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Application of Stochastic Gradient Descent Technique for Method of Moments

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Abstract

This paper studies the feasibility of solving matrix equations in the method of moment (MoM) based on the stochastic gradient descent (SGD) technique (SGD-MoM). We adopted the optimization techniques in machine learning to solve the matrix equations in MoM. Numerical result demonstrate the feasibility of the proposed method, and its accuracy and efficiency, compared with conventional iterative methods like conjugate gradient(CG), generalized minimal residual algorithm (GMRES), and etc.

Introduction

Numerical electromagnetic analysis has been widely applied in electromagnetic engineering, such as electromagnetic compatibility and interference, antenna design, wireless communication, target detection, and etc. Among numerical electromagnetic method, method of moments (MoM)[1] is one of the most widely used because its efficiency and accuracy in modeling open boundary problems, with the help of Green's function of the surrounding background.

investigated its application to solve electromagnetic problems. By translating traditional computational tasks into ML-process, conventional MoM can be cast into ML framework by training. One of the techniques in deep learning is the stochastic gradient descent technique (SGD). It is widely applied inthe training stage to solve large-scale optimization problems. Because solving matrix equations can be formulated as an optimization process, we studied its applicability in solving the matrix equations in MoM in this paper. Numerical study shows that SGD can help to improve the efficiency in solving the matrix equations, compared with tradition iterative solvers.

Formulation

1) *Moment Method*

Considering a PEC target illuminated by a uniform plane wave, the induced electric current $\mathbf{J}(r)$ on the surface satisfies the electric field integral equation as

$$\mathbf{E}^{inc}(\mathbf{r})|_S = -\mathbf{E}^{sca}(\mathbf{r})|_S = j\omega\mu \int_s G(\mathbf{r},\mathbf{r}') \left[\mathbf{J}(\mathbf{r}') + \frac{1}{k^2}\nabla'\nabla' \cdot \mathbf{J}(\mathbf{r}')\right] d\mathbf{r}'$$

By discretizing the current and galerkin testing, a matrix equation can be set up using a testing procedure, which can be written as

$$\overline{A} \cdot x = b$$

How to solve?

2) *Stochastic Gradient Descent Method*

SGD only uses some random samples of the data to update the solution. This is equivalent to drawing submatrices of $\overline{A}$ to update the solution. Adam (Adaptive Moment Estimator) is a typical self-adaptive SGD method, it stores the root mean squared (RMS) of past gradient in different directions and keeps the exponential decay mean of past gradient to update the next weight.

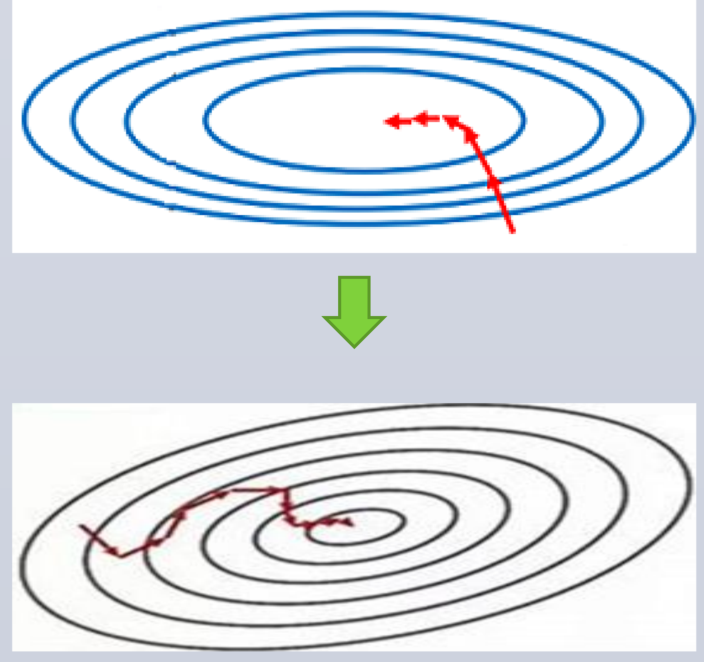
$$\mathbf{x^{n+1}} = \mathbf{x^n} - \frac{\alpha}{\sqrt{\hat{v}_n} + \varepsilon}\hat{\mathbf{m}}_\mathbf{n}$$

$$\hat{v}_n = \frac{v_n}{1-\beta_2^n}$$

$$\hat{\mathbf{m}}_\mathbf{n} = \frac{\mathbf{m_n}}{1-\beta_1^n}$$

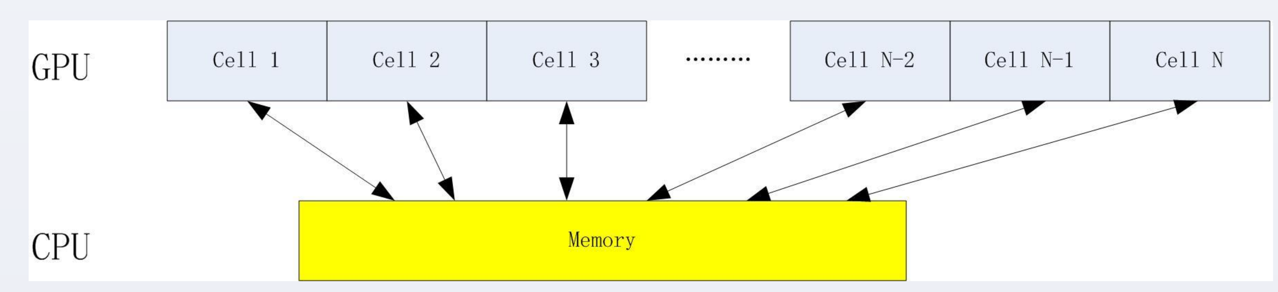
$$v_n = \beta_2 v_{n-1} + (1-\beta_2)\mathbf{g_n^2}$$

$$\mathbf{m_n} = \beta_1 \mathbf{m_{n-1}} + (1-\beta_1)\mathbf{g_n}$$



3) *Implement Strategy*

SGD-MoM calculates the impedance matrix by CPU (For high operator), and stores them in CPU (For large memory), Then communicates with GPU (For multi-cells) in the solver at a pre-defined scale.



Numerical Examples

1) *A PEC Almond*

✓Size: 1.26m × 0.49m × 0.16m;
✓Frequency: 1.5GHz with HH;
✓Scan RCS: incident: (90°, 180°)
✓scatter: (90°, 0° ~90°, 180°) with step 1°

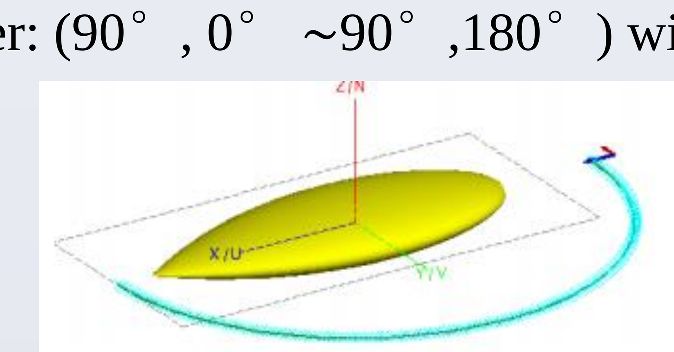


Fig 1. Simulating model

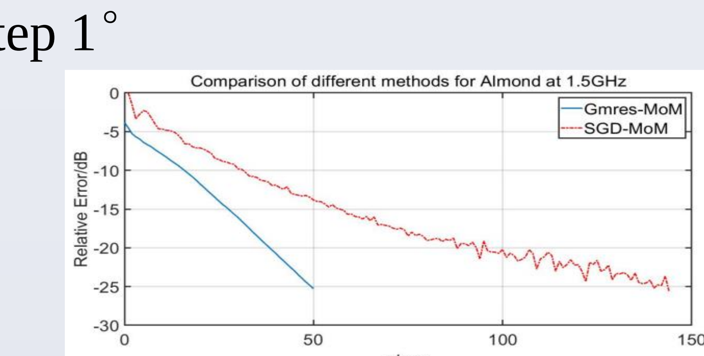


Fig 1. Convergent Curve

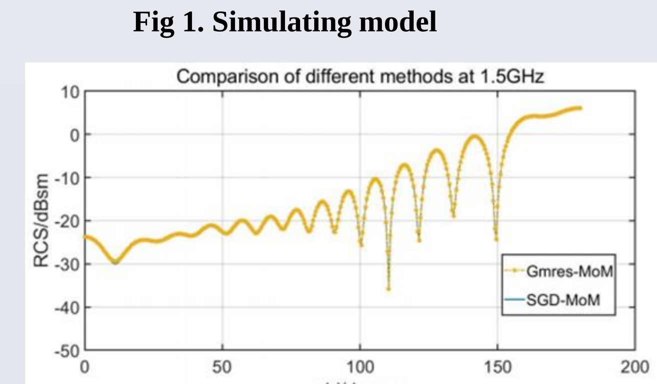


Fig 3. Rcs Result

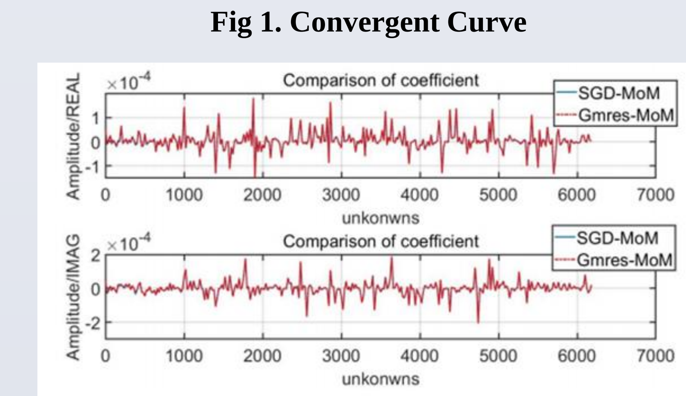


Fig 4: Comparison of the unknowns

2) *A PEC Sphere*

✓Radius: 1m; Frequency: 300MHz &10MHz;
✓Adam can give the better accuracy than CG for LF-problems.

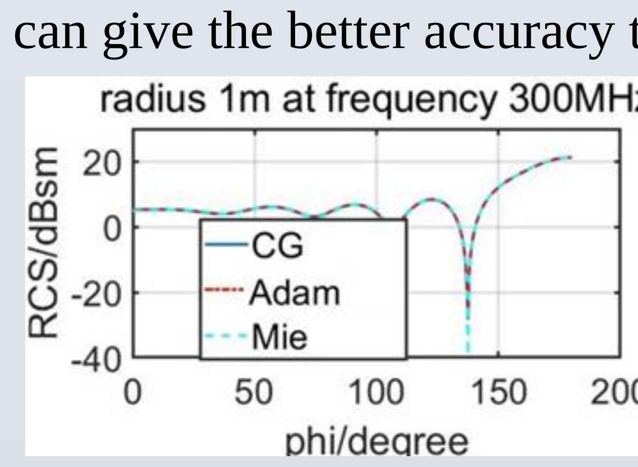


Fig 1. Rcs Result at 300MHz

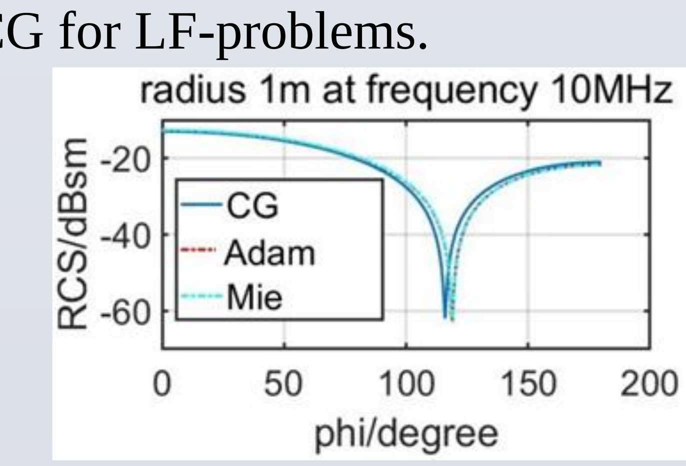


Fig 2. Rcs Result at 10MHz

3) *A PEC Ogive*

✓Size: 1.9m×0.51m×0.51m, Frequency: 1.5GHz;

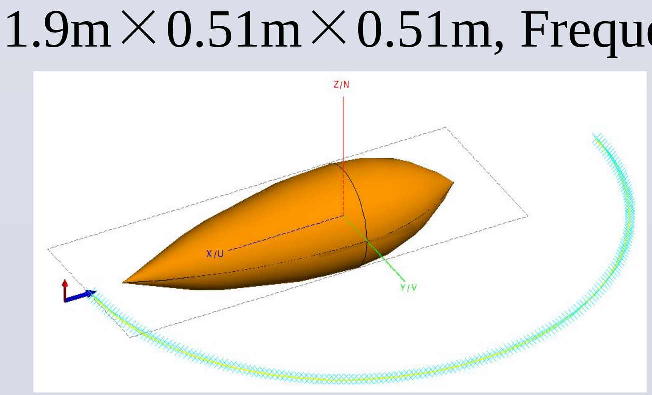


Fig 1. Simulation model

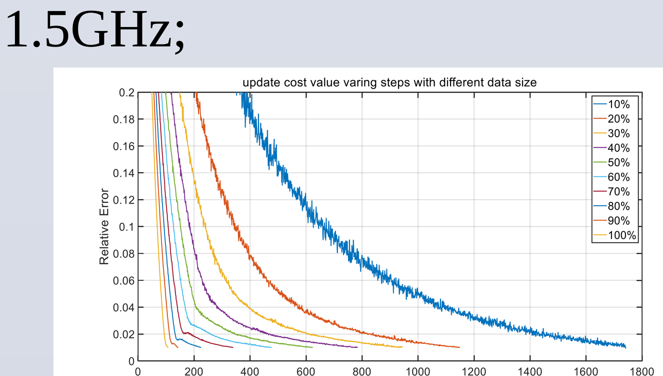


Fig 2. Convergent Curve

Conclusion

The stochastic gradient descent methods can help to improve the efficiency in solving the matrix equation in MoM. Numerical example validates the accuracy and efficiency of the proposed method. For the targets with complex structures, the proposed method is valid too.

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