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SPACE-TIME MODELLING AND PROCESSING OF METEOROLOGICAL RADAR RAINFALL DATA

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Introduction

Increasing interest has recently been focused on the development of real-time monitoring systems which are able to improve the flashflood forecasting capability of classical raingauge networks.

In this concern the use of meteorological radars is recognized as a necessary step for implementing an effective real-time monitoring system, because of their inherent, but not exploited yet, capability in measuring the space-time distribution of rainfall rate with higher resolution than that obtainable with the presently used raingauges networks.

The main problem in this concern is to devise suitable hydrometeorological models, as well as suitable data processing techniques which can correct the hydrometeorological measurement data, acquired by radar systems, which are affected by a lack of accuracy with respect to the measurement data obtained through raingauges.

Recent research studies and applications show also that meteorological radar measurements can be considerably improved if multiparametric techniques and calibration systems are used in the acquisition process of rainfall data.

In this paper the problem of estimating, through a meteorological radar, the space-time distribution of the rainfall rate with a sufficient precision is discussed.

To this end the following subjects should be deeply analyzed:

i) stochastic modelling and digital simulation of radar derived rainfall field data associated with critical meteorological events which can cause flashfloods;

ii) adaptive space-time processing of radar derived rainfall measurement data for estimating the current (filtered) and a-head (predicted) space distribution of the rainfall rate, so that the dynamic structure of rainfall events can be exploited in order to reduce the intrinsic non-stationary error of the radar measurements.

With reference to the above mentioned point i) meteorological phenomena, as well as the influence of climatology and orography on both rainfall and radar rainfall estimate errors, call for developing such an analysis.

In this paper, however, more attention is devoted to the point ii). Simple stochastic models are adopted for digital simulation of space-time distribution of rainfall rate measurements. These simulated data have been just used to test the performance and robustness of a particular adaptive space-time data processing procedure, suitably devised for improving the radar rainfall quantitative estimate.

The adopted data processing procedure, which refers to the above point ii), is derived from the stochastic method proposed by Johnson and Bras /1/ to predict rainfall rate, based upon measurements obtained through a raingauge network.

The extension of such a method and its application to the processing of the radar rainfall measurement data are considered in this paper.

Some results are also presented and discussed. These are obtained through digital simulations which apply the models and the radar data processing procedure mentioned above.

The presented results refer to the simulation of simple and critical rainfall events hypothesized over the Arno basin, wherein the city of Florence is located.

The model

The method proposed by Johnson and Bras /1/ is based upon a non stationary stochastic multivariate rainfall space-time model, whose parameters are adaptively estimated through the raingauge network measurement data. The rainfall rate process is decomposed in two separate parts: the average value and the residual of such a process at each time and location; the latter being the difference between the measured and average rainfall rate.

If $\underline{i}(t)$ is the rainfall rate vector, whose elements are the rainfall rates in N different locations (N raingauges in the prediction scheme), it can be decomposed as:

(1) $$\underline{i}(t) = \underline{m}(t) + \underline{r}(t)$$

where $\underline{m}(t)$ is the vector of mean values and $\underline{r}(t)$ is the vector of residuals, both at time step t.

The two parts can be described by two different models /1/.

a) The rainfall rate mean value and variance models.

A deterministic model is devised for both the mean value and the variance: these quantities are made functions of the storm counter s (Storm Counter Method).

The storm counter is defined as the number of time steps running from the rainfall start at a determined location. Such a definition is based on the hypothesis that the time history of the mean and variance values is identical for all locations, in relation to the time that storm arrives at each location.

Then, at each time step, the mean value of rainfall rate and the variance are estimated for all values of s less than or equal to a chosen value of the storm counter. This is made by taking into account the locations of a proper subset of raingauges, constituted by all raingauges whose actual storm counter is set at a value grater than that considered.

Then the estimated mean value can be written as /1/:

(2)

$$\hat{m}(s) = \frac{1}{n(s)} \sum_{\substack{i=1 \\ t(i,s)\neq 0}}^{M} q_i(t(i,s))$$

$n(s)$ number of locations with storm counter at least as high as s (sample size for storm counter s),

$t(i,s)$ time step for storm counter s at gauge i,

$q_i(t)$ rainfall rate at gauge i and time step t,

M total number of locations in the considered network.

We can also write the estimated variance $\hat{\sigma}^2(s)$ for storm counter s:

(3)

$$\hat{\sigma}^2(s) = \frac{1}{n(s)-1} \sum_{\substack{i=1 \\ t(i,s)\neq 0}}^{M} [q_i(t(i,s)) - m(s)]^2$$

A negative value of s indicates the number of time steps before the rainfall begins; such a value can be predicted by applying a linear regression method.

b) Model for residuals

The evolution of residuals is described by a stochastic, time varying, non-stationary Markov process, in which the state is represented by the vector of residuals.
The transition state equation is given by /1/:

(4)

$$\underline{r}(t+\tau) = \phi(t,\tau)\, \underline{r}(t) + \Gamma(t,\tau)\, \underline{w}(t,\tau)$$

where $\phi(t,\tau)$ is the transition state matrix; $\Gamma(t,\tau)\, \underline{w}(t,\tau)$ is the model error term, which is supposed to be zero mean, white and uncorrelated.
The vector of measured residuals is given by:

(5)

$$\underline{y}(t) = \underline{q}(t) - \underline{m}(t) = \underline{r}(t) + \underline{v}(t)$$

both in time and with respect to the error term of the model.
These equations can be used to obtain a Kalman filter, which is able to provide the estimates $\underline{r}(t+\tau|t)$ and $\underline{r}(t|t)$, namely: the predicted residual vector and the filtered residual vector at time t, respectively.
The Kalman filter parameters can be determined by calculating $\phi(t,\tau)$ and the second order moment properties of the noise terms.
The filter is initialized before the rainfall start, when $\underline{r}(0)=0$. Then the filtered residual takes on zero value in the starting time at time t=0 and the covariance matrix of the predicted residual errors is equal to the covariance matrix of the measurement errors at the same time.

The covariance matrices of the noise terms, pertaining to different windows, are expressed according to the following hypotheses:

- The covariance matrix $Q(t,\tau)$, of the noise state term is obtained as:

$$Q(t,\tau) = \Sigma(t+\tau)\{F(t+\tau,\, t+\tau) - F(t+\tau,\, t)\, F^{-1}(t,t)\ \ F^{T}(t+\tau,\, t)\}\Sigma(t+\tau)$$

  where: $\Sigma(.)$ is a diagonal matrix; each term of which is the variance of the corresponding $r(.)$, computed through the expression (5);
  $F(.,.)$ is the covariance matrix of residuals, normalized with respect to the variance, varying in accordance with an exponential law.
- The covariance matrix of the measurement errors is assumed to be diagonal:

$$E\,[v_i(t)\ \ v_j(t)] = S_i\ \ \delta(i,j)$$

where i,j are range cell indices, $\delta(i,j)$ is the Kroenecker function.
In the case of raingauge measurements, the quantity S_i can be considered as constant with respect to their locations.

c) Model extension to radar measurements affected by noise and clutter errors.

The above model has been directly extended to the radar case. Errors in the radar derived rainfall measurements include clutter induced errors beyond the background noise already considered with raingauge measurements. It is assumed that the resolution cells affected by clutter are a-priori known.

In the present paper some results are indeed presented which refer to rainfall data in the presence of clutter noise. Such a disturbance can be localized by using dry maps of the radar coverage. In this condition the data processing method described for the raingauge case is still applied, but in those locations where high probability of clutter presence is expected, the corresponding quantity S_i in eq. (7) is adapted by a suitable factor, in order to decrease the measured residual weight in the filtered estimate.

Application of the model to simulated radar data

As previously highlighted, radar data have been obtained by digitally simulating the space-time distribution of rainfall rate measurements.

The radar data were simulated with the following specific assumptions:

- the radar data are acquired within resolution cells whose size is 0.9 km range x 1° azimuth, the time resolution is about 6 min.
- the radar coverage is: 360° azimuth, 100Km range;
- the radar system is supposed to acquire data at a proper site within the Arno basin, which is placed within the Tuscany region (ITALY) [See map reported in Fig.1, where the evolution of rainfall events is also shown].

In the performed analysis, we have supposed that radar data be acquired within a sector of the total radar coverage, whose size is about one fourth of the total monitored area. Since, in this condition a great lot of data still need to be processed, some problems can arise in applying the mentioned Markov model, to overcome these problems a simplified model of residuals has been implemented by applying the Kalman filter to small windows, with a maximum size of 7x7 radar resolution cells. They have been analysed sequentially to cover the entire area under observation.

The storm counter method can be instead directly applied, in order to obtain a deterministic model of the mean value and variance of the rainfall rate.

The sector scanning is thus made by moving a sample window first in range and then in azimuth so as no superpositions can occur between adjacent surfaces. The data acquired from each window within the scanned sector are processed independently, in time, and sequentially, in space.

The described method is applied only when the processed window is classified as affected by rainfall: i.e. rainfall is present in a number of cells overstepping a set threshold. This test is made for reducing the total processing time.

The simulated date refer to critical rainfall events, which are supposed to occur in a sector within the Arno Basin. It is located within Tuscany Region whose map is reported in Fig. 1, where the evolution of rainfall event is also shown.

The rainfall rate pertaining to each resolution cell is simulated by supposing that its evolution in time be well described by a Gaussian curve, corresponding to a bidimensional space distribution of rainfall rate, moving with constant speed (m/s) along a set direction. The rainfall data, measured by radar, are obtained by superimposing a white, Gaussian and zero mean process to real data (true rainfall rate).

In Fig. 2 rainfall rate is reported as a function of time steps in a sample resolution cell: the Gaussian curve refers to the real data. In such a figure are also reported the measured rainfall rate curve and the behaviors of the filtered and predicted rainfall rate distributions obtained by applying the over described procedure.

It can be noticed that the filter improved the required estimate with respect to the measured data behavior, while the estimate is degradated in the predicted data curve.

In Fig. 3 the curves refer to real, measured, filtered and predicted rainfall rate in a resolution cell, as a function of time steps. They are obtained by accumulating rainfall values, recorded in the same resolution cell during a predetermined time interval. Better behavior of filtered and predicted estimates than the previous ones can be noticed.

In Fig. 4 measured rainfall rate is supposed to be affected by a non-stationary error, due to clutter, within a sample window. Such a disturbance can be attributed to clutter noise in the observed area. The clutter distribution in space is known through a simulated clutter map.

The measured rainfall rate curve is thus obtained in the case of the presence of both white, Gaussian noise and clutter noise. The reported curves show that even in this case the filter works satisfactorily.

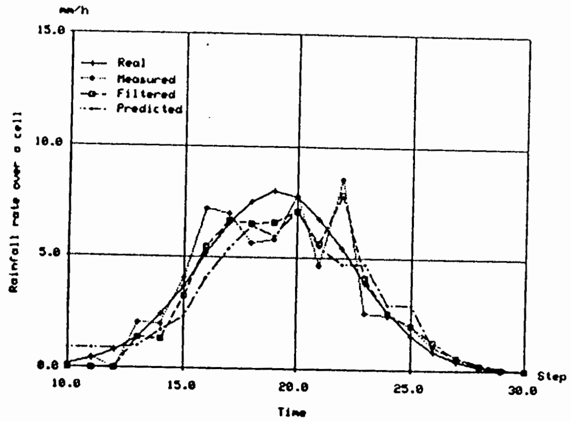

Fig. 2: Rainfall rate estimates vs. time steps for a set radar cell.

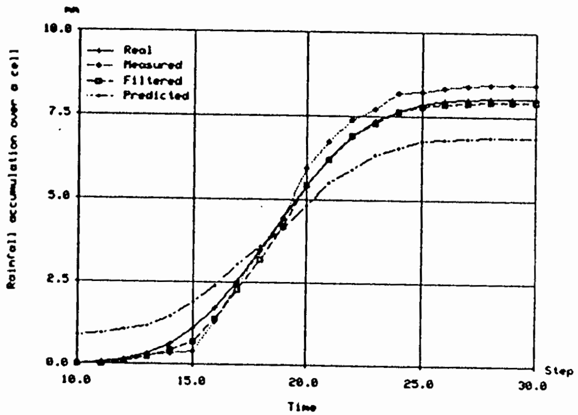

Fig. 3: Accumulated rainfall estimates vs. time for a set radar cell.

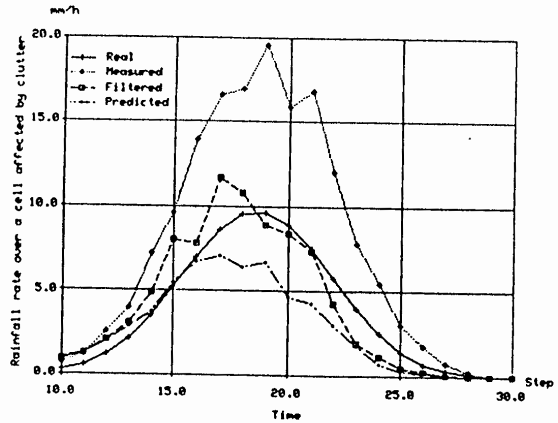

Fig. 4: Rainfall rate estimates vs. time over a sample window affected by clutter.

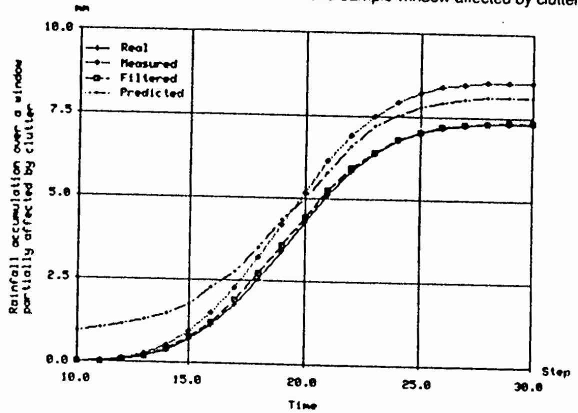

Fig. 5: Accumulated rainfall estimates vs. time over a sample window affected by clutter

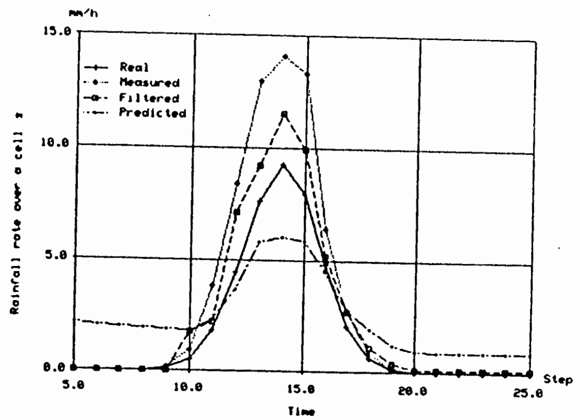

Fig. 6: Rainfall rate estimates vs. time over a set radar cell in the presence of several radar reflectivity error sources.