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Signal Decoding in Massive-MIMO Systems Using Deep Learning Algorithm

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ABSTRACT: Massive Multiple Input Multiple Output (MIMO) is a key technology for future 5G communication systems. In this paper we have considered a Deep Learning based network for multi user MIMO decoding. In this we have considered an uplink time-varying Gaussian random MIMO channel perfectly known to the decoder, and based on the knowledge of this MIMO channel and the received signal the proposed deep decoder is decoding the messages of all the users.The architecture of this deep decoder is based on the projected gradient descent algorithm. We compare the BER performance, and runtime requirement of the proposed method and achieve comparable results with many well established methods such as sphere decoding and semidefinite relaxation based MIMO decoders.The obtained result shows that this deep learning based MIMO decoder achieves state of the art BER performance and remarkably low run time requirement with lesser complexity.

KEYWORDS*:* MIMO Decoding, Neural Network, Deep Learning, Massive MIMO.

I. INTRODUCTION

Multi antenna technique such as Multiple input Multiple output (MIMO) technology is one of the key techniques for future 5G developments. This enables the use of large antenna array to increase the data rates, coverage, link reliability and enhance the spectral efficiency by using the multipath characteristics of the wireless channel. Conventionally, the user equipment communicates with the base station (BS) in orthogonal time-frequency resource which is not optimal from resource point of view. Lower BER and higher spectral efficiency can be achieved if the communication between many user equipment and base station takes place in same time-frequency resource [3] [4 Energy and Spectral Efficiency of very large].

In next generation communication system a diverse range of impairments such as amplifier distortion, quantization loss, propagation loss, fading, multipath need to be addressed.Not only this, the degree of freedom required to successfully operate the 5th Generation communication system goes on increasing day by day. These impairments along with increasing number of degree of freedom makes current system very difficult to optimise if not impossible.Currently available MIMO detectors has solid roots in mathematics and statistics and these detectors only captures the approximate behaviour of the system. That's why it is not possible to perform end-to-end optimization of the communication system in practical and these systems give suboptimal performance.

In 5G communication technologies for higher data rate and reliability requirement it is necessary to implement a large number of antenna array on transmitter as well as receiver side. Large number of antenna makes this system very complex during detection and the receiver system need to process very large matrix operations. These increasing complexity requirement makes conventional system prone to bit error and higher time consuming whiledecoding the message.

In the past few years Deep Learning shows a great potential in the field of image processing, computer vision and natural language processing. Deep learning algorithms captures the practical state of the system and learns the task beyond human level of accuracy [6],[7 An introduction to deep Learning]. In deep learning a neural network algorithm learns to perform classification task directly from the data fed to it. In neural network, there are two phases, training phase and classification phase. During training phase the deep network takes known data and adjust its weight of network connection in order to meet the correct result. During classification phase, the deep network uses its intelligence to provide the correct output.

Now a day's people uses deep learning models to solve the problem of communication system. Apart from this, Deep Learning based MIMO Detector does not requires a statistical and mathematical model to implement the communication system. Deep learning models can be optimized for a particular hardware configuration and a particular wireless channel

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model. This end to end optimization of the system is done through rigorous training of the Deep Network on the data obtained from communication hardware and channel models in real world. This Deep detector captures the hardware and channel system model in a better manner than its conventional MIMO detectors such as Maximum likelihood (ML) detector, Minimum mean square error (MMSE) detector or zero forcing (ZF) receiver [7 Sparsely Connected Neural Network]. Several researchers have already investigated deep learning based MIMO Detectors. Resent development in Deep Learning for communication develop alternative solutions to enhance conventional communication system. In [An introduction to deep learning (self)] a deep auto encoder based communication system has been proposed in which whole transmitter-channel-receiver system is assumed as a single end-to-end deep learning system and optimised accordingly. In [Deep learning based channel estimation] the MIMO channel estimation is formulated as image recovery problem. In this Deep learning based LDAMP network is used to recover the enhance MIMO channel at the receiver. In [Deep learning for massive mimocsi feedback Deep learning based CSI feedback] the MIMO channel is estimated and compressed using DEEP network at receiver and receiver feed this compressed CSI back to transmitter where Deep network based decoder is used to decode the MIMO channel.In [12] and [13] a multi-layer neural network Detection network has been proposed in which author uses a real valued Gaussian random channel to train the network. For creating the deep network authors first increase the input data to a higher dimension and also add some standard non linarites into it. These additional non linearity increases the complexity of the network and this network takes longer time for training as well as decoding.

In this paper our main contribution is to design a Deep Learning based MIMO detector. This detector is based on MIMO system model which has exact knowledge of channel and takes received signal as input to decode the transmitted bits. Simulation shows that this Deep network based MIMO decoder achieves near optimal BER performance and takes less time than many conventional MIMO decoders.Tis algorithm can be implemented in real time and capable of decoding a MIMO system having large number of transmit receive antenna. Its accuracy is comparable with Semi Definite Relaxation based MIMO decoder but it is 30 times faster than it.Once trained, this proposed deep learning based MIMO decoder can perform decoding of not only fixed MIMO channels but time varying MIMO channels also. This ability to perform decoding on time varying MIMO channels makes this system suitable for practical purpose.

In this paper, we are denoting the mean and variance of a random variable as mand σ^2 respectively. Normal distribution with mean *m* and variance σ^2 as N (m, σ^2). The uniform distribution between *a* and*b* as U (*a, b*). Matrices are denoted by bold uppercase alphabets whereas bold lowercase alphabets are representing row or column vectors.$x_i$will be the ith element if a vector. And the superscript $(\square)^T$ denotes transpose of a matrix.

The rest of this paper is organised in five sections. Section I is the introduction to this work in which we have discussed some benefits of Deep network based communication system design. In this section some related work done is also presented. In section II

II. System Model

In this section, we have presented the conventional MIMO system model and formulate the MIMO detection system as a Deep Learning problem.

A. *MIMO System*

Consider uplink of a Multi User MIMO system where N_T single transmit antenna users used to transmit data to a base station (BS) having N_R receive antennas. The propagation path between each receive-transmit antenna pair is assumed to be Frequency flat fading and remain constant for one transmitted packet. The standard MIMO channel model for this scenario is given below:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \qquad 1$$

Where $\mathbf{y} \in \square^{N_R}$ is received message vector, $\mathbf{x} \in [+1,-1]^{N_T}$ is unknown transmitted message vector of equiprobable and independent symbols, $\mathbf{H} \in \square^{N_R \times N_T}$ is $N_R \times N_T$ MIMO channel matrix and $\mathbf{n} \in \square^{N_R}$ is independent identically distributed Gaussian noise of zero mean and variance σ_n^2. In this paper we have assumed that channel matrix $\mathbf{H}$ has randomcoefficients with known distribution and is perfectly known to the receiver.

The main goal of a MIMO detector is to detect the transmitted signal of all the users or antennas from the received signal with minimum error. There are so many classical MIMO detectors available in theory which are being used in practical MIMO receivers. One of the classical MIMO detector known as Maximum Likelihood (ML) detector gives near optimal performance. It minimizes the joint probability of error of all the symbols simultaneously. ML decoder estimates the transmitted signal based on the nearest Euclidian distance from the knowledge of received signal and the channel states. Minimizing the joint probability of error means maximizing the probability of correctly estimating $\mathbf{x}$ .i e

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$$P\left(\mathbf{s}=\hat{\mathbf{s}}\middle|\mathbf{y},\mathbf{H}\right)=\frac{P\left(\mathbf{s}=\hat{\mathbf{s}}\right)f_{y|s,H}\left(\mathbf{y}\middle|\mathbf{s}=\hat{\mathbf{s}},\mathbf{H}\right)}{f_{y|H}\left(\mathbf{y}\middle|\mathbf{H}\right)} \qquad 2$$

After maximizing expression (2), one can get the solution which is known as ML estimator:

$$\hat{\mathbf{x}}_{ML}=\underset{\hat{\mathbf{x}}\in\{\pm1\}^{N_T}}{\arg\min}\left\|\mathbf{y}-\mathbf{H}\hat{\mathbf{x}}\right\|^2 \qquad 3$$

Since ML decoder searches all the possible signals, with increasing number of users and receive antennas, the computational complexity increases exponentially and requires a search of $O\left(2^{N_T}\right)$.

B. Deep MIMO DecoderArchitecture

In [Deep MIMO Detection] the architecture of the MIMO detector is based on the projected gradient descent where:

$$\hat{\mathbf{x}}_{l+1}=\prod\left[\hat{\mathbf{X}}_l-\lambda_l\frac{\partial\left\|\mathbf{y}-\mathbf{H}\mathbf{x}\right\|^2}{\partial x}\bigg|_{\mathbf{x}=\hat{\mathbf{x}}_l}\right]$$

$$=\prod\left[\hat{\mathbf{x}}_l-2\lambda_l\mathbf{H}^T\mathbf{y}+\lambda_l\mathbf{H}^T\mathbf{H}\mathbf{x}_l\right] \qquad 4$$

Where $\prod[\cdot]$ represents a nonlinear projection operator, the estimate of **x** and the step size in l^{th} iteration is $\hat{\mathbf{x}}_l$ and λ_l respectively. Our deep learning based MIMO decoder follows the same paradigm. It consists of L repetitive layer where each layer consists of some sub layers. The architecture of the proposed MIMO detector is shown in Fig.1. This detector takes channel matrix **H**, received signal **y** and $\mathbf{x}_l$ as input where **H** and **y** is fixed for all the layers and $\mathbf{x}_l$ is the estimate of **x** in the l-1th layer of this detector. One main layer of this network has two sub layers, which are represented through following mathematical expression.

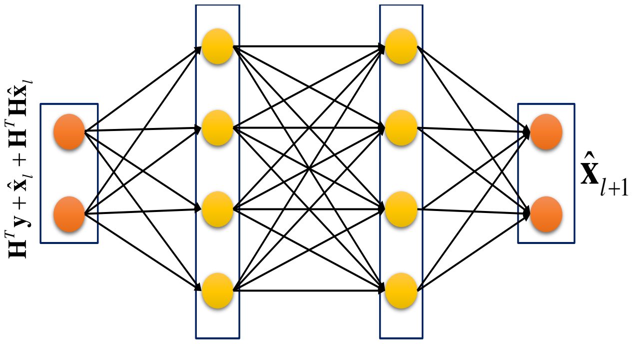

Fig. 1. Layer Structure of the proposed MIMO Detector

$$\begin{aligned}Z_l&=\operatorname{Re}Lu\left(W_{4l}[p_l+q_l+r_l]+b_{4l}\right)\\ \hat{\mathbf{x}}_{l+1}&=\Psi_l\left(W_{5l}Z_l+b_{5l}\right)\end{aligned} \qquad 5$$

Here, $p_l=W_{1l}\mathbf{H}^T\mathbf{y}+b_{1l}$, $q_l=W_{2l}\hat{\mathbf{x}}_l+b_{2l}$, $r_l=W_{3l}\mathbf{H}^T\mathbf{H}\hat{\mathbf{x}}_l+b_{3l}$, ReLu is the rectified linear unit defined as ReLu(x) = max{0, x}, l = 1,2,3,…L, and $\Psi_t(\cdot)$ is a piecewise linear signum operator defined in [Deep MIMO Detection] equation (6) and plotted in Fig. 3 for different value of t.

$$\Psi_t\left(x\right)=-1+\frac{\operatorname{Re}Lu(x+t)}{|t|}-\frac{\operatorname{Re}Lu(x-t)}{|t|} \qquad 6$$

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The expression of Z_l and $\hat{\mathbf{x}}_{l+1}$ is derived from gradient descent algorithm where we are applying standard non linearity in the terms of W_{kl} as random weight and b_{kl} as bias term in l^{th} layer. These non-linearity lifts the input to a higher dimension which are common in Deep learning.The dimension of p, q and r is $N_t \times 1$ whereas after addition of p,q and r, the dimention of Z_l is also $N_t \times 1$. The single layer of the proposed MIMO detector is represented in Fig. 2.The parameters of this deep learning based MIMO detector that need to be optimized during the training are:

$$\{W_{kl}, b_{kl}\}_{k=1, l=1}^{k=5, l=L}$$

The loss function used in this decoder is mean square error (MSE) between the transmitted and the estimated symbols at each layer.

$$loss = \sum_{l=1}^{L} \left\| \mathbf{x} - \hat{\mathbf{x}}_l \right\|^2 \qquad 7$$

Using sochastic gradient descent[20,21 Deep MIMO Detection] algorithm with Adam Optimizer [12 Deep Learning based MIMO Communication] weight updates are computed by using the loss gradient. During training, we have used batch processing in which we have used 5000 data samples at a time in each iteration. Here for proper learning of the MIMO decoder, we have trained our decoder for 50000 iterations. Training was done on a standard intel Xeon 4114 (10C/20T 2.2G 13.75M 9.6GT UPI) processors with 2x11 GB nvidia GTX 1080 Ti GPU cards took 5 hours.

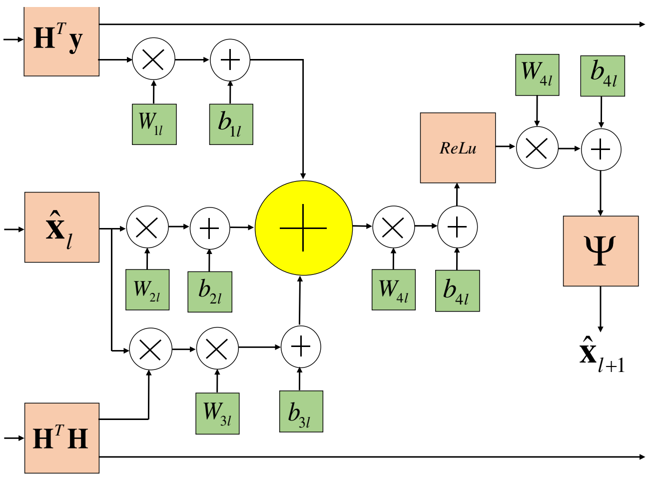

Fig. 2. Network structure of l^{th} layer of proposed MIMO Detector.

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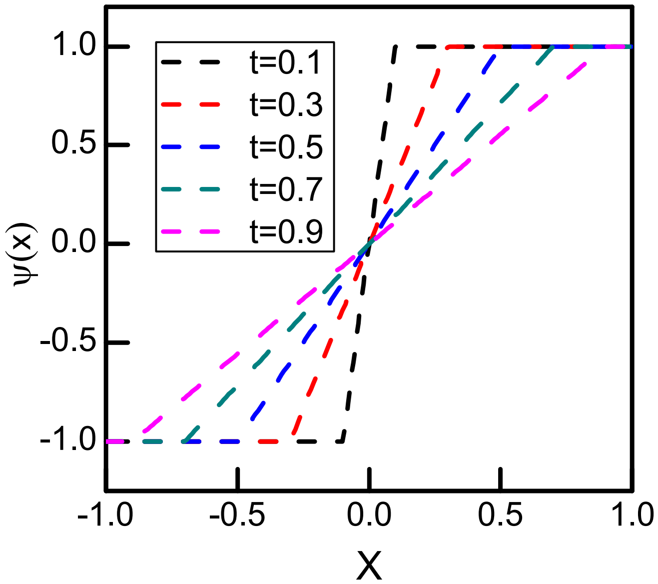

Fig. 3. A graph of signum function $\Psi_t(x)$ for different value of t

III. Simulation Results

In this section we have trained the proposed deep learning based MIMO decoder described in previous section and evaluate the Bit Error Rate (BER) performance, complexity and timing analysis over a wide range of SNRs.

For training of this model, we have generated the channel matrix **H** having channel coefficients as independent identically distributed Gaussian random variable with mean zero and variance one (N (0,1)). For each batch the matrix **H** is independently generated in each iteration. We have compared the performance of the proposed decoder with following MIMO decoding algorithms.

ZF: This is the least square Zero Forcing (ZF) detector also known as decorrelator [1 Deep MIMO Detector].

MMSE: This is Minimum mean square error based MIMO detector. This detector provides optimal solution [].

SDR: Semi Definite Relaxation (an optimization technique) based MIMO decoder.

SD: Sphere decoding algorithm based MIMO decoder [].

We have simulated all these conventional MIMO system in Matlab and Tensorflow backend with numpy in Python is used to simulate the proposed Deep Learning based MIMO decoder using GPU backend.

A. Accuracy Performance

We have simulated the proposed MIMO decoder for different number of Transmit (Tx) and Receive (Rx) antennas in a wide range of SNRs. In first experiment we have chosen 30 Tx antenna with 60 Rx antenna and results are presented in Fig. 4. In this experiment, we obtained that our DNN based MIMO detector shows better performance than ZF and DetNet. Compared to SDR, our DNN based MIMO decoder gives better performance up to 13 dB SNR value and after 13 dB both the decoders have same accuracy performance. In second experiment, we have chosen 20 Tx antenna with 30 Rx antenna and results are presented in Fig. 5. In this experiment, we obtained that our presented MIMO detector shows better performance than ZF and DetNet whereas it manages to provide similar accuracy than SDR in low SNR range.

B. Timing and Complexity Analysis

One of the main aspect of any decoding algorithm in communication system is timing and complexity analysis means how much time a decoder takes to decode one frame of message. For timing analysis we have simulated DetNet, ZF and proposed decoder on the same hardware platform. In Fig. 6, we have shown the graph of time taken by DetNet and SDR based decoders for a wide range of SNR. In this graph on y axis, values are normalized with respect to time taken by our presented decoder. This simulation shows our proposed decoder runs 164 times faster than DetNet whereas it

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runs 28200 times faster than SDR based MIMO decoder. In Table I. complexity of the deep learning networks DetNet and the proposed detector is presented.

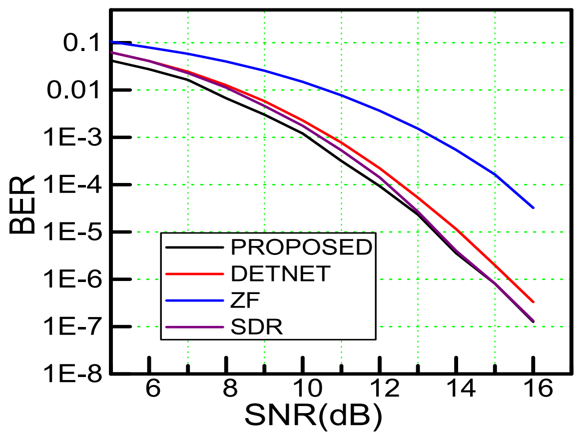

Fig. 4. Accuracy performance (BER vs SNR) graph of MIMO decoders. For Tx= 30, Rx= 60 antennas.

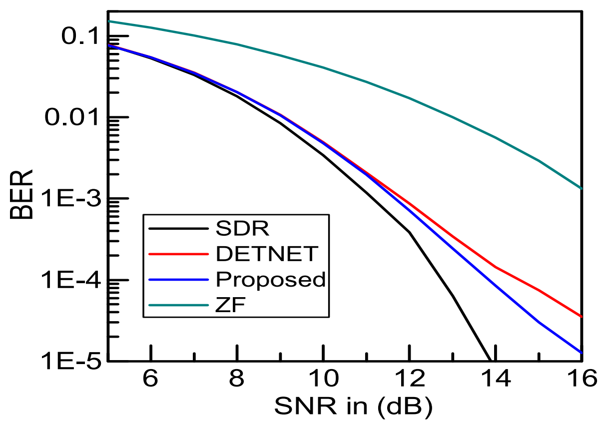

Fig. 5. Accuracy performance (BER vs SNR) graph of MIMO decoders. For Tx= 20, Rx= 30 antennas.

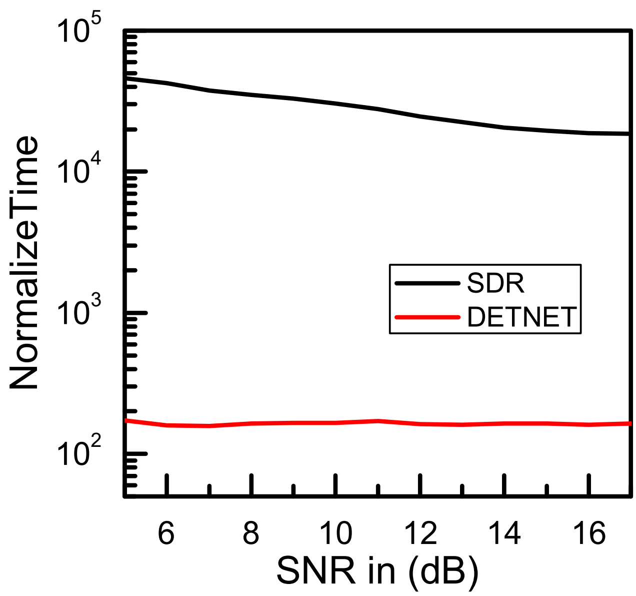

Fig. 6. Normalize Time(Time/Time taken by proposed Decoder) vs SNR for DetNet and SDR based decoders.

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TABLE I: Number of Network Unit Edge Comparision

No of Tx and Rx Antennas	Network	Unit Edges
Tx=30, Rx= 60	Proposed	4400
	DetNet	85600
Tx= 20, Rx= 30	Proposed	3300
	DetNet	62300

IV. CONCLUSION

Conventional MIMO decoders decodes the received signal in an iterative manner. The algorithms of these are based on approximate behavior of real word systems, and thus they provides suboptimal solution giving a possibility of further improvement. The proposed MIMO decoder has proven to be less complex, computationally efficient and has optimal accuracy. This detector is suitable for time varying channel scenario where channel state is perfectly known to receiver. Simulation shows that presented MIMO decoder can decode signal accurately over a wide range of channels after a single time training.

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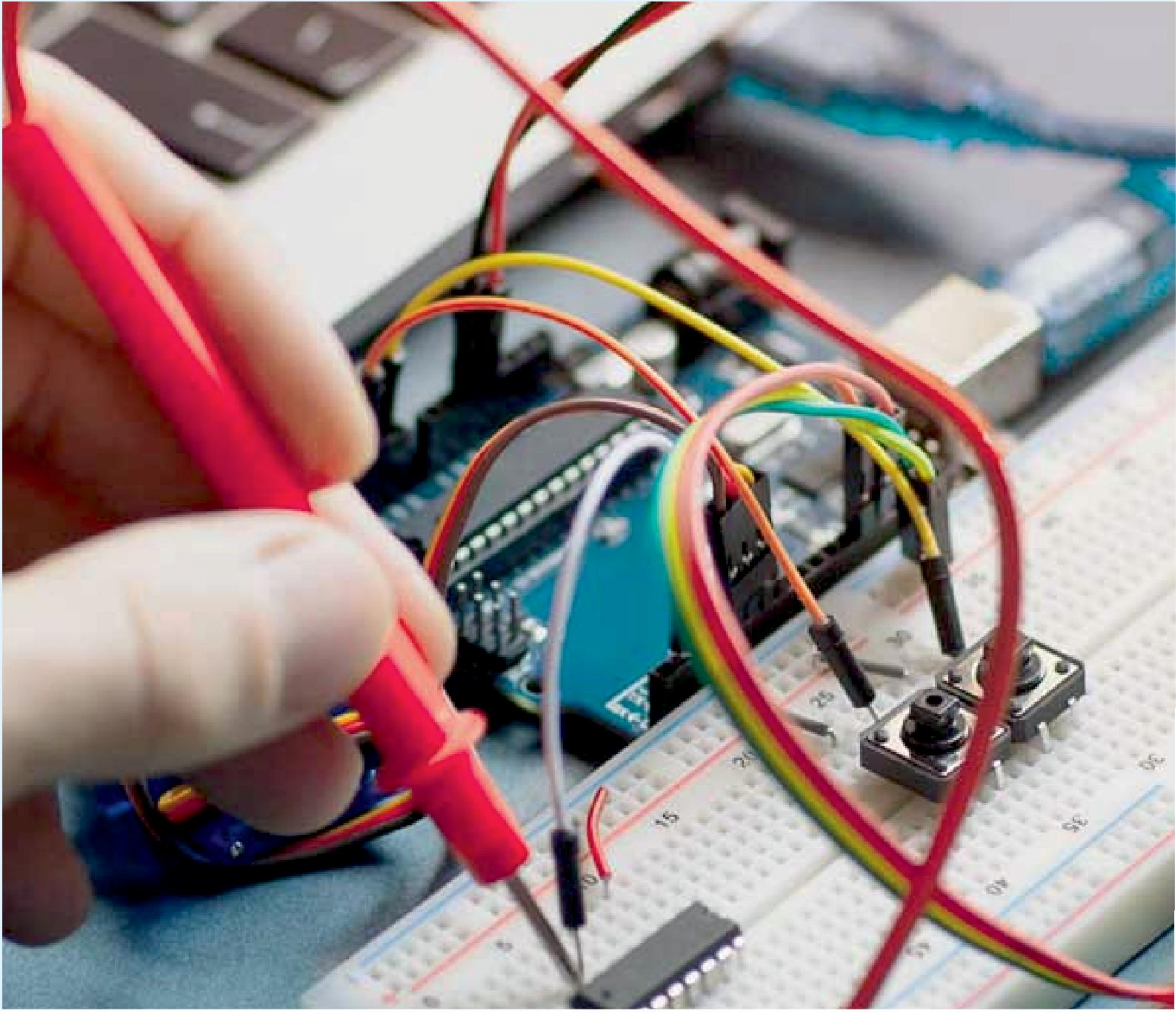

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