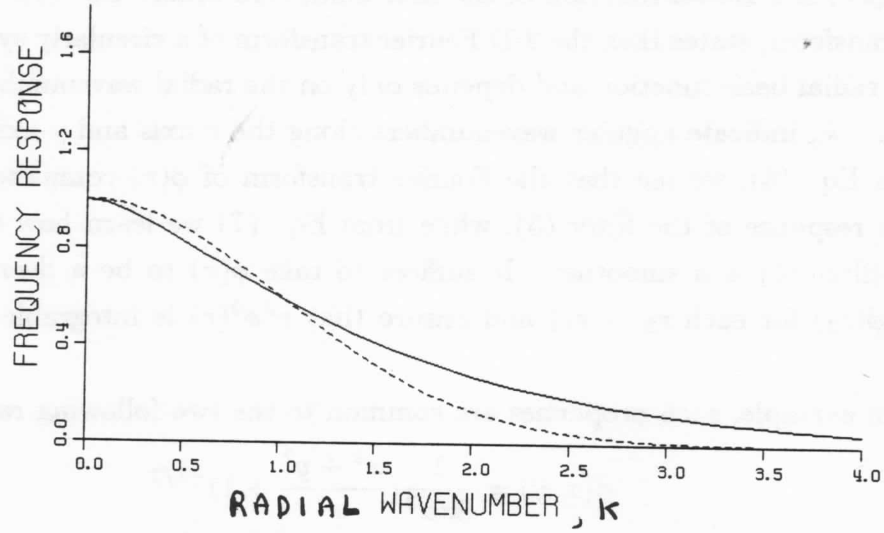

Fig. 2 - Gaussian frequency response (dashed line) and frequency response of the function 8.1 (arbitrary units on the x-axis).

where

$$\tilde{F}(a_k) = \frac{1}{N_p} \sum_{\substack{n,m \\ (n-i)^2+(m-j)^2=a_k^2}} F(n,m) \tag{11}$$

represents the average value of F on a circle of radius a_k. In (10) and (11) N_p indicates the number of points in the summation and (i,j) denotes the position in the grid of the FOV we want to filter. Furthermore, the weights W_i are given by:

$$W_i = \frac{1}{s^2} \int_0^{a_i} \rho\phi(\rho) d\rho; \quad i = 1, \ldots, n, \ldots \tag{12}$$

where ρ is the dimensionless radial distance: $\rho = r/\Delta l$; s is the dimensionless tuning parameter $s^2 = \sigma^2/(\Delta l)^2$; r is the radial distance and Δl indicate the grid spacing. It can be shown that the summation of the weights in (10) is equal to 1, that is the filtering scheme preserves the linear gradient of the field.

Eq. (10) is suitable for smoothing/filtering processes. However, from such a relation we can derive the prediction form of the filter, too. Formally it suffices to put $F(i,j)$ in the right-hand-side of Eq. (10) equal to $\hat{F}(i,j)$, then solving for the unknown $\hat{F}(i,j)$ we have:

$$\hat{F}(i,j) = \frac{1}{1 - \frac{1}{2}W_1} \cdot \frac{1}{2} \left[\tilde{F}(a_1) J_2 + \sum_{k=2}^{\infty} \tilde{F}(a_k)(W_{k+1} - W_{k-1}) \right] \tag{13}$$

which elegantly solves the problem of designing a *smooth* interpolant. We note that again the weights in (13) are normalised to 1 properly, thus the restoring scheme preserves linear gradients in the field.

Prediction in 2-D can be stated as the problem of restoring a given field from sparse data. Restoring techniques, including the objective ones described above, are very powerful if the data are randomly distributed within the area of interest. Thus, applying such tools in real conditions, we need some suitable control index in order to know how far we are from the optimal condition. Towards this objective we introduce the "average minimum distance", d_m, which gives, on average, the distance between a missing data (e.g. cloudy FOV) in the grid and its nearest neighbour node with an available datum (e.g. clear FOV).

Let us suppose the node (n_o, m_o) is cloudy, then we search for the nearest neighbour clear node, say (n_c, m_c), and compute the distance, $d(k)$ (in units of Δl):

$$d(k) = \left((n_o - n_c)^2 + (m_o - m_c)^2 \right)^{1/2} \tag{14}$$

where $k = 1, \ldots, N_m$, with N_m the number of cloudy FOVs. The average of these distances over the field is the average minimum distance, d_m:

$$d_m = \frac{1}{N_m} \sum_{k=1}^{N_m} d(k) \tag{15}$$

Together with d_m we also compute the "random average minimum distance", d_r, that is the value of d_m that would be observed if the original N_c clear FOVs were uniformly distributed across the grid.

We note that it is always $d_m \geq d_r$. Furthermore the effectiveness of the technique depends only on the difference $d_m - d_r$, the optimal condition being $d_m - d_r = 0$.

3. A NEW HIRS CLOUD-CLEARING SCHEME

Based on the methodology above, we developed (Andretta et al, 1990, Serio et al., 1990, Cuomo et al, 1991) a new Objective and Optimal Filtering scheme (2-OO) aiming at processing radiances, for each infrared measuring channel, to produce a field of cloud cleared values with sufficiently well defined statistical properties and error structures. Basically the method uses *clear measurements only* and treats cloudy data as unmeasured or missing data. The problem then consists of restoring a two dimensional radiance field from sparse data and the solution is seeked using the following sequential procedure:

A - a Gaussian objective interpolation scheme to obtain preliminary estimates of clear-column radiances at cloudy FOVs by the nearest neighbour clear data;

B - A method to fill gaps left at the first step using regression relations relying on other source of measured data;

C - A method to eliminate local biases eventually produced in phase B;

D - An optimal recursive filtering scheme to produce a final smooth version of the radiance field.

These steps above are specifically designed to take into account the horizontal consistency or spatial continuity expected in atmospheric temperature and humidity structures used in numerical weather prediction and, a fortiori, in the clear column radiance fields and, on the whole, the new scheme is a low-pass filter.

3.1 PHASE A: GAUSSIAN OBJECTIVE INTERPOLATION

In this phase only the infrared radiances which are detected as clear by means some suitable preliminary cloud-clearing (Eyre and Watts, 1987) are used in order to obtain estimates of clear-column radiances at cloudy FOVs using the Gaussian interpolation scheme.

In practice we need to truncate the summation in (13) at a suitable radius, that is we have to select a value for the tuning parameter s, which, in turn, determines the resolution in the restored field.

For the HIRS cloud-clearing problem it turns out to be useful to design the Gaussian filtering scheme with a tuning parameter s equal to 0.4 or $\sigma = 0.4\Delta l$. The choice implies that only a box of 3x3 HIRS soundings will be used to get an estimate of the clear-column radiance.

3.2 PHASE B AND C: MICROWAVE REGRESSION AND BIAS REMOVAL

The Gaussian restoring scheme above takes into account only the nodes which are inside or on the circle of radius $a_2 = \sqrt{2} \approx 1.41$. Thus the scheme will be successful in restoring the entire field only if $d_m \leq \sqrt{2}$. If $d_m \geq \sqrt{2}$, the technique will not be able to provide estimates of radiance at every FOV unless, with a suitable choice of the tuning parameter σ of the filter, we take into account FOVs whose distance from the central FOV is larger. Since the value of d_m determines the mean spatial resolution of the final field (for d_m is equal to 6 the final resolution is not better than $6\Delta x$) it is better to use exogenous information when available. The MSU (Microwave Sounding Unit) is part of the operational TOVS sounding system (Smith et al. 1979) and its horizontal resolution is about $4\Delta l$ where Δl is the mean HIRS grid spacing. In practice regression relations can be used (Eyre and Watts, 1987) to derive clear-column infrared radiance values from microwave measurements.

Unfortunately any regression relation produces biased results and since the effect of such biases can be quite serious, they have to be removed.

At nodes where estimates of clear radiance $\hat{F}_C(i,j)$ are obtained via phase A, we can also obtain values, $\hat{F}_M(i,j)$, from the regression and hence derive estimates, $B(i,j)$, of the bias between the two:

$$B(i,j) = \hat{F}_M(i,j) - \hat{F}_C(i,j) \tag{16}$$

Such sparse estimates of bias can be used in order to get values for the bias at all FOVs. Subsequently these values can be used to correct the radiance at FOVs where only the regression relation is used.

Towards this objective we have only to design a suitable Gaussian restoring scheme. We compute for the bias field the average minimum distance, d_m and choose a value of the tuning parameter, σ, in such a way that $a_{max} = d_m$, where a_{max} denotes the maximum radius in the Gaussian scheme.

We note that the MSU regression method yields estimates highly correlated locally. Thus we expect the bias field to have a very high consistency which allows us to design a Gaussian interpolation scheme with a very large tuning parameter, as large as we need in order to restore the bias field at every FOV on every line. However, now, we cannot assume uncorrelated errors in order to propagate the variance according the usual rules, even though the de-biasing procedure yields residual errors which can be treated as largely uncorrelated. Since The MSU regression method yields residual errors that are affected by bias, i.e. their mean value, say $< B(i,j) >$, is not zero. Let us RMS denote the root mean square error in the MSU method regression, then:

$$RMS^2 = < B(i,j) >^2 + \text{var}(B(i,j)) \tag{17}$$

where var$(\cdot)$ denotes variance. Thus if the de-biasing procedure is successful to remove the bias, the root mean square error will be equal to the second term in the right-hand-side of (17) only.

Using the values of $B(i,j)$ as defined in (16), we compute var$(B(i,j))$ according to:

$$\text{var}(B(i,j)) = < B^2(i,j) > - < B(i,j) >^2 \tag{18}$$

and use such a value as the error value for subsequent processing.

3.3 PHASE D: OPTIMAL RECURSIVE FILTERING

The field after phase C, being obtained using possibly heterogeneous pieces of information, may not be sufficiently smooth and may contain gross errors as well. For such a reason it is desirable to produce a smoother version of the radiance field. Towards this objective we have implemented a recursive Kalman filtering which use both row-sequential and column-sequential mappings. In both mappings the filter runs forward and backward, therefore at ecah FOV (i, j), we obtain four estimates which are combined to obtain the final estimate.

4. NUMERICAL EXAMPLES

In this section we shall show numerical examples based on one test field. The test field consists of simulated HIRS/2 channel 7 brightness temperatures, computed as in Andretta et al. (1990). It contains 3976 FOVs arranged in 71 rows and 56 columns and is shown as a mesh surface in fig. 3.

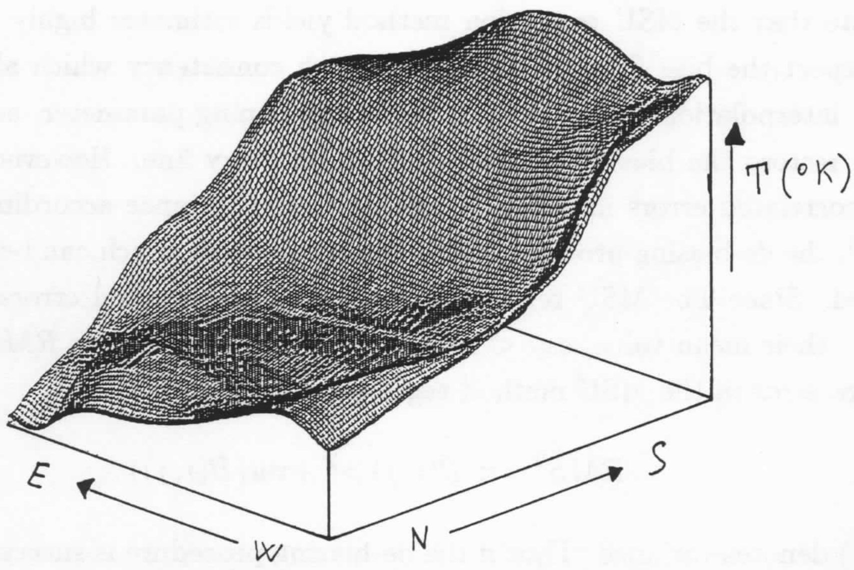

Fig. 3 - Mesh surface of the test field: HIRS brightness temperature in channel 7

The x-axis runs along the rows of the grid and the y-axis along the columns. According the geometry of the HIRS scan pattern, the x-axis is approximately orientated along the direction North-South, whereas the y-axis along the direction West-East.

The fields to be cleared consist of the test field with Gaussian white noise, with zero mean and standard deviation equal to 0.1 K, added to simulate the effect of measurement errors. The "cloudy" information in included in our exercise by considering missing a value in any FOV which is defined as cloudy by a predefined cloud mask. All the cloud masks used for this exercise are the result of preprocessing of real measurements with a very high cloud content, in order to simulate worst case real situations. The cloudy data set is the starting point for the clearing algorithms, while the test field is used for comparing the results after the clearing phases.

In the first example, data in the test field are flagged as cloudy according to the cloud pattern shown in Fig. 4.

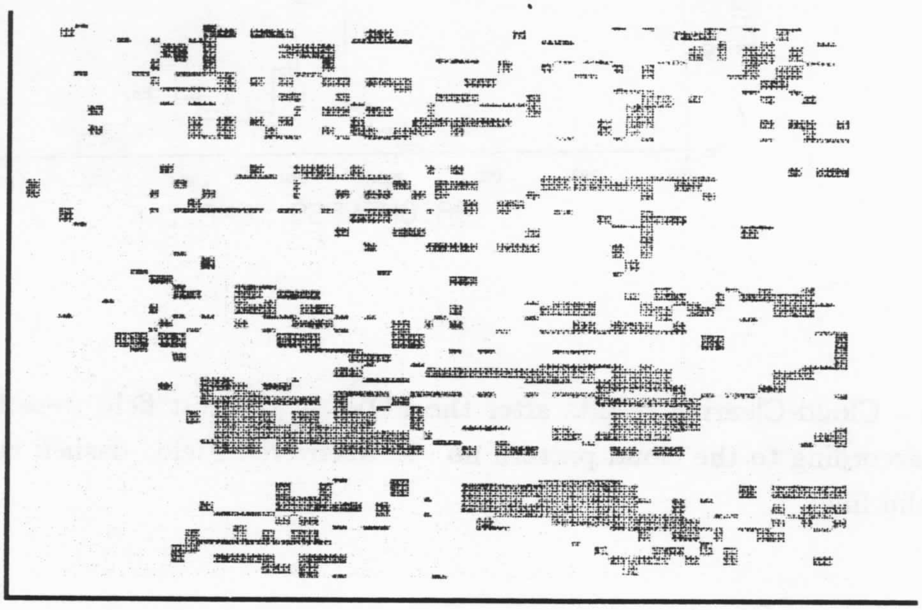

Fig. 4 - Cloud pattern no. 1; dark grey: clear FOVs, light grey: cloudy FOVs.

The value of d_m for this case is 2.2 against $d_r = 1.3$ and the amount of cloudy FOVs is 3132 (79%) out of 3976 data points. Fig. 5a shows a comparison between the test field and that recovered, while fig. 5b provides a summary of the error analysis.

The error, ΔT, is computed at every *cloudy* FOVs according to:

$$\Delta T = T_{rf} - T_{tf} \tag{19}$$

with rf standing for *recovered field* and tf for *test field.*

In the second example, data in the test field are flagged as cloudy according to the cloud pattern shown in Fig. 6.

Now $d_m = 6.3$ against $d_r = 1.7$. The amount of cloudy FOVs is 3466 (90%) out of 3976 data points. Figure 7a compares the test field with the restored one, while fig. 7b shows an histogram of the errors. On the whole the cloud clearing scheme permits to reconstruct the test field with a root mean square error lower than 0.7 K.

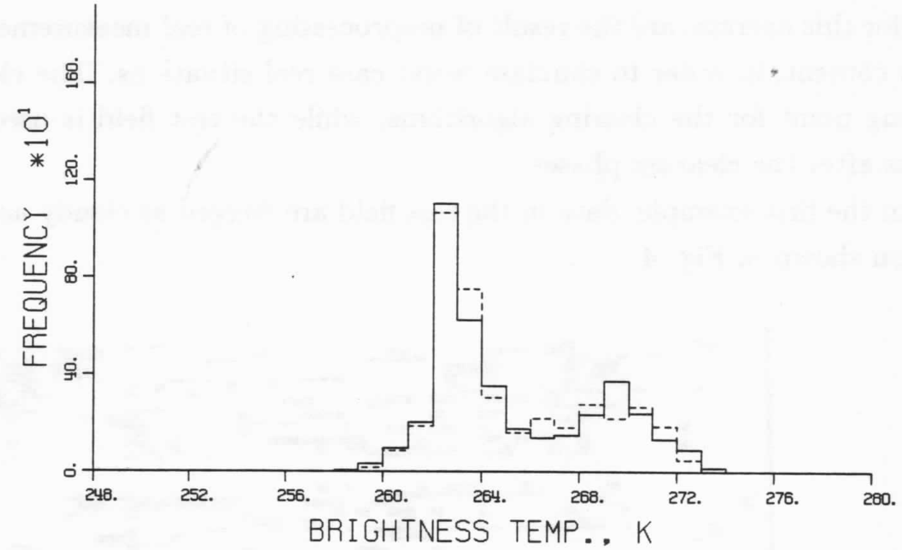

Fig. 5a - Cloud-Clearing results after the FOVs in the test field were flagged as cloudy according to the cloud pattern no. 1. Recovered Field: dashed curve; Test field: solid line

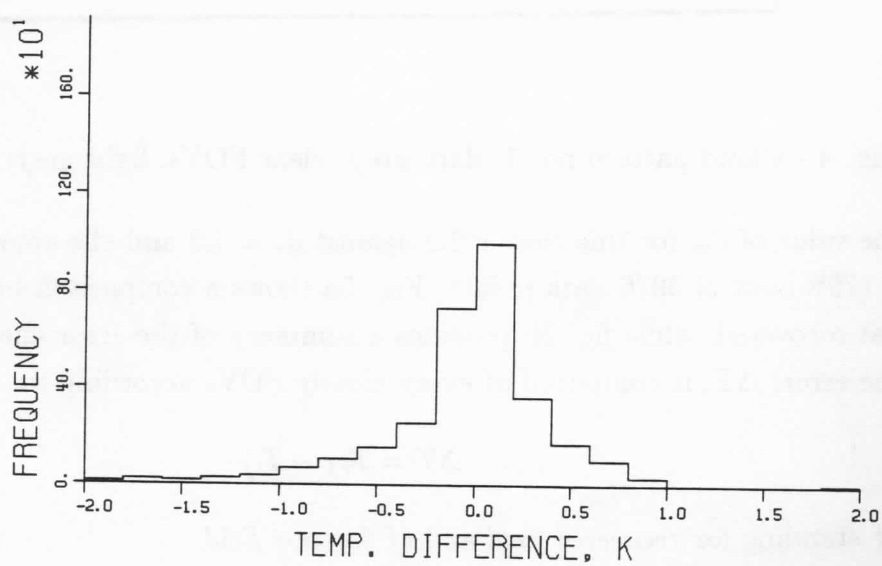

Fig. 5b - Histogram of the residual error.

5. CONCLUSIONS

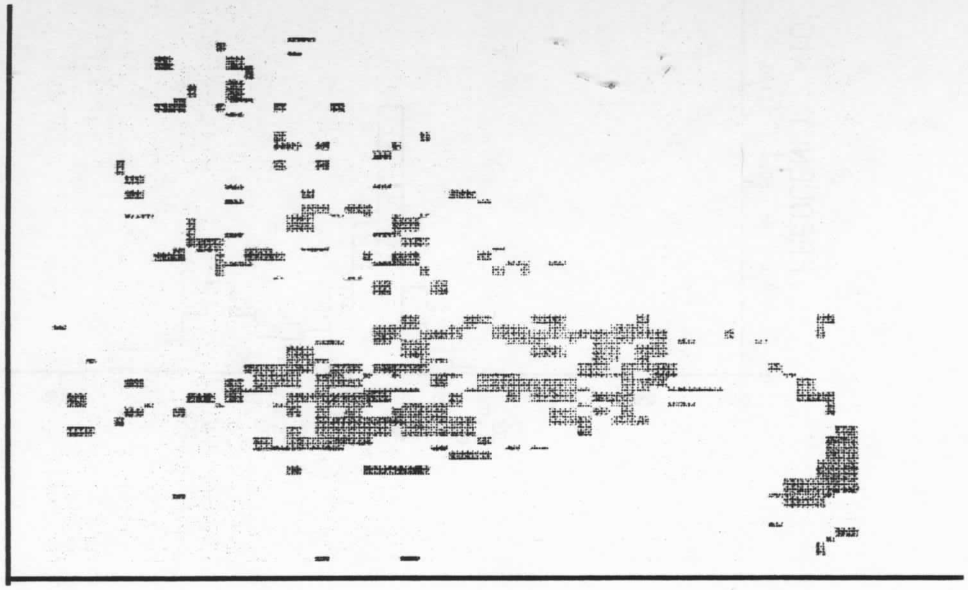

Fig. 6 - Cloud pattern no. 2; dark grey: clear FOVs, light grey: cloudy FOVs.

In this paper, we have described a general methodology to design objective filter based on radial basis functions. Furthermore, we have demonstrated numerically that combined objective analysis and optimal estimation can be successfully applied to the problem of cloud-clearing infrared tropospheric radiance measurements. The new scheme has been designed to derive soundings with the highest horizontal resolution attainable with any given radiance data set. The method is mainly founded on the horizontal continuity expected in atmospheric temperature and humidity and in cloud cleared radiance fields to be used in numerical weather prediction. Taking into account such general characteristics, first we use Gaussian interpolation to obtain estimates of clear-column radiances at cloudy FOVs by the nearest neighbour clear FOVs. This technique ensures greater horizontal consistency in clear-column fields derived from the data, since, unlike N^* method, the scheme smooths the data, too. However to avoid this occurring at the expense of severely reducing the amplitude of real small-scale features in the field, we apply the Gaussian interpolation scheme to box of 3x3 HIRS soundings at a time.

To fill the gaps that most certainly are left after the first processing (phase A) a method has been developed for estimating HIRS radiances from MSU data with little local bias, based on regression relations involving microwave measurements (phase B) and a Gaussian interpolation scheme (phase C).

After phase C the generated clear-column field, being obtained by using possibly heteregenous pieces of information, may be not sufficiently smooth and may contain gross

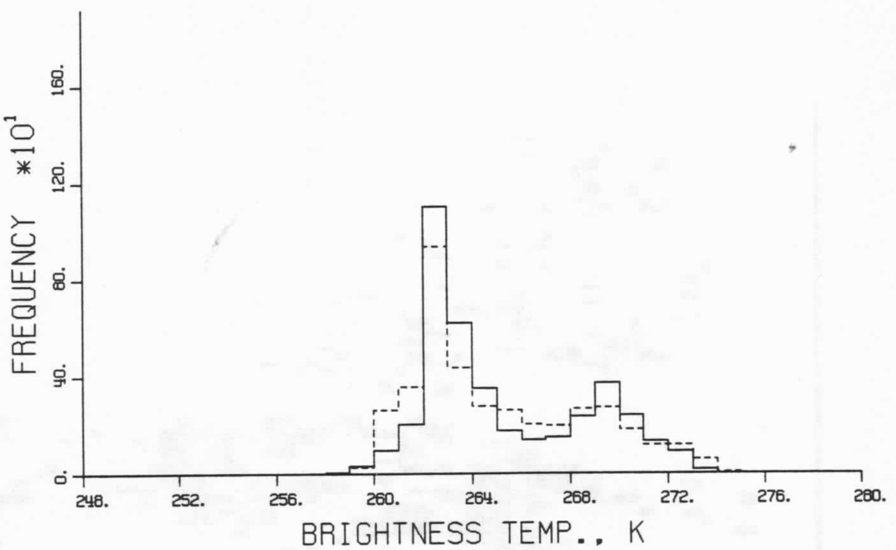

Fig. 7a - Cloud-Clearing results after the FOVs in the test field were flagged as cloudy according to the cloud pattern no. 2. Recovered Field: dashed curve; Test field: solid line.

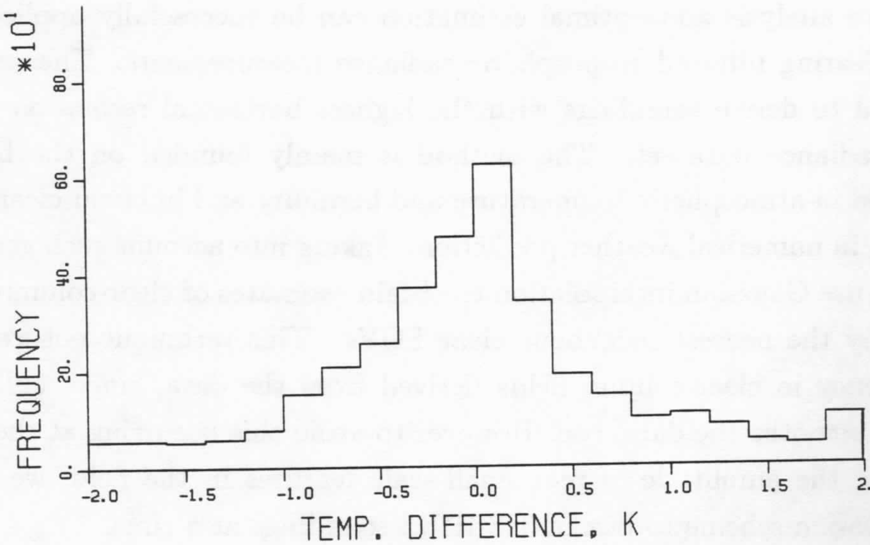

Fig. 7b - Histogram of the residual error.

errors as well. In order to produce a smoother version of the radiance field after the steps above we filter the data using an optimal (in the Least Squares sense) estimator (phase D).

Within the processing we have introduced quality indicators, e.g. the average minimum distance, d_m, which allow us to evaluate the quality of the final product, that is bias, resolution, root mean square error. Other indexes, e.g. the tuning parameter ρ_1, which permit to control and modify the resolution in the final field are also introduced.

The effectiveness of the scheme has been demonstrated by numerical examples performed using as test field simulations of clear column brightness temperatures. Such examples show that the scheme can provide realistic result accounting for realistic measurement noise even for extremely critical cloud conditions.

Finally, the new cloud-clearing method produces estimates of the errors for the clear column radiance field and the basic approach has the flexibility to include extra information from many data sources.

Some problems are left to future work. The effectiveness of the scheme should be checked using test fields with horizontal resolution comparable to that of HIRS measurements. A wide range of simulated cloud patterns could be used in investigating some possible relations between the mean square error in the field, d_m and the bias. Also the possible correlations among the residual errors in the final field need to be investigated in more detail. However, the technique presented here already seems to us to be capable of yielding results of noteworthy practical value.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

Andretta, A., M.M. Bonzagni, V. Cuomo, R. Rizzi and C. Serio, 1990: A three-step cloud clearing procedure for infrared sounder measurements. J.Rem.Sens., Vol. 11, 8 1349–1368.

Cuomo, V., R. Rizzi and C. Serio, 1991: An objective and optimal scheme to cloud-cleraing for infrared sounder measurements. J.Rem.Sens., submitted.

Dyn, N., D. Levin and S. Rippa, 1986: Numerical procedures for surface spline fitting of scattered data by radial basis function. SIAM J. Sci. Stat. Comput., 7 p. 639

Ekstrom, M.P., 1982: Realizable Wiener filtering in two Dimensions. IEEE Trans.

Acoustics, Speech and Signal Processing, Vol. ASSP-30, No.1, 31–40 Eyre J.R., 1989: Inversion of cloudy satellite sounding radiances by nonlinear optimal estimation: application to TOVS data. Q.J.R. Meteorol. Soc. 115, 1027–1037.

Eyre J. R. and P. D. Watts, 1987: A sequential estimation approach to cloud-clearing for satellite temperature sounding, Q.J. Meteorol. Soc., 113, 1349–1376.

Powell M.J.D., 1985: Radial basis functions for multivariate interpolation: a review. preprint, Univ. of Cambridge

Robinson E. A. and M. T. Silvia, 1981: Digital Foundations of time series analysis. Wave equation, space-time processing. Holden-Day, S. Francisco.

Serio, C., 1989: Objective and optimal filtering with applications to HIRS cloud-clearing. Third Autumn Workshop on Atmospheric Radiation and Cloud Physics 27 Nov.–15 Dec. 1989, ICTP Trieste, Italy.

Serio, C. R. Rizzi and V. Cuomo, 1990: Cloud-cleraing for infrared sounder measurements: an objective and optimal filtering approach. GEWEX workshop, Draft

Smith W.L., Woolf H.M., Hayden C.M., Wark D.Q. and McMillin L.M., 1979: The TIROS-N operational vertical sounder. Bull. Am. Meteorol. Soc.,60, 1177–1187.

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