Survey on Deep Learning Techniques for Wireless Communications*

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I. INTRODUCTION

In a typical wireless communication system, channels are modeled, signaling schemes are devised, and detection algorithms are mathematically described. This detection algorithm must be reliable, implementable, and sufficiently close to optimal (under certain assumptions). Most deployed wireless communication systems use electromagnetic signals with channel models based on Maxwell's equations. At widely-used frequencies, channels conform to tractable mathematical models and describe propagation with reasonable accuracy. Often, these signals are bound by certain simplifying assumptions (e.g. linearity, stationarity), and detection algorithms have been explored and optimized. However, some signals of interest do not fit this category.

We will focus on two categories of these signals: electromagnetic signals with channel models that have hard-to-learn or quickly changing parameters; and non-electromagnetic signals with no known channel models. The former category includes mmWave channels, which offer large amounts of bandwidth to support high data rates in next-generation systems. In this category, channel models might be known, but they are too complex and/or change too fast to estimate with reasonable accuracy. This estimation of channel state information (CSI) is essential for many current detection algorithms. The latter category includes molecular signals [1], which offer a means to communicate when electromagnetic propagation is impossible or impractical. In this category, channel models are unknown or difficult to derive analytically, so traditional detection algorithms are unreliable. These considerations prompted researchers to turn to techniques from other fields.

Deep learning techniques have recently exhibited unprecedented success in classification problems for which no well-defined mathematical model exists [2]. For example, the mapping of pixels to object, or of spoken language to meaning. In this survey, we explore current research on deep-learning based detection and compare methods. We aim to provide an overview of current methods being explored, and we hope to suggest promising areas of further exploration. The following section details how literature is to be surveyed, compared, and evaluated.

II. PROPOSED METHOD

We explore several points of comparison in the surveyed literature [1], [3]–[5]. These points are listed below:

- Channel to which deep learning is applied and motivations for doing so
- Implementation (network architecture used)
- Performance and results

Unfortunately, performance of implementation in different works is difficult to compare. To ameliorate this, we will suggest metrics for quantitative comparison of different neural network detector implementations. These might include training time, robustness to certain factors (e.g. changes of noise distribution), and probability of symbol error.

III. PROMISING APPLICATIONS

Next, we will analyze which applications of deep learning in wireless communications present the most promising areas of future research based on the surveyed literature. This analysis will be done in the context of each individual subfield (e.g. molecular, MIMO, mmWave).

IV. FUTURE WORK

To conclude, we will present three areas of future research and detail next steps. If time permits, one or more of the following areas will be explored in greater depth.

A. *Comparison of Architectures across Channel Models*

To support the proposed metric for evaluation of deep learning detectors, we will propose a selection of channels and neural network implementations for a communications system. This future work would entail the calculation and evaluation of the proposed comparison method across these channels and implementations.

B. *mmWave Channel Modeling and Detection*

We will propose next steps to apply deep learning to challenges in the mmWave band, including channel modeling and detection. We will both highlight what these challenges are and explore potential solutions.

C. *End-to-end Deep Learning Communication Systems*

Communication systems traditionally consist of several distinct blocks. As an extension of detection using deep learning, we will propose next steps to explore learned end-to-end communication systems [3], [5] and comment on advantages and disadvantages of these techniques.

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