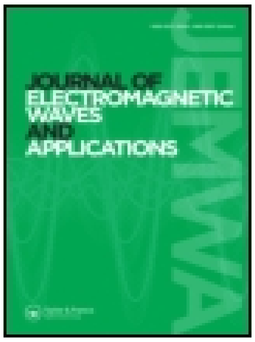

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INVITED REVIEW ARTICLE

Learning-by-examples techniques as applied to electromagnetics

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ABSTRACT

There is a wide number of problems in electromagnetic (*EM*) engineering that require a real-time response or in which the input–output relationship is not a-priori known or cannot be defined due to the complexity of the scenario at hand. These issues have induced researchers toward the development and application of Learning-by-Examples (*LBE*) techniques thanks to their extremely high computational efficiency and to their capability to emulate the behavior of complex systems on the basis of a set of collected examples. In this framework, this paper aims to present an overview of the state-of-the-art and recently developed *LBE*-based strategies as applied to the solution of engineering problems in the field of Electromagnetics. Starting from a general and basic introduction to *LBE* techniques, the most popular *LBE* methods used in *EM* engineering will be re-called. Afterwards, a review on how the *LBE* methodologies have been applied by various researchers in different application contexts, including among others antennas, microwave circuits, inverse scattering and remote sensing, will be given. Finally, current research trends and envisaged developments are discussed.

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Learning-by-examples; artificial neural networks; support vector machines; Gaussian processes; engineering electromagnetics; antennas; direction-of-arrival estimation; microwave circuits; electromagnetic scattering; remote sensing; electromagnetic compatibility

1. Introduction

Learning-by-examples techniques are computer-aided approaches based on machine learning (*ML*) [1] that are aimed at solving complex real-world problems. The “complexity” can be related either to the need of computing the solution in real-time, otherwise not feasible by means of other methods despite the continuous growth of the computational power of modern computers, and/or of predicting the behavior of a system characterized by an uncountable number of features and variabilities so as its analytic/numerical modeling turns out to be unfeasible/practically-intractable. To address these problems, *LBE* strategies are characterized by two phases: the *training* phase and the *testing* phase. In the training phase, a *LBE* technique learns the behavior of a function from a set of input–output pairs. The goal of the training is the creation of a surrogate model able to emulate the real system. In the testing phase, the *LBE* technique is applied to input samples not observed during the training phase and is able to generalize what learned. Thanks to their effectiveness to mimic the human problem solving through learning [2], *LBE* techniques have been widely

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applied with success in several areas of computer science, signal processing, and electrical engineering [3].

Basically, two kinds of problems are addressed by using *LBE* strategies: *classification* and *regression*. The objective is the identification of the "nature" (i.e. the class) of unlabeled input samples and the prediction of the output value of an unknown function, respectively. Accordingly, the surrogate model represents a *discriminant function* in case of classification problems and an *estimation function* in case of regression problems. Of course, the capability to correctly classify the input samples or predict the function values strongly depends from the learning and the adopted *LBE* technique. Albeit not discussed in the present work, several strategies have been proposed for improving the effectiveness (i.e. the *LBE generalization* capability) of the training phase and avoid the so-called *curse of dimensionality* and *over-fitting* issues,[1] typical of *ML* [4]. In particular, feature selection and extraction methods have been proposed and jointly used with smart sampling strategies in order to define the minimum set of representative training samples fully catching the variability of the input–output relationship [5]. Moreover, different types of *LBE* techniques based on linear, quadratic, and higher order non-linear models have been developed with the aim of defining the simplest surrogate model better explaining the input data trend [6–9].

In the field of *EM* engineering, many progresses have been done in the last years toward the development of versatile numerical techniques (i.e. full-wave solvers) for the accurate analysis of complex systems and devices and of advanced tools for parametric design and optimization (e.g. see [10–12] and the references cited therein). However, full-wave solvers, based for example on the method-of-moment (*MoM*), finite-element method (*FEM*), or the finite-difference time-domain (*FDTD*), although very precise, are time-consuming. Therefore, they are not suitable for dealing with real-time problems and neither for optimization-based design or Monte Carlo sensitivity analysis in which there is the need to repeat a large number of full-wave simulations. In this framework, *LBE* techniques have been exploited in order to build surrogate/meta models for emulating or predicting the behavior of the high-fidelity simulations but with a minimal computational effort [13–15]. Several other problems dealing complex environments and materials, like in the framework of subsurface imaging [16], weather condition estimation [17], and human detection and activity classification [18], have been profitably addressed by means of *LBE* methods. In other cases, conventional *EM* problems have been properly reformulated as classification ones in order to make them efficiently tractable by means of *LBE*-based techniques [19,20]. Overall, *LBE* techniques have enabled the solution of a new class of problems also in the field of *EM* engineering and have been widely applied [21–23].

The goal of this work is that of providing an overview, to the best of the authors' knowledge, of the state-of-the-art and of the more recent advances of *LBE* techniques as applied to engineering problems in the framework of Electromagnetics with main focus on antennas, direction-of-arrival (*DoA*) estimation, microwave circuits and devices, electromagnetic scattering, remote and radar sensing, and electromagnetic compatibility (Figure 1). The most widely adopted learning strategies are revised, first recalling their basic formulation, pointing out the motivations of their use, the points of strength and limitations. Moreover, the current trends will be discussed and future developments envisaged on *LBE* techniques as applied to Electromagnetics.

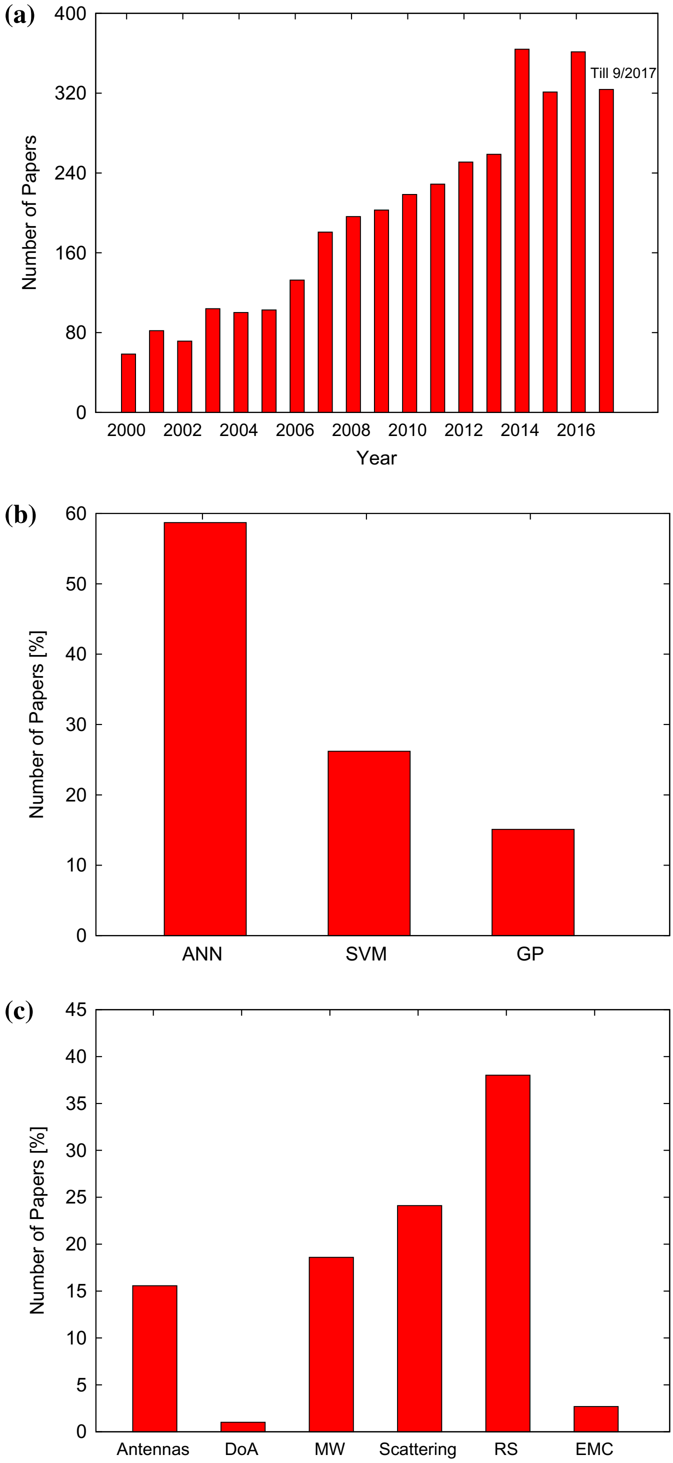

Figure 1. *LBE* Techniques – Statistics of *LBE*-related papers: (a) number of papers vs. year; (b) percentage of papers of Figure 1(a) vs. *LBE* technique; (c) percentage of papers of Figure 1(a) vs. application [based on *IEEE Xplore* databases and search referred to the IEEE Transactions on Antennas and Propagation, Geoscience and Remote Sensing, Instrumentation and Measurement, and Microwave Theory and Techniques journals].

Toward this end, the paper is organized as follows. After a brief recall of the basic problems addressed by means of *LBE* techniques (Section 2), a survey of the *LBE* strategies that have been mainly applied to *EM* problems is reported in Section 3, namely Artificial neural networks (*ANN*) (Section 3.1), Support vector machines (*SVM*) (Section 3.2), and Gaussian processes (*GP*) (Section 3.3). Afterwards, a review of the applications of *LBE* techniques in the framework of *EM* engineering is given in Section 4, starting from antenna analysis and synthesis (Section 4.1), estimation of the directions-of-arrival (Section 4.2), analysis and synthesis of microwave circuits and devices (Section 4.3), direct and inverse scattering (Section 4.4), remote and radar sensing (Section 4.5), and electromagnetic compatibility (Section 4.6). Eventually, some conclusions are drawn and future trends envisaged (Section 5).

2. *LBE* problems definition

The training of a *LBE*-based technique, aimed at building the surrogate model $\hat{\Phi}(\cdot)$ mapping the input to the output space and at emulating the behavior of a real system $\Phi(\,\cdot\,)$, is conducted offline and before using the *LBE* algorithm for solving (online) the problem of interest during the testing phase. In general, the training samples are taken from previously available measurements or ad-hoc numerical simulations. In case of regression problems, the training input–output pairs are $\left(\mathbf{x}^{(n)}; y^{(n)}\right)$, $n = 1, \dots, N$, where $y^{(n)} = \Phi(\mathbf{x}^{(n)})$ is the actual system response for a generic K-dimensional input $\mathbf{x}^{(n)} = \left\{x_k^{(n)} : k = 1, \dots, K\right\}$. Differently in case of classification problems, the training pairs are $\left(\mathbf{x}^{(n)}; \chi^{(n)}\right)$, $n = 1, \dots, N$, where $\chi^{(n)} = \{-1; +1\}$ is a binary value identifying the class of the input sample $\mathbf{x}^{(n)}$.[2]

Accordingly, the regression and classification problems in the framework of *LBE* techniques can be stated as follows:

Regression Problem - Given the training set $\left\{\left(\mathbf{x}^{(n)}; y^{(n)}\right) : n = 1, \dots, N\right\}$ and selected the *LBE* technique, define the estimation function $\hat{\Phi}(\,\cdot\,)$ that better represents the behavior of the real system $\Phi(\,\cdot\,)$ in order to determine its response $y = \hat{\Phi}(\mathbf{x})$ for a specific and arbitrary input $\mathbf{x}$ in the testing phase [Figure 2(a)];

Classification Problem - Given the training set $\left\{\left(\mathbf{x}^{(n)}; \chi^{(n)}\right) : n = 1, \dots, N\right\}$ and selected the *LBE* technique, define the discriminant function $\hat{\Phi}(\,\cdot\,)$ that better separates the samples of the two input classes in order to determine the class/label $\chi = sgn\left\{y = \hat{\Phi}(\mathbf{x})\right\}$, being $sgn\{\cdot\}$ the sign function, for a specific and arbitrary unlabeled input $\mathbf{x}$ in the testing phase [Figure 2(b)].

In case of both regression and classification problems, the common goal of the training is the definition of $\hat{\Phi}(\,\cdot\,)$ and more precisely of the control parameters of the *LBE* algorithm by exploiting the information content of the training set. Toward this aim, several different *LBE* techniques have been proposed and those mainly applied to *EM* problems are revised in the following section.

3. *LBE* techniques

The principal *LBE* techniques applied to *EM* engineering problems are the *ANN*, the *SVM*, and the *GP*.

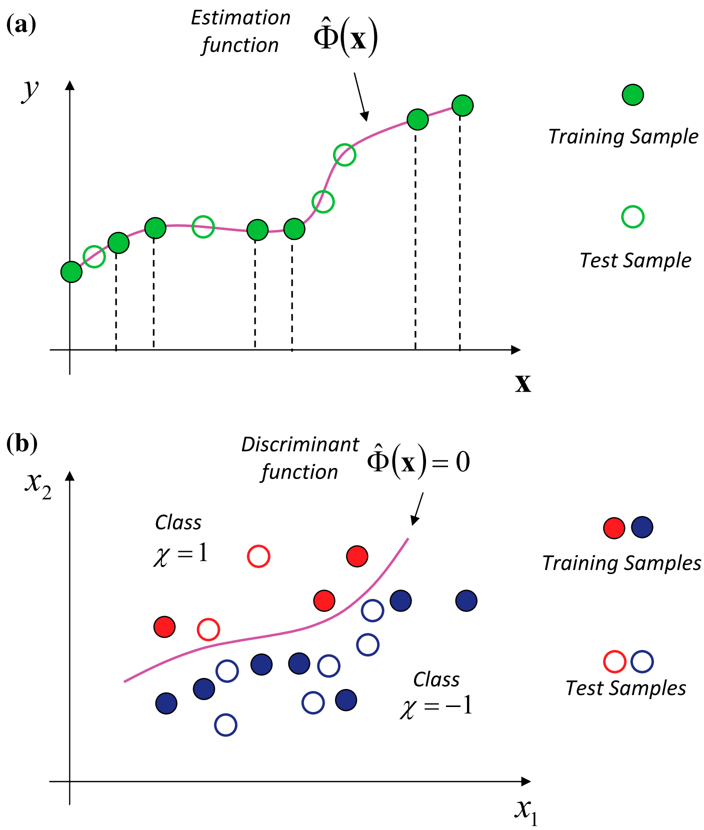

Figure 2. *LBE* Techniques - Example of (a) regression problem and (b) classification problem.

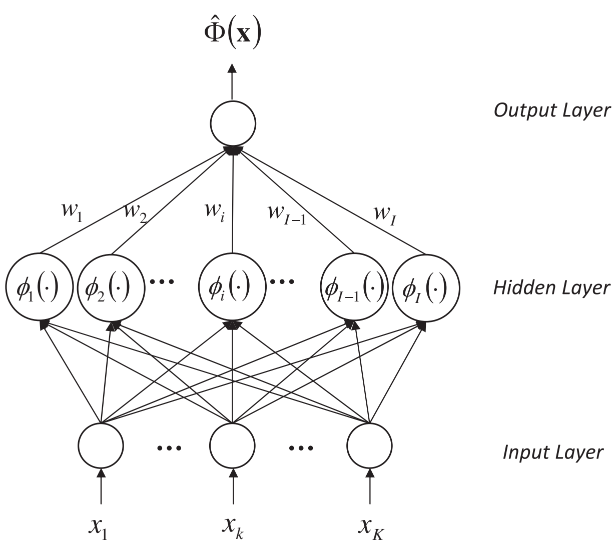

Figure 3. *Artificial Neural Network* - Architecture of a single hidden layer *ANN*.

3.1. Artificial neural networks

ANN are based on a non-linear parametric model which is able to provide an 'universal' approximation capability for emulating the functions describing the behavior of complex systems [24,25]. The definition of an *ANN* requires two steps that are: (i) the selection of the *ANN* architecture and (ii) its training. A basic architecture for an *ANN* is shown in Figure 3. In this case, the network is characterized by an input layer, an output layer, and (at least) an additional hidden layer emulating the nonlinear behavior of $\Phi(\cdot)$ in mapping $\mathbf{x}$ into y.

The input–output relationship of the surrogate model is expressed as

$$y = \hat{\Phi}(\mathbf{x}) = a\left(\sum_{i=1}^{I} \phi_i(\mathbf{x}) w_i + \theta\right) \tag{1}$$

where $\phi_i(\mathbf{x})$, $i = 1, \ldots, I$ (being $I \leq N$) is the function implemented in the neurons/nodes of the hidden layer, w_i, $i = 1, \ldots, I$ the weights connecting the hidden nodes with the network output, and θ a threshold (bias) value aimed at compensating the difference between the average value of the training data with respect to the average value of the expected testing samples. Moreover, $a\left(\cdot\right)$ is the activation function and can be for example a sigmoid function, a hyperbolic tangent function, or simply the identity function [26].

One of the most common implementations of $\phi_i(\mathbf{x})$, $i = 1, \ldots, I$ is based on the use of radial basis functions (*RBF*), like for example Gaussian functions. In this case,

$$\phi_i(\mathbf{x}) \triangleq exp\left(-\frac{\left\|\mathbf{x} - \mathbf{m}^{(i)}\right\|^2}{2\sigma_i^2}\right) \tag{2}$$

where $\mathbf{m}^{(i)}$ and σ_i^2 are the (K-dimensional) mean and the variance of the i-th Gaussian function, and $\|\cdot\|$ is the norm operator.

An example of *RBF*-based *ANN* is that aimed at defining $\hat{\Phi}(\cdot)$ in order to exactly fit/interpolate the values of the N training samples [26]. In this case, $I = N$ and $\mathbf{m}^{(i)} = \mathbf{x}^{(n)}$, $i = n = 1, \ldots, N$, namely the number of the Gaussian functions is equal to the number of training samples and the Gaussian bells are centered at the location of the training points. Moreover, $\theta = 0$, the activation function is the identity function, namely $a\left(\sum_{i=1}^{I} \phi_i(\mathbf{x}) w_i\right) = \sum_{i=1}^{I} \phi_i(\mathbf{x}) w_i$, and a constant variance (i.e. $\sigma_i = \sigma, \forall i$) is chosen for all radial basis functions. The weights w_i, $i = 1, \ldots, I$ of (1) are obtained during the training phase as the solution of a system of equations $\boldsymbol{\phi}\mathbf{w} = \mathbf{y}$, where $\mathbf{w} = \{w_i : i = 1, \ldots, N\}$, $\mathbf{y} = \{y_n : n = 1, \ldots, N\}$ are the outputs of the training samples, and $\boldsymbol{\phi}$ is a $N \times N$ matrix whose in-th entry is $\phi_{in} = \phi_i(\mathbf{x}^{(n)}) \triangleq exp\left(-\left\|\mathbf{x}^{(n)} - \mathbf{x}^{(i)}\right\|^2 / 2\sigma^2\right)$. Accordingly, $\phi_{nn} = 1$, $n = 1, \ldots, N$, namely the elements along the principal diagonal are unit values, since $\mathbf{x}^{(n)} \equiv \mathbf{x}^{(i)}$ if $i = n$.

In many real applications, the matrix $\boldsymbol{\phi}$ is ill-conditioned [27]. Thus, the weighting vector $\mathbf{w}$ is computed by exploiting some regularization strategy, like

$$\mathbf{w} = (\boldsymbol{\phi} + \lambda\mathbf{I})^{-1}\mathbf{y} \tag{3}$$

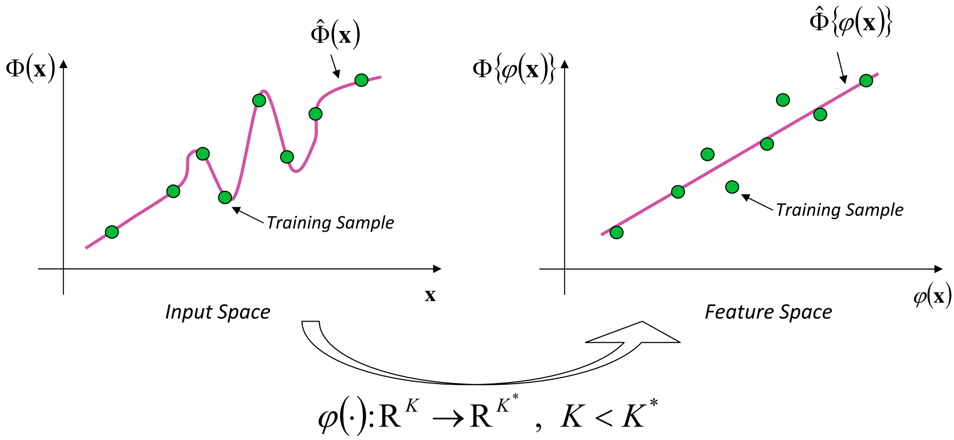

Figure 4. *Support Vector Machines* - Nonlinear mapping of the input space to the feature space through $\boldsymbol{\varphi}(\mathbf{x})$.

being λ a positive-values regularization parameter and $\mathbf{I}$ the identity matrix, or through least-square minimization

$$\mathbf{w} = \arg\left\{\min_{\mathbf{w}} \|\boldsymbol{\phi}\mathbf{w} - \mathbf{y}\|^2\right\}. \tag{4}$$

Moreover, the perfect matching of the training set is not desired (e.g. when the data are noisy). Therefore, the number of hidden nodes is reduced (i.e. $I < N$) in order to obtain a 'smoother' (i.e. with higher generalization capability) surrogate function. In this case, the number of basis functions is determined during the training together together with the values of w_i, $i = 1, \ldots, I$, σ_i, $i = 1, \ldots, I$, and θ [28].

3.2. Support vector machines

In some cases, *ANN* require a large number of training samples to obtain a proper surrogate model which could therefore be affected by over-fitting if the *ANN* architecture is not properly selected [29]. To avoid this drawback, the *SVM*-based procedures allow to find the best trade-off between the capability of learning from the training samples and the complexity of the surrogate model [30,31]. As a matter of fact, *SVM* are built on a solid theoretical framework, the statistical learning theory [7], in which the definition of the control parameters of $\hat{\Phi}(\cdot)$ is formulated as a quadratic optimization problem ensuring a global optimum. Moreover, the resulting model turns out being sparse, since only training samples associated to non-vanishing coefficients (i.e. the so-called 'support vectors') are exploited to make predictions, thus controlling the model complexity and avoiding over-fitting.

In the *SVM* theory, the discriminant/estimation function is given by

$$\hat{\Phi}(\mathbf{x}) = \boldsymbol{\alpha} \cdot \boldsymbol{\varphi}(\mathbf{x}) + b \tag{5}$$

that is the expression of a hyperplane, $\boldsymbol{\alpha}$ and b being an unknown normal vector and a bias coefficient, respectively, to be defined during the training phase. Moreover, $\boldsymbol{\varphi}(\mathbf{x})$ is a nonlinear function mapping the original input data, $\mathbf{x}$, to a higher dimensional space, called *feature space*, where the surrogate model can be defined through a simple linear function (5) (Figure 4).

The values of the parameters that univocally define $\hat{\Phi}(\cdot)$ are determine in the training phase by minimizing the following cost function

$$\Psi(\boldsymbol{\alpha}) = \frac{\|\boldsymbol{\alpha}\|^2}{2} + C\sum_{n=1}^{N}(\eta_+^{(n)} + \eta_-^{(n)}) \tag{6}$$

subject to

$$\begin{cases} \boldsymbol{\alpha}\cdot\boldsymbol{\varphi}\left(\mathbf{x}_+^{(n)}\right) + b \geq 1 - \eta_+^{(n)} \\ \boldsymbol{\alpha}\cdot\boldsymbol{\varphi}\left(\mathbf{x}_-^{(n)}\right) + b \leq \eta_-^{(n)} - 1 \end{cases}, n = 1, \dots, N \tag{7}$$

in case of classification problems, being $\mathbf{x}_+^{(n)}$ and $\mathbf{x}_-^{(n)}$ the training samples belonging to the class $\chi^{(n)} = +1$ or the class $\chi^{(n)} = -1$, respectively, or to

$$\begin{cases} y^{(n)} - \left[\boldsymbol{\alpha}\cdot\boldsymbol{\varphi}\left(\mathbf{x}^{(n)}\right) + b\right] \leq \varepsilon + \eta_+^{(n)} \\ -y^{(n)} + \left[\boldsymbol{\alpha}\cdot\boldsymbol{\varphi}\left(\mathbf{x}^{(n)}\right) + b\right] \geq \varepsilon + \eta_-^{(n)} \end{cases} \tag{8}$$

in case of regression problems [7,8]. In (6), C is a user-defined hyperparameter that controls the trade-off between the flatness of $\hat{\Phi}(\cdot)$ and the model complexity to avoid over-fitting. Moreover, $\eta_+^{(n)}$ and $\eta_-^{(n)}$ are the so-called *slack variables* ($\eta_+^{(n)}, \eta_-^{(n)} \geq 0$) related to the possibility to tolerate some errors in the training samples in order to guarantee the definition of $\hat{\Phi}(\cdot)$. In particular, they are used since the training data cannot be completely separable in the feature space by means of a linear hyperplane [(7) - classification problem] or since an ε-sensitive tube does not exist that includes all training samples [(8) - regression problem].

The minimization of (6) subject to either (7) or (8) is performed by exploiting the so-called *kernel trick method* [32] in which a dual formulation is used and the objective is the minimization of a Lagrange function including both the cost function (6) as well as the constraints (7)(8). The definition of b in (5) is then carried out by exploiting the Karush–Kuhn–Tucker condition [7,8].

In case of classification problems, it is of interest in some applications to obtain additional information also on the reliability of the classification by determining the 'degree of belonging' of an input sample to the class identified in the testing phase [19,20]. This can be obtained for example by computing the a-posterior probability as

$$\frac{1}{1 + exp\left\{p\hat{\Phi}(\mathbf{x}) + q\right\}} \tag{9}$$

which directly depends on the value of the estimation $\hat{\Phi}(\mathbf{x})$, where p, q are unknown parameters to be determined [32].

3.3. Gaussian processes

The *GP* are *LBE* techniques that recently received a great attention in the framework of *EM* engineering thanks to their capability to build surrogate models also providing the approximation error (i.e. a value of uncertainty/confidentiality) of the predictions over the

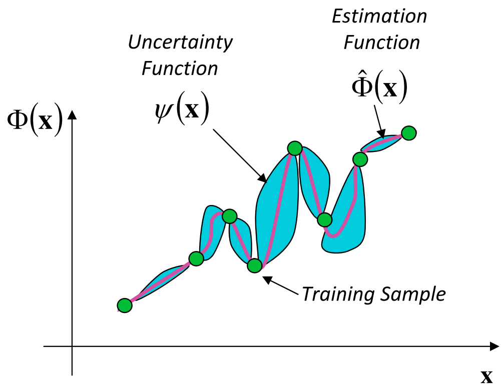

Figure 5. *Gaussian processes* - Example of definition of the surrogate function $\hat{\Phi}(\mathbf{x})$ and uncertainty $\psi(\mathbf{x})$ through Kriging regression.

whole input space (Figure 5) without the need of testing samples [9]. Among the different *GP*-based methods, one of the most widely used, the regressor based on *Ordinary Kriging* (*OK*), is recalled in the following. In this case, the expression of $\hat{\Phi}(\cdot)$ is given by

$$\hat{\Phi}(\mathbf{x}) = \mu + \mathbf{r}^T(\mathbf{x})\,\mathbf{R}^{-1}(\mathbf{y} - \mathbf{I}\mu) \tag{10}$$

where μ is a constant term computed as

$$\mu = \frac{\mathbf{I}^T\mathbf{R}^{-1}\mathbf{y}}{\mathbf{I}^T\mathbf{R}^{-1}\mathbf{I}}, \tag{11}$$

$\mathbf{I}$ an N-dimensional unitary vector $\mathbf{I} = [1, 1, \ldots, 1]^T$, T identifying the transpose operation, and $\mathbf{R}$ the $N \times N$ correlation matrix representing the correlation between the training samples, whose nj-th entry, $n, j = 1, \ldots, N$ is equal to

$$R_{nj} = \prod_{k=1}^{K} \exp\left(-\gamma_k \left|x_k^{(n)} - x_k^{(j)}\right|^{\beta_k}\right) \tag{12}$$

being $\boldsymbol{\gamma} = \{\gamma_k : k = 1, \ldots, K\}$ and $\boldsymbol{\beta} = \{\beta_k : k = 1, \ldots, K\}$ two sets of control hyperparameters. Moreover, $\mathbf{r}(\mathbf{x})$ is an N-dimensional vector whose n-th entry is expressed as

$$r^{(n)}(\mathbf{x}) = \prod_{k=1}^{K} \exp\left(-\gamma_k \left|x_k^{(n)} - x_k\right|^{\beta_k}\right). \tag{13}$$

It is evident from (10) that the prediction of the system response value $\hat{\Phi}(\mathbf{x})$ is proportional to the correlation/distance between the new testing input $\mathbf{x}$ and the N training samples (13), the correlation between the training samples (12), and their fitness values $\mathbf{y}$.

The optimal values of two set of hyperparameters $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ are obtained by maximizing the following *likelihood function*

$$\Xi(\boldsymbol{\gamma}, \boldsymbol{\beta}) = -\frac{N}{2} ln\left(\tau^2\right) - \frac{1}{2} ln\,|\mathbf{R}| \tag{14}$$

Table 1. List of selected publications on *LBE* techniques as applied to antennas.

Antennas		
Problem	LBE	Ref.
Array analysis	*ANN*	[33]
	SVM	[29]
	GP	[36]
Antennas analysis	*GP*	[35,37]
Array synthesis	*ANN*	[17,38]
	SVM	[40–44]
	GP	[48,49]
Antenna synthesis	*SVM*	[44]
Antenna synthesis	*GP*	[45–47]

Table 2. List of selected publications on *LBE* techniques as applied to *DoA* estimation.

Direction-of-arrival estimation	
LBE	Ref.
ANN	[57–60,62]
SVM	[20,63–66]

Table 3. List of selected publications on *LBE* techniques as applied to microwave circuits and devices.

Microwave circuits and devices		
Problem	LBE	Ref.
Analysis	*ANN*	[67,68]
	SVM	[73–75]
	GP	[78]
Design	*ANN*	[70,71]
	SVM	[76,77]
	GP	[79]

where

$$\tau^2 = \frac{(\mathbf{y} - \mathbf{I}\mu)^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{I}\mu)}{N} \tag{15}$$

and $|\mathbf{R}|$ is the determinant of $\mathbf{R}$.

In practical applications, Gaussian ($\beta_k = 2, \forall k$) and exponential ($\beta_k = 1, \forall k$) correlation models are mainly used since they are suitable for representing smooth and peaked cost function behaviors, respectively, and in order to reduce the computational load of the training phase.

As mentioned above, jointly with the prediction of the function response (10), the *OK* provides an estimation of the uncertainty $\psi(\mathbf{x})$ on $\hat{\Phi}(\mathbf{x})$ that is computed as

$$\psi(\mathbf{x}) = \sqrt{\tau^2 \left[1 - \mathbf{r}^T(\mathbf{x})\,\mathbf{R}^{-1}\mathbf{r}(\mathbf{x}) + \frac{\left(1 - \mathbf{I}\mathbf{R}^{-1}\mathbf{r}(\mathbf{x})\right)^2}{\mathbf{I}\mathbf{R}^{-1}\mathbf{I}}\right]}. \tag{16}$$

Table 4. List of selected publications on *LBE* techniques as applied to electromagnetic scattering.

Electromagnetic scattering		
Problem	LBE	Ref.
Forward scettering	*ANN*	[82]
	SVM	[85]
	GP	[86]
Inverse scattering	*ANN*	[87,88,90,91]
	SVM	[19,89,93,99,102,103,107]
	GP	[108,109]

Table 5. List of selected publications on *LBE* techniques as applied to remote and radar sensing.

Remote and radar sensing		
Problem	LBE	Ref.
Soil moisture estimation	*ANN*	[110]
	SVM	[111]
	GP	[112]
Subsurface characterization	*SVM*	[16,113,114]
Landmine detection	*ANN*	[116]
	SVM	[117–119]
Human detection	*ANN*	[18]
	SVM	[120]

Table 6. List of selected publications on *LBE* techniques as applied to electromagnetic compatibility.

Electromagnetic compatibility		
Problem	LBE	Ref.
EM field estimation	*ANN*	[121]
	GP	[122–124]

4. Application of *LBE* to electromagnetics

In this section, a review on the use of *LBE* methodologies to problems in the framework of engineering electromagnetics is provided by focusing on six main application domains: antennas (Table 1), direction-of-arrival (*DoA*) estimation (Table 2), microwave circuits and devices (Table 3), electromagnetic scattering (Table 4), remote and radar sensing (Table 5), and electromagnetic compatibility (Table 6).

4.1. Antennas

Antennas can be very complex devices that require many computational resources and complex tools for the evaluation of their performance and their design. This is especially true nowadays, where the wide proliferation of wireless applications and portable devices has imposed stringent requirements on the antenna structure and performance. Compact, low-power, multiband/wideband, reconfigurable antennas are more and more requested. Therefore, it is of extreme importance to simulate the antenna not stand-alone but also considering the effects of the surrounding structures (e.g. other antennas, feeding network, electronic components) and materials (e.g. packaging, radome). Therefore, *LBE* techniques have found to be particularly suitable for antenna analysis and synthesis/design.

4.1.1. Antenna analysis

The analysis of antenna arrays is a time-consuming task especially when non-ideal effects must be encompassed, like the consideration of the nonlinear characteristics of lumped loads as well as the coupling effects between the array elements. In this context, an *ANN* with *RBF* has been used to model the scattering of nonlinearly loaded antenna arrays including mutual coupling [33]. The proposed method has shown to predict the scattering responses of finite and infinite antenna arrays at different harmonic frequencies obtaining values in good agreement with those achievable using accurate numerical methods like the harmonic balance technique [34]. A similar problem has been addressed in [29] in which a strategy for the prediction of the radiation pattern of a real antenna array including the coupling effects between all array elements has been proposed. The approach, based a regression model defined with the *SVM*, namely the Support Vector Regression (*SVR*), has been compared with an *ANN* when also taking into account experimental data in the training phase. The *SVR* has demonstrated higher generalization capabilities than the *ANN* in exploiting the information from a reasonable number of training samples, also available from typical antenna measurement systems, unlike the *ANN* requiring a much larger number of training pairs.

A strategy for the definition of advanced surrogate antenna models for the efficient analysis of ultra-wideband (*UWB*) dipole antennas, dielectric resonator antennas (*DRA*) [35] as well as planar antenna arrays [36] has been also proposed. The relationship between the simulation results obtained from coarsely discretized antennas, fast to simulate, and high-fidelity antenna models, but computationally expensive, has been learned by using a Kriging based approach in order to predict an approximate high-fidelity training set. The reported results have shown that it is possible to obtain satisfactory and accurate predictions even if the training set only contains a number between 10% and 20% percent of fine-discretization simulations [36]. A strategy exploiting the computation of the gradient of the function values of the training samples has shown requiring a reduced training set as compared to a standard Kriging approach without affecting the prediction capability of the surrogate model [37].

4.1.2. Antenna synthesis

The capability to react to the changing conditions is a problem of great interest for future wireless systems (e.g. cognitive radio). In this framework, the synthesis of the weighting coefficients of adaptive antenna arrays has been carried out by means of a three-layer *ANN* using *RBF* in order to quickly and efficiently suppress the interferences in a mobile communication system in which the directions of the users and of the undesired signals continuously vary [38,39]. The proposed *LBE* method was able to deal with both linear and planar arrays and to track multiple users while jointly suppressing the interferences, also caused by cochannel signals. Approaches based on the *SVM* have been also proposed [40–42]. In [40], the beamforming of linear arrays has been optimized for interference suppression. The results have proved the superior performance of the *LBE* method as compared to a minimum mean square error (*MMSE*) approach thanks to the improved generalization capability of the *SVM* even when small data sets are available for the training phase. The proposed approach has been applied to a six elements antenna array with interfering signals also close to the desired ones, thus producing a non-Gaussian noise. The method has been then extended [41] to include sidelobe suppression capabilities as well as the possibility to estimate the directions of arrival of the impinging signals. The problem of a dense interfering scenario in which the number of interferences received from different directions is higher than the number of antenna array elements has been also addressed in [42], still exploiting small training sets.

The problem of defining the optimum weight vector for a robust and fast beamformer in phased array weather radars to accurately estimate the precipitation profiles (i.e. the Doppler velocity and reflectivity) has been addressed by using a three-layer *ANN* using *RBF* [17]. The approach has shown nearly optimal performance in various precipitation simulations, also against real weather data, and to outperform traditional beamforming methods such the Fourier beamforming, Capon beamforming, and a nature-inspired optimization algorithm named flower pollination algorithm. The synthesis of the feeding coefficients of an antenna array in order to obtain a radiation pattern with desired specifications has been addressed in [43] through *SVR* and the pattern of a GSM-DCS1800 base station has been designed for illustrative purposes.

The *SVM* has been used in [44] for the design of a rectangular patch antenna and a rectangular patch antenna array. In this case, the *SVM* has been first trained to estimate the antenna performance (e.g. resonant frequency, gain, and voltage standing wave ratio) as a function of the geometric parameters of the patch. Afterwards, trial values of the antenna geometrical parameters have been given as input to the *SVM* in order to define the best configuration fitting the user-defined electrical properties.

A class of design methodologies based on surrogate-based optimization techniques and aimed at reducing the computation costs of full-wave simulations in computing the objective function values has been recently introduced. After building the surrogate model, the optimization has been run by evaluating the fitness of the trial solutions through the cheap surrogate model and occasional considering high-fidelity *EM* simulations. This has enabled the optimization-based design of complex *EM* systems and devices. Several works based on *GP* and Kriging derived surrogate models have been carried out [45–52]. The different methodologies has been applied for the design, for example, of a planar monopole, a *DRA*, and a wideband slot antennas [45], omnidirectional antennas [46], an UWB monocone and a planar Yagi antenna [47], a 60 GHz on-chip wireless antenna, a four-element linear array antenna, and a two-dimensional antenna array [48], and microstrip antenna subarrays operating at 10 GHz [49]. Toward this aim, the approach in [45] is based on a type of reinforcement learning strategy in which the initial surrogate model, build using coarse-discretisation *EM* simulations, is enhanced during the optimization by exploiting high-fidelity *EM* simulations done in order to check the prediction accuracy of the emulator. Differently, a multi-objective optimization has been considered in [47,50] to provide a set of possible trade-off solutions between conflicting design objectives. The surrogate-assisted differential evolution optimization method of [48] has been compared to standard differential evolution (*DE*) and particle swarm optimization (*PSO*) showing a 3 to 7 improvement of the design speed. A hybrid method based on Kriging and *ANN* with *RBF* has been proposed in [52] as a tool for efficient global optimization of antennas characterized by a large number of parameters, with the aims to avoid local optima and increase the convergence rate.

Still based on *LBE* techniques, a new strategy named System-by-Design (*SbD*) has been introduced in [15] for enabling the effective and reliable use of global optimizers for addressing complex *EM* design problems. The *SbD* is based on the combination of several elementary design blocks, each one aimed at the analysis and/or configuration of a sub-part of the overall system. In order to enable the design of complex *EM* systems and devices complying with the user-defined requirements and constraints, the *SbD* consists of four interconnected functional blocks aimed at (i) the mathematical definition of the problem requirements and constraints, (ii) the formulation of the design problem, (iii) the efficient computation of the cost function, achieved for example through a suitable *LBE* technique, and (iv) the methodology for the exploration of the solution space, generally based on evolutionary optimization [10]. Several instances of the *SbD* have been proposed for the design of complex metamaterial-based antennas [53,54] and three-dimensional (3*D*) electrically large radomes [55,56].

4.2. Direction-of-arrival estimation

Another important problem in *EM* engineering in which there is the need to provide a fast response also in complex environments is related to the estimation of the *DoA* of signals impinging on an antenna system. This is especially true nowadays since the continuous growth of wireless system is pushing towards the development of efficient solutions able to maximize the spatial reuse of the wireless channel. In this framework, techniques based on *ANN* with *RBF* have been proposed [57–60]. The *ANN* has been used in [57] to learn (also considering experimental data) the direction finding function for a single source of an eight-element X-band array characterized by multiple and unknown failures and degradations. In [58], a three-layer *RBF*-based *ANN* has been applied to deal with the *DoA* estimation of multiple sources in a six-element array and successfully compared with the *MUSIC* (MUltiple SIgnal Classification, [61]) algorithm in case of both uncorrelated and correlated signals. A different approach has been used in [59] where a family of *RBF*-*ANN* has been used to perform both detection and *DoA* estimation. More specifically, a pair *RBF*-*ANN* has been assigned to a specific angular sectors in order to cover the whole antenna field of view. At the first stage, the networks detect the presence of incoming signal/s in their angular region and, only in this case, the second stage network/s are activated to estimate the signal bearing. The reported results have demonstrated the accuracy of the approach also in case of signal sources characterized by random signal-to-noise ratio. The main advantages was the important reduction in the size of the training set and the ability of dealing with a number of signals greater than the number of the array elements [59]. Different *ANN*-based strategies have been proposed in [60,62] with the objective to dynamically reconfigure the architecture of the neural network and to avoid an heuristic decision for its structure. Accordingly, a self-constructing neural fuzzy inference network (called *SONFIN*) has been presented in which there are nodes in the hidden layers functioning as membership functions (activation functions) and fuzzy logic rules (connection types), dynamically determined on the fly [60]. Differently, a sequential learning strategy has been adopted in [62] for dealing with the *DoA* estimation in presence of array sensor failure in a noisy environment where the number of hidden neurons have been increased/reduced on the basis of the input data.

More recently, *LBE* techniques based on *SVM* have been applied to the *DoA* estimation problem. In this framework, a *SVR*-based procedure has been presented in [63] for dealing with linear arrays. In this case, a *SVM* has been used to estimate the *DoA* of each signal starting from a training set where the *DoA* of the signals were uniformly distributed in the antenna field of view. Moreover, a-priori information on the signal number and pre-fixed angular separations between the *DoA* have been taken into account for improving the robustness of the approach. An extension of such a model has been presented and experimentally validated in [64], successfully comparing with the *MUSIC* method. In [20], the problem of the *DoA* estimation has been formulated as a two-step classification problem in which the first step is aimed at detecting the presence of a signal impinging on a planar array from a particular sector through a proper decision function and afterwards the output of the decision function is mapped into an a-posterior probability in the second step. Moreover, an iterative zooming approach improving the discretization of the field of view only in those angular regions where the signals have been estimated at the previous iteration has been implemented in order to increase the accuracy of the *DoA* estimation process [20]. Examples considering both non-correlated and correlated signal sources have been reported [65]. A hybrid approach exploiting the advantages of the high resolution properties of the *MUSIC* algorithm and the robustness against over-fitting of *SVM* has been introduced [66].

4.3. Microwave circuits and devices

Microwave (*MW*) circuits and components can be characterized by a complex structure and several parameters that prevent sometimes the testing of a wide set of possible configurations due to the high computational costs of a single accurate/high-fidelity simulation. In order to address this issue, *LBE* techniques have been proposed for their analysis and design. For example, the analysis of practical multilayered shielded microwave circuits has been addressed in [67,68]. An *ANN* has been trained to approximate the Green's functions of an accurate integral-equation method. Two advanced training strategies has been proposed in [68], the first subdividing the input space into several spatial and frequency regions and the second combining the regions with an adaptive selection of the neuron/*RBF* variances in each region to analyze more complex circuits with higher precision. The design of various MW devices, namely a double waveguide window, a loaded MW oven, and a patch antenna with two long slits, has been instead addressed in [69] and other *LBE* methods also using multilayer perceptron (*MLP*) *ANN* [24,25] have been considered in [70,71]. More specifically, a methodology able to mitigate the problem of the non-uniqueness of the input–output relationship, arising when a training data can correspond to multiple solutions, has been introduced in [70] and applied to the modeling of waveguide filter. The *LBE* predictions, compared to full-wave *EM* simulation and measurements of *Ku*-band circular waveguide dual-mode pseudoelliptic bandpass filters, have shown a high degree of reliability [70]. The synthesis of radio-frequency planar on-chip spiral inductors has been carried out in [71] by exploiting a particle swarm optimization to explore the space of the design parameters, namely, the spiral outer diameter, number of turns, width of metal traces, and metal spacing, to match the desire inductance, quality factor, and self-resonance frequency. A different method based on *RBF* interpolation and adaptive sampling has been used in [72] to minimize the number of training samples to achieve an accurate surrogate model.

Several methods based on *SVM* have been also proposed in this context. A surrogate modeling strategy using a least-square (*LS*) *SVM* has been considered in [73] for the analysis of microwave filters showing good prediction accuracy and reducing the computation time by up to 70% as compared to a full-wave *FDTD* based solver. A *SVM* model to forecast the small-signal and noise behaviors of microwave transistors has been presented in

[74] and compared with an *ANN* model. The *SVR* has been also taken into account for the modeling of low temperature co-fired ceramic multilayer interconnect [75] and to determine the resonances of elliptic substrate integrated waveguide resonators [76] as well as for designing the transmission lines for the microwave integrated circuits [77] with the aim of achieving the highest possible accuracy using the minimum number of accurate training samples.

As for the use of *GP* and Kriging interpolation for analyzing and designing microwave devices, several methodologies have been proposed as well. The relationship between low-fidelity and high-fidelity *EM* simulations has been defined through a Kriging based strategy in order to achieve a low-cost and reliable modeling [78] while a hierarchical surrogate model using response surface approximations defined through Kriging interpolation has been introduced in [79]. The surrogate model has been exploited for the optimization-based design of a wideband microstrip bandstop filter, a fourth-order ring resonator bandpass filter, and a microstrip bandpass filter with open stub inverter.

Other *LBE* techniques have been proposed to determine the relation between the operation frequency and the circuit dimensions [80] and the design of waveguide filters and microstrip hairpin filters [81] through an approach exploiting an approximation-based modeling of suitably selected features of the filter response.

4.4. Electromagnetic scattering

The study of the interactions between the *EM* waves generated by intentional or unintentional sources and object/s present in the surrounding environment is a problem of great interest in many applications, like radar and *EM* imaging. The goal can be either the analysis of the *EM* scattering behavior or the retrieval of the qualitative/quantitative information about the object/s. In this framework, *LBE* techniques have demonstrated to be very helpful for addressing real-time problems as well as complex scenarios in both the analysis of the scattering (forward scattering) and the reconstruction of the objects (inverse scattering).

4.4.1. Forward scattering

An approach based on *ANN* has been used to solve an electrical capacitance tomography problem for monitoring the metal fill profile in the lost foam casting process [82]. The nonlinear forward problem is approximated through a linear solution plus a correction factor, this latter estimated through the *ANN*, accounting the nonlinear effects caused by the shielding of the metal. The training of the *ANN* has been conducted by exploiting features extracted from the metal distributions available as training samples. This has allowed to reduce the complexity of the network as well as to simplify the training phase and improve the *LBE* generalization capability. In [83], the time-domain/transient analysis of *EM* problems has been addressed by means of an interpolation meshless techniques based on *RBF* in order to avoid the direct solution of Maxwell's equations. The approach has been validated by considering an air-filled H-shaped cavity with perfect electric conducting walls and an air-filled quarter ring resonator. An *RBF*-based interpolation strategy has been also exploited to improve the computational efficiency of full-wave *EM* simulations using the multi-level Green's function interpolation method [84]. The proposed approach has provided more accurate results in approximate the integral kernel of the integral equation as compared to other interpolation techniques. A hybrid approach using *LS-SVM* and *PSO* has been proposed for *FDTD* time-series forecasting and applied to the analysis of *MW* filters [85]. In this case, the *PSO* has been used to optimize the hyperparameter of the *SVM* algorithm. In order to build a cheap surrogate models, able to minimize the computation time still maintaining good precision requirements, a Kriging based method has been considered for function approximation starting from an 'optimal' database of pre-computed testing samples [86]. In particular, a customized approach for the generation of the database has been proposed to achieve an optimal sampling of the input space.

4.4.2. Inverse scattering

The *ANN* has been applied to the detection of cylindrical objects inside an inaccessible investigation domain and to recover their geometric and electrical features [87]. The importance of the spatial sampling of the scattered electric field data in order to obtain good prediction performance when using an *ANN*-based inversion technique has been discussed in [88]. By considering the inversion of dielectric cylinders either in free space or buried in a lossy half space, it has been shown the dependence of the scatterer localization capabilities on the spatial sampling rate of the scattered electric field and its spatial bandwidth. The estimation of the features of defects or cracks in metallic objects from eddy current nondestructive data has been performed in [91]. Feature extraction approaches based on the principal component analysis, wavelet decomposition, and discrete Fourier transform have been used to define the working space of the *ANN*. A similar problem still in the framework of nondestructive eddy-current testing has been addressed by using a metamodel-based optimization method in which the defect parameters are retrieved by means of the *PSO* and the forward simulation (i.e. the analysis) is carried out with a *RBF*-based interpolation method [13]. The surrogate model has been defined by considering an ad-hoc database of previously generated samples and the method has been validated against both synthetic and laboratory-controlled experimental data. Another *RBF* interpolation strategy has been proposed [92] for real-time target identification where specific features have been extracted to improve the effectiveness of the approach.

Another class of inversion techniques based on *SVM* has been proposed for dealing with inverse scattering problems. In [93], the localization of a buried object has been formulated as a regression problem and solved by means of *SVR*. Two different kernel functions, namely the Gaussian and polynomial functions, have been used for the definition of $\hat{\Phi}(\,\cdot\,)$ in the *kernel trick* [94] and the results have demonstrated better reconstructions when using polynomial kernels. The limited number of collectable information because of the aspect-limited nature of the available measurement setup has been avoided by considering multiple illumination sources. A customized *SVM*-based inversion technique has been thus proposed, showing improved accuracy regardless to the modeled environmental noise, particularly in predicting the horizontal coordinate of the target [95]. Other inversion problems dealing with the estimation of the permeability of ferromagnetic materials when using as measurement cell a microstrip transmission-line [96], of the geometrical features of cracks inside metallic objects in eddy current testing [89,97–99], and of retrieving the thicknesses and permittivity of pavement layers with ground-penetrating radar (*GPR*) data [100] have been addressed by means of *SVM*-based regression techniques. In [99], a feature extraction strategy based on partial least squares and a customized output space filling adaptive sampling scheme have been integrated for generating an optimal database of training samples. Comparisons with *ANN* have been conducted in [89,93,101] showing the superior performance of *SVM* thanks to the constrained-quadratic structure of the optimization problem solved for the learning process and the solid statistical theory on which *SVM* are based.

In some applications, the identification of the presence/absence of subsurface objects and their concentration, instead of their specific localization, is sufficient. In this context, several inversion problems have been re-formulated as suitable classification problems in which the *SVM* has been suitably exploited. In [19], the probability of presence of dangerous targets in a buried region has been determined through support vector classification (*SVC*) starting from the measurement of the scattered *EM* field data. A similar approach has been then exploited for biomedical imaging to estimate the probability of tumor presence when considering a 3*D* model of the breast [102]. A comparison between *ANN* and *SVM* methods has been carried out for the classification of subsurface metallic objects, meant to resemble unexploded ordnance, and three different types of objects have been discriminated on the basis of their size [90]. Both methods have demonstrated to be robust with respect to noise although the *SVM* has provided also in this case better performance. The problem of the localization and tracking of passive targets (e.g. people without transponders) has been formulated as an inverse problem and solved through a *SVC* method [103–106]. Here, the perturbation of the *EM* scenario due to the presence/movement of the target/s, sensed through the measurements of the received signal strength index available at the nodes of a wireless sensor network, has been exploited. The method, experimentally validated, has shown accurate localization and tracking performance in both outdoor and indoor scenarios. Another *SVM*-based classification strategy has been proposed in [107] to classify the gestures of arms and legs by using the *EM* signals backscattered from the tags positioned on the body and collected by a fixed reader antenna.

Efficient techniques for solving *EM* nondestructive testing problem have been proposed that exploit the accurate and 'cheap' forward simulations available from a Kriging-based surrogate model trained with optimal database samples [86]. The inverse problem has been solved in this case through the solution of several forward problems considering different trial solutions defined by means of suitable optimization techniques for solution space exploration [108,109].

4.5. Remote and radar sensing

There are several problems in the area of remote and radar sensing in which *LBE* techniques have been widely and profitably used due to the complexity of the *EM* scenarios at hand as well as the need of real-time reactions. The estimation of the soil moisture has been carried out by means of a strategy based on *ANN* starting from the brightness temperatures and scattering coefficients values of soil moisture and ocean salinity data [110]. Thanks to the efficiency of *LBE* methods, it has been enabled to globally estimate the soil moisture on a daily basis. Other approaches based on *SVM* [111] and *GP* (i.e. Kriging interpolation) [112] have been introduced for the prediction of the soil moisture, also integrating meteorological information.

Different *LBE* techniques have been proposed for dealing with the characterization of subsurface environments [16,113–115]. In this framework, a *SVM*-based approach has been used to delineate the geologic facies and to estimate their properties from sparse data [16]. It has been shown that estimation error logarithmically reduces with the increment of the sampling density. A simple automatic classification system based on *SVC*, avoiding the need of an expert user for interpreting *GPR* acquired signals, has been introduced to assess railway-ballast conditions [113]. The identification/classification of underground utility materials has been addressed again through *SVC* when using as features the discrete cosine transform coefficients of *GPR* images [114].

The problem of landmine detection has been also widely studied and different *LBE* techniques based on both *ANN* and *SVM* algorithms have been proposed for the processing of *GPR* data. In particular, an *ANN* regression model has been developed in [116] for real-time landmine detection in which the surrogate model has been trained to estimate the signal-to-clutter ratio with respect to the properties of the soil, the target depth, and the pulse central frequency. The processing of Bscan data taken from *GPR* measurements has been carried out by means of a *SVM*-based procedure in order to detect and localize landmines through the an abrupt changes detection strategy in [117]. Differently in [118], the *SVC*, also extended to multiple classes, has been used for the detection and classification of buried unexploded ordnances. In order to cope with the typical clutter noise arising in landmine detection, a fuzzy *SVM*-based classifier has been proposed in [119] in which hypersphere classification boundaries have been used. In this case, the membership of each training sample has been adaptively assigned also considering new testing results, so performing an online training procedure, to improve the detection performance.

The detection of a human subject has been carried out by using a *SVC* in [120]. Towards this aim, suitable features (e.g. frequency of the limb motion, stride, bandwidth of the Doppler signal, and distribution of the signal strength) have been extracted from a spectrogram to discriminate between humans, dogs, bicycles, and vehicles. More recently, the same problem has been addressed through a deep convolutional *ANN*, also including the possibility to classify the human activity [18].

4.6. Electromagnetic compatibility

LBE techniques have been also exploited for the solution of problems in the field of *EM* compatibility. More precisely, an *ANN*-based approach using *MLP* has been presented [121] to reconstruct the profile of the magnetic near field starting from few sparse acquisitions in order to reduce the time, and thus the costs, for performing near-field electromagnetic compatibility (*EMC*) measurements. An analogous problem has been addressed using Kriging based interpolation in order to deduce the local behavior of the *EM* field given a set of field values obtained by simulations or experiments [122]. The main advantage of this method is the fact that the Kriging provides, together with the estimation of the *EM* field values, also a spatial statistical information about the confidence of the estimated field. In [123,124], the Kriging interpolation has been exploited to build a surrogate model of the field distribution and the next measurements to be carried out has been selected on the basis of statistical criteria using the confidence level information (16). An important aspect of these techniques is that they do not need any prior knowledge about the device or the localization of radiation source. The Kriging has been also used to interpolate the values of measured data and predict the magnitude of the electric field in order to minimize the number of measurement points to assess the exposure [125]. The approach has allowed to obtain information about the field level anywhere inside the volume of interest as well as to know the uncertainty associated to the assessed value, since this information is obtained as a byproduct of the *GP*-based technique.

5. Final remarks and future trends

It is certain that the availability of *LBE* techniques has represented a breakthrough and has enabled the solution of novel and challenging problems in the field of Electromagnetics. In this framework, this paper was aimed at giving a review of recent contributions on selected *EM* engineering applications in which either standard or customized *LBE* methodologies have been proposed and used. Starting from a general introduction to the regression and classification problems, defined as two-step processes based on an initial training phase aimed at building the surrogate model exploiting the available input–output relationships and followed by a testing phase in which the surrogate model is used for the online problem solution, the basics of the principal *LBE* techniques presented in the selected publications have been reported to highlight the similarities and differences in their formulations, requirements, and outcomes. Although the proposed review has focused on six application fields, namely antennas, microwave circuits and devices, electromagnetic scattering, remote and radar sensing, and electromagnetic compatibility, *LBE* techniques has been successfully used for other *EM* applications like electromagnetic planning [126], failure detection [127], and the substrate material characterization for antenna design [128].

The continuous proliferation of wireless services and devices, the growing complexity of the scenarios and applications in which *EM* solutions are enabling technologies (e.g. 5*G* communications, internet-of-things), the availability of very large databases of data (i.e. big data) are requiring the study and development of new algorithms able to quickly adapt and learn (also continuously and online) from the previous experience. In conclusion, although *LBE* techniques have demonstrated to represent reliable and efficient tools for the solution of many problems, it is also worth to emphasize that future and further investigations about *LBE* techniques for specific *EM* engineering problems are needed because of the expected high impact of such approaches.

Notes

1. The *curse of dimensionality* is the problem related to the fact that the size of the training set needs to exponentially grow with the dimensions of training samples to maintain a constant sampling density of the input space. Differently, the *over-fitting* arises when the surrogate function matches the training data with a too high degree of accuracy.
2. The extension to multi-class classification problems is straightforward and in that case $\chi^{(n)}$ is a discrete (e.g. integer) value [8].

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