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Direct Search Methods for Nonlinear Optimization Problem used ART Theory

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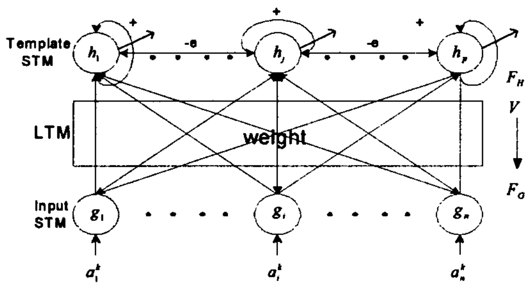
Abstract - In this paper, the search is conducted along each of the coordinate directions for finding the minimum. If e_i is the unit vector along the coordinate direction i, we determine the value a, minimizing $f(\alpha)=f(x+\alpha e_i)$, where a is a real number. A move is made to the new point $x+\alpha_i e_i$ at the end of the search along the direction i. In an n dimensional problem, we define the search along all the directions as one stage. The function value at the end of the stage is compared to the value at the beginning of the stage in establishing the convergence. The gradient appears to be zero at point. We can safeguard this by introducing an acceleration step of one additional step along the pattern direction developed by moves along the coordinate directions.

1. Introduction

Multi-variable minimization can be approached using gradient and Hessian information, or using the function evaluations only. We have discussed the gradient or derivative based methods in earlier chapters. We present here several algorithms that do not involve derivatives. We refer to these methods as direct methods. These methods are referred to in the literature as zero-order methods or minimization methods without derivatives. Direct methods are generally robust. Direct methods lend themselves to be valuable tools when gradient information is not readily available or when the evaluation of the gradient is cumbersome and prone to errors. The concepts of simulated annealing and genetic algorithms are also discussed. All these algorithms are implemented in computer programs.

2. ART2 Neural Network

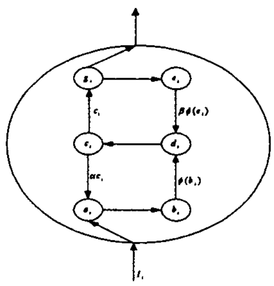
ART2 is principally a two-layer architecture, each input layeractually consists of six inter-PEs Working in synchrony as shown in Fig. 1. These inter-PEs normalize the input and stored patterns to allow for equitable comparison. The function of each inter-PE in the $ith F_G$ is as follows: α_i holds the analog input value for the ith component of the kth input pattern (a_i^k), b_i holds a normalized representation of a_i's value, c_i holds a normalized LTM/input pattern comparison, d_i holds the analog LTM pattern readout/input pattern comparison, e_i holds the normalized LTM pattern readout, and g_i holds the analog LTM pattern readout. The links between g_i and e_i and d_i and c_i and a_i and b_i are transparent and unit valued. The link from e_i to d_i caries a linearly regulated sigmoid threshold signal $(\beta\phi(e_i))$, the link from b_i to d_i carries a sigmoid-threshold signal, the link from c_i to g_i carries the value of c_i, and the link from c_i to a_i carries a linearly regulated c_i. Signal.



<Fig. 1> ART Model

Fig. 1 is topology of the analog adaptive resonance theory (ART2) ANS, an unsupervised learning feedback recall ANS. There are inter-layer connections between the F_G and $F_H PEs$ that store analog spatial patterns. The $F_G PEs$ accept input patterns from the environment and the $F_H PEs$ each represent a pattern class.

During operation, the $F_B PEs$ employ an invisible on-center/off-surround competition that is used to choose the proper class for the presented input. These lateral interactions are shown in the figure as shaded self-exciting/neighbor-inhibiting connections to emphasize this point. This is a continuous time ANS that classifies analog patterns. To keep the presentation uncluttered, all connections are not shown-there is actually a connection from each $F_G PE$ each $F_H PE$ and vice versa, a shaded negative lateral connection from each $F_G PE$ every other $F_H PE$, and a shaded positive recurrent connection from every $F_H PE$ to itself[1-3].



<Fig. 2> ART Unit Model

Fig. 2 is an expanded view of the $F_G PE$ showing the six inter-PEs that are used for normalization of the analog patterns stored in LTM(the connections between F_G and F_H and the input patterns. The shaded connections inherently carry information concerning the other PEs of the same type (information necessary for the normaliztion process to occur). Pattern normalization allows an equitable comparison to be made between the stored and input pattern.

Like ART1, ART2 is a field feedback paradigm: $F_G PE$ receive signals from both the external inputs (A_k) and the top-down V_{ji} connections, and $F_H PEs$ receive signals from bottom-up (W_{ji}) connections. The encoding procedure is outlined as follows:

1. Present an input pattern $A_k=(a_1^k, \cdots\cdots, a_n^k)$ to the $F_G PEs$.
2. Inside each $F_G PE$ the analog input pattern is normalized and fed through the $a_i \to b_i \to d_i \to c_i \to g_i$ inter-PE path, and sends the resultant signal through the F_G to F_B LTM connections.
3. Each F_B competes with the others using Shunting Grossberg interactions until only one $F_H PE$ remains active.
4. The winning $F_H PE$ sends a top-down signal through its LTM connections, V_{ji} back to F_G.
5. The top-down signal is sent through the $g_i \to e_i \to d_i \to c_i$ inter-PE path resulting in a possibly new c_i signal.
6. The combined normalized top-down LTM/bottom-up input signal at c_i is compared with the top-down stored signal g_i.

7. If the difference between these two activations c_i and g_i exceeds a value deter mined by the vigilance parameter then the winning F_HPE does not represent the proper class for A_i and it is removed from the set of allowable F_H winners. Control branches at this point in one of two directions:

a. If there are still F_GPEs remaining in the set of allowable winners, go to step 2.

b. If there are no remaining F_GPEs in the set of allowable winners, recruit an uncommitted F_HPE and encode the normalized input onto this's connections.

8. If the difference between the two activations meets the criterion established by the vigilance parameter, then the F_HPE is determined to be the proper class for the for the input pattern A_i and the input pattern is merged onto the weights with the stored pattern. We will call this match between the input and stored patterns resonation, and we shall call the length of time that the match occurs the resonation period[4-6].

3. Case Study

3.1 Problem Model

Define z_0, z_1, z_2, z_3, z_4, determine x_0, x_1, x_2, x_3, x_4, determine y_i by RHR. This robot-arm system has four motor.

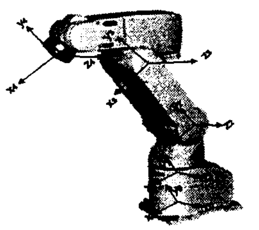


Fig. 3 Robot-arm system

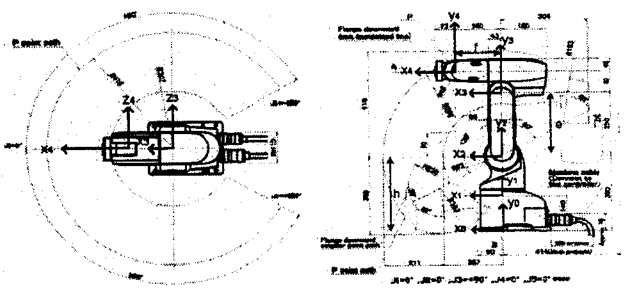


Fig. 4 Robot-arm system design sketch

3.2 Modeling

Each transformation matrix each column into gives and it must be complex calculation.

$$T_0^1=\begin{bmatrix} C_1 & -S_1 & 0 & 0 \\ S_1 & C_1 & 0 & 0 \\ 0 & 0 & 1 & h \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad T_1^2=\begin{bmatrix} C_2 & -S_2 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ S_2 & C_2 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad T_2^3=\begin{bmatrix} C_3 & -S_3 & 0 & 0 \\ S_3 & C_3 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad T_3^4=\begin{bmatrix} 1 & 0 & 0 & f \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Therefore the overall transformation becomes

$$T_0^4=T_0^1T_1^2T_2^3T_3^4=\begin{bmatrix} C_1C_{23} & -C_1S_{23} & S_1 & eC_1C_2+fC_1C_{23} \\ S_1C_{23} & -S_1S_{23} & -C_1 & eS_1C_2+fS_1C_{23} \\ S_{23} & C_{23} & 0 & h+eS_2+fS_{23} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

3.3 Result

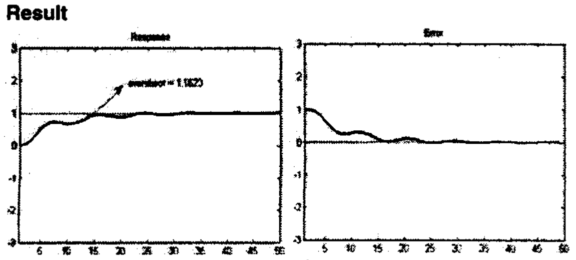


Fig. 5 Powell's method

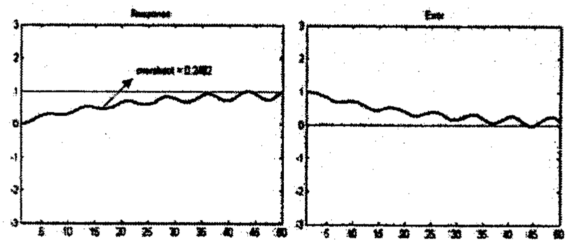


Fig. 6 Nelder & Mead method

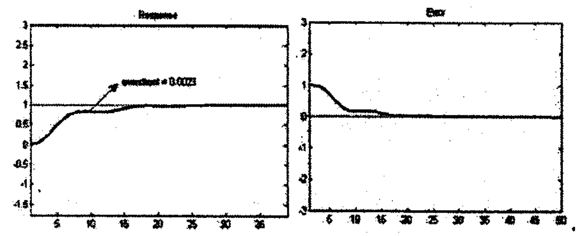


Fig. 7 ART2 neural network

4. Conclusion

Table 1 is comparison error rate and overshoot of each method.

Table 1

Method / Content	POWELL'S METHOD	NELDER & MEAD METHOD	ART2 Neural Network
Overshoot	1.1623	0.2482	**0.0023**
Error rate	0.321	0.736	**0.138**

In this paper, we described a neural network architecture that can solve classical robot-arm system problem with a massively parallel algorithm. The algorithm is based on the logarithmic barrier function approach to robot-arm system problem. In other to solve the basic dynamics of these network, we simulated robot-arm system problem using the differential-equation approach. Thus far, we have simulated the effects of limited numerical precision of analogue devices and of random noise that may be described. As you see the Fig. 5-7 and Table 1 about case study, this paper demonstrated robot-arm system problem used ART Neural Network.

[Reference]

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