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Hybrid Multilayer Perceptron Back Propagation Using Channel Equalization in Neural Networks

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ABSTRACT

Inmostdigitalcommunicationsystems,bandwidthlimitedchannelalongwithmultipathpropagationcausesISI(InterSymbolInterference)tooccur.Thisphenomenoncausesdistortionofthegiventransmittedsymbolduetoothertransmittedsymbols. WiththehelpofequalizationISIcanbereduced.ThispaperpresentsasolutiontotheISIproblembyperformingblindequalizationusingANN(ArtificialNeuralNetworks).ThesimulatednetworkisamultilayerfeedforwardPerceptronANN,whichhasbeentrained byutilizingtheerrorback-propagationalgorithm.Theweightsofthenetworkareupdatedinaccordancewithtrainingofthenetwork.Thispaperpresentsaveryeffectivemethodforblindchannelequalization,beingmoreefficientthanthepre-existingalgorithms.Theobtainedresultsshowavisiblereductionin the noisecontent.

KeyWords: BlindChannelEqualization,NeuralNetworks,NoisySignal,MultiLayerPerceptron, Error-BackPropagation.

I. INTRODUCTION

With the passage oftime, digital communicationhasalmostprevailedanalogcommunication.Prominentfactorsbehindthecurrentsituationaretheescalatingdemandandfalling prices of digital equipment.Digitalcommunicationbasicallyincludes transferringofcertaindigitalinformation for instance voice, images or data from the transmitting end to the receiving end, but the data transferred should bereceivedintheactualform[12].Practicallythiscannot be achieved. ISI is one of the most influential problems faced practically in digital communication.Thiscausesdistortiontosomeofthetransmittedsymbolsduetoother transmitted symbols. Performingequalizationonthechannelcanminimizethe ISI.ThetwomajorreasonsofISIinachannelareasfollows:

(1) As the channel used for communication has a limitedbandwidth,itcausesthepulsewaveform passing through it, to disperse or spread. If we considerachannelwithamuchlargerbandwidth incomparisontothepulsebandwidth,thespread ordispersingofthepulseshouldbeminimal.On the other hand when the bandwidth of the channelisalmostsameasthesignalbandwidth, the spreading will exceed the symbol duration andcausethesignalpulsestooverlap[2-4].This overlapping of symbols is called interference betweensymbols.

(2) Multipath is a signal propagation phenomenon due to which signals may reach the receiving antenna by two or more paths. This causesthetransmittedsignaltobedispersedintime,which sults in overlapping of different transmitted symbols. This is also known as ISI, which can causehigherrorrates,ifnotcompensated[2,4].

The ISI problem can be solved by devising a means to offset or minimize the ISI at thereceivingendbeforedetection.Anequalizercanbeusedasacompensatorforthe ISI.Manyequalizationtechniqueshavebeenproposed and implemented. In some techniques, there is a need to transmit a training sequence prior to signal transmission and some perform equalization without using a training sequence[5-6].Studyingtheprevioustechniquesshowedthepresenceofnoiseevenaftertheequalizationprocess. Thismotivatedustoproposeamethodwhichwouldreduce the noise to a minimal level. This can be achieved usingANNs,whichhastheadvantageofaccuracyandprovidesuswithfasterresponse.Inthefollowingsectionwehave discussed channel equalization and itstypes.

II. CHANNEL EQUALIZATION AND BLINDEQUALIZATION

One of the most prominent functions for the receivers in many data communication systemsischannelequalization.Therequirementfordatacommunicationisthataspecificanalogmediumbeusedtotransmitthedigitalsignalsfrom the source to the receiver. Practical restraints in analog channels make them imperfect and may causeundesired distortions to be introduced [7-8]. In linearly distorted channels, the distortion can be effectively removed and compensated with the help of channel equalization. In other words inter symbolinte

rferencecanbemitigatedby performingequalization. Here the equalizer coefficients are initially adjusted by transmitting a known trail sequence to the receiver.
However,incertainsituationssendingatrainingsequenceiseithernotfeasibleoriscostly.Ablindequalizerattemptstorecovertheobliquely ISIseveredtransmittedsignalwithoutusing a training sequence. This can be achieved bycomputingtheinverseofthechannel.Undersuchcircumstancesitis required that the receiver synchronizes itself with the received signalandadjusttheequalizeraccordingly.This is known as blind equalization. The input signal andthechannel characteristicsdefinetheperformanceofablindequalizer[8-9].Theprobabilitydistributionforthechannel input should also be known. The general function of a blind equalizer can be understood by Fig. 1.
Somegoodexamplesofblindequalizationarecablemodem and digital cable TV. The blind equalization technique makes use of the transmitted sequence statistics.Givenaresomebasictechniques/algorithmsusedforperforming blindequalization.

LeastMeanSquareAlgorithm

This is a linear adaptive filtering algorithm that is based on the stochastic gradient algorithms [2]. Stochastic gradient defines a cost function based on mean of the squared error [10-11]. Then the steepest descent is computed by considering the minimal error on the error surface. This algorithmis made upoftwoparts.Inthefirst half, the transversal filter output is calculated using the tap inputs and by computing difference between output of the filter and the desired/required response, an errorterm.Inthesecondhalf,usingtheerrortermthetapweights are adjustedaccordingly.

ConstantModulusAlgorithm

CMA(ConstantModulusAlgorithm)isoneof themajorly used adaptive algorithms for performing blindchannelequalization.Inthistechnique,theconstantmodularityof the applied signal is used as the requiredproperty.Hereanytransmittedsequencewhichpresentsaconstantphase offset can be considered as the right sequence at the receiversince thephaseshiftdoesnotchangetheconstant modularity property of a signal. This contrary to LMS (LeastMeanSquare)errorsurfacegivesusmultipleminima. Out of which the most acceptable solution will beconsideredastheglobalminimaandallotherwillbelocal minima. Due to this fact, the CMA has a slower convergence rate than LMS [2,10]. CMA provideslowcomputationalcomplexity.Itisrobustagainstadditive

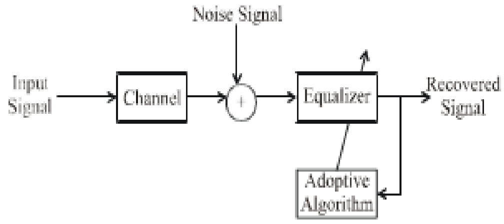

FIG. 1. BLIND EQUALIZATION GENERAL BLOCK DIAGRAM

noise and it also provides absence of cost dependentlocalminima.ThesearethereasonswhyCMAispreferred over otheralgorithms.

FractionallySpaceConstantModulus Algorithm

By using fractionally spaced equalizers, we can develop another variation of transverselinearfilters[5,12].InFSECMA(FractionallySpaceConstantModulusAlgorithm)thespacingintervalbetweentheequalizertapsisasmallpartofthetotaltimingofthesymbol.Itsamplesthereceived signal at a rate higher than the input signal. This factor makes fractionally spaced equalizers to produce error in terms of time. Performancewise, FSE saresuperiortoother transverse equalizers[12].

III. ARTIFICIALNEURALNETWORKS

ANNisbasicallyacomputationalsystem,whichisbasedonthestructure,theabilitytolearnandprocessingmethodjustlikethehumanbrain.AnANNbasically comprisesof a huge amount of very simple elements inspired by neurons, along with a huge number of weighted connections between these processing elements [11]. Having distributed representation of knowledge overthe connections, ANNacquiresknowledgethroughadefined learningprocess.
The distinct features of ANNs include

- Hugeparallelism
- Distributiverepresentation
- Ability tolearn
- Ability togeneralize
- Faulttolerance

There are three fundamental elements of ANNs; Processing Units, topology and learning algorithm [11].

Perceptron/Multilayer Perceptron Network

The perceptron model comprises of only one neuron having a linear weighted net function and a threshold activation function. Every neuron in a given layer thatis arranged in such a fashioniscalled as a perceptron[11,13].

Inputwillbeinparalleltoalltheneuronsinsuch alayersimultaneously.Perceptronnetworkshavingonly onelayer are able to classify linearly separable problems only. In situations where we have non-separable problems, one layer is not enough, and thus, it is required to use more layers.Networkwherealongwiththeoutputlayeroneor more hidden layers that are made up of hidden neurons are introduced, are known as Multi-layer (feed-forward) network, as shown in Fig.2.

In such a network each layer of neurons (i.e. eachperceptron) is capable to dividing a space linearly. Considering this division process in two dimensionswouldbelikedrawingastraightlineacrosstheCartesiangridandlikeslicingacubeintohalvesalong anyarbitrary plain in three dimensions. A similar partition can be considered for higher dimensions but that cannot be visualized. However, we can considermultiplecascadedlayers,eachlayerperforminganumberofsuchprocesses,i.e. each neuron linearly partitioning a plane, but this partitioning must be along a different (hyper) plane for each layer. Considering one set of lines on the grid will giveusbinarypartitioning:0or1[11,14]however,ifwefurtherpartitionthealreadypartitionedspace,itwillfurtherrefineourspecificregion.Againifweconsiderthatregionandlinearlydivideit,wewillobtainanevenmorerefinedregion.Andsoon.Informallywecanevenshowthat anyregioncanbedefinedinnspacebyjustusingthreelayers[11].Herethefirstlayerwilldrawthelines.Theselines will then be combined into convex hulls by the second layer. The third layer combines the convex hulls and forms arbitrary regions. In this way we can build a three layer cascaded perceptron NN known as MLP (Multilayer Perceptron). The MLP swereputintopracticeonlywhenlearningalgorithmsweredevelopedforthem,oneofthembeingtheerrorback propagationalgorithm[11,14].

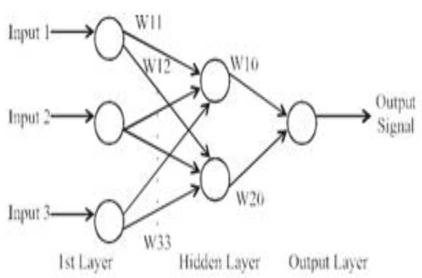

FIG. 2. A FULLY CONNECTED MLP NETWORK

ErrorBack-PropagationAlgorithm

One of the most popular learning paradigms for MLP networksistheErrorback-propagationalgorithm[11].This algorithmusesthesquarederrormeasureforoutputnodes,i.e. it works on the principle ofthedeltarule. Consideraperceptronweightw_{ji};generalizeddeltarule isusedtoupdatetheweightcorrespondingtoaconnectionfromneuroni to neuron j. There are two phases of the generalized delta rule. During the first phase the output values for each unit are computed for the applied inputs. The computed output value is then compared with the required value. This comparison gives an error term for each output unit. During the second phase a reversepass takes place throughout the network. This involves the error term proceeding towards each unit within network and the required weight alterations are computed accordingly[10-11,14].simulations were performed in MATLAB and its Neural Network Toolbox.

3.1 Simulation andResults

ThebasicgoalofthedesignednetworkistoperformblindequalizationbyusingMultiLayerPerceptronnetworkand then comparing the obtained results with the previouslyimplementedalgorithmsdesignedforconventionalblindchannelequalization.MATLABwasusedtoperformthe simulations on M-QAM (M-Ary Quadrature Amplitude Modulation) modulated signals[15].TheinputsignalissubjectedtowhiteGaussiannoise.LMSAlgorithm,CMAandFSECMAwerealsosimulated[5,9].Fig.3showsthe4QAMconstellation diagram of our transmitted signal and Fig. 4 shows the transmitted signal after being subjected to noisewhich,inourcaseisAWGN(Adaptive

$$w_{ji}= w_{ji}+\Delta w_{ji}$$

$$\Delta w_{ji}= -\eta\left(\frac{\partial \varepsilon}{\partial w_{ji}}\right)$$

WhiteGaussianNoise).Figs.5-7showthereceivedsignal after being equalized using LMS, CMA and FSE-CMA blind equalization methodsrespectively[5,9].Asitcanbe seen that the transmitted symbols have been recovered but the presence of noise is still visible. Fig. 8 showthe

Where shows the instantaneous sum of squared errorsand isthelearningrate.Thislearningratewilldecidethespeedinwhichtheweightswillbeabletoadjustforeverytimeadvance.Thenegativesignshowsthatthechangingofweightswillreducetheerror[11].

IV. NETWORK DESIGN OF MLP BASED BLINDEQUALIZER

In this paper we have designed an MLPnetwork architecture.Thenetworkisa3-layerfeedforwardnetwork. The network comprises of nine neurons; eight neurons areused within the hidden layer andoneneuronisusedin the output layer. Tangent sigmoid activation function is used for the hidden layer and linear activation function fortheoutputlayer[7,10-11].

Errorbackpropagationlearningalgorithmisusedtotrai n the network. The network weights and biases are automatically adjusted with training process.ThetrainingofourMLPbasedequalizer.Heretthegoalwassetto0.0001andournetworkachieveditin366epochs.Fig.9 showstherecoveredsignalusingourMLPnetworkandit clearly has the least noise content than the previously developedalgorithms.

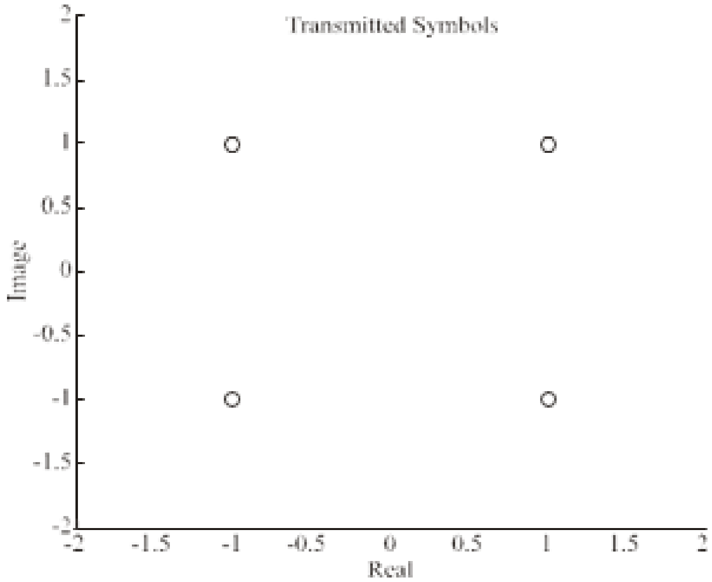

FIG. 3. CONSTELLATION DIAGRAM OF 4 QAM SIGNAL

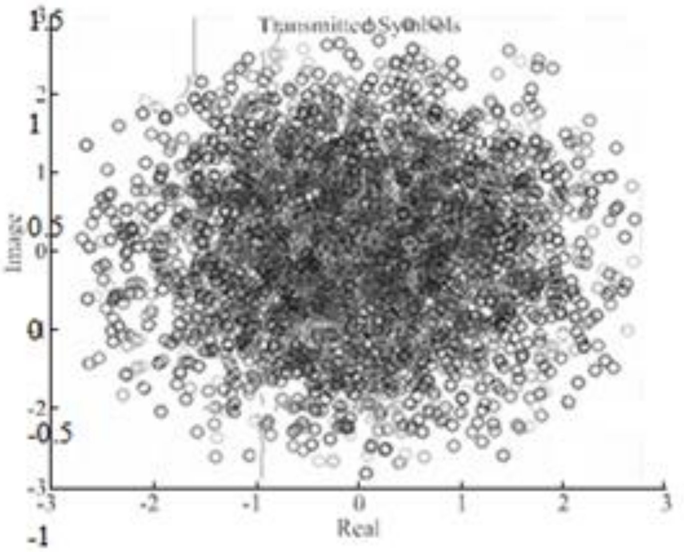

FIG. 4. RECEIVED 4 QAM NOISY SYMBOLS

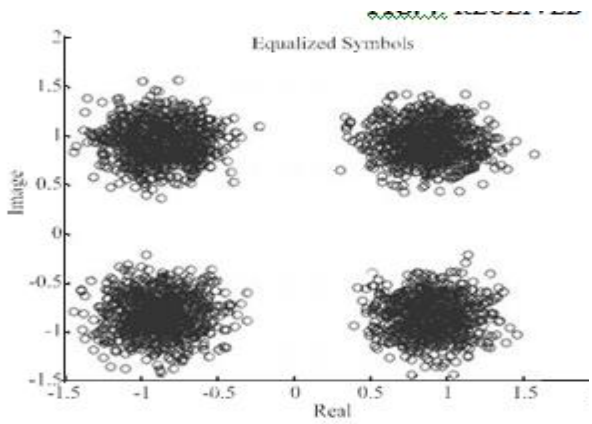

FIG. 5. 4-QAM EQUALIZED SYMBOLS USING LMS ALGORITHM

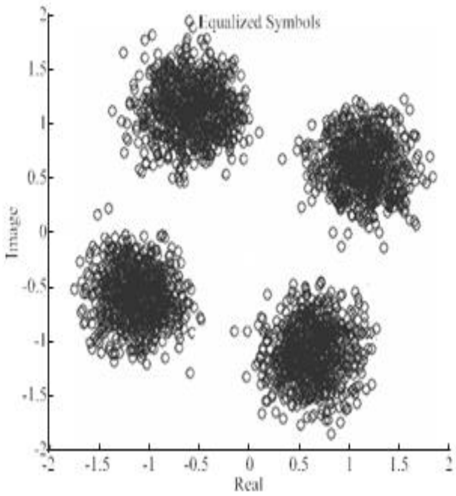

FIG. 6. EQUALIZED 4-QAM SYMBOLS USING CMA ALGORITHM

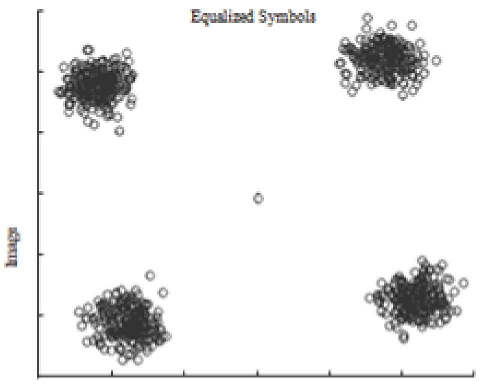

FIG. 7. EQUALIZED 4-QAM SYMBOLS USING FSE-CMA

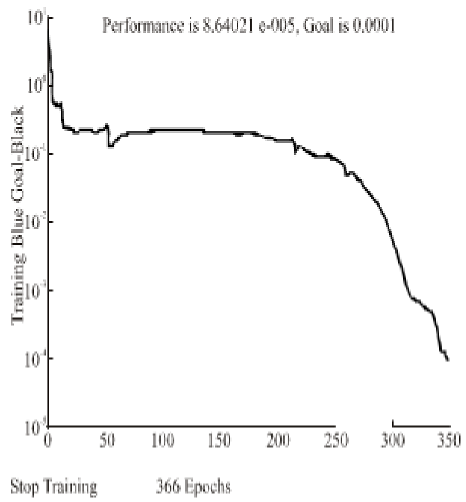

FIG. 8. TRAINING OF THE MLP BASED NEURAL NETWORK EQUALIZER-ACHIEVING GOAL IN 366 EPOCHS

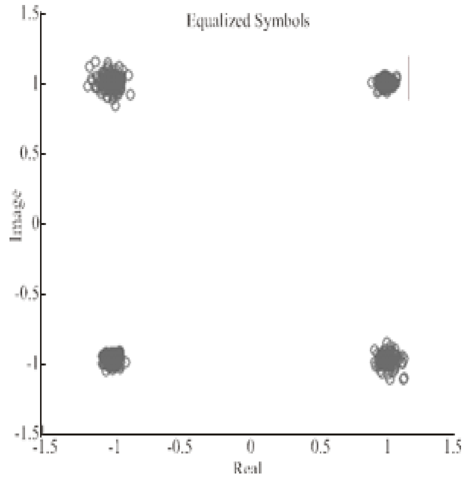

FIG. 9. EQUALIZED 4-QAM SYMBOLS USING MLP NETWORK, NEURAL NETWORKS

V. CONCLUSIONS

In this paper blind equalization using ANNs was performed. This was achieved by using the neural networks toolbox in MATLAB. By using MATLAB communicationtool box, noisyanddistortedsignals were generated by subjecting the randomly generated QAM or Q-PSK modulated symbols with AWGN. The ANN based on MLP was trained using the error back-propagation algorithm. The same noisy data was then applied to some of the most common blind equalization methods (LMS, CMA and FSE-CMA). The ANN, MLP network showed much better results than the above mentioned methods. According to the previous work done, some algorithms converged fast and responded quickerbutlackedintermsoffullyeliminatingthenoise term from the received signals and some algorithms mitigated the noise signal present but converged or responded slower. By using ANN we are able to achieve both advantages, i.e. the network training time was very less and according to the results our network showed minimum noise in the received signal. Our network is simpler in terms of calculations and computations and apart from requiring fewer taps, it takes lesser time in decoding the channel inputs than CMA blind equalizers. This shows that MLP based blind equalizer proves to be a good alternate for channels with severeISI.

This research can be further extended by considering higher bit rates such as 8-QAM or even 16-QAM. Different ANN models and learning methods can be implemented along with varying the number of neurons and hidden layers.

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