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SURVEY

A Review of the State of the Art and Future Challenges of Deep Learning-Based Beamforming

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ABSTRACT The key objective of this paper is to explore the recent state-of-the-art artificial intelligence (AI) applications on the broad field of beamforming. Hence, a multitude of AI-oriented beamforming studies are thoroughly investigated in order to correctly comprehend and profitably interpret the AI contribution in the beamforming performance. Starting from a brief overview of beamforming, including adaptive beamforming algorithms and direction of arrival (DOA) estimation methods, our analysis probes further into the main machine learning (ML) classes, the basic neural network (NN) topologies, and the most efficient deep learning (DL) schemes. Subsequently, and based on the prior aspects, the paper explores several concepts regarding the optimal use of ML and NNs either as standalone beamforming and DOA estimation techniques or in combination with other implementations, such as ultrasound imaging, massive multiple-input multiple-output structures, and intelligent reflecting surfaces. Finally, particular attention is drawn on the realization of beamforming or DOA estimation setups via DL topologies. The survey closes with various important conclusions along with an interesting discussion on potential future aspects and promising research challenges.

INDEX TERMS Artificial intelligence, beamforming, deep learning, deep neural networks, direction of arrival estimation, intelligent reflecting surfaces, machine learning, massive MIMO, MIMO, neural networks.

I. INTRODUCTION

With today's rapid technological advancements and the tremendous increase in data volume, the main challenge is to minimize interference and optimize the capacity of wireless communication systems. Also, the demand for transmission with the highest possible quality and coverage is gradually escalating, thus opting for more efficient antennas in order to meet all 5G challenges. Lately, beamforming – defined as a real-time procedure which can create a main lobe that corresponds to the direction of the desired signal and several nulls toward the directions of interference signals – has gained remarkable recognition in the area of modern wireless communications and radar systems. In essence, beamforming has been comprehensively studied during the last decades by means of deterministic and evolutionary methods. Despite their advantages in calculating optimum weights and estimating the direction of arrival (DOA), such techniques are very difficult to consistently treat changing environments, where the emitters move and therefore the weights must continuously be computed. Not to mention the significant risk of performance degradation due to mismatches between the expected and the actual signal steering vectors.

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On the other hand, real-time evaluations of weight coefficients for large numbers of antenna array elements have been proven to be computationally expensive. As already known, a small mismatch between the actual and expected array responses to the desired incoming signal has a serious effect on the performance of adaptive and reconfigurable array algorithms, which aim at reinforcing the reception of the desired signal [1]. Earlier research focused on one of the robust adaptive beamforming (RAB) techniques, namely the array steering vector estimation [2], which manages to improve the signal to interference-plus-noise ratio (SINR), yet at a rather high complexity. In this context, massive multiple-input multiple-output (MIMO) is a modern cellular network architecture, which is capable of providing spectral efficiency, when increasing the number of antennas, and also capable of enhancing system capacity without the need for small cells. It must be noted that massive MIMO structures account for radiation pattern, mismatching, and mutual coupling issues. The latter can be addressed by placing a dielectric layer superstrate [3] or periodic square split ring resonator (SRR) components [4] above the antenna arrays. Due to its flexibility in satisfying many beamforming requirements, such as SINR enhancement [5] and output power minimization of the uplink or downlink channel, which lead to increased antenna apertures [6], the application of beamforming to massive MIMO has triggered a remarkable research effort. To this objective, several algorithms have been launched, the most popular of which is the null steering beamforming (NSB). Despite its effectiveness, the technique is proven to be complex thus resulting in a performance loss. Also, the mean square error (MSE) and the weighted minimization MSE schemes have been used in MIMO systems to solve the sum-rate maximization problem (SRM), but with a high computational complexity [7]. Hence, while a larger degree of freedom is obtained with a larger number of antennas, the overall complexity is augmented when attempting to derive the weights of massive MIMO antenna array elements and simultaneously performing beamforming.

Being an excellent solution in a variety of challenging fields, artificial intelligence (AI) has already begun to be used by researchers as a possible solution to realistic beamforming problems. Actually, the implementation of AI techniques, and especially deep learning (DL), in the antenna array beamforming area is very efficient for changing environments, where weights must be repeatedly calculated. Due to their fast response, rapid convergence rates, successful failure detection, and proactive decision capability, most adaptive beamforming (ABF) techniques are now based on DL realizations [8]-[10]. These key aspects along with the latest and future AI contributions in beamforming are thoroughly discussed in this paper.

II. ALGORITHMS APPLIED TO SMART ANTENNAS

Smart antennas are beam-steered array radiators with signal processing algorithms that can separate signals transmitted by multiple sources. Among their most significant functions, one can discern the ABF techniques [8] for their ability to achieve the highest SINR. The use of fixed array weights is assumed to apply to signals with fixed DOA (i.e., fixed beamforming). On the contrary, the array weights must be repeatedly calculated in ever-changing environments, where DOAs of the incoming signals vary with time (i.e., ABF). The general structure of a beamformer is illustrated in Fig. 1, where several signals are assumed to be received by the antenna array from various DOAs.

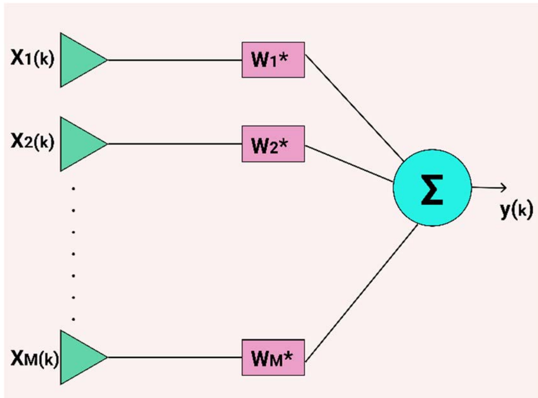

FIGURE 1. Beamformer receiving samples of signals $x_1(k), \ldots, x_M(k)$ at the inputs of the M array elements, due to incoming signals from various DOAs.

A. ADAPTIVE BEAMFORMING

ABF algorithms fine tune the feeding weights of the antenna array. There exist a lot of ABF optimization techniques based on various concepts, such as the steepest or gradient descent, the blind adaptive mechanism, the constant module, or the signal coherence concept. However, convergence and computational complexity are their chief drawbacks [11]. The most well-known ABF techniques are the least mean squares (LMS) method and the normalized LMS (NLMS) algorithm, which are gradient-based approaches to control the weights and improve the SINR of the desired incoming signal. Since they may require many iterations prior to reaching a satisfactory convergence, they rather face difficulty in tracking rapidly changing signals [11], [12]. The constrained NLMS (CNLMS) method is widely used in sparse array beamforming and has a higher convergence rate than other ABF algorithms [13], [14]. The convergence hindrance can also be overcome through the sample matrix inversion (SMI) method, which, although better in convergence rate than the LMS one [15], it may be prone to misleading outcomes due to potential singularities and the fact that the correlation matrix may be ill-conditioned [11]. Moreover, several ABF algorithms have been examined in [15], where it is shown that the recursive least square (RLS) method can converge faster (at the expense of additional complexity) than the LMS scheme. In comparison to the LMS and RLS methods, the SMI method has higher computational cost due to the correlation matrix inversion involved in the SMI process, especially in cases of large numbers of antenna array elements.

Regarding performance, two of the most distinct candidates are the minimum variance distortionless response (MVDR) method and the NSB technique. The former minimizes the beamformer output power and maintains the desired incoming signal undistorted, particularly when the array steering vector of this signal is known. Nonetheless, the MVDR method suffers from high sidelobe levels, which affect the overall performance, especially in the case of high noise presence. To alleviate this shortcoming, an interesting solution based on the Lagrange multipliers technique has been presented in [16], whereas [17]–[20] discuss various ways to increase the beamforming robustness. Conversely, the NSB technique suppresses the beamformer output due to interference signals while keeping the desired incoming signal undistorted at the output of the beamformer. For this purpose, the main lobe is steered to DOA of the desired signal, while, at the same time, radiation pattern nulls are placed toward DOAs of respective interference signals. Therefore, DOAs of all incoming signals must be known a priori, and this is a fact that limits the NSB competence [21], [22].

B. DIRECTION OF ARRIVAL ESTIMATION

Known, also, as angle of arrival (AOA) estimation, the specific scheme is critical for location-based services and applications of 5G communications. To fulfill this goal, numerous methods have been explored, including the Bartlett AOA estimate and the Capon AOA estimate, which do not require any prior knowledge of specific statistical properties of the signals. Additionally, special attention has been drawn to highly accurate schemes, such as the multiple signal classification (MUSIC) [23] and the estimation of signal parameter via rotational invariance technique (ESPRIT) [24], which offer unbiased estimates of DOAs of the incoming signals. However, they necessitate precise array pattern modeling and a huge number of samples [25]. Furthermore, the parameter-based methods involve algorithms such as the maximum likelihood [26] and the compressed sensing technique, that is an on-grid estimation approach capable of achieving a high-resolution DOA [27]. In fact, DL methods outperform all standard DOA methods in terms of accuracy, and thus become an essential signal processing alternative to advanced DOA estimation [28], [29].

III. BACKGROUND

AI enables man-made systems to "think" and "act" rationally, like humans, in order to replace the latter at certain tasks or procedures. Fig. 2 summarizes the main AI regions. DL is an important sector of machine learning (ML) that focuses on the involvement of two or more hidden layers in a neural network (NN) structure. In essence, DL has overcome the inherent ML feature engineering problem by mapping the raw input data into a new representation process known as "representation learning", i.e. the more data we have, the better results we obtain. Thus, this section discusses the fundamental DL principles, including highlights of the ML characteristics, representation learning, NN types, and a brief overview of their applications in the beamforming field.

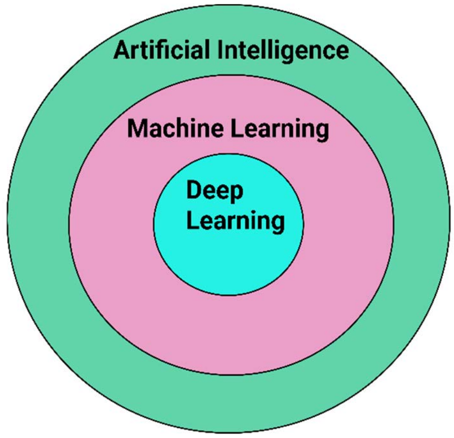

FIGURE 2. The key AI regions.

A. MACHINE LEARNING

ML is an essential AI region that allows learning from data and making proactive decisions. In fact, ML includes a wide field of concepts [30], and it can be grouped in three main categories: (i) supervised learning, where input and output training samples are available for building prediction models, (ii) unsupervised learning, where no training data are available, and (iii) reinforcement learning, where analysis is conducted through encouragement, as in Markov decision processes and online games [31].

On the other hand, there are three categories of hybrid learning. The first one is the semi-supervised learning, which requires unlabeled data in addition to a small amount of labeled data. The second is the self-supervised learning, which requires only unlabeled data to make predictions (the generative adversarial networks fall into this category). The third category is the multi-instance learning, which is actually supervised learning but, instead of having instances individually labeled, the instances are grouped and labeled in bags.

Although the present survey concentrates on DL applications in the beamforming field, it should be stressed that DL is not the only application of ML. Probabilistic modeling (e.g., naive Bayes) is a type of ML classifier as well as the logistic regression, both of which are still being used today. Additionally, linear regression methods, kernel methods, decision trees, random forests, and gradient boosting machines are some indicative ML realizations that continue to offer reliable estimations for several modern scenarios [32].

B. LITERATURE REVIEW OF MACHINE LEARNING BASED BEAMFORMING

Even though the majority of recent research is based primarily on DL, we will share some of the most recent applications of ML in the beamforming field. ML plays an important role in reducing the power and time consumption in millimeter-wave (mm-wave) communications during the beam selection and switching (BSS) process, where an ML algorithm with a single-resolution codebook is selected to obtain an eigen-beam set [33]. Likewise, in [34], the inter-cell interference of mm-wave signals, when using large antennas, is avoided by a data-driven method based on a fuzzy support vector machine (SVM). Furthermore, AOA estimation with the lowest possible complexity in intricate environments has been achieved in [35], where a data-driven approach employs a MUSIC algorithm in several regression models. In [36], a linear regression model is used in combination with ordinary least squares to accurately predict DOAs of the incoming signals. The support vector regression (SVR) model proposed in [37] proves its ability to faster obtain a precise result of DOAs of signals that do not exist in the learning phase through generalization. An SVM classifier has been applied in [38] for near-field sound localization in the presence of noise, thus increasing the accuracy of the weighted MVDR (WMVDR) used here to preserve the signal with a specific DOA and distort the rest of the signals from other directions. Also, in [39], the SVM method is found to be superior to a WMVDR-based radial basis function neural network (RBFNN) in a near-field sound localization process. Another application of SVM [40], requires a two-stage approach to obtain an accurate real-time AOA estimation in vehicular communications. In an effort to compensate for the steering vector mismatching problem caused by the MVDR, a RAB technique based on an SVM is proposed in [41], where MVDR is reformulated as an SVR problem. To this aim, optimal beamforming weights and maximum SINR are achieved in [42], where a reinforcement learning approach is used to compute the optimal positions of relays in fading environments.

As mentioned above, there are numerous contributions of ML in mm-wave communication systems, particularly the SVM algorithm, due to its straightforward implementation and its ability to provide precise results.

C. NEURAL NETWORKS

NNs comprise simple processing interconnected nodes and three types of layers. In particular, these are (i) the input layer, which includes the NN feeding data, (ii) the hidden layers, which are responsible for all computations, and (iii) the output layer, which produces the final outcome. In the following, we will refer to some of the most popular NNs [43].

The feedforward NN (FNN) is the simplest type of NN, composed of several simple neurons organized in layers, as described in Fig. 3. Every unit in a layer relates to all units of the previous layer, while there are not any feedback connections on the model outputs.

The convolutional NN (CNN) is a significant class of NNs, which employ convolutions instead of the multiply-add type of neurons (see Fig. 4). For example, the generation of image

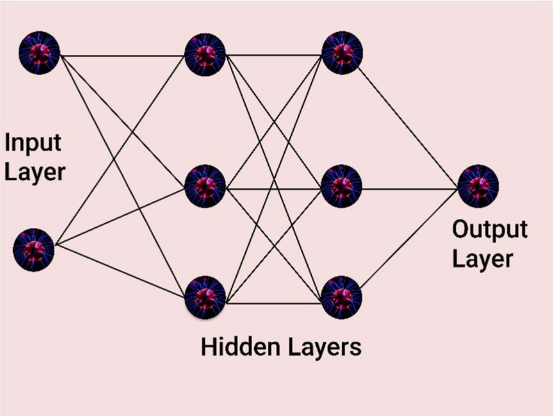

FIGURE 3. FNN structure with two hidden layers.

features is performed by running a filter over the image, since it can exploit the correlation among the pixels. Such NNs are popular for classification tasks and for obtaining the spatial features of the input layer [44], [45]. Actually, they have outperformed many traditional NN models at the enhancement of ultrasound image [46] and cancer detection [47].

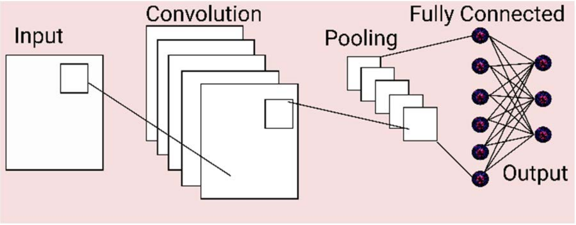

FIGURE 4. CNN structure.

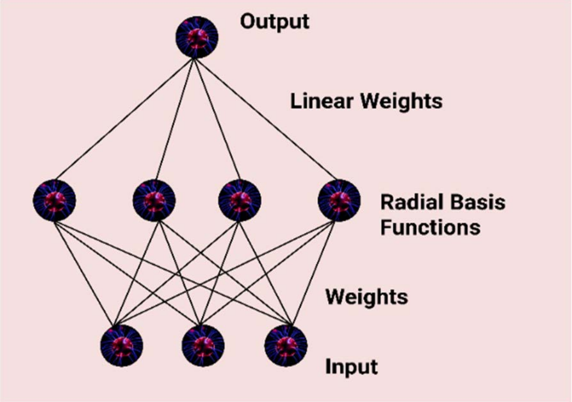

FIGURE 5. RBFNN structure.

The RBFNN employs a radial basis function, which varies with distance from a location and acts as an activation function. As presented in Fig. 5, it comprises an input, a hidden, and an output layer. Depending on its basis function and the number of hidden layers, the RBFNN can be deemed nonlinear. It can be utilized for time series prediction and function approximation [48], [49].

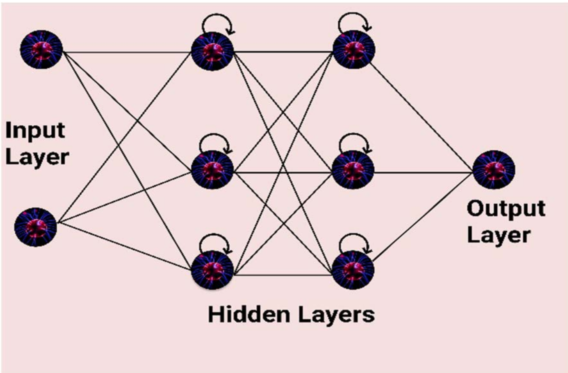

FIGURE 6. RNN structure with two hidden layers.

The recurrent NN (RNN), displayed in Fig. 6, differs from FNN in the existence of a feedback loop and the exploitation of previous input data to influence the next inputs due to its memory. As a consequence, they are mainly used for temporal tasks [50]. Due to their key impact in various research fields, two advanced RNN structures are discussed below, i.e., the long short-term memory (LSTM) and the gated recurrent unit (GRU).

The LSTM cell is a special structure that can successfully manipulate the vanishing and exploding gradient in order to protect the learning process during backpropagation through time [51]. It has three gates to control the memory access, designated as forget, input, and output gates [52]. As shown in Fig. 7, $x(t)$ is the input to the LSTM cell, $c(t)$ is the cell state, $f(t)$ is the forget gate's activation, $i(t)$ is the update gate's activation, $\tilde{c}(t)$ is the cell input activation, $o(t)$ is the output gate's activation, $h(t)$ is the hidden state (or cell output), σ is the sigmoid function, and *tanh* is the hyperbolic tangent function.

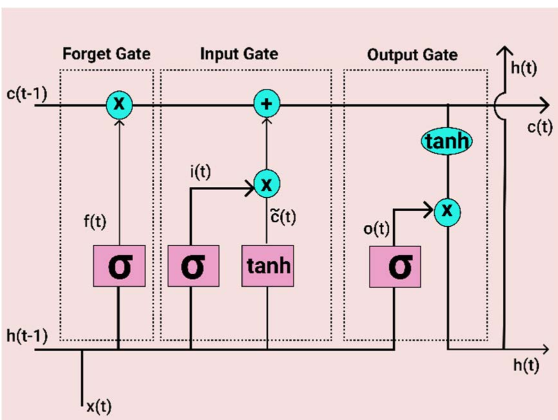

FIGURE 7. Structure of the LSTM cell.

The GRU cell is also an improved RNN variant, and it can also serve in a similar manner as the LSTM cell. The main difference between the GRU and LSTM structures is that the GRU has only two gates (see Fig. 8), namely the reset and update gates, instead of three as is the case with the LSTM structure. Hence, the GRU requires fewer training samples, which translates into reduced memory and CPU time resources. Generally, the LSTM is proven to be better in terms of accuracy, while the GRU is faster and computationally more economical. Fig. 8 illustrates the detailed structure of the GRU cell, where $x(t)$ is the input vector, $r(t)$ is the reset gate vector, $z(t)$ is the update gate vector, $\tilde{h}(t)$ is the candidate activation vector, $h(t)$ is the output vector, σ is the sigmoid function, and *tanh* is the hyperbolic tangent function.

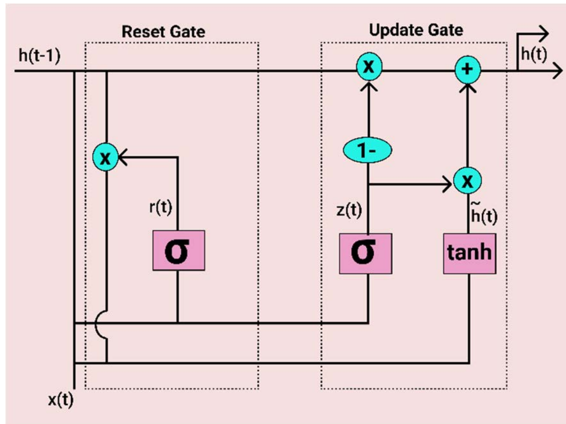

FIGURE 8. Structure of the GRU cell.

D. LITERATURE REVIEW OF NEURAL NETWORK BASED BEAMFORMING

One of the most important NN contributions is the treatment of the SRM problem, which is critical in massive MIMO systems [53], [54]. So, the drop algorithm based on NNs is used in [55] to select users that would be dropped, therefore leading to SRM. In [56], the sampling function NN has been proposed to manage the weights calculation of an adaptive antenna array thus resulting in an improved performance compared to the conventional RBFNN. Also, in [57], the non-identical characteristics of the antenna channel and their drift over time have been addressed through a direct distribution of a NN. An FNN has been trained in [58] to evaluate the optimum weights of a uniform linear array (ULA) and optimize them with a better performance than an LMS-based beamforming algorithm. In addition, a NN is employed in [59] for DOA estimation of signals received by a ULA with the lowest MSE. The Lagrange programming NN, based on Lagrange multipliers, is employed in [60] for anti-jamming in real-time. Finally, to accomplish a secure and realistic transmission system, a backpropagation NN is utilized in [61]. Note that only a few indicative contributions of NN in the beamforming field are reported in this section, as the current trend opts for DL applications in order to achieve extra accuracy, even if it comes at the expense of complexity.

E. REPRESENTATION LEARNING

The efficiency of ML techniques is strongly influenced by the type of the used data representation. As a result, feature engineering has become an important part of leveraging the innovations to compensate for the shortcomings of existing ML algorithms. Data representations intend to make learning easier to extract meaningful information from data in order to construct reliable predictors. There are numerous learning presentation applications, such as inference techniques, which involve inductive learning that relies on specific rules to make the general output decision, and deductive learning that follows general rules to make the specific output decision [62]. In this context, transduction learning methodologies, such as the k-nearest neighbors algorithm, have accordingly been introduced. Also, multi-task learning (a supervised learning technique) has been proven to be instructive when multiple tasks are learned simultaneously from a single model. In this way, useful relationships included in related tasks can be utilized, thus resulting in improved prediction accuracy for specific tasks compared to models that are trained individually. Apart from active learning, online learning, ensemble learning, and transfer learning, distinct parts of the resulting model (or the entire model) may be employed for relevant tasks, thus reducing complexity by minimizing data size [63].

One of the key methods of learning presentation is DL, which relies on the multi-layer structure of a NN to learn and find the optimal solution. On the other hand, ML needs algorithms to analyze data, learn from data, and construct solutions. ML relies on users to generate new features, whereas DL relies on its techniques. Also, ML is much simpler than DL, since it does not require a large amount of data or extremely expensive hardware, while DL has much higher reliability when compared to ML.

The star of DL has emerged in the early 2010s, although it has already been known long before. Its important breakthrough occurred when computing systems included GPU processing power. Since then, it has undeniably been proven to be the best choice in several fields and constantly gains the interest of several others. In fact, DL has managed to approach the way of analysis of human brain through the use of data inputs, weights, and bias in diverse scientific areas, like image classification, speech recognition, handwriting transcription, autonomous car driving, and improved internet search results, to name a few [64]. Moreover, its contribution in medicine has been decisive, and particularly in the early detection of malignant diseases, by improving the accuracy of ultrasound imaging.

IV. STATE OF THE ART IN DEEP LEARNING BASED BEAMFORMING

Essentially, the principal goal of this survey is to demonstrate the implementation of DL techniques in the wide region of beamforming, including DOA estimation, massive MIMO-beamforming, and the impact of different realizations on the solution of certain problems.

By applying beamforming, the main lobe of the antenna array is aligned along DOA of the signal of interest to ensure a reliable connection with the source of this signal [9]. The DOAs of the desired and undesired signals change over time, therefore the feeding weights must be calculated upon every change. This is exactly what makes most of the evolutionary optimization techniques fail to simultaneously achieve the required accuracy and provide the required time response, due to their iterative structure [65]. On the contrary, a NN-based beamformer provides immediate response as demanded in 5G and beyond-5G wireless networks, which are deployed in fast-changing environments. In addition, the majority of the research does not consider realistic parameters of the antenna array, like the non-isotropic radiation pattern of the antenna array elements and the mutual coupling between them, as discussed in [10]. Such realistic parameters increase the complexity of the beamforming problem. However, the DL structure of an NN-based beamformer is capable of providing the required accuracy, while maintaining immediate response even when these parameters are taken into account. Herein, we conduct an overview of the latest DL applications on the beamforming and DOA estimation fields.

Recently, a combination between a CNN and a bidirectional LSTM (BLSTM) implementation was proposed to calculate the antenna array weights in the presence of noise and interference without prior knowledge of DOAs [66]. Compared to the minimum mean square error (MMSE) beamformer, a CNN performs better with varying numbers of interference signals, while the LSTM architecture excels in estimating the desired signal. The combination between the two architectures appears to be more effective than using only a CNN, such as in [67] and [68]. Such a CNN examined in [67] determines the phases required for designing the antenna array pattern, while a convolutional massive beamforming NN (CMBNN) is used for the optimization with varying numbers of users in [68]. Moreover, in [69], a deep CNN is proposed for a fast suboptimal solution of a real-time antenna synthesis problem. This model significantly reduces the operational time, while maintaining a high accuracy.

In addition, there are various models for DOA estimation using DNNs. In [70], a multi-layer perceptron (MLP) with several fully connected (FC) layers is divided in two stages to separately perform signal detection and DOA estimation with a higher rate of convergence than previous approaches. In [71], a DNN outperforms a maximum likelihood estimator in efficiency when the number of sources is unknown, while at the same time providing lower complexity. However, in the case of on-grid estimation, such a DNN performance is very sensitive, when DOA estimation is conducted at the boundaries of bins used to divide the AOA space [72]. In this context, [73] converts a traditional DOA estimation problem to a multilabel classification one, based on a CNN, to discriminate between various sound sources, as well as to reduce the array aperture limitation. On the other hand, [74] faces DOA estimation as a regression problem. Here, a CNN estimator minimizes the time complexity, while retaining a

TABLE 1. Primary characteristics of DL applications.

REF	Architecture	Array properties	Application
[66]	CNN (6-layers)	ULA (4 elements)	Interference vector assessing and removing
	BLSTM (6-layers)		Desired signal estimation
[67]	CNN (8-layers)	Microstrip phased antenna array (8×8 elements)	Patch antenna phases estimation
[68]	CMBNN (3-layers)	Massive MIMO system (single cell- multiuser)	Antenna array weights estimation
[69]	CNN (8-Layers)	2D planar array (149 elements)	ABF, optimum currents calculation
[70]	MLP (4-FC layers)	ULA (10 elements)	DOA estimation
[71]	MLP (8-FC layers)	ULA (16 elements)	DOA estimation
[72]	MLP (6-FC layers)	ULA (5 elements)	DOA estimation
[73]	CNN (7-layers)	Microphone array (8 receivers)	DOA estimation (nonlinear mapping learning)
[74]	CNN (4-layers)	Uniform circular array (UCA) with 8 elements	DOA estimation (inverse mapping learning)
[75]	Deep CNN	Optimal sparse array (10 elements)	DOAs estimation
[76]	FNN (3- layers)	ULA (11 elements)	ABF
[77]	FNN (2-layers)	ULA (5 elements)	Optimum weights calculation

high degree of frequency generalization. Also, deep sparse arrays have recently been proposed using DL to limit the hardware cost in radar systems and ensure the validity of the approach in DOA recovery with performance comparable to that of the conventional sparse arrays [75].

In [76], an FNN-based beamformer is trained based on a modified adaptive dispersion invasive weed optimization (i.e., an invasive weed optimization variant) to maximize the SINR and minimize the sidelobe level with the fastest response. Also, in [77] an FNN that uses a Levenberg-Marquardt scheme achieves good performance in computing the antenna array optimal weights, at the expense of a rather increased memory consumption. Further details about the aforementioned general DNN contributions in the beamforming field are summarized in Table 1.

It should be stressed that 5G systems can localize users due to active directional antenna arrays. However, most of the methods rely on channel state information (CSI), which is not always feasible to obtain. In [78], a new approach is proposed, which does not require any CSI (only information about the received signal strength) and is based on a fully connected network with two hidden layers trained for fingerprints with better performance than deep CNNs. The use of a model-driven DL for beamforming can be deemed as an advancement, since a signal processing module is introduced in the NN structure to reduce the overall complexity [79]. Based on available CSI in [80], a DL estimation of user allocation achieves the optimal accuracy by managing resources and thus provides the desired services to the user equipment. The most recent DNN contributions in beamforming subdomains are discussed in the following paragraphs.

A. MASK-BASED BEAMFORMING

In noisy environments with a low SNR, conventional ABF algorithms cannot enhance the noise-robust automatic speech recognizer (ASR) in the same way that a DNN-based mask estimator can, although it is used as a preprocessor for speech recognition [81]. For more clarification, a deep FNN combined with an MVDR beamforming algorithm is proposed in [82], using the ideal ratio mask (IRM), followed by the ideal binary mask (IBM). As a result, the performance of the MVDR beamformer is improved, and the noisy speech is excluded. The performance of the proposed algorithm is evaluated using the sentence error rate (SER), which seems to be beneficial in scenarios with low SNR.

The majority of the research in this field focuses on the far-field speech recognition, which remains a significant process, since speech signals can be vulnerable to a lot of noise and reverberation. A deep FNN-based acoustic model composed of six hidden layers is used in [83] to compute the optimum weights from the generalized cross-correlation (GCC). The available AOAs are used here to train this model. Also, the option of improving the far-field ASR performance is considered by employing an LSTM-based acoustic model in the same manner. In [84], a DNN-based beamformer with spatial attention is developed to evaluate the weights. It is noted that spatial attention indicates how instructive each direction is for the recognition of the target speech. In [85], a FNN is proposed to provide a more accurate estimation of audio signal DOAs than the least-squares approach in noisy and reverberant environments using features extracted from GCC vectors.

The use of DL as an acoustic model associated with the availability of training data has significantly improved the ASR performance. Nonetheless, it has a few drawbacks, due to additive Gaussian noise and reverberation. To mitigate these issues, a notable progress is made in [86] and [87], where the same NN structure is used in different ways to estimate spectral masks and thus provide robust acoustic beamforming. Specifically, noise estimation is critical in beamforming, and it can be accomplished by estimating spectral masks for speech and noise using a data-driven technique like that described in [86]. This approach, which uses BLSTM and a simple FNN to estimate the beamformer coefficients and spectral masks of multi-channels, has proven to be efficient even when using only pure talk, though it does not leverage the full multi-channel information. Despite its efficiency, the data mismatching between training and testing datasets has an impact on the DNN performance when using supervised learning. This mismatching is avoided using the unsupervised approach of [87]. The coefficients of the complex Gaussian mixture model are calculated in an unsupervised way using a combination of a BLSTM layer and three FNN layers to build the IRM and IBM. However, [88] proposes an acoustic beamformer based on supervised DL time-frequency mask estimation model. Time-frequency masking is a method for separating speech from noise in order to improve speech quality by adding weights to the time-frequency feature bins. Since the beamformer in this model does not require information about steering vectors of signals, any mismatching issues can be avoided.

In [89], an LSTM adaptive beamformer is trained alongside a deep LSTM acoustic model to adaptively estimate the beamforming filter coefficients at each time frame, and performs filter-and-sum beamforming over the short-time Fourier transform coefficients. A similar approach is used for multichannel waveform signals in [90]. The approach proposed in [86] is also used in [91], where a CNN, an LSTM architecture, and a DNN are concatenated to estimate frame-level speech and noise masks, thus improving the far-field ASR performance.

B. ULTRASOUND BEAMFORMING

The main goal of the rapidly evolving area of ultrasound imaging is to achieve a real-time detection capability, to avoid harmful rays, and to offer low-cost setups. Beamforming plays an important role in this field, and the MVDR method is the typical choice, yet with a large computational overhead. So, the standard delay and sum (DAS) beamforming method is useful to compensate for this overhead as well as to improve the quality of the reconstructed images, despite some shortcomings. To alleviate them, [92] proposes three alternative DNN architectures, i.e., a fully connected network, a convolutional autoencoder, and a U-Net-like network (its architecture is similar to that of a convolutional autoencoder but with skipped connections from the encoder to decoder layers, thus achieving better feature preservation in the decoding process). In this manner, the speckle noise is suppressed and the required time for image reconstruction is reduced. For the same purpose, [93] presents a DNN with four fully connected layers, which can reconstruct high-quality ultrasound images for a wide range of imaging systems with a faster response time and less complexity than conventional beamforming methods. Furthermore, [94] proposed a fully connected DNN architecture with seven hidden layers to extend the contrast ratio dynamic range in the presence of reverberation clutter, thus outperforming DAS beamforming.

The plane-wave ultrasound imaging technique has become very important because it can reach high real-time frame rates up to 18000 frames per second [95]. It must be noted that a single plane wave is not enough to produce an image with enhanced quality in acoustic clutter conditions. However, by using a single plane wave in each simulation, the generative adversarial networks (GANs) in [96] are able to improve the image quality and extract enough data to rebuild a DAS B-mode image, while also providing segmentation information. An improved approach of [96] with a simpler architecture is proposed in [97], where a fully CNN manages to consume less time in training compared to a GAN, and thus it becomes a promising alternative to the traditional DAS beamforming technique for the detection and tracking of anechoic cysts surrounded by tissue. Similar implementations have been proposed in [98] and [99] by applying a fully convolutional encoder-decoder and a fully CNN, respectively, hence increasing the total accuracy and speed. The aforementioned concept of plane-wave ultrasound imaging techniques via DNNs in comparison to the conventional pipeline process is summarized in Fig. 9.

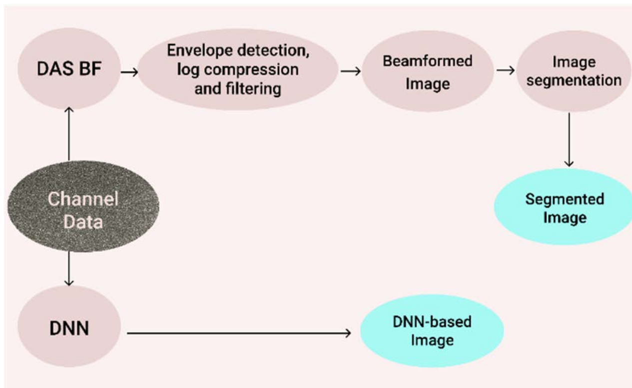

FIGURE 9. Two alternative ways for ultrasound image formation: conventional pipeline process, which uses a DAS beamformer, and DL process.

Based on the above, we can conclude that DL has become a qualitative alternative to previously used methods to improve the quality of reconstructed ultrasound imaging. It has the ability to predict beamformed signals, while it can also reduce noise in reconstructed images by improving the DAS beamformer performance. Moreover, DL has been proven to be efficient in classification tasks, without extra computational complexity, primarily when used in autoencoders. An autoencoder can be trained with noisy images and outputs noise-free images. In addition, when large datasets are used, the autoencoder increases the likelihood of deriving more accurate results. Particularly in the commercial field, the contrast-to-noise ratio and signal-to-clutter ratio are greatly improved when using DL to fill gaps created by the DAS beamformer. Furthermore, when using the coherence factor at the lowest SNR, DL can improve the performance of filter-and-sum beamforming methods.

C. INTELLIGENT REFLECTING SURFACES

The intelligent reflecting surface (IRS) is considered to be one of the most promising components of massive MIMO technology, and it will play a decisive role in 6G wireless networks. It is mainly an array of many reflecting metamaterial elements, most of which can passively radiate electromagnetic waves, when controlled and placed near the transmitter or receiver. Note that some of the elements are active if connected to the IRS baseband controller in order to operate as channel sensing devices, and thus should be placed near the receiver. Furthermore, it is noteworthy to mention that in majority, due to their own amplitude-phase regulation, the IRSs have the advantage of beam steering without the use of phase shifters or other RF components. In fact, MIMO and IRS technologies are related to each other, except that the latter can provide spectral and energy efficiency by tuning the wireless environment to compensate for any hole caused in the coverage area [100]. Also, IRS-assisted systems may be more complex due to the large number of communication links [101]. So far, a lot of research has been conducted to compare various trends of IRS usage [102], as in the case of mm-wave communications [103] and others [104].

The beamformer and phase shifter must optimally be designed in IRS-assisted wireless systems. Indeed, the joint optimization has been a critical issue due to the coupling between the transmitting and reflecting antennas as well as the nonconvex constraints. Most of the research uses alternating optimization-based frameworks to solve this problem. Specifically, a point-to-point IRS-assisted multiple-input single-output (MISO) communication system has been proposed in [105], using two algorithms, fixed-point iterations, and manifold optimization techniques. Also, to avoid the separation of the nonconvex problem into two sub-problems, several methods which perform simultaneous optimization have been introduced, so far. Among them, one can discern the DL-based IRS as an important tool for signal detection that does not require the use of a pilot signal and has the lowest bit error rate (BER), thus resulting in a reduction of overhead [106]. Moreover, we can distinguish beamforming and channel estimation with a comparatively small number of active elements and the highest data rates [107], [108], where most of the elements are passive, and the system learns to estimate the channel performance via DL only at the IRS active elements [107], while most traditional estimation methods would increase training and architecture complexity. The proposed channel estimation scheme in [109] employs DL models and a two-stage NN, which has an architecture less complex than those of conventional compressed sensing algorithms. It must be noted that conventional compressed sensing algorithms necessitate the extraction of precise phase information from measured data and thus they become highly complex. However, they are prone to failure in cases of low SNR. The DNN-based method in [110] is designed to improve the received signal strength in IRS-based indoor environments. Finally, due to controlling an IRS without the use of a base station, the deep reinforcement learning model developed in [111] is able to predict the IRS reflection matrices with even less training and higher rates than supervised approaches.

Overall, in IRS-assisted systems, the DL outperforms compressed sensing techniques, because it does not require a large number of active elements or prior knowledge of array statistics. However, it requires a large number of training samples. More details on the contribution of DL in IRS-assisted systems can be found in Table 2.

TABLE 2. Features of DL-based IRS-assisted applications.

REF	Architecture	IRSs properties	Application
[106]	MLP (5-FC layers)	32 active elements, 64 reflecting elements, and 2 channel paths	Signal detection, and channel estimation
[107]	MLP (4-FC layers)	64 antennas, 8 active elements, and 10 channel paths	Reflection matrices prediction
[108]	2-CNNs (9-Layers)	64 antennas, 100 reflecting elements, and 10 channel paths	Channel estimation (massive MIMO)
[109]	MLP (5-FC layers)	128 antennas, 32 reflecting elements, and 3 channel paths	Channel estimation (THz MIMO)
[110]	MLP (5-FC layers)	32 antennas, and 8, 32, or 64 reflecting elements	RIS configuration
[111]	MLP (4-FC layers)	32 antennas, 4 active elements, and 1-15 channel paths	RIS configuration

D. ANTENNA BEAMFORMING COMBINED WITH MASSIVE MIMO

The use of DNN in massive MIMO systems has made a remarkable progress, such as the deep adversarial reinforcement learning model in [112], which has greatly improved the performance and capacity of massive MIMO beamforming by defining the amplitude and phase shift of each antenna element using a small set of training data.

Due to the large number of antennas and the variable number of potential users, the training complexity in massive MIMO beamforming increases, thus limiting the ability of DNNs to provide optimal performance. In particular, a CMBNN is proposed in [68] to minimize the training complexity by combining supervised and unsupervised learning, thus achieving SRM with high speed and system efficiency for a variable number of users. Furthermore, the CNNs have made a serious contribution in massive MIMO. To perform BSS, a deep CNN is used in [113] to classify the narrow and strongly focused beams with high reliability and low complexity. The reliable specification of transceiver locations is achieved in [114] using two CNNs in less time and high accuracy when compared to a deterministic method. Apart from the above topics, CNNs have successfully been applied for power allocation, uplink beamforming prediction, and SRM, with performance similar to that of conventional methods [115]. Calibration state diagnosis of a massive antenna array is performed in [116], assisted by DL to avoid possible deviations, and enhance the downlink pilot matrix,

TABLE 3. Characteristics of DL-based massive MIMO applications.

REF	Architecture	Application
[112]	Deep adversarial reinforcement learning	Two competing NNs (for realistic radiation pattern production) Referee network (to evaluate the created antenna efficiency)
[113]	Deep CNN	Beams allocation prediction (massive MIMO with 64 users)
[114]	Deep CNN	Binary classifier (select the antenna array from input images) Beam classifier (beams configuration prediction and SNR maximization)
[115]	Deep CNN	Beams allocation prediction and SRM
[116]	Deep CNN	Selection of antennas that require calibration and optimization of downlink pilot matrix (massive MIMO with 64 or 128 antennas)
[117]	Multi-layer perceptron	SRM with MISO with 2 users
[118]	GAN	DOA estimation
[119]	MLP	Prediction of beamforming directions in highly mobile mm-wave systems (mm-Wave MIMO with 256 antennas)
[120]	MLP (autoencoder) includes digital and analog beamforming, and noise layer	Complexity reduction of hybrid precoding in mm-wave MIMO
[121]	Neural hybrid beamforming (autoencoder), includes digital and analog beamforming, and noise layer	Complexity reduction of hybrid precoding in mm-wave MIMO

while the massive MIMO system allows the use of the same channel for uplink and downlink.

It should be stressed that MISO systems have also been analyzed. For instance, in [117], a DNN makes a choice between two popular schemes, i.e., maximum ratio transmission beamforming and NSB, for each user in two-user MISO interference channels, in order to achieve the maximum sum rate.

Moreover, there are numerous applications that use massive MIMO technology and are installed on wireless body area networks (WBANs). The use of DL has played an important role in the reliability of these applications. In this context, [118] proposes the application of deep adversarial reinforcement learning to predict the beamforming direction in mm-wave WBANs with high flexibility, even under conditions of lack of data. Also, there are DL-based applications that take into account the user mobility in massive MIMO networks. A DL model composed of six fully connected layers is proposed in [119] to support high mobility in mm-wave MIMO systems with low latency, reliable coverage, and minimum training overhead, by using each user's signature. Due to the availability of small antennas at the mm-wave 5G WBANs, the application of DL achieves promising results in terms of reliability and flexibility, in contrast to the shortcomings of conventional methods in exploiting the beamforming benefits in that field.

Finally, it is noteworthy to briefly refer to the DL-oriented hybrid beamforming (HB) system. Such structures are typically employed in conjunction with multiple radio frequencies to offer an adjustable trade-off between design complexity and transmission rate. Thus, they are considered to be a promising tool for mm-wave massive MIMO networks. A DNN-based MIMO-HB approach is proposed in [120] to minimize BER and enhance the spectrum efficiency of mm-wave massive MIMO networks, thus demonstrating that hybrid precoding provides better performance in comparison with conventional schemes. Also, an autoencoder-based DNN is proposed in [121] for operation in mm-wave massive MIMO networks in order to unify various HB schemes in a DNN-based HB scheme, which is found to outperform traditional methods in terms of BER. Beam allocation and non-convex SRM are two of the most challenging topics in mm-wave massive MIMO analysis. In fact, DL is deemed a promising solution for these topics, due to its small overheads and its precise results, when compared to existing methods with iterative structures. Further details on DL implementations are given in Table 3.

V. CONCLUSION

It becomes apparent that beamforming is deemed as a critical and promising technological advancement for contemporary wireless communication systems. Amid the challenges faced by this real-time procedure, there is a need for rigorous optimization schemes to accurately solve the beamforming problem and reduce the computational complexity. Beamforming techniques have proven to be capable of properly adapting the radiation pattern of an antenna array in real time at a satisfactory convergence rate, and in the presence of interference signals and steering vector mismatching. Based on these aspects, a brief overview of the latest research in AI-based beamforming applications, with an emphasis on DL realizations, has been presented in this survey. Several approaches have been mentioned regarding the best use of DL in beamforming and DOA estimation techniques in conjunction with other applications including ultrasound imaging, massive MIMO, and IRSs.

In the era of 5G communication systems, due to high propagation losses in the mm-wave band, beamforming-based MIMO systems become constantly more necessary for high spectral efficiency and coverage. To the best of our knowledge, there are still challenges in the development of intuitive learning-based massive MIMO beamforming architectures. Indeed, as the total number of antenna elements increases, the required NNs will become more complex, thus making it more difficult to achieve fast training and more expensive to implement them, especially in the case of fast-changing environments. Undoubtedly, the DNN family can be very efficient with regard to beamforming, and can easily replace conventional implementations, provided that all algorithmic properties are meticulously adjusted. There are many challenges related to DL applications, such as the features engineering, the existence of hyper parameters, the capacity, the construction complexity, and the necessity to conduct numerous experiments to find a suitable architecture. However, the key merit is their accuracy in solving complex problems, acknowledged to be nearly equal to that of human analysts but with a faster time response. The principal requisites, nowadays, is: (a) to enhance the evolution level of NNs in order to obtain better results by the profitable comprehension of their structure and consistent training, and (b) to attain a balance of the tradeoff between accuracy and complexity in order to promptly demonstrate their general superiority over traditional approaches.

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