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Back Propagation Artificial Neural Network Structure Error Reduction by Defined Factor of Capacity and Algorithm Reinforcement Method

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Abstract—This paper investigates how to reduce error and increase speed of Back propagation ANN by certain defined Capacity factor. For the years from 1965 to 1980 the use of a variety of ANNs for problem solving was relented significantly because of limitations in one layer networks that weren't good enough for enhancements of a specific issue, although there were low expectancies for even simple tasks and mathematical operations. Multi-layer networks have a serious covenant to improve this privation by more effective error reduction for example by least squares error method and a better learning factor like the one that is considered in MLP which is modified, enhanced version of Perception network that has provided a better chance of using these networks for intelligent signal processing. But the purpose of this paper is not showing capabilities of these networks alone but to consider error reduction while the weighting equations both satisfy ordinary task of algorithm and at the same time reduces presumptions of errors by a predetermined Capacitance factor that is not very anomalous to other bunch of clustering pedagogy styles anent the other types of ANNs. Unlike a single layer network with many limitations in learning, approximating and estimating a mapping function, multi-layer networks are well prepared for estimation of any uniformly continues subordination with tunable accuracy. Hidden layer in many applications does the job of enhancement, but sometimes poly-layer methods are used for this error reduction separately by some factor definitions (and new hidden parts that paper adds to gets error reduced) that paper tries to measure for exact improvements which were envisaged in design process. And as a result understand how to use Capacity factor for BPANN algorithm, and error reduction in general that holds convergence, speed improvement and error smoothing at the same time.

Index Terms—BPANN enhancement, Error smoothing, MLP, Intelligent signal processing

I. INTRODUCTION

It was always interesting for authors to use some gimmicks to make certain ANN algorithms faster by defining a new factor [1] that modifies weighting matrix to resemble a faster convergence because of inline algorithm code modifications that steps down the possibility of producing error because of σ_k factor that keeps its gradient parameter dynamically changed respect to slope parameter [2-10], this is also proportional to better learning of certain machines.

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Seemingly for latent (hidden) layers the same story but this time for Δw_{ij} occurs using small case indices while calculating first derivative of error minimized as it is equal to $-[t_k - y_k]f'(y_{in_k})z_j$ that for us will be considered as a new factor like δ_k which this new factor will be altered to get a modified optimized attenuated factor of δ'_i error by Capacity factor mostly for networks like latent type the acute new method will be applied and gets error reduced by a smoldering algorithm modification in hidden layers themselves [11,12,13]. An important fact is that the prediction capability of a Back propagation ANN or other ANNs for a large set of data is not very accurate and finally the users will (still) keep doubts about the resonating error that ignores wisdom of the application of that network because the level of trust is shrunk very high and the new algorithm cannot even change this story. As mentioned in abstract this is one of the reasons that using certain networks scaled down and the possibility of using them in real world problems applications like active drone navigation systems with atmosphere condition variations and unpredictable confronting issues is not even considered yet [14,15,18,19,22,23]. Main issue is how to have one main ANN with error reduction strategy that fulfills the need of system and at the same time gives a simple slant reduction for δ_k so each round of sums for hidden layers that uses this factor reclusively is not rectified well and this all happens in the existence of arbitrary activation function [20-30]. If user needs to design a Back propagation ANN algorithm some considerations for weighting and hidden layers should be added to scheming process in which a harmonic single stage inline error reduction happens [31] exactly at the time of weighting vectors and because error itself is used for calculation of δ_k that is for single output node y_k error compared to target t_k and it happens in learning process, the error reduction also involves hidden nodes joint with Y_k at timepieces. Weighting for first layer cannot [32,33,34,35] be modified while the new weights for other layers are not ready; the reason is simple and because δ_k is not treated as a multi stage factor for layers and weighting must be done for all layers at the same time, for e.g. Z_j with hidden value z_j and weight of v_{ij} that primarily is calculated by δ_j and because this is essential for original structure of algorithm new method wouldn't reclaim structure but tries to enhance error cutback by some strong mathematically supported ideas. As learning process for these types of networks have 3 main steps of Feed forward for input pattern, calculation and Back propagation of error and weight calculation, paper also uses the same specimen for speed improvement but using its own definitions inside new algorithm to eke learning ratio and acquisition

Capacity [36-50]. As title inculcates, improvement for error reduction has to be gathered by factor of Capacity which will be shown and this factor itself is calculated by Reliability factorr_i that is the result of calculation of p_c and p_w according to δ_j coefficient for each round of algorithm and is considered fully in algorithm implementation part [51-55].

II. APPROXIMATIONS V POINT TRACKING

A good Feed forward function estimator ANN that is used as Universal Approximator for any continues function like *Kolmogorov* that solves an important problem of multi variable function survey by single variable functions as (1-1):

$$\boldsymbol{f}\,(\boldsymbol{x}) = \sum_{j=1}^{2n+1} \chi_j\Big(\sum_{i=1}^{n} \boldsymbol{\psi}_{ij}(\boldsymbol{x}_i)\Big) \qquad (1\text{-}1)$$

Is an example of successful point tracking while the rest of the mathematically algorithm don't get even near error like it. For a network with 2 latent layers of nodes, $\boldsymbol{Z}$ and $\boldsymbol{ZZ}$ unites that can be used by bias or without any diagonal predefined value shown by $\boldsymbol{w_{0k}}$ for any output node $\boldsymbol{Y_k}$ and latent nodes bias value of $\boldsymbol{v_{0j}}$ for hidden bias node of $\boldsymbol{Z_j}$.

Robot Path Planning: Now what about a robot *path-planning* techniques that is simply divided into 2 main categories, first by current points that robots get from sensors and is called *local planning* and the second type is *global path-planning* from a map that is saved in memory and is processable and also accessible for each error reduction variable that depends on ANN type and its algorithm. The best idea for reducing error in this case is using both strategies because a map can be misleading if the path is changed fundamentally or a local planning has issue of *non-optimal solution choice*, means the path is okay but complex. For applications, robot uses several sensor data maps and compares it using for example *Cognitron* for path detecting and for this detection *excitatory* and *inhibitory* inputs denoted by e and h are considered separately and by Fukushima notations:

$$u(k) = F\left[\frac{1+e}{1+h} - 1\right] \qquad (1\text{-}2)$$

$$e - h = \frac{\epsilon - \eta}{2\eta}\left(1 + \tanh\left(\frac{1}{2}log\eta x\right)\right) \qquad (1\text{-}3)$$

Please care that an ordinary one to one correspondence relation is used for *activation function* and note how this approach can show distinction when an excitatory input must be distinguished from inhibitory one; as an example imagine movement of an object by an engine force andexternal power. If you switch machine [73] on and start to move while having an ordinary soaring speed by input variable f_e force of engine or when you push/pull that object by outer power, movement appears as that expected output but this time engine is off and the source of potency is different and dynamic response of object is different too! By this notation it is possible to distinguish 2 different types of variables that both have the same result.

III. ALGORITHM CONSIDERATIONS

Generalized Back propagation single layer ANN can have several latent layers in which each input node receives one input signal (rare cases the input itself can be divided separately and receives mixed signal like adders or a bias can have similar task) and sends this signal to latent layers nodes of Z_i in first stage. Activators, then calculate correct value and send it back for ZZ_i unites again activation process happens for second latent layer to find network response of input pattern using y_i for Y_i [56-70].

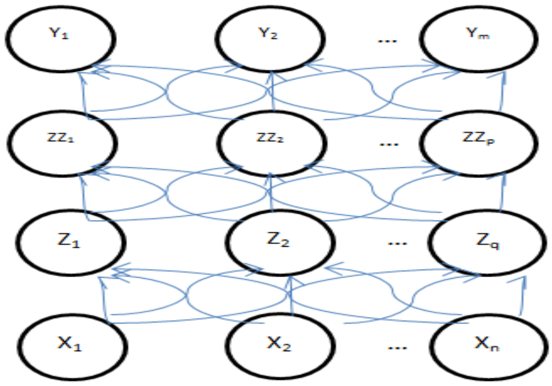

Fig. 1 Original Backpropagation Network with 2 Latent Layers and no Capacity Factor Modifications

In the whole process of weighting and learning each obsolete output node collates with target value t_i to verify and calculate error related factor δ_i that will be used for next layers outputs to update weights of latent and output layer as weighting process is essential and vital in all ANN structures (even ordinary dynamic Fuzzy [6] unites have to decide according to *IF* statements of non-dynamic, non-linear rules). Weighting v_{hi} is done by hiddenZ_h to ZZ_i respect to δ_i and activation of unit Z_h while u_{ih} weight from input node X_i is also measured by δ_h and input activation for both Feedforward and Backpropagation structures.By these written considerations Capacity factor can be added to process that is mentioned by authors in [1] so recall that for a group of problems in Gp_m Capacity factor defined by (2) and (3):

$$C' \triangleq \frac{1}{m}\sum_{i=1}^{m} r_i \qquad (2)$$

$$r_i \triangleq \frac{p_{c\,i}}{1 + p_{w\,i}} \qquad (3)$$

Here Gp_m for SOM is equivalent for multi weightings problem for Backpropagation algorithm of similar kind that aforesaid earlier and p_w and p_c have same compliments but are calculated for each round before changing weight matrix because as mentioned δ_k is not a multi stage average [72]form constant and its modifications have to be inline and dynamic as calculated Capacity factor in last research [1]. Fig. 1 shows a Backpropagation network with 2 latent layers, n inputs without bias and m output nodes.

IV. ALGORITHM IMPLEMENTATIONS

Feed Forward

In this section a vivid process for implementation of a Back propagation ANN with two latent layers and also M successful subsumed clusters is studied. In this type of ANN bound for number of samples that was needed, is minimum of number of inputs and latent nodes multiplied by M [59]. Now consider an ANN with two latent layers, and n input unites of X_i that send signals to hidden parts called Z_h so to calculate input signal consider (4):

$$Z_{in_h} = u_{0h} + \sum_{i=1}^{n} x_h u_{ih} \tag{4}$$

Now the activation function for output nodes is as (5):

$$z_h = f(z_{in_h}) \tag{5}$$

So output is also injected to second (hidden) layer for preprocessing and generating output main signal, which are ZZ_j nodes. Now to calculate input signal consider (6):

$$zz_{in_j} = v_{0j} + \sum_{h=1}^{q} z_h v_{hj} \tag{6}$$

Again output activation process to get updated value is defined this time by (7):

$$zz_j = f\left(zz_{in_j}\right) \tag{7}$$

Each m output node Y_k by weighted input signal is as (8):

$$y_{in_k} = w_{0k} + \sum_{j=1}^{p} zz_j w_{jk} \tag{8}$$

And once again activation function defines outputs nodes deal as (9):

$$y_k = f(y_{in_k}) \tag{9}$$

Back Propagation of Error

This part contains ordinary modified main Back propagation algorithm plus C' calculation which is inline and dwindles error by some important considerations as follow:

A) *Algorithm Enhancement*

a. C' is calculated inline, unlike SOM based optimizations this factor is essential to each step calculation of δ_k and not each new input vector, the one estimated successfully for SOM based nets(check ***proof 1***).

b. p_c and p_w are calculated for each stage in which weights have to be updated by $\Delta u_{ih} = \alpha \delta_h x_i$.

Consider each output unit as Y_k then error for current existing learning pattern is (10):

$$e_k = (t_k - y_k) \tag{10}$$

And dip of the activation function multiplied by error gives static δ_k :

$$\delta_k = e_k f'(y_{in_k}) \tag{11}$$

Here the C' factor shows its inscription after calculation of p_c and p_w for each stage:

$$\delta'_k = C' e_k f'(y_{in_k}) \tag{12}$$

$$\Delta w_{jk} = \alpha \delta'_k zz_j \tag{13}$$

And bias fixing with new error correction is (14):

$$\Delta w_{0k} = \alpha \delta'_k \tag{14}$$

$$\delta_{in_j} = \sum_{k=1}^{m} \delta'_k w_{jk} \tag{15}$$

$$\delta'_j = \delta'_{in_j} f'\left(zz_{in_j}\right) \tag{16}$$

Then weight has to be updated through $\Delta v'_{hj}$ and consider (17) and (18) for bias:

$$\Delta v'_{hj} = \alpha \delta'_j z_h \tag{17}$$

$$\Delta v_{0j} = \alpha \delta'_j \tag{18}$$

For first hidden layerz_h , $h = 1,2, \ldots, q$, then consider (19):

$$\delta \tag{19}$$

And weight correction is (20):

$$\Delta u_{ih} = \alpha C' e_k f'(y_{in_k}) x_i \tag{20}$$

This will lead to an improvement which has been done once for a chosen *Self-Organizing-Map*[1]for example *Kohonen Map* of certain inputs (multi vector improvement) by calculation of C' as an inline factor of improvement and modifying static weighting process [74-78].

B) *Theorem 1*

Error reduction in presented algorithm is achieved if and only if $\rho = 0$ as follows:

$$\rho = \begin{vmatrix} \Delta u_{ih} & \dfrac{\Delta u_{ih}}{C'} \\ \Delta u_{ih} & C' \Delta u_{ih} \end{vmatrix} \tag{21}$$

C) *Proof 1*

To prove this identity,let's make sure that these assumptions all hold:

1- Preserved error of each round is near zero, and the convergence criterion holds.

2- C' Renewed for every new input vector (unlike SOM type and because δ_k has to be calculated separately and our assumptions have to be based on assumption of original algorithm).

3- Weighting process is independent of C' calculation process.

Now consider (22) and (23):

$$E \to 0 \; then \; \delta_k = 0 \; so \; t_k = y_k \tag{22}$$

$$\rho \to 0 \; because \; t_k = y_k \; and \; C' \to 1 \; so \; \rho \to 0 \tag{23}$$

And again and again ρ tends to zero in this loop in a few rounds as C' calculated for every δ_k, in fact $\rho = 0$ is a detector for us that shows how to end our calculations, because slightest mistake will make too much error mostly for *upcoming event predictions* that heavily relies on existed information (mapped data). As mentioned in literature the most interesting effect of Back propagation method applications is on nonlinear models and many have tried to improve multilayer networks because of their abilities of problem solving. Researchers have arrived at this point that even by using Back propagation training methods it is still hard to achieve best performance (Fast learning) because of intrinsic parts of algorithms themselves and modifications have to be done to both reduce error and to elevate speed proficiency. The aim of this paper will be accomplished if the new defined Capacity factor is used for algorithm enhancements as next part objective is to show this fact.

V. RESULTS

In this section the results of simulations that have led to speed enhancement and error reduction of a simple Back propagation algorithm with 2 latent layers is brought. Indeed speed improvement is because of better convergence that is the result of error reduction. This new Capacity factor makes algorithm faster and is calculated inline while the algorithm is doing its weight correction as mentioned by (20) and reliability factor is also part of C' calculations as each round of algorithm is done. Unlike SOM this method won't be calculated for every new single vector, but consider that in algorithm the C' does not affect propagation between layers, because in more than 2 latent based networks time complexity is $O(t^2)$ which is for both upper and lower layers and is complex enough not to be further modified. Error is also calculated in this algorithm which is difference of target and output node value so this is implemented while output layer Net and error is calculated. So error is distinguished for different number of inputs and change of prediction error while the prediction model is fixed, and also target values are fixed too. In other words, error reduction for such cases that user has more than enough number of data sets for best prediction is expected. As in Fig. 2. Shows error reduced smoothly in C' based algorithm with $\rho = 0$ because reliability is calculated inline, and main algorithm also experiments error reduction by increasing number of data sets but it is not as smooth as new algorithm. What mentioned as smooth error reduction has an important mathematical background, because if predication has less error it also estimates real function of that experiment deterministically not because the process is necessarily deterministic, but mostly when designer deal with natural events in real world which are the results of several known and some unknown parameters. While main algorithm error reduction is not very smooth it behaves obscure and is unpredictable. The interesting fact is that smoothing gives an explicit predictable functional equation for sides of algorithm while non-smoothed error reduction is not even safe, and it doesn't mean that new method always does the task of smoothing.

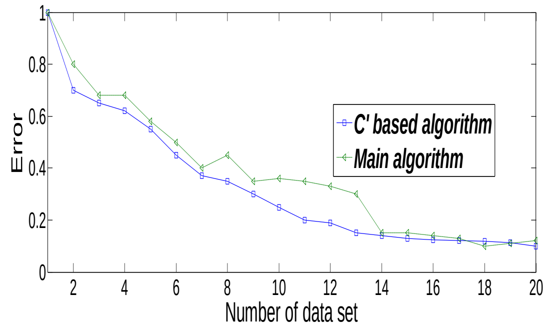

Fig. 2 C′ Based Algorithm VS Main Back Propagation Algorithm that Smoothed Error Function

Next in Fig. 3, The same algorithm for new set of data plus Feed forward modified version that leaves accuracy up to 2 digits after decimal point with $\rho = 0.01$ is tested. As it is clear in some cases the new algorithm has more error because number of rounds is also reduced and C' based algorithm with $\rho = 0$ is in fact slower than C' based algorithm with $\rho = 0.01$ but $\rho = 0$ is more accurate because (21) is calculated up to desired level.

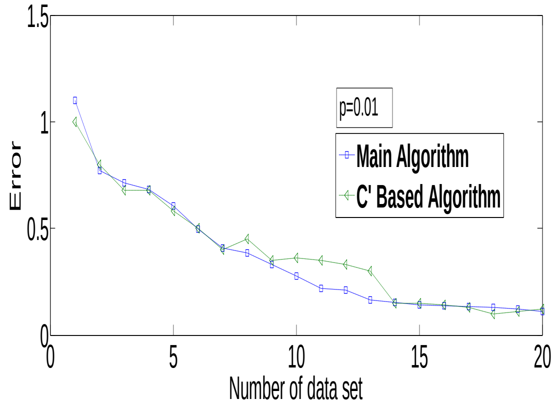

Fig. 3 C′ Based Algorithm VS Main Back Propagation Algorithm for Error Measurement

If the number of data sets is increased significantly by some logical assumptions it is easy to show that error have to be reduced respect to other prediction methods. Here a relevant error can be defined but for simplicity it was ignored and instead considered the error reduction for both algorithms which is connected to number of data sets and ρ factor. This fact is illustrated in Fig. 4. That shows error reduction happened at the expense of speed and increased number of samples. Reduction of ρ or error also makes error function smoother, that has a relation to exact prediction modeling which authors don't consider in this document. Exact prediction modeling leads us to exact function that resembles a process in which several parameters are involved and as a simple case a process like $p(t_i)$ in (24):

$$p(t_i) = \sum_{j=1}^{n} k_j t_j^{\lambda(j)} \tag{24}$$

Almost any process can be modeled using (24) that employs different types of $\lambda(j)$ with some considerations that are out of the topic of this manuscript.

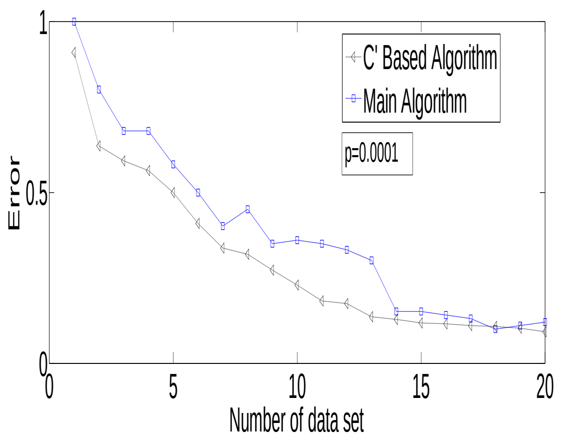

Fig. 4 C′ Based Algorithm Reduced Error at Expense of Time Complexity by ρ More than Main Algorithm

VI. CONCLUSION

This paper investigated a method that was first done before for a *chosen Self Organizing Map*and improvement of convergence and also reduction of error for a faster response of ANN for a certain problem that were all achieved too. But this time instead of SOM, paper did the same task on a Back propagation Network that can also be *MLP*, so pay attention that learning rules and weightings for biases can be calculated but separately (without ignoring convergence criterion of Capacity factor, in this paper using ρ) and readers cannot do this unless they consider convergence criterion for weighting matrix that must be considered for each network alone. Capacity factor calculated inline for several data sets and reduced error was calculated, but concept of error smoothing was not considered in this paper but instead an error reduction strategy was introduced. Paper claimed if error function is smoothed well, regardless of prediction model or shape and even deterministic or ideterministic input signals, the error will be zero for infinity many samples (similar result is not possible for ordinary linear predictors). In other words and with better insight may say, "*error smoothing is more valuable than error reduction"* because authors can show that unlike indeterministic rough functions, smoothed functions can be predicated better. Finally paper demonstrated that error was decreased better while factor ρ was almost equal zero, and the maximum time of calculation occurs when this factor is exactly equal to zero.

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