

# Model Parameter Estimation for 2D Noncausal Gauss-Markov Random Field

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**An original procedure for estimating the model of a noncausal Gauss-Markov Random Field (GMRF) observations is proposed. Starting from a suitable 'local' observation of the field and taking into account the symmetry of the so-called 'potential fields' [3] describing the GMRF, a linear equation system relating the model parameters to the (non-stationary) 2D autocorrelation function (acf) of the field is derived. Its solution for a known (or estimated) acf yields the parameter estimates of the GMRF. The unknown observation noise can be also estimated jointly with the model parameters.**

## SUMMARY

Let  $\{x(\underline{s})\}$  be a zero-mean Gaussian random process over a rectangular lattice  $I$  and constituting a noncausal homogeneous GMRF with respect to (wrt) an assigned 'support neighbourhood system' [3,4])  $\eta(d)$  admits the 'innovations process' [1,2]

$$\sum_{\underline{r} \in \eta(d)} \phi(\underline{r}) x(\underline{s} + \underline{r}) + u(\underline{s}), \quad \underline{s} \in I_-(\eta(d)). \quad (1)$$

where  $\eta(d)$  is assumed symmetric and constituted by an even number of sites  $2L(d)$  [4];  $I_-(\eta(d))$  is the set of 'internal points' of  $I$  wrt  $\eta(d)$ ;  $\{\phi(\underline{r})\}$  are the so-called 'field potentials', related as [2] to the acf  $\{R_u(\underline{r})\}$  of the 2D stationary zero-mean innovations process'  $\{u(\underline{s})\}$  over  $I_-(\eta(d))$ , with variance

due to the obvious symmetry property  $R_u(\underline{r}) = R_u(-\underline{r})$  we have:  $\phi(\underline{r}) = \phi(-\underline{r})$ . This allows to partition of the support region  $\eta(d)$  in the set  $\eta_-(d) \subset \eta(d)$ , each constituted by  $L(d)$  sites and such that  $\eta_-(d) \cup \eta_+(d) = \eta(d)$  for every  $\underline{r} \in \eta(d)$ . In this way (1) can be

$$\sum_{\underline{r} \in \eta_-(d)} \phi(\underline{r}) [x(\underline{s} + \underline{r}) + x(\underline{s} - \underline{r})] + u(\underline{s}), \quad \underline{s} \in I_-(\eta(d)). \quad (2)$$

The representation of the GMRF in (2) is then completed by the associated boundary conditions (b.c.), i.e. the statistics of the vector constituted by the r.v.s extracted from the random process at the boundary points of the lattice  $I$ .

It is assumed that the GMRF is corrupted by a 2D stationary

Walker equations for the parameter identification of 1D processes. From the field potentials, writing (3) for  $\underline{s} \in I_-(\eta(d))$  and any  $\underline{m} \in \eta_-(d)$  such that  $\phi(\underline{m}) \neq 0$ , the noise variance  $\sigma_u^2$  is calculated; finally, the parameter  $K_u$  is computed from (3).

The illustrated parameter estimation procedure is *full* in the sense that it is valid for GMRFs defined on both *finite or infinite* fields for *any kind* of assumed boundary conditions, periodic or aperiodic, their influence being embedded in the acf of the field itself. The procedure can be easily particularized to the case when the noise variance is known, or when the observation noise is absent.

Comparing the proposed solution to alternative methods found in the literature, some improvements can be outlined. Method [1] having exploited the symmetry  $\phi(\underline{r}) = \phi(-\underline{r})$  gives an algorithm with *half size* with respect to the system in [1]. On the other hand, the procedure in [4] is based on an iterative search algorithm, whose computational complexity is proportional to the size of the field. The proposed solution is based on a 'local' description of the GMRF and does *not* involve time-consuming iterative search algorithms. Its computational complexity is *independent* from the size of the field. In the proposed approach the variance of the observation noise is estimated *together* with the model parameters while the procedures in [1] and [4] requires that it is known (or separately estimated). The results of computer simulations of the above procedure are reported in [7].

## REFERENCES

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