

# A Hybrid Method for Nonlinear Least Squares Problems

Zhongyi Liu<sup>1,\*</sup> and Linping Sun<sup>2</sup>

<sup>1</sup> School of Sciences, Hehai University, Nanjing 210098, China.

<sup>2</sup> Department of Mathematics, Nanjing University, Nanjing 210093, China.

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**Abstract.** A negative curvature method is applied to nonlinear least squares problems with indefinite Hessian approximation matrices. With the special structure of the method, a new switch is proposed to form a hybrid method. Numerical experiments show that this method is feasible and effective for zero-residual, small-residual and large-residual problems.

**Key words:** Nonlinear least squares; switch; hybrid method; negative curvature; BP factorization.

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## 1 Introduction

Consider nonlinear least squares problems

$$\min_{x \in \mathbb{R}^n} F(x) = \frac{1}{2} f(x)^T f(x) = \frac{1}{2} \sum_{i=1}^m f_i(x)^2 \quad (1)$$

where  $m \geq n$ ,  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m \in C^2(\Omega)$ ,  $\Omega \in \mathbb{R}^n$  is an open convex set and  $f_i(x)$  is the component function of  $f(x)$ . The gradient of  $F(x)$  is

$$g(x) = J(x)^T f(x), \quad (2)$$

where  $J(x)$  is the Jacobian matrix of  $f(x)$ , and the Hessian matrix is

$$G(x) = J(x)^T J(x) + \sum_{i=1}^m f_i(x) \nabla^2 f_i(x).$$

Set

$$M(x) = J(x)^T J(x), \quad W(x) = \sum_{i=1}^m f_i(x) \nabla^2 f_i(x). \quad (3)$$

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\*Correspondence to: Zhongyi Liu, School of Sciences, Hehai University, Nanjing 210098, China. Email: zhyi@hhu.edu.cn

Then

$$G(x) = M(x) + W(x). \quad (4)$$

Using the special structures of the object function  $F(x)$  and the Hessian matrix  $G(x)$ , many effective methods have been developed. Among them a fundamental method is Gauss-Newton method which neglects the nonlinear term  $W(x)$  in  $G(x)$ . In other words, a search direction is given by

$$J(x_k)^T J(x_k) p_k = -J(x_k)^T f(x_k). \quad (5)$$

The following theorem shows the convergence of the Gauss-Newton method.

**Theorem 1.1.** *Suppose that  $F(x) \in C^2(\Omega)$ ,  $x^*$  is a local minimum of (1),  $J(x)$  and  $G(x)$  are Lipschitz continuous in  $\Omega$ , and for all  $x \in \Omega$ ,  $J(x)$  is of full rank. If  $\|J(x)\| \leq \delta$ ,  $\|(J(x)^T J(x))^{-1}\| \leq \tau$ , where  $\delta$  and  $\tau$  are constants, then Gauss-Newton iteration is well-defined for all  $x \in \Omega$ , and*

$$\|x^{(k+1)} - x^*\| \leq \|(J(x^*)^T J(x^*))^{-1} W(x^*)\| \|x^{(k)} - x^*\| + \mathcal{O}(\|x^{(k)} - x^*\|^2). \quad (6)$$

From the theorem above, whether Gauss-Newton method can succeed depends on whether the neglected term  $W(x)$  is important, that is to say, whether  $W(x)$  is a small part in  $G(x)$ . The Gauss-Newton method has quadratic rate of convergence for zero residual problems where  $f(x^*) = 0$  or  $W(x^*) = 0$ .

The search direction can also be obtained by

$$(J(x^{(k)})^T J(x^{(k)}) + \lambda_k I) p^{(k)} = -J(x^{(k)})^T f(x^{(k)}) \quad (7)$$

where the nonnegative scalar  $\lambda_k$  is used to make  $J(x^{(k)})^T J(x^{(k)}) + \lambda_k I$  positive definite. This formula is first proposed by Levenberg [4] and Marquardt [5], and is therefore called Levenberg-Marquardt method.

Another method takes advantage of  $W(x)$  in  $G(x)$ , which is necessary for large residuals. One of this type of methods is due to Dennis-Gay-Welsh [6]. Since

$$\nabla^2 f_i(x^{(k+1)}) s^{(k)} = \nabla f_i(x^{(k+1)}) - \nabla f_i(x^{(k)}), \quad (8)$$

we have

$$f_i(x^{(k+1)}) \nabla^2 f_i(x^{(k+1)}) s^{(k)} = f_i(x^{(k+1)}) (J_{k+1} - J_k)^T e_i, \quad (9)$$

which leads to

$$\sum_{i=1}^m f_i(x^{(k+1)}) \nabla^2 f_i(x^{(k+1)}) s^{(k)} = (J_{k+1} - J_k)^T f^{(k+1)}. \quad (10)$$

Set  $y^\sharp = (J_{k+1} - J_k)^T f^{(k+1)}$ . Then  $W_{k+1}$  satisfies

$$W_{k+1} s = y^\sharp. \quad (11)$$

The Dennis-Gay-Welsh method gave the updating formula for  $W_k$  and scale strategy as follows:

$$W_{k+1} = \tau W_k + \frac{(y^\sharp - \tau W_k s) y^T + y (y^\sharp - \tau W_k s)^T}{y^T s} - \frac{(y^\sharp - \tau W_k s)^T s}{(y^T s)^2} y y^T, \quad (12)$$