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Recurrent Neural Network Based Multi-user Detection

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Summary of theses

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1 Introduction

Novel telecommunication systems has been evolved in an unpredictable way recently. Behind the development of such systems one can find several reasons, including users' satisfaction, competition in economic sense and efficient usage of radio resources. As an engineer, I focused on the latter one. In the dissertation I propose methods, with which more efficient usage of available frequencies becomes possible in exchange for non-expensive algorithmical complexity.

Though the reader may find it a hackneyed phrase, radio resources are finite and expensive: mobile service providers pay millions for small frequency bands. Thus available resources should be exploited in a clever manner. To reach greater efficiency, more complex devices are of use, i. e. demand for frequency is replaced by algorithmic complexity. More complicated devices help us to support more gross datarate on the same channel. As an example, satellite based diffusion provided one sole channel in 7 Mhz in the past, but nowadays more digital channels can be broadcasted in the same medium. Here, algorithmical complexity is represented by the digital video coder and decoder. Without those, the stream cannot be transmitted or received.

In the case of mobile service providers, one channel is shared among many users, i. e. there are more traffic in the same frequency band and time slot, in every cellular system independently of its technology. Sharing the resources yields interference (joint disturbation of traffics), which can seriously deteriorate the performance of the receivers. In the literature, the effect of interfering signals was first payed attention in the early 1980s, when the application of interference limited systems (e. g. code division multiple access, CDMA) became a topic. To eliminate the effect of interference, Verdú proposed the application of multi-user detectors [1], where the detector differs from the traditional one, by taking into account the disturbing effect of other users. This makes the detection algorithmically more complicated, however there could be much more users sharing the same bandwidth in the system. Thus spectral efficiency (transmitted information per unit frequency and unit time) increases. As one can see the aim of multiuser detection is the same as explained previously; algorithmical complexity is introduced to obtain higher efficiency.

Of course it is also important how complicated the method is. The optimal multi-user detector is useless since one cannot implement it for real-time operation. Engineers should provide algorithms which can be implemented in existing devices with this end in view. Since the performance and the complexity of a method are proportional to one another, the other task of the engineer is to make a compromise. The least complex, but sufficiently efficient algorithm should be applied here. The algorithm proposed in the dissertation fulfills both requirements.

2 Methods of research

Multi-user detection methods which are capable of providing sufficiently good link quality are in the focus of the research [1]. While the optimal detector is given in a closed formula, but its computational complexity grows exponentially ($\sim O(|\mathcal{A}|^M)$, where M denotes the size of the problem and $|\mathcal{A}|$ is the size of the constellation set), suboptimal multi-user detectors with polinomial complexity ($\sim O(M^n)$, where n is a finite number) are of great interest. The earliest linear solutions had a typical complexity of $\sim O(M^3)$, since a matrix is inverted (and used in a multiplication, which itself raises a complexity of $\sim O(M^3)$). Many non-linear architectures have been proposed as a multi-user detector [1]. The inventory of really novel structures is obviously hard, because the literature of the topic is rich. In the dissertation I propose a suboptimal solution (the stochastic recurrent neural network based detector), which had not been published in scientific journals or conferences, while its complexity is simply $\sim O(M^2 \log(M))$.

Publications in this area usually start with the mathematical model of the radio communication link, which yields remarkably complex description. Thus analytical investigation is almost impossible in most cases. In the dissertation I show that applying linear modulation the mathematical model yields a linear form—independently of the propagation model in the channel, the multiple access scheme, and the receiver algorithm—thus it can be given in vector–matrix form. The linear model makes it possible to easily describe, compare and simulate the algorithms.

The derivation detailed in the dissertation is not similar to any other method which can be found in the literature of this area, but draws on the theory of Boltzmann machines[2]. It is possible to prove mathematically that there is a quadratic energy function, which monotonously decrease in each iteration, for every recurrent neural network [3]. Thus the recurrent neural network minimizes the energy function locally [3]. A noise source inside the stochastic recurrent neural network assures that the network does not stuck into local optima. The variance of the noise must be continously decreased as iterations pass. Stochastic recurrent neural networks have a great advantage over Boltzmann machines that they inherit engaging properties of recurrent neural networks. That is, they are capable of finding the global supervalue of the energy function coupled to the network. The optimal multi-user detector also provides the supervalue of a quadratic form, thus stochastic recurrent neural network algorithm is ideal for suboptimal multi-user detection.

Another related research activity is supporting adaptivity (i. e. the detector should be able to adapt to the changing environment), and the development of blind procedures (the detector is able to work without a-priori knowledge about the channel). In the dissertation I deal with both areas. My proposed methods are based on Kohonen's Linear Vector Quantizer (LVQ) and Self-Organizing Map (SOM). Since these methods can estimate vectors, and we need to estimate a matrix, some modifications are required to make it applicable. The method was mentioned in previous publications [4], although the description of the modification have not been found in any articles. The mathematical description is also detailed in the dissertation.

3 Novel Scientific Results

Every scientific result is connected to multi-user detection or recurrent neural network theory, thus the organization of theses was based on dismemberment of these topics. There are 10 subtheses in 4 theses formulated here in total.

Thesis Group 1 *Behaviour of discrete stochastic recurrent neural networks. (See Section 3.2 in the dissertation.)*

Thesis 1.1 *I proved that the complex logistic distribution*

$$F(z,\gamma) = \frac{1}{1 + e^{-\gamma \mathrm{Re}\{z\}} + e^{-\gamma \mathrm{Im}\{z\}} + e^{-\gamma(\mathrm{Re}\{z\}+\mathrm{Im}\{z\})}},$$

and QPSK alphabets for the neurons

$$\mathcal{A} = \frac{1}{\sqrt{2}}\{\pm 1 \pm j\},$$

then the stochastic recurrent neural network stays at the state belonging to the global supervalue of the energy function with the highest probability. [6] (See Theorem 3.10 in the dissertation.)

The binary case was proven by Prof. Levendovszky in his D.Sc. theses. The QPSK case is more difficult than the binary, since computations in the complex plane are more complicated. In the dissertation I proved that in the complex plane the global optimum has the highest probability, if QPSK constellation is applied.

Thesis 1.2 *I proved that applying complex logistic distribution to generate the noise inside the neurons, the QPSK alphabet stochastic recurrent neural network globally optimizes the quadratic energy function of the network asymptotically with one probability. Likewise, I proved that applying real logistic distribution*

$$F(x,\gamma) = \frac{1}{1 + e^{-\gamma x}},$$

to generate noise values inside a binary ($\mathcal{A} = \{\pm 1\}$) stochastic recurrent neural network, it globally optimizes the quadratic energy function of the network asymptotically with one probability. [8] (See Theorem 3.11 in the dissertation.)

As a consequence of the previous theorem one can find the global optimum with one probability if the noise variance is decreased to zero (independently of the method of "cooling"). In the dissertation I show that both in the binary and in the QPSK case the global optimum is reached with one probability independently of the decrease of the noise variance.

Thesis 1.3 *Stochastic recurrent neural networks can be modelled as Markovian processes, if the states of the chain are defined by the outputs of neurons. I defined a condition on matrix $\boldsymbol{P}$ containing the state transition probabilities of the Markovian process, which makes stationary probabilities of different states comparable:*

$$\frac{\pi_A}{\pi_B} = \frac{P_{BB} + \boldsymbol{p}_{B*}^{\mathsf{T}}(\boldsymbol{I} - \boldsymbol{P}_*)^{-1}\boldsymbol{p}_{*B} - 1}{P_{AA} + \boldsymbol{p}_{A*}^{\mathsf{T}}(\boldsymbol{I} - \boldsymbol{P}_*)^{-1}\boldsymbol{p}_{*A} - 1},$$

where A and B denote states, P_{ij} is the probability of arriving at state i if state j was left. Asterisk ($*$) denotes every other states. The stationary probability of staying at state i is denoted by π_i. (See Theorem 3.7 in the dissertation.)

For Markovian description, the stochastic recurrent neural network must have Markovian properties and it must be aperiodic and irreducible too. All three properties can be easily proven. This thesis defines a condition on comparing the stationary probabilities of any two states which is purely based on the knowledge of state transition probability matrix. Note that the computation of the above equation does not need any information about the stationary probability vector, which is the solution of $\boldsymbol{p} = \boldsymbol{P}\,\boldsymbol{p}$. Moreover, the inverted matrix must contain positive elements: $(\boldsymbol{I} - \boldsymbol{P}_*)_{ij}^{-1}$ tells how much time is needed on average to reach state j from state i, if both states A and B are visited.

Thesis Group 2 *Multi-user detection applying recurrent neural networks. (See Section 4.5 in the dissertation.)*

Thesis 2.1 *I have proven [6, 12, 14] that there is an equation between the parameters of the communication system model ($\boldsymbol{y} = \boldsymbol{R}\,\boldsymbol{d} + \boldsymbol{n}$) and the ones of the recurrent neural network. For the general receiver, one gets the following equalities:*

$$\begin{aligned}\boldsymbol{W} &= \boldsymbol{R}^{\mathsf{H}}\boldsymbol{C}^{-1}\boldsymbol{R}\\ \boldsymbol{u} &= \boldsymbol{R}^{\mathsf{H}}\boldsymbol{C}^{-1}\boldsymbol{y}.\end{aligned}$$

For the channel matched filter, matrix $\boldsymbol{R}$ is Hermitian, the covariance matrix of the noise equals $\boldsymbol{R}$ too, thus the parameters become simply

$$\begin{aligned}\boldsymbol{W} &= \boldsymbol{R}\\ \boldsymbol{u} &= \boldsymbol{y}.\end{aligned}$$

(See Equations (4.39)–(4.41) and the corresponding explanations in the dissertation.)

The quadratic optimization exercise describing the optimal multi-user detection is given by the parameters of the communication system. On the other hand the energy function of recurrent neural networks is also a quadratic function (with the parameters of the network of course) and it is known that the neural network converges to a supervalue of this energy function in every iteration. We make contact between the two by representing the quadratic form of the optimal multi-user detector in the energy function of the neural network. Thus the neural network executes the optimization exercise of the optimal multi-user detector. One should not forget though that recurrent neural network can find local supervalues which is not mandatory to be the global one. The optimal detector finds the global supervalue, thus the method is a suboptimal one.

Since the stability of recurrent neural networks merely depends on the Hermitian property of matrix $\boldsymbol{W}$, it is a must for matrix $\boldsymbol{W}$ to be Hermitian. For both cases detailed above, this property is self-explanatory. The thesis proves in general that any receiver algorithm (even without channel matched filtering) can apply recurrent neural networks for multi-user detection.

Thesis 2.2 *In the dissertation it is shown that the sequentially updated multi-stage detector hides the same structure as the sequentially updated interference canceller, and the sequentially updated recurrent neural network based multi-user detector, if the number of stages is sufficiently large. The statement is analogously extended to the paralelly updated structures [6, 14]. (See Theorem 4.1 in the dissertation.)*

This statement had not been published in scientific publications before. Due to the different system models of different articles, the statement is not trivial. Articles dealing with multi-stage detection usually have different system models than articles applying recurrent neural networks for multi-user detection. At first glimpse, one may miss the identity. Due to the general model of the communication system introduced in the dissertation, mathematical equations show the similarity of different structures.

Multi-stage detectors and interference cancellers have decision stages, likewise neural networks perform iterations. The number of stages in the former ones is pre-defined before the algorithm is started, the number of iterations is determined automatically in the recurrent neural network (it is iterated until the network reaches its supervalue). If the number of stages is not less than the number of iterations of the neural network, the two method is completely equivalent with each other. Otherwise, the two method can produce different outputs.

Thesis 2.3 *I showed how the stochastic recurrent neural networks can be applied for multi-user detection, if the system model is given as* $\boldsymbol{y} = \boldsymbol{R}\,\boldsymbol{d} + \boldsymbol{n}$ *[13, 6, 12, 14]. (See Section 4.5.1 in the dissertation.)*

Recurrent neural networks have been applied to the problem of multi-user detection several times beforehand. However, the modified (stochastic) structure provides much better performance in exchange for some more computational complexity. I showed in simulations that the original structure must be modified a trifle (neurons should be extended with the additional noise sources inside), to have improved performance in the detection. Simulation results prove that notable performance improvements (fewer erroneus symbols) can be reached by a minimal increase in the number of iterations.

Thesis Group 3 *Further reduction in the computational complexity of recurrent neural networks based multi-user detectors. (See Sections 3.3 and 3.4 in the dissertation, where the funcamentals are explained and Sections 4.5.3 and 4.5.4, where the specific description is detailed.)*

Thesis 3.1 *I proposed the application of hysteresis non-linearity as the decision function. I derived an equation which lower bounds the probability of finding the global optimum. The bound depends on the parameter of the hysteresis decision function [7]. (See Section 3.3.2 and the corresponding Theorem 3.13 and Section 4.5.3, respectively in the dissertation.)*

Based on previous results [5] I showed analytically how the application of hysteresis decision function effects the network. I derived how the probability of finding the global optimum can be computed, taking into consideration the unbounded nature of noise in the communication equation. Since greater noise may still enable finding the optimal solution, the probability computed should be regarded as a lower bound. Based on simulation results one can state that hysteresis also decreases the average number of iterations in the network. As an explanation, the hysteresis prevents state changes in the case of small input values, thus state changes happen less frequent. Decrease in the number of iterations results in subsidence of computational complexity.

Thesis 3.2 *I proposed a simplified neural network, which has smaller dimensions and it is capable of handling non-bursty (continous) symbol streams. (See Sections 3.4 and 4.5.4 in the dissertation.)*

The computational complexity of recurrent neural network equals $\sim O(M^2 \log(M))$. If the neural network is divided into k independent pieces of networks, each with dimension n, where $M = kn$, then the computational complexity of the modified structure yields $\sim O(k \cdot n^2 \log(n))$, which is approximately k times less than the original one. If k is great, the method results in a remarkable saving in processing power. In the dissertation I show a method how the neural network can be simplified, if it is applied as a multi-user detector.

The simplified structure contains fewer neurons, thus it requires less computations. Moreover, due to the small size of the network, the number of iterations does also decrease. On the other hand, the modification yields less complex derivations for computing the parameters of the network, as detailed in the section of simulations. Another advantage of the algorithm is its applicability in non-bursty (continous) systems.

Thesis Group 4 *Estimation of the weight parameters of the recurrent neural network based multi-user detectors – adaptive, and blind detection with recurrent neural networks. (See Section 4.6 in the dissertation.)*

Thesis 4.1 *I showed how the linear vector quantizer (LVQ) algorithm can be used to estimate the discrete-time channel matrix and thus the parameters of the recurrent neural network based on a training sequence [7, 15, 16]. (See Section 4.6.2.2 and the corresponding Theorem 4.3 in the dissertation.)*

The previously proposed method [4], which has never been published with the mathematical proof, is applied for the estimation of the input parameter of the network, which is computed based on the discrete-time channel matrix. For proper operation, the channel matched filter is not required, however using channel matched filtering yields directly the weight matrix of the neural network. Analytical investigations have not been conducted in this non-linear network with multiple feedbacks, the author compared the adaptive and coherent solutions based on simulation results (coherent means known channel matrix in this case). As results show, the blind adaptive solution (see the next thesis) can also provide the same performance in excess of some minimal signal-to-noise ratio.

Thesis 4.2 *I derived how the modified self-organizing map (SOM) can be applied for the blind estimation of discrete-time channel matrix. (See Section 4.6.2.1 and the corresponding Theorem 4.2 in the dissertation.)*

Like in the previous case, SOM is applied as a blind estimation algorithm, and its applicability is also analytically shown. Its performance is highlighted using the simulations, and the results show its superiority among any other methods.

4 Possible Application of New Results

Multi-user detectors can be applied in any interference limited systems, where interference plays an important role (also in GSM). Systems, where interference is the most important restrictive component (like code division multiple access based systems, e. g. UMTS, or orthogonal frequency division multiplexing without guarding intervals), require the application of multi-user detection. Since third and fourth generation mobile systems belong to this category, the algorithm proposed by the author can be potentially useful for any company producing 3G or 4G detection devices.

General statements related to recurrent neural networks might be exploitable for any quadratic optimization exercise. Thus stochastic recurrent neural networks may be applied for the travelling salesman problem, or for the N-queens problem, etc. There is a research in progress in the Department of Telecommunications, in which the algorithm is applied for active noise control by acoustics colleagues.

5 Future Works

The general theorems related to stochastic recurrent neural networks (Theorems 1.1 and 1.2) are proven for binary (BPSK) and QPSK (or 4-QAM) alphabets in the dissertation. The train of thoughts applied during these proofs is supposed to be unapplicable in the case of higher constellation schemes (8-QAM, 16-QAM, etc.). However, there can be another method which can justify the above statements for general alphabets/constellations.

It was proven that the global optimum is asymptotically found with probability one by the stochastic recurrent neural network, independently of the cooling schedule (the function describing the decrease of noise variance) applied. In practice, it is not possible to iterate the network infinitely. The user must find a compromise: the function describing the cooling should yield the fastest possible convergence and the least possible performance loss at the same time. There has not been any analytical results on this function yet. However, it is mandatory if stochastic recurrent neural network is willing to work in practical applications. The linear function applied in the dissertation is obviously not optimal.

Another open issue connected to the noise inside the neurons is the nature of this noise. It is possible that noise following a distribution function other than the logistic one can provide better performance. See e. g. the simulation results, where Gaussian noise powered stochastic recurrent neural networks resulted in better performance than the one with logistic noise. Since it can be generated easily, the Gaussian noise seems to be a good choice in practical applications. However, this issue should be addressed in more details as a future work.

There are several operation modes in the modified multi-user detector. For proper operation, an artificial intelligence is needed, which can choose between different operation modes, and it can set the parameters of the detector ("parameters" include the parameter of the hysteresis decision function, the initial value of the noise, etc.). The applicability of self-organizing maps (SOM) has been considered by the author, however—due to the lack of time—it has not been worked up yet thoroughly. Other artificial intelligence methods may be potential solutions too.

The actual form of channel matrix estimation algorithms LVQ and SOM is not applicable in the case of higher level constellation schemes. The author supposes that it can be derived based on the results of the dissertation, though it has not been done yet.

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