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## Non Gaussian Matrix-Valued Random Fields for Nonparametric Probabilistic Modeling of Elliptic Stochastic Partial Differential Operators

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### Abstract

This paper deals with the construction of a non Gaussian positive-definite matrix-valued random field whose mathematical properties allow elliptic stochastic partial differential operators to be modeled. Such a matrix-valued random field can directly be used for modeling random uncertainties in computational sciences with a stochastic model having a small number of parameters. For instance, in three-dimensional linear elasticity, the fourth-order elasticity tensor of a random non homogeneous anisotropic elastic material is constituted of 21 dependent random fields which have to be such that the positive-definiteness property of this fourth-order tensor be verified in a given probabilistic sense. If the usual parametric probabilistic approach is used, then the identification of such a probabilistic model by using experimental data seems to be difficult. The non Gaussian positive-definite matrix-valued random field presented in this paper allows such a probabilistic model of the fourth-order tensor-valued random field to be constructed and depends only of 4 scalar parameters: three spatial correlation lengths and one parameter allowing the level of the random fluctuations to be controlled. Such a model can directly be used in the stochastic finite element method.

### 1. Introduction

A great challenge is the construction of construct stochastic representations for uncertain parameters for which probabilistic data are known and can be identified by using experimental data. Such a probabilistic model is useful in computational sciences and in particular for stochastic finite elements (Kleiber *et al.*, 1992; Ghanem and Spanos, 2003). For instance, consider the following deterministic elliptic partial differential operator  $\underline{A}$  on a bounded open domain  $\Omega$  of  $\mathbb{R}^3$ , related to the three-dimensional linear elasticity for a non homogeneous anisotropic elastic material,

$$\underline{A} \underline{\mathbf{u}} = - \sum_{i=1}^3 \mathbf{e}^i \sum_{j=1}^3 \frac{\partial}{\partial x_j} \left\{ \sum_{k,h=1}^3 \underline{c}_{ijkh}(\mathbf{x}) \varepsilon_{kh}(\underline{\mathbf{u}}) \right\} \quad , \quad (1)$$

in which  $\mathbf{x} = (x_1, x_2, x_3) \in \Omega \subset \mathbb{R}^3$ , where  $\mathbf{e}^1 = (1, 0, 0)$ ,  $\mathbf{e}^2 = (0, 1, 0)$  and  $\mathbf{e}^3 = (0, 0, 1)$  are the vectors of the canonical basis of  $\mathbb{R}^3$  and where  $\mathbf{x} \mapsto \underline{\mathbf{u}}(\mathbf{x}) = (\underline{u}_1(\mathbf{x}), \underline{u}_2(\mathbf{x}), \underline{u}_3(\mathbf{x}))$  is a twice differentiable function from  $\Omega$  into  $\mathbb{R}^3$ . The second-order strain tensor is such that  $\varepsilon_{kh}(\underline{\mathbf{u}}) = (1/2) (\partial \underline{u}_k / \partial x_h + \partial \underline{u}_h / \partial x_k)$ . The fourth-order elasticity tensor  $\underline{c}_{ijkh}(\mathbf{x})$  has to verify the symmetry property  $\underline{c}_{ijkh}(\mathbf{x}) = \underline{c}_{jikh}(\mathbf{x}) = \underline{c}_{ijhk}(\mathbf{x}) = \underline{c}_{khij}(\mathbf{x})$  and, for all symmetric second-order real tensors  $\{z_{ij}\}_{ij}$ , has to verify the positive-definiteness property,  $\sum_{i,j,k,h=1}^3 \underline{c}_{ijkh}(\mathbf{x}) z_{kh} z_{ij} \geq \underline{c}_0 \sum_{i,j=1}^3 z_{ij}^2$ , in which  $\underline{c}_0$  is a positive constant independent of  $\mathbf{x}$ . For a random medium, for all  $\mathbf{x}$  fixed in  $\Omega$ , tensor  $\{\underline{c}_{ijkh}(\mathbf{x})\}_{ijkh}$  is replaced by a fourth-order tensor-valued random variable  $\{C_{ijkh}(\mathbf{x})\}_{ijkh}$  whose mean value is  $\{\underline{c}_{ijkh}(\mathbf{x})\}_{ijkh}$  and which has to verify the symmetry and the positive-definiteness properties in a probabilistic sense which has to be defined. Nevertheless, for the random case, the deterministic constant  $\underline{c}_0$  (introduced above) cannot generally be justified from a probabilistic modeling point of view. Finally,  $\mathbf{x} \mapsto \{C_{ijkh}(\mathbf{x})\}_{ijkh}$  is a fourth-order tensor-valued random field indexed by  $\Omega$ , constituted of 21 mutually dependent random fields and the stochastic partial differential operator  $\mathbf{A}$  associated with operator  $\underline{A}$  written as

$$\mathbf{A}\mathbf{U} = - \sum_i^3 \mathbf{e}^i \sum_{j=1}^3 \frac{\partial}{\partial x_j} \left\{ \sum_{k,h=1}^3 C_{ijkh}(\mathbf{x}) \varepsilon_{kh}(\mathbf{U}) \right\} . \quad (2)$$

It should be noted that the probability distribution of this fourth-order tensor-valued random field (that is to say the system of the marginal distributions) is required because the unknown solution of the stochastic boundary value problem is a nonlinear mapping of random field  $\mathbf{x} \mapsto \{C_{ijkh}(\mathbf{x})\}_{ijkh}$ . If the usual parametric probabilistic approach is used, then the identification of this probability model by using experimental data seems to be difficult. This paper deals with a nonparametric construction of a random field such as  $\mathbf{x} \mapsto \{C_{ijkh}(\mathbf{x})\}_{ijkh}$ . For that, an ensemble of non Gaussian positive-definite matrix-valued random fields is constructed and studied which allows, for instance, the fourth-order tensor-valued random field  $\mathbf{x} \mapsto \{C_{ijkh}(\mathbf{x})\}_{ijkh}$  to be modeled. Then, such a tensor-valued random field will depend only on 4 scalar parameters: three spatial correlation lengths and one parameter allowing the level of the random fluctuations to be controlled. With such a model, the inverse problem related to the experimental identification seems to be more feasible.

The following algebraic notations are used. Let  $\mathbf{x} = (x_1, \dots, x_n)$  be a vector in  $\mathbb{R}^n$ . The Euclidean space  $\mathbb{R}^n$  is equipped with the usual inner product  $(\mathbf{x}, \mathbf{y}) \mapsto \langle \mathbf{x}, \mathbf{y} \rangle = \sum_{j=1}^n x_j y_j$  and the associated norm  $\|\mathbf{x}\| = \langle \mathbf{x}, \mathbf{x} \rangle^{1/2}$ . Let  $\mathbb{M}_{n,m}(\mathbb{R})$  be the set of all the  $(n \times m)$  real matrices,  $\mathbb{M}_n(\mathbb{R}) = \mathbb{M}_{n,n}(\mathbb{R})$  be the set of all the square  $(n \times n)$  real matrices,  $\mathbb{M}_n^S(\mathbb{R})$  be the set of all the  $(n \times n)$  real symmetric matrices and  $\mathbb{M}_n^+(\mathbb{R})$  be the set of all the  $(n \times n)$  real symmetric positive-definite matrices. We then have  $\mathbb{M}_n^+(\mathbb{R}) \subset \mathbb{M}_n^S(\mathbb{R}) \subset \mathbb{M}_n(\mathbb{R})$ . We denote (i) the trace of the matrix  $[A] \in \mathbb{M}_n(\mathbb{R})$  as  $\text{tr}[A] = \sum_{j=1}^n [A]_{jj}$ ; (ii) the transpose of  $[A] \in \mathbb{M}_{n,m}(\mathbb{R})$  as  $[A]^T \in \mathbb{M}_{m,n}(\mathbb{R})$ ; (iii) the operator norm of the matrix  $[A] \in \mathbb{M}_{n,m}(\mathbb{R})$  as  $\|A\| = \sup_{\|\mathbf{x}\| \leq 1} \|[A]\mathbf{x}\|$ ,  $\mathbf{x} \in \mathbb{R}^m$ , which is such that  $\|[A]\mathbf{x}\| \leq \|A\| \|\mathbf{x}\|$ ,  $\forall \mathbf{x} \in \mathbb{R}^m$ , and if  $m = n$ , then  $\|A\| = |\lambda_n|$ , in which  $|\lambda_n|$  is the largest modulus of the eigenvalues of  $[A]$ ; (iv) for  $[A] \in \mathbb{M}_{n,m}(\mathbb{R})$ , we note  $\|A\|_F^2 = \text{tr}\{[A]^T[A]\} = \sum_{j=1}^n \sum_{k=1}^m [A]_{jk}^2$  and for  $[A]$  in  $\mathbb{M}_n(\mathbb{R})$ , we have  $\|A\| \leq \|A\|_F \leq \sqrt{n}\|A\|$ .

## 2. Construction and properties of the ensemble $\text{SFG}^+$ of homogeneous and normalized non Gaussian positive-definite matrix-valued random fields

### 2.1. Random field $U$ as the germ of ensemble $\text{SFG}^+$

*Definition.* Let  $d \geq 1$  be an integer. Let  $\mathbf{x} \mapsto U(\mathbf{x})$  be a second-order centered homogeneous Gaussian random field, defined on probability space  $(\Theta, \mathcal{T}, P)$ , indexed by  $\mathbb{R}^d$ , with values in  $\mathbb{R}$ . Let  $L_1, \dots, L_d$  be positive real numbers. Its autocorrelation function  $R_U(\boldsymbol{\eta}) = E\{U(\mathbf{x} + \boldsymbol{\eta})U(\mathbf{x})\}$ , defined for all  $\boldsymbol{\eta} = (\eta_1, \dots, \eta_d)$  in  $\mathbb{R}^d$ , is written as  $R_U(\boldsymbol{\eta}) = \rho_1(\eta_1) \times \dots \times \rho_d(\eta_d)$  in which, for all  $j = 1, \dots, d$ , we have  $\rho_j(0) = 1$  and  $\rho_j(\eta_j) = 4L_j^2/(\pi^2\eta_j^2) \sin^2(\pi\eta_j/(2L_j))$  for  $\eta_j \neq 0$ .

*Properties.* For all  $\mathbf{x}$  in  $\mathbb{R}^d$ ,  $E\{U(\mathbf{x})\} = 0$  and  $E\{U(\mathbf{x})^2\} = 1$ . The random field  $U$  is mean-square continuous on  $\mathbb{R}^d$ . Let  $\mathbf{k} = (k_1, \dots, k_d)$  be a point in  $\mathbb{R}^d$  and let  $d\mathbf{k} = dk_1 \dots dk_d$  be the Lebesgue measure. Then, there is a power spectral density function  $\mathbf{k} \mapsto S_U(\mathbf{k})$  from  $\mathbb{R}^d$  into  $\mathbb{R}^+$ , integrable, such that  $\forall \boldsymbol{\eta} \in \mathbb{R}^d$ ,  $R_U(\boldsymbol{\eta}) = \int_{\mathbb{R}^d} e^{i\langle \boldsymbol{\eta}, \mathbf{k} \rangle} S_U(\mathbf{k}) d\mathbf{k}$  which can be written as  $S_U(\mathbf{k}) = s_1(k_1) \times \dots \times s_d(k_d)$  in which, for all  $j = 1, \dots, d$ , the function  $k_j \mapsto s_j(k_j)$  from  $\mathbb{R}$  into  $\mathbb{R}^+$  is defined by  $s_j(k_j) = (L_j/\pi) q(k_j L_j/\pi)$ . The function  $\tau \mapsto q(\tau)$  is continuous from  $\mathbb{R}$  into  $\mathbb{R}^+$ , has a compact support  $[-1, 1]$  and is such that  $q(0) = 1$ ,  $q(-\tau) = q(\tau)$  and  $q(\tau) = 1 - \tau$  for  $\tau \in [0, 1]$ . This means that

$S_U$  has a compact support. Introducing  $L_j^U$  as the spatial correlation length relative to coordinate  $x_j$  and defined by  $L_j^U = \int_0^{+\infty} |R_U(0, \dots, 0, \eta_j, 0, \dots, 0)| d\eta_j$ , it can easily be deduced that  $L_j^U = L_j$ . Consequently, parameters  $L_1, \dots, L_d$  represent the spatial correlation lengths of random field  $U$ .

*Representation of the random field  $U$  adapted to its numerical simulation.* The spatial discretization of this random field will directly be related to the spatial discretization of the elliptic stochastic partial differential operator for which germ  $U$  will be used. In general, the problem is setted on an arbitrary bounded domain  $\Omega$  of  $\mathbb{R}^d$  and the finite element method is utilized. Consequently,  $U$  has to be simulated in  $N$  given points  $\mathbf{x}^1, \dots, \mathbf{x}^N$  in  $\Omega \subset \mathbb{R}^d$  (for instance, located in the integrating points of the finite elements of the finite element mesh of domain  $\Omega$ ). We then have to simulate realizations of the random vector  $\mathbf{U} = (U(\mathbf{x}^1), \dots, U(\mathbf{x}^N))$ . A first representation adapted to a large value of  $N$  is based on the usual numerical simulation of homogeneous Gaussian vector-valued random field  $U$  constructed with the stochastic integral representation of homogeneous stochastic fields. A second representation adapted to a small or moderate value of  $N$  consists in writing  $\mathbf{U} = [L_U]^T \mathbf{V}$  in which  $\mathbf{V} = (V_1, \dots, V_N)$  is an  $\mathbb{R}^N$ -valued random variable whose components  $V_1, \dots, V_N$  are  $N$  independent normalized Gaussian random variables ( $E\{V_j\} = 0$  and  $E\{V_j^2\} = 1$  for  $j = 1, \dots, N$ ) and where  $[L_U]$  is the upper real triangular matrix corresponding to the Cholesky factorization  $[C_U] = [L_U]^T [L_U]$  of the covariance matrix  $[C_U]$  in  $\mathbb{M}_N^+(\mathbb{R})$  such that  $[C_U]_{ij} = R_U(\mathbf{x}^i - \mathbf{x}^j)$ .

## 2.2. Ensemble SFG<sup>+</sup>

*Defining the family of functions  $\{u \mapsto h(\alpha, u)\}_{\alpha > 0}$ .* Let  $\alpha$  be a positive real number. The function  $u \mapsto h(\alpha, u)$  from  $\mathbb{R}$  into  $]0, +\infty[$  is such that  $\Gamma_\alpha = h(\alpha, U)$  is a gamma random variable with parameter  $\alpha$  while  $U$  is a normalized Gaussian random variable ( $E\{U\} = 0$  and  $E\{U^2\} = 1$ ). Consequently, for all  $u$  in  $\mathbb{R}$ , we have  $h(\alpha, u) = F_{\Gamma_\alpha}^{-1}(F_U(u))$  in which  $u \mapsto F_U(u) = P(U \leq u)$  is the cumulative distribution function of the normalized Gaussian random variable  $U$ . The function  $p \mapsto F_{\Gamma_\alpha}^{-1}(p)$  from  $]0, 1[$  into  $]0, +\infty[$  is the reciprocal function of the cumulative distribution function  $\gamma \mapsto F_{\Gamma_\alpha}(\gamma)$  from  $]0, +\infty[$  into  $]0, 1[$  of the gamma random variable  $\Gamma_\alpha$  with parameter  $\alpha$ , which is such that, for all  $\gamma$  in  $\mathbb{R}^+$ ,  $F_{\Gamma_\alpha}(\gamma) = \int_0^\gamma \frac{1}{\Gamma(\alpha)} t^{\alpha-1} e^{-t} dt$  in which  $\Gamma(\alpha)$  is the gamma function.

*Defining the ensemble SFG<sup>+</sup> of the random field  $\mathbf{x} \mapsto [\mathbf{G}_n(\mathbf{x})]$ .* The ensemble SFG<sup>+</sup> is defined as the set of all the random fields  $\mathbf{x} \mapsto [\mathbf{G}_n(\mathbf{x})]$ , defined on the probability space  $(\Theta, \mathcal{T}, P)$ , indexed by  $\mathbb{R}^d$  where  $d \geq 1$  is a fixed integer, with values in  $\mathbb{M}_n^+(\mathbb{R})$  where  $n \geq 2$  is another fixed integer, and defined as follows: (i) Let  $\{U_{jj'}(\mathbf{x}), \mathbf{x} \in \mathbb{R}^d\}_{1 \leq j \leq j' \leq n}$  be  $n(n+1)/2$  independent copies of the random field  $\{U(\mathbf{x}), \mathbf{x} \in \mathbb{R}^d\}$ . Consequently, for  $1 \leq j \leq j' \leq n$ , we have  $E\{U_{jj'}(\mathbf{x})\} = 0$  and  $E\{U_{jj'}(\mathbf{x})^2\} = 1$  and the random field  $\mathbf{x} \mapsto U_{jj'}(\mathbf{x})$  is completely defined. (ii) Let  $\delta$  be the real number, independent of  $\mathbf{x}$  and  $n$ , such that  $0 < \delta < \sqrt{(n+1)(n+5)^{-1}} < 1$ . This parameter will allow the dispersion of the random field to be controlled. (iii) For all  $\mathbf{x}$  in  $\mathbb{R}^d$ ,  $[\mathbf{G}_n(\mathbf{x})] = [\mathbf{L}_n(\mathbf{x})]^T [\mathbf{L}_n(\mathbf{x})]$  in which  $[\mathbf{L}_n(\mathbf{x})]$  is the upper  $(n \times n)$  real triangular random matrix defined as follows. The  $n(n+1)/2$  random fields  $\mathbf{x} \mapsto [\mathbf{L}_n(\mathbf{x})]_{jj'}$  for  $1 \leq j \leq j' \leq n$ , are independent. For  $j < j'$ , the real-valued random field  $\mathbf{x} \mapsto [\mathbf{L}_n(\mathbf{x})]_{jj'}$ , indexed by  $\mathbb{R}^d$ , is defined by  $[\mathbf{L}_n(\mathbf{x})]_{jj'} = \sigma_n U_{jj'}(\mathbf{x})$  in which  $\sigma_n$  is such that  $\sigma_n = \delta(n+1)^{-1/2}$ . For  $j = j'$ , the positive-valued random field  $\mathbf{x} \mapsto [\mathbf{L}_n(\mathbf{x})]_{jj}$ , indexed by  $\mathbb{R}^d$ , is defined by  $[\mathbf{L}_n(\mathbf{x})]_{jj} = \sigma_n \sqrt{2h(\alpha_j, U_{jj}(\mathbf{x}))}$  in which, for  $j = 1, \dots, n$ ,  $\alpha_j = (n+1)/(2\delta^2) + (1-j)/2$ .

*Basic properties.*  $\mathbf{x} \mapsto [\mathbf{G}_n(\mathbf{x})]$  is a homogeneous second-order mean-square continuous

random field indexed by  $\mathbb{R}^d$  with values in  $\mathbb{M}_n^+(\mathbb{R})$ . In addition, the trajectories of random field  $\mathbf{x} \mapsto [\mathbf{G}_n(\mathbf{x})]$  are continuous from  $\mathbb{R}^d$  into  $\mathbb{M}_n^+(\mathbb{R})$  almost surely. For all  $\mathbf{x} \in \mathbb{R}^d$ , we have  $E\{\|[\mathbf{G}_n(\mathbf{x})]\|_F^2\} < +\infty$  and  $E\{[\mathbf{G}_n(\mathbf{x})]\} = [I_n]$ . The parameter  $\delta$  is such that  $\delta = \{\frac{1}{n}E\{\|[\mathbf{G}_n(\mathbf{x})] - [I_n]\|_F^2\}\}^{1/2}$  which shows that  $E\{\|[\mathbf{G}_n(\mathbf{x})]\|_F^2\} = n(\delta^2 + 1)$ . For all  $\mathbf{x}$  fixed in  $\mathbb{R}^d$ , the probability distribution on  $\mathbb{M}_n^+(\mathbb{R})$  of random matrix  $[\mathbf{G}_n(\mathbf{x})]$  is explicitly calculated in (Soize, 2001) and shows that, for all  $\mathbf{x}$  in  $\mathbb{R}^d$ , the random variables  $\{[\mathbf{G}_n(\mathbf{x})]_{ij}, 1 \leq i \leq j \leq n\}$  are mutually dependent. The system of the marginal probability distributions of random field  $\mathbf{x} \mapsto [\mathbf{G}_n(\mathbf{x})]$  is well defined but cannot be explicitly calculated. Random field  $\mathbf{x} \mapsto [\mathbf{G}_n(\mathbf{x})]$  is non Gaussian. There exists a positive constant  $c_0$  independent of  $n$  and independent of  $\mathbf{x}$ , but depending on  $\delta$ , such that  $E\{\|[\mathbf{G}_n(\mathbf{x})]^{-1}\|^2\} \leq c_0 < +\infty$  for all  $n \geq 2$  and for all  $\mathbf{x} \in \mathbb{R}^d$ . We then have  $E\{\|[\mathbf{G}_n(\mathbf{x})]^{-1}\|_F^2\} \leq c_n < +\infty$  for all  $n \geq 2$  and for all  $\mathbf{x} \in \mathbb{R}^d$  in which  $c_n = n c_0$ . It should be noted that, since  $[\mathbf{G}_n(\mathbf{x})]$  belongs to  $\mathbb{M}_n^+(\mathbb{R})$  almost surely, then  $[\mathbf{G}_n(\mathbf{x})]^{-1}$  exists almost surely. However, since almost sure convergence does not yield mean-square convergence, the previous result cannot simply be deduced (see Soize, 2001).

*Fundamental property.* Let  $\Omega$  be a bounded open domain of  $\mathbb{R}^d$  and let  $\overline{\Omega} = \Omega \cup \partial\Omega$  be its closure in which  $\partial\Omega$  is the boundary of  $\Omega$ . We then have

$$E\{(\sup_{\mathbf{x} \in \overline{\Omega}} \|[\mathbf{G}_n(\mathbf{x})]^{-1}\|)^2\} = c_G^2 < +\infty \quad , \quad (3)$$

in which sup is the supremum and where  $0 < c_G < +\infty$  is a finite positive constant.

*Remark concerning the proof of Eq. (3).* Let us consider the case  $d = 1$  with  $\overline{\Omega}$  be a compact interval of  $\mathbb{R}$ . Since the stochastic process  $\{\|G_n(\mathbf{x})^{-1}\|, \mathbf{x} \in \overline{\Omega} \subset \mathbb{R}\}$  is not a continuous local martingal with respect to an increasing family of  $\sigma$ -fields, the following fundamental Doob maximal inequality (Doob, 1953)  $E\{\sup_{\mathbf{x} \in \overline{\Omega}} \|[\mathbf{G}_n(\mathbf{x})]^{-1}\|^2\} \leq 4 E\{\|[\mathbf{G}_n(\mathbf{x})]^{-1}\|^2\}$  cannot be used. In addition, we have to consider the non Gaussian random field case  $d \geq 2$ . Consequently, there is no known result allowing a direct proof of Eq. (3) to be obtained and a complete proof of this fundamental result is given in (Soize, 2004).

### 3. Construction and properties of the ensemble SFE<sup>+</sup> of non Gaussian positive-definite matrix-valued random fields

#### 3.1. Definition of the ensemble SFE<sup>+</sup>

Let  $d \geq 1$  and  $n \geq 2$  be two fixed integers. Let  $\Omega$  be an open (or closed) bounded (or not) domain of  $\mathbb{R}^d$  (we can have  $\Omega = \mathbb{R}^d$ ). Let  $\mathbf{x} \mapsto [\underline{a}_n(\mathbf{x})]$  be a matrix-valued field from  $\Omega$  into  $\mathbb{M}_n^+(\mathbb{R})$ . Then, for all  $\mathbf{x}$  fixed in  $\Omega$ , there is an upper triangular invertible matrix  $[\underline{L}_n(\mathbf{x})]$  in  $\mathbb{M}_n(\mathbb{R})$  such that  $[\underline{a}_n(\mathbf{x})] = [\underline{L}_n(\mathbf{x})]^T [\underline{L}_n(\mathbf{x})]$ . It is assumed that: (i) there is a real positive constant  $0 < \underline{c}_0 < +\infty$  independent of  $\mathbf{x}$  such that, for all  $\mathbf{x}$  in  $\Omega$  and for all  $\mathbf{y} \in \mathbb{R}^n$ ,  $\langle [\underline{a}_n(\mathbf{x})] \mathbf{y}, \mathbf{y} \rangle \geq \underline{c}_0 \|\mathbf{y}\|^2$ ; (ii) there is a real positive constant  $0 < \underline{c}_1 < +\infty$  independent of  $\mathbf{x}$  such that, for all  $\mathbf{x}$  in  $\Omega$ , we have  $\|[\underline{L}_n(\mathbf{x})]\| \leq \sqrt{\underline{c}_1}$  which yields  $\langle [\underline{a}_n(\mathbf{x})] \mathbf{y}, \mathbf{y} \rangle \leq \underline{c}_1 \|\mathbf{y}\|^2$ , for all  $\mathbf{y}$  in  $\mathbb{R}^n$  and for all  $\mathbf{x}$  in  $\Omega$ . Consequently, for all  $\mathbf{x}$  in  $\Omega$ , we have  $\|[\underline{a}_n(\mathbf{x})]\| \leq \underline{c}_1$  and  $\|[\underline{a}_n(\mathbf{x})]\|_F \leq \sqrt{n} \underline{c}_1$ . The ensemble SFE<sup>+</sup> is then defined as the set of all the random fields  $\mathbf{x} \mapsto [\mathbf{A}_n(\mathbf{x})]$ , defined on probability space  $(\Theta, \mathcal{T}, P)$ , indexed by  $\Omega$ , with values in  $\mathbb{M}_n^+(\mathbb{R})$ , such that

$$\forall \mathbf{x} \in \Omega \quad , \quad [\mathbf{A}_n(\mathbf{x})] = [\underline{L}_n(\mathbf{x})]^T [\mathbf{G}_n(\mathbf{x})] [\underline{L}_n(\mathbf{x})] \quad , \quad (4)$$

in which  $\mathbf{x} \mapsto [\mathbf{G}_n(\mathbf{x})]$  is the random field in SFG<sup>+</sup>, defined on  $(\Theta, \mathcal{T}, P)$ , indexed by  $\mathbb{R}^d$  and with values in  $\mathbb{M}_n^+(\mathbb{R})$  (see Section 2.2).



### 3.2. Properties of the random field $\mathbf{x} \mapsto [\mathbf{A}_n(\mathbf{x})]$

*Basic properties.* For all  $\mathbf{x}$  in  $\Omega$ ,  $[\mathbf{A}_n(\mathbf{x})]$  is a random matrix with values in  $\mathbb{M}_n^+(\mathbb{R})$ , the mean function is such that  $\mathbf{x} \mapsto E\{[\mathbf{A}_n(\mathbf{x})]\} = [\underline{a}_n(\mathbf{x})] \in \mathbb{M}_n^+(\mathbb{R})$  and  $E\{\|[\mathbf{A}_n(\mathbf{x})]\|^2\} \leq E\{\|[\mathbf{A}_n(\mathbf{x})]\|_F^2\} \leq n \underline{c}_1^2 E\{\|[\mathbf{G}_n(\mathbf{x})]\|^2\} \leq n \underline{c}_1^2 E\{\|[\mathbf{G}_n(\mathbf{x})]\|_F^2\} < +\infty$  which proves that  $\mathbf{x} \mapsto [\mathbf{A}_n(\mathbf{x})]$  is a second-order random field on  $\Omega$ . In general, since  $[\underline{a}_n(\mathbf{x})]$  depends on  $\mathbf{x}$ , then the random field  $\{[\mathbf{A}_n(\mathbf{x})], \mathbf{x} \in \Omega\}$  is non homogeneous. Nevertheless, if  $[\underline{a}_n(\mathbf{x})] = [\underline{a}_n]$  is independent of  $\mathbf{x}$ , then the random field  $\{[\mathbf{A}_n(\mathbf{x})] = [\underline{L}_n]^T [\mathbf{G}_n(\mathbf{x})] [\underline{L}_n], \mathbf{x} \in \Omega\}$  can be viewed as the restriction to  $\Omega$  of a homogeneous random field indexed by  $\mathbb{R}^d$ . We have  $E\{\|[\mathbf{A}_n(\mathbf{x})] - [\underline{a}_n(\mathbf{x})]\|_F^2\} = \{\delta^2/(n+1)\}\{\|[\underline{a}_n(\mathbf{x})]\|_F^2 + (\text{tr}[\underline{a}_n(\mathbf{x})])^2\}$ . The dispersion parameter, defined by  $\delta_{A_n}(\mathbf{x}) = \{E\{\|[\mathbf{A}_n(\mathbf{x})] - [\underline{a}_n(\mathbf{x})]\|_F^2\}/\|[\underline{a}_n(\mathbf{x})]\|_F^2\}^{1/2}$ , is such that  $\delta_{A_n}(\mathbf{x}) = (\delta/\sqrt{n+1})\{1 + (\text{tr}[\underline{a}_n(\mathbf{x})])^2/\text{tr}\{[\underline{a}_n(\mathbf{x})]\}^2\}^{1/2}$ .

*Spatial correlation lengths for the homogeneous case.* Then (see above),  $\delta_{A_n}(\mathbf{x}) = \delta_{A_n}$  is independent of  $\mathbf{x}$ . Let  $\boldsymbol{\eta} = (\eta_1, \dots, \eta_d) \mapsto r^{A_n}(\boldsymbol{\eta})$  be the function defined from  $\mathbb{R}^d$  into  $\mathbb{R}$  by  $r^{A_n}(\boldsymbol{\eta}) = \text{tr} E\{([\mathbf{A}_n(\mathbf{x} + \boldsymbol{\eta})] - [\underline{a}_n])([\mathbf{A}_n(\mathbf{x})] - [\underline{a}_n])\}/E\{\|[\mathbf{A}_n(\mathbf{x})] - [\underline{a}_n]\|_F^2\}$ . We have  $r^{A_n}(0) = 1$  and  $r^{A_n}(-\boldsymbol{\eta}) = r^{A_n}(\boldsymbol{\eta})$ . For all  $j = 1, \dots, d$ , the spatial correlation length  $L_j^{A_n}$  of the homogeneous random field  $\mathbf{x} \mapsto [\mathbf{A}_n(\mathbf{x})]$  indexed by  $\mathbb{R}^d$ , relative to coordinate  $x_j$ , can then be defined by  $L_j^{A_n} = \int_0^{+\infty} |r^{A_n}(0, \dots, 0, \eta_j, 0, \dots, 0)| d\eta_j$ .

## 4. Elliptic stochastic partial differential operator

The presentation is limited to the second-order stochastic differential operator defined by Eq. (2) on an open bounded domain  $\Omega$  of  $\mathbb{R}^3$  whose boundary  $\partial\Omega$  is written as  $\Gamma_0 \cup \Gamma$ . On  $\Gamma_0$ , there is a zero Dirichlet boundary condition. We introduce the real Hilbert spaces  $H = (L^2(\Omega))^3$  and  $V = \{\mathbf{u} \in (H^1(\Omega))^3, \mathbf{u} = 0 \text{ on } \Gamma_0\}$  whose inner products are denoted by  $\langle \mathbf{u}, \mathbf{w} \rangle_H$  and  $\langle \mathbf{u}, \mathbf{w} \rangle_V$  respectively, and where the associated norms are denoted by  $\|\mathbf{u}\|_H$  and  $\|\mathbf{u}\|_V$  respectively. Let  $\mathbb{H} = L^2(\Theta, H)$  and  $\mathbb{V} = L^2(\Theta, V)$  be the real Hilbert spaces of all the second-order random variables  $\theta \mapsto \{\mathbf{x} \mapsto \mathbf{U}(\mathbf{x}, \theta)\}$  defined on probability space  $(\Theta, \mathcal{T}, P)$ , with values in  $H$  and  $V$  respectively, equipped with the inner products  $\ll \mathbf{U}, \mathbf{W} \gg_{\mathbb{H}} = E\{\langle \mathbf{U}, \mathbf{W} \rangle_H\}$  and  $\ll \mathbf{U}, \mathbf{W} \gg_{\mathbb{V}} = E\{\langle \mathbf{U}, \mathbf{W} \rangle_V\}$  respectively, and where the associated norms are denoted by  $\|\mathbf{U}\|_{\mathbb{H}}$  and  $\|\mathbf{U}\|_{\mathbb{V}}$  respectively.

### 4.1. Weak formulation of the elliptic stochastic partial differential operator.

Let  $n = 6$  and let us introduce the new indices  $I$  and  $J$  belonging to  $\{1, \dots, 6\}$  such that  $I = (i, j)$  and  $J = (k, h)$  with the following correspondence:  $1 = (1, 1), 2 = (2, 2), 3 = (3, 3), 4 = (1, 2), 5 = (2, 3)$  and  $6 = (3, 1)$ . Thus, for all  $\mathbf{x}$  in  $\Omega$ , we introduce the matrix  $[\underline{a}_n(\mathbf{x})]$  in  $\mathbb{M}_n^+(\mathbb{R})$  such that  $[\underline{a}_n(\mathbf{x})]_{IJ} = \underline{c}_{ijkh}(\mathbf{x})$  and the random  $(n \times n)$  real matrix  $[\mathbf{A}_n(\mathbf{x})]$  such that  $[\mathbf{A}_n(\mathbf{x})]_{IJ} = C_{ijkh}(\mathbf{x})$ . A nonparametric probabilistic model of the random fourth-order elasticity tensor  $C_{ijkh}(\mathbf{x})$  consists in choosing the random field  $\mathbf{x} \mapsto [\mathbf{A}_n(\mathbf{x})]$  in  $\text{SFE}^+$  with the mean value  $[\underline{a}_n(\mathbf{x})] = E\{[\mathbf{A}_n(\mathbf{x})]\}$ . The weak formulation of the stochastic partial differential operator defined by Eq. (2) leads the random bilinear form  $(\mathbf{U}, \mathbf{W}) \mapsto \mathbf{K}(\mathbf{U}, \mathbf{W})$  on  $\mathbb{V} \times \mathbb{V}$  to be introduced, such that

$$\mathbf{K}(\mathbf{U}, \mathbf{W}) = \int_{\Omega} \langle [\mathbf{A}_n(\mathbf{x})] \mathbf{e}(\mathbf{U}(\mathbf{x})), \mathbf{e}(\mathbf{W}(\mathbf{x})) \rangle d\mathbf{x} \quad , \quad (5)$$

in which  $\mathbf{e}(\mathbf{u}) = (\varepsilon_{11}(\mathbf{u}), \varepsilon_{22}(\mathbf{u}), \varepsilon_{33}(\mathbf{u}), 2\varepsilon_{12}(\mathbf{u}), 2\varepsilon_{23}(\mathbf{u}), 2\varepsilon_{31}(\mathbf{u}))$ .

### 4.2. Ellipticity of the random bilinear form

Let  $(\mathbf{U}, \mathbf{W}) \mapsto \mathcal{K}(\mathbf{U}, \mathbf{W})$  be the bilinear form on  $\mathbb{V} \times \mathbb{V}$  defined by  $\mathcal{K}(\mathbf{U}, \mathbf{W}) = E\{\mathbf{K}(\mathbf{U}, \mathbf{W})\}$ . If the following property was introduced: for all  $\mathbf{x} \in \Omega$  and for all  $\mathbb{R}^n$ -valued random

variable  $\mathbf{Y}$  defined on  $(\Theta, \mathcal{T}, P)$ ,  $\langle [\mathbf{A}_n(\mathbf{x})] \mathbf{Y}, \mathbf{Y} \rangle \geq c \|\mathbf{Y}\|^2$  a.s in which  $0 < c < +\infty$  is independent of  $\mathbf{x}$ , then the bilinear form  $(\mathbf{U}, \mathbf{W}) \mapsto \mathcal{K}(\mathbf{U}, \mathbf{W})$  on  $\mathbb{V} \times \mathbb{V}$  would be coercive in  $\mathbb{V}$  (i.e.  $\mathbb{V}$ -elliptic) because, we would have  $\mathcal{K}(\mathbf{U}, \mathbf{U}) \geq cE\{\int_{\Omega} \|\mathbf{e}(\mathbf{U}(\mathbf{x}))\|^2 d\mathbf{x}\} \geq c_{\mathcal{K}} \|\mathbf{U}\|_{\mathbb{V}}^2$  with  $0 < c_{\mathcal{K}} < +\infty$ . This property, which is generally not coherent with the available information which can be deduced from objective data, does not hold for the random field  $\mathbf{x} \mapsto [\mathbf{A}_n(\mathbf{x})]$  belonging to  $\text{SFE}^+$  and consequently, the usual analysis given above cannot presently be used. Another analysis has to be developed using the fundamental property defined by Eq. (3): it is proved (Soize, 2004) that, for all random field  $\{\mathbf{x} \mapsto \mathbf{U}(\mathbf{x})\}$  in  $\mathbb{V}$ , we have

$$\sqrt{E\{\mathbf{K}(\mathbf{U}, \mathbf{U})^2\}} \geq c_K \|\mathbf{U}\|_{\mathbb{V}}^2, \quad (6)$$

in which  $c_K$  is a positive finite real constant. It should be noted that Eq. (6) differs from equation  $E\{\mathbf{K}(\mathbf{U}, \mathbf{U})\} \geq c_{\mathcal{K}} \|\mathbf{U}\|_{\mathbb{V}}^2$  due to the fact that the two positive-valued random variables  $\sup_{\mathbf{x} \in \bar{\Omega}} \|\mathbf{G}_n(\mathbf{x})\|^{-1}$  and  $\mathbf{K}(\mathbf{U}, \mathbf{U})$  are dependent.

#### 4.3. Existence and uniqueness of a weak second-order stochastic solution for a stochastic BVP

Let  $\mathbf{w} \mapsto f(\mathbf{w})$  be a given continuous linear form on  $V$ , that is to say such that  $|f(\mathbf{w})| \leq c_f \|\mathbf{w}\|_V$  with  $0 < c_f < +\infty$ . Then, the following random problem: find a random field  $\{\mathbf{x} \mapsto \mathbf{U}(\mathbf{x})\}$  in  $\mathbb{V}$  such that, for all  $\mathbf{W} \in \mathbb{V}$ ,  $\mathbf{K}(\mathbf{U}, \mathbf{W}) = f(\mathbf{W})$  a.s, has a unique stochastic solution  $\{\mathbf{x} \mapsto \mathbf{U}(\mathbf{x})\}$  in  $\mathbb{V}$ .

The proof can easily be constructed. From equations  $\mathbf{K}(\mathbf{U}, \mathbf{W}) = f(\mathbf{W})$  and  $|f(\mathbf{w})| \leq c_f \|\mathbf{w}\|_V$ , we deduce that  $\mathbf{K}(\mathbf{U}, \mathbf{U}) \leq c_f \|\mathbf{U}\|_V$  and consequently,  $E\{\mathbf{K}(\mathbf{U}, \mathbf{U})^2\} \leq c_f^2 E\{\|\mathbf{U}\|_V^2\}$ . Using Eq. (6) yields  $c_K^2 \|\mathbf{U}\|_{\mathbb{V}}^4 \leq c_f^2 \|\mathbf{U}\|_{\mathbb{V}}^2$  which can be rewritten as  $\|\mathbf{U}\|_{\mathbb{V}} \leq c_U < +\infty$  with  $c_U = c_f/c_K$  and yields the existence. Finally, the proof of the uniqueness is straightforward because, if  $\mathbf{U}$  and  $\mathbf{U}'$  are two solutions in  $\mathbb{V}$ , for all  $\mathbf{W}$  in  $\mathbb{V}$ , we have  $\mathbf{K}(\mathbf{U} - \mathbf{U}', \mathbf{W}) = 0$  a.s and thus  $E\{\mathbf{K}(\mathbf{U} - \mathbf{U}', \mathbf{W})^2\} = 0$ . Taking  $\mathbf{W} = \mathbf{U} - \mathbf{U}'$  and from Eq. (6) yield  $\|\mathbf{U} - \mathbf{U}'\|_{\mathbb{V}}^2 = 0$ , i.e.,  $\mathbf{U} = \mathbf{U}'$  in  $\mathbb{V}$ .

## 5. Conclusions

We have presented the mathematical construction of a non Gaussian positive-definite  $(n \times n)$  real matrix-valued random field, indexed by any domain of  $\mathbb{R}^d$ , depending only on its mean function and on a smaller number of scalar parameters constituted of a dispersion parameter and  $d$  spatial correlation lengths. Such a random field is adapted to the inverse problem relative to the experimental identification. A fundamental mathematical property is proved and allows the ellipticity of stochastic partial differential operators to be obtained.

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