Positive Definiteness of Symmetric Rank 1 (H-Version) Update for Unconstrained Optimization

Saad Shakir Mahmood  Jaafer Hmood Eidi  Jinan Adel Jasem

Department of Mathematics, College of Education, University of Mustansiriyah, Baghdad, Iraq

1Corresponding author: saadshakirmahmood@uomustansiriyah.edu.iq, drijaffarmath@uomustansiriyah.edu.iq, jinanadel78@uomustansiriyah.edu.iq

ORCID ID: https://orcid.org/0000-0001-5433-9710, https://orcid.org/0000-0002-9010-7527, https://orcid.org/0000-0002-5128-1522

Received 24/4/2020, Accepted 3/12/2020, Published Online First 20/9/2021

This work is licensed under a Creative Commons Attribution 4.0 International License.

Abstract:

Several attempts have been made to modify the quasi-Newton condition in order to obtain rapid convergence with complete properties (symmetric and positive definite) of the inverse of Hessian matrix (second derivative of the objective function). There are many unconstrained optimization methods that do not generate positive definiteness of the inverse of Hessian matrix. One of those methods is the symmetric rank 1 (H-version) update (SR1 update), where this update satisfies the quasi-Newton condition and the symmetric property of inverse of Hessian matrix, but does not preserve the positive definite property of the inverse of Hessian matrix where the initial inverse of Hessian matrix is positive definiteness. The positive definite property for the inverse of Hessian matrix is very important to guarantee the existence of the minimum point of the objective function and determine the minimum value of the objective function.

Keywords: Hessian matrix, Positive definite, Quasi-Newton condition, Symmetric rank 1 Update, Unconstrained optimization

Introduction:

Symmetric Rank 1 (SR1 H-version) update is important in theoretical research and practical computing. However, the drawback that SR1 (H-version) update does not retain the positive definiteness of updates hurts its performance in computing. Fortunately, the drawback can be avoided if the modified quasi-Newton condition has been employed to modify the SR1 (H-version) update.

Zhang and Ch introduced the modified quasi-Newton equation which uses both gradient and function value information in order to yield a higher order accuracy for approximating the second curvature of an objective function. Yabe, H and M considered a modified Broyden family which includes the BFGS (Broyden–Fletcher–Goldfarb–Shanno) update. Guo and J modified the BFGS update based on the new quasi-Newton equation, \( B_{k+1} s_k = y_k + A_k s_k \), where \( A_k \) is a matrix.

Mahmood and S proposed a modified Broyden update based on the positive definite property of Hessian matrix, via updating the vector \( y \) (the difference between the next gradient of the objective function and the current gradient of the objective function) and provided the global and superlinear convergence of the proposed method. Razieh, B and H introduced the modified BFGS method for solving the system of non-linear equations by using Taylor theorem, this proposed method is derivative-free, so the gradient information is not needed at each iteration. Razieh, B and H introduced a modified quasi-Newton equation to get a more accurate approximation of the second curvature of the objective function by using Chain rule. Then, based on this modified secant equation, they present a new BFGS method for solving unconstrained optimization problems. Bojari and R proposed a new family of modified BFGS update to solve the unconstrained optimization problem for nonconvex functions based on a new modified weak Wolfe – Powell line search technique. Yuan proposed a modified
BFGS algorithm which requires that the function value is matched, instead of the gradient value, at the previous iterate. This new algorithm preserves the global and local superlinear convergence properties of the BFGS algorithm.

In this research a modified update for the SR1 (H-version) update has been proposed to guarantees the positive definite property and preserves the symmetry property for the inverse of Hessian matrix via updating the vector s which represents the difference between the next solution and the current solution. The proof of convergence for the proposed method is given, and then tow numerical examples has been solved by the original SR1 (H-version) update and also solved by the proposed method.

Modified SR1 (H-version) Update:

In this section the positive definite property for the inverse of Hessian matrix has been guarantee by updating the vector s. K. Then for this purpose let us consider the objective function \( f: \mathbb{R}^n \rightarrow \mathbb{R} \) with the following assumptions:

1. \( f \) is twice continuously differentiable.
2. \( f \) is uniformly convex, i.e. \( \exists m_1, m_2 \in \mathbb{R}^+ \) \( \exists m_1 \|a\|^2 \leq a^T \nabla^2 f a \leq m_2 \|a\|^2 \) \( \forall a \in \mathbb{R}^n \)

SR1 update (7) try to update the Hessian matrix by using the formula

\[
B_{k+1} = B_k + \frac{(y_k-B_k s_k)(y_k-B_k s_k)^T}{y_k-B_k s_k}, \quad \text{and by using}
\]

Sherman-Morrison-Woodbury formula \(^{11}\), the inverse of the Hessian matrix can be write as

\[
H_{k+1} = H_k + \frac{(s_k-H_k y_k)(s_k-H_k y_k)^T}{s_k-H_k y_k} y_k
\]

Which represent the solution of the quasi-Newton condition \(^{12}\)

\[
H_{k+1} y_k = s_k
\]

where \( \alpha_k \in \mathbb{R} \), and form Eq. 2

\[
H_{k+1} y_k = s_k = \alpha_k s_k
\]

This is called the modified quasi-Newton condition.

The formula of inverse of Hessian matrix for the SR1 (H-version) update has been considered with replacing each \( s_k \) by \( \alpha_k s_k \), in Eq. 1, and hence:

\[
H_{k+1} = H_k + \frac{(\alpha_k s_k-H_k y_k)(\alpha_k s_k-H_k y_k)^T}{(\alpha_k s_k-H_k y_k)^T y_k}
\]

Set

\[
w_k = (\alpha_k s_k - H_k y_k)
\]

and by substitution Eq. 6 in Eq. 5, then

\[
H_{k+1} = H_k + \frac{w_k w_k^T}{w_k^T y_k}
\]

Now, set \( w_k^T y_k > 0 \) and by Eq. 6, \( (\alpha_k s_k - H_k y_k)^T y_k > 0 \) and then, \( \alpha_k > \frac{y_k^T H_k y_k}{y_k^T s_k} \)

Now set

\[
\alpha_k = 2 \frac{y_k^T H_k y_k}{y_k^T s_k}
\]

Note that, one can choose another value of \( \alpha_k \) but must be satisfies the inequality \( \alpha_k > \frac{y_k^T H_k y_k}{y_k^T s_k} \).

Now to show that \( \frac{y_k^T H_k y_k}{y_k^T s_k} \) is positive, where \( s_k = x_{k+1} - x_k \), \( x_{k+1} = x_k + \lambda_k p_k \), and the direction \( p_k = -H_k \nabla f(x_k) \), and \( \lambda_k > 0 \), where \( \lambda_k \) is the step size \(^{12}\), \( x_k \) is the current solution, \( x_{k+1} \) is the next solution, and \( \nabla f(x_k) = \nabla f_k \) is the current gradient of the objective function \( f \).

Now

\[
\frac{S_k^T B_k s_k}{y_k^T s_k} = \frac{-\lambda_k S_k^T \nabla f_k}{s_k^T (\nabla f_{k+1} - \nabla f_k)} = \frac{-\lambda_k S_k^T \nabla f_k}{s_k^T (\nabla f_{k+1} - \nabla f_k)}
\]

where \( H_k = B_k^{-1} \) and \( y_k^T s_k = s_k^T y_k \).

Since \( S_k^T \nabla f_{k+1} = 0 \) (conjugate direction property) \(^1\) then,

\[
\frac{S_k^T B_k s_k}{y_k^T s_k} = \frac{-\lambda_k S_k^T \nabla f_k}{-S_k^T \nabla f_k} = \lambda_k > 0
\]

and since \( B_k = H_k^{-1} \) is positive definite (\( S_k^T B_k s_k > 0 \) and \( y_k^T H_k y_k > 0 \)), then \( y_k^T s_k > 0 \) and then \( y_k^T H_k y_k > 0 \) which means that \( \alpha_k = 2 \frac{y_k^T H_k y_k}{y_k^T s_k} > 0 \).

In addition, by more simplifying from Eq. 5 and Eq. 8, \( H_{k+1} \) can be write as follows:

\[
H_{k+1} = \frac{1}{\alpha_k} \frac{1}{y_k^T s_k} \left( \frac{(2 \frac{y_k^T H_k y_k}{y_k^T s_k} s_k - H_k y_k)(2 \frac{y_k^T H_k y_k}{y_k^T s_k} s_k - H_k y_k)^T}{y_k^T H_k y_k} \right)
\]

This is called the modified SR1(H-version) update. The sequence of inverse Hessian matrix produced by Eq. 9, never go to a near singular matrix which make the computation never break before get the minimizer of the objective function.
Theorem 1

The modified SR1 (H-version) update generate a positive definite inverse of Hessian matrix if the current inverse of Hessian matrix is positive definite.

Proof:
Let $0 \neq z \in \mathbb{R}^n$, then

$$
z^T H_{k+1} z = 
\left( \frac{(\nabla^2 f(x_k y_k) s_k - H_k y_k)}{y_k^T H_k y_k} \right)^T z
\left( \frac{(\nabla^2 f(x_k y_k) s_k - H_k y_k)}{y_k^T H_k y_k} \right) z
$$

By substituting Eq. 6 in Eq. 10,

$$
z^T H_{k+1} z = z^T H_k z + z^T w_k^T I + \|w_k\|^2 = z^T H_k z + \|w_k\|^2
$$

Since $y_k^T H_k y_k > 0$, and $z^T H_k z > 0$ by the positive definiteness of $H_k$, and $\|w_k\|^2$ is always positive, therefore, $z^T H_{k+1} z > 0$ and $H_{k+1}$ is positive definite.

SR1 (H-version) update algorithm:
1. Choose the starting point $x_0$ and the initial approximation $H_0 = I$, $error = \epsilon > 0$, set $k = 0$.
2. Compute $\nabla f(x_k)$
3. If $\|\nabla f(x_k)\| < \epsilon$ then, stop and $x_k$ is the optimal solution, else continue to the next step.
4. Solve the system $p_k = -H_k \nabla f(x_k)$ for $p_k$.
5. Find $\lambda_k > 0, \exists f(x_k) + \lambda_k p_k < f(x_k)$.
6. Set $s_k = x_{k+1} - x_k, y_k = \nabla f(x_{k+1}) - \nabla f(x_k)$.
7. Compute $H_{k+1}$ from Eq. 9.
8. Set $k = k + 1$ and go back to the step 2.

Convergence of the method:
In this section, the convergence of the modified SR1 (H-version) update is provided. The following assumptions are needed.

Assumption 1.
(A): $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is twice continuously differentiable on convex set $D \subset \mathbb{R}^n$.
(B): $f(x)$ is uniformly convex, i.e., there exist positive constants $c$ and $C$ such that for all $x \in L(x) = \{x \mid f(x) \leq f(x_0)\}$, where $x_0$ is starting point, we have $c \|u\|^2 \leq u^T \nabla^2 f(x) u \leq C\|u\|^2, \forall u \in \mathbb{R}^n$.

The assumption (B) implies that $\nabla^2 f(x)$ is positive definite on $L(x)$, and that $f$ has a unique minimizer $x^*$ in $L(x)$.

Lemma 2, 12
Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ satisfy Assumption 1, then

$$
\|s_k\| \|y_k\| \leq \frac{s_k^T y_k}{y_k^T y_k} \|y_k\| \leq \frac{\|s_k\|^2}{\|y_k\|^2} \leq \frac{s_k^T y_k}{y_k^T y_k} \|y_k\|^2
$$

Note that, from Assumption 1, and since $s_k^T B_k s_k, y_k^T y_k$ are bounded, and by lemma 2 then

$$
\|s_k\| \|y_k\| \leq \frac{s_k^T y_k}{y_k^T y_k} \|y_k\|^2
$$

Since $y_k^T y_k > 0$, and $\|s_k\|^2$ are bounded, which gives $\frac{s_k^T y_k}{y_k^T y_k} \|y_k\|^2$ is convergent.

Lemma 3, 7
Under exact line search, $\sum \|s_k\|^2$ and $\sum \|y_k\|^2$ are convergent.

Note that, from lemma 2 and lemma 3, clearly that $\sum \|s_k\|^2$ is convergent, which gives $\frac{\|s_k\|^2}{\|y_k\|^2}$ is convergent and bounded.

Theorem 4
For modified SR1 (H-version) update, the determinant of the new inverse of Hessian matrix is given by:

$$
H_{k+1} = |H_k| \frac{w_k^T r_k}{w_k^T w_k}
$$

where $w_k = (H_k y_k - \alpha_k s_k), r_k = y_k - B_k w_k$

Proof:
From 5, set $w_k = (H_k y_k - \alpha_k s_k)$ then, $|H_{k+1}| = |H_k| \frac{w_k^T r_k}{w_k^T w_k}$, since $H_k$ is positive definite then, exist a triangular matrix $L_k \in \mathbb{R}^{n \times n} \exists H_k = L_k L_k^T$, and therefore

$$
|H_{k+1}| = |H_k| \left| I - \frac{L_k^T w_k L_k^T w_k}{w_k^T w_k} \right| = |H_k| \left| I - \frac{L_k^T w_k B_k w_k}{w_k^T w_k} \right|
$$

and apply Sherman-Morrison-Woodbury formula for the last Eq. 6, then

$$
|H_{k+1}| = |H_k| \left[ 1 - \frac{L_k^T w_k L_k^T w_k}{w_k^T w_k} \right]
$$

where $B_k = L_k^T L_k - I$, and $|H_{k+1}| = |H_k| \left[ w_k^T y_k - B_k w_k \right] = |H_k| \left[ w_k^T y_k - B_k w_k \right], w_k^T w_k

Set $r_k = y_k - B_k w_k$, then

$$
|H_{k+1}| = |H_k| \frac{w_k^T r_k}{w_k^T w_k}
$$

(11)

One can use Eq. 11 to compute the determinant of the inverse of Hessian matrix at every iteration which must be always positive to ensure that the matrix is positive definite.
Theorem 5
Suppose that \( f(x) \) satisfies Assumption 1, then the sequence \( \{x_k\} \) generated by Eq. 5, is convergent.
Proof:
Consider Eq. 5
\[
H_{k+1} = H_k + \frac{(\alpha_k s_k - H_k y_k)(\alpha_k s_k - H_k y_k)^T}{(\alpha_k s_k - H_k y_k)^T y_k} = H_k - \frac{y_k w_k}{w_k^T y_k}
\]
where \( w_k \) as in theorem 4.
Define \( \eta_k = \frac{w_k^T r_k}{y_k^T y_k} \), where \( w_k \), and \( r_k \) are as in theorem 4, therefore
\[
\eta_k = \frac{w_k^T r_k}{y_k^T y_k} = \frac{w_k^T (y_k - B_k w_k)}{y_k^T y_k} = \frac{w_k^T H_k y_k - H_k y_k^T H_k y_k}{\|w_k\|^2}
\]
(12)
which is bounded by lemma 2 and lemma 3.
Define \( \phi(H_k) = tr(H_k) - ln\left(\|H_k\|\right) > 0 \)
By replacing \( H_k \) by \( H_{k+1} \) into \( \phi(H_k) \), then
\[
0 < \phi(H_{k+1}) = tr(H_{k+1}) - ln\left(\|H_{k+1}\|\right) = tr(H_k) - \frac{w_k^T w_k}{y_k^T y_k} - ln\left(H_k\right) - \frac{w_k^T r_k}{w_k^T y_k} - \frac{y_k^T y_k}{\|w_k\|^2}
\]
\[
ln\left(\|H_k\|\right) - ln(w_k^T \eta_k) + ln(w_k^T y_k) > 0
\]
(13)
\[
\eta_k = \frac{w_k^T r_k}{y_k^T y_k} = \frac{w_k^T (y_k - B_k w_k)}{y_k^T y_k} = \frac{w_k^T H_k y_k - H_k y_k^T H_k y_k}{\|w_k\|^2}
\]
where \( q_k = \frac{w_k^T y_k}{\|y_k\|^2} \) and \( \cos \theta_k = \frac{w_k^T y_k}{\|w_k\| \|y_k\|} \) by add and subtract \( ln(y_k^T y_k) \) to the right hand side of Eq. 13, therefor
\[
0 < \phi(H_{k+1}) = \phi(H_k) - \frac{q_k}{\cos \theta_k} = ln(w_k^T y_k)
\]
(14)
Now consider the function \( f(t) = 1 - t + ln(t) \)
\[
f'(t) = -1 + \frac{1}{t} = 0
\]
\[\Rightarrow t = 1 \] is extreme point.
\[
f''(t) = -\frac{1}{t^2}
\]
(15)
where
\[
\phi(H_{k+1}) < \phi(H_k) - \frac{q_k}{\cos \theta_k} + ln(\frac{q_k}{\cos \theta_k}) 
\]
\[
0 < \phi(H_{k+1}) < \phi(H_k) + C(k+1) + \Sigma j=0 \Sigma k_j \ln(\cos \theta_j)
\]
(16)
\[
\Sigma j=0 \Sigma k_j \ln(\cos \theta_j) < -2C
\]
From Eq. 17, and since \( \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) = \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) + \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) \) then
\[
0 < \phi(H_{k+1}) < \phi(H_0) + C(k+1) + \Sigma j=0 \Sigma k_j \ln(\cos \theta_j)
\]
(17)
Where the constant \( C \) is assumed to be positive without loss of the generality. From Zoutendijk condition (1) (if \( f \) satisfy assumption 1, then \( \Sigma \cos \theta \|\nabla f\| < \infty \) and hence
\[
\lim _{k \rightarrow \infty} \|\nabla f\| \cos \theta_k = 0.
\]
If \( \theta_k \) is bounded away from \( 90^\circ \), \( \forall \mu \in R^+ \exists \cos \theta_k > \mu > 0 \), for \( k \) sufficient large and hence \( \|\nabla f\| \rightarrow 0 \) and by the first order necessary condition theorem (1), the prove is complete.
Now, assume by contradiction that \( \cos \theta_k \rightarrow 0 \), then \( \exists k_1 > 0 \) \( \forall j > k_1 \),
\[
\ln(\cos \theta_j) < -2C
\]
(18)
From Eq. 17, and since \( \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) = \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) + \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) \), then
\[
0 < \phi(H_{k+1}) < \phi(H_0) + C(k+1) + \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) + \Sigma j=0 \Sigma k_j \ln(\cos \theta_j)
\]
(19)
By substitution Eq. 18 in Eq. 19
\[
0 < \phi(H_{k+1}) < \phi(H_0) + C(k+1) + \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) + \Sigma j=0 \Sigma k_j \ln(\cos \theta_j) - 2C(k - k_1)
\]
0 < \varphi(H_{k+1}) < \varphi(H_0) + \sum_{j=0}^{k} \frac{\ln(\cos^2 \theta_j)}{2C. k_j + C - C, k < 0, \text{for } k \text{ sufficiently large, which is a contradiction, then } cos^2 \theta_j \to 0 \text{ is not true and } \lim_{k \to \infty} \ln \| \nabla f \| = 0, \text{ and again by the first order necessary condition theorem (1) and the prove is complete.}

**Numerical Examples:**

In this section, two numerical examples are studied by modifying SR1 (H-version) update. The results are compared with the results obtained by the original method.

**Example 1:**

*In this example the objective function* \( f(x) = (1 - x_1)^2 + (x_2 - x_1)^2 \)\(^1\), *has been solved by using the original method firstly, and then also solved by our method.*

**Min.** \( f(x) = (1 - x_1)^2 + (x_2 - x_1)^2 \), with \( x^0 = \begin{bmatrix} 0 \\ -0.5 \end{bmatrix} \), \( H_0 = I, \text{ error} = 0.005 \)

**Iteration 1**

\[ \nabla f(x) = \begin{bmatrix} 4x_1 - 2x_2 - 2 \\ -2x_1 + 2x_2 \end{bmatrix}, \nabla f(x^0) = \begin{bmatrix} -1 \\ 1 \end{bmatrix}, \]

\[ P_0 = -H_0 \nabla f(x^0) = \begin{bmatrix} 1 \\ 1 \end{bmatrix}. \]

\( x^1 = x^0 + \lambda_0 P_0 = \begin{bmatrix} 0.5 \\ -0.5 + \lambda_0 \end{bmatrix}, \quad f(x^1) = (1 - \lambda_0)^2 + (-0.5 + \lambda_0 - \lambda_0)^2 \)\( = (1 - \lambda_0)^2 + 0.25, \)

\[ \frac{\partial f(x^1)}{\partial \lambda_0} = 1 - \lambda_0, \lambda_0 = 1, \text{ and hence } x^1 = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}, \]

\[ s_0 = x^1 - x^0 = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}, \quad \nabla f(x^1) = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}. \]

\[ y_0 = \nabla f(x^1) - \nabla f(x^0) = \begin{bmatrix} 2 \\ 0 \end{bmatrix}, \quad H_1 = H_0 + \frac{(s_0 - H_0 y_0)(s_0 - H_0 y_0)^T}{y_0^T s_0 - H_0 y_0} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}, \quad \text{and since } \| \nabla f(x^1) \| > \text{error}. \]

**Iteration 2**

\[ P_1 = -H_1 \nabla f(x^1) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad x^2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad s_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \]

\[ \nabla f(x^2) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, y_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \text{ and since } \| \nabla f(x^2) \| = 0 < \text{error}, \text{ therefore the method is terminated at the solution } x^* = \begin{bmatrix} 1 \\ 0.5 \end{bmatrix}, \text{ and the minimum value of the objective function is } f(x^*) = 0.25. \]

Now the same example has been solved by our method as follows:

**Iteration 1**

\[ \nabla f(x) = \begin{bmatrix} 4x_1 - 2x_2 - 2 \\ -2x_1 + 2x_2 \end{bmatrix}, \nabla f(x^0) = \begin{bmatrix} -1 \\ 1 \end{bmatrix}, \]

\[ P_0 = -H_0 \nabla f(x^0) = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad x^1 = x^0 + \lambda_0 P_0 = \begin{bmatrix} 0.5 \\ -0.5 + \lambda_0 \end{bmatrix}, \quad f(x^1) = (1 - \lambda_0)^2 + (-0.5 + \lambda_0 - \lambda_0)^2 \] \( = (1 - \lambda_0)^2 + 0.25, \)

\[ \frac{\partial f(x^1)}{\partial \lambda_0} = 1 - \lambda_0, \lambda_0 = 0, \lambda_0 = 1, \text{ and hence } x^1 = \begin{bmatrix} 1 \\ 0.5 \end{bmatrix}. \]

**Example 2:**

*In this example the Freudenstein and Roth function (1), has been solved by using program MATLAB, and the final results firstly by the original method, and then by our method has been given.*

**Min.** \( f(x) = \{-13 + x_1 + [(5 - x_2)x_2 - 2]x_2^2 \} + \{-29 + x_1 + [(x_2 + 1)x_2 - 14]x_2^2 \}, \)

with \( x^0 = \begin{bmatrix} 5 \\ 10 \end{bmatrix}, H_0 = I, \text{ error}=0.0005. \)

Maximum number of function evaluations exceeded;
increase options.MaxFunEvals

\[ x = -3514897 \quad 8.2397 \]

FVAL = 14596e+005

**OUTPUT =**

iterations: 43
funcCount: 202
stepsize: -3.6779e-032
algorithm: 'medium-scale: Quasi-Newton line search'

GRAD = 1.0e+005 *
-0.0105
5532
INVHESSIAN = 1.0e-005 *
0.0908 -0.1254
-0.1254 0.3665

301
Now the same example has been solved by our method:

\[ x = \begin{bmatrix} 10.8384 \\ 3.8545 \end{bmatrix} \]

\[ FVAL = 1.0383e-015 \]

\[ OUTPUT = \begin{bmatrix} \text{iterations: 24} \\ \text{funcCount: 202} \\ \text{stepsize: 2.9014e-016} \\ \text{algorithm: 'medium-scale: Quasi-Newton line search'} \end{bmatrix} \]

From example 1, SR1 (H-version) update cannot terminate successfully at the minimum (min. \( f =0.25 \)), because of the non-positive definite of inverse of Hessian matrix \( H_1 \) generated in first iteration \( (|H_1| = 0) \), and hence the method terminated at a saddle point which is not minimizer of the objective function, but clear that the modified SR1 (H-version) update can terminate successfully at the minimizer of the objective function. Moreover, the inverse of Hessian matrix generated by our method is positively definite at every iteration. From example 2, the function evaluation (FVAL) at the last iteration for the original method is very far from the exact value (min. \( f = 0 \)), but in our method, it is clear that the function evaluation (FVAL) at the last iteration is very close to the exact value (min. \( f = 0 \)). This means that the original method cannot successfully terminate at the minimum because of the not positive definite of inverse Hessian matrix generated by the method in iteration number 43 where

\[ INVHESSIAN = \begin{bmatrix} 1.0e+005 \\ 12018 & 0.7665 \\ 0.7665 & 0.1424 \end{bmatrix} \]

is very close to zero \( (|H_{43}| = 0.0000000176) \) or near singular matrix.

**Conclusion:**

In this paper, the SR1 (H-version) update has been modified to preserve the positive definite property for the next inverse of Hessian matrix at each iteration if the current inverse of Hessian matrix is positively definite which makes the computation continue until the objective function terminates at the minimum of the objective function. Moreover, theorem 1 proves the positive definiteness property and theorem 5 proves the convergence of our method and also two numerical examples are established to support our method.

**Authors’ declaration:**

- Conflicts of Interest: None.
- Ethical Clearance: The project was approved by the local ethical committee in University of Mustansiriyah.

**Author’s Contributions statement:**

The first author makes a conception and design for this paper while the second author makes the analysis and the third author makes the revision and proofreading.

**References:**

التحديث الايجابي لتحديد الرتبة 1 المتماثل (النسخة $H$) للمثلية غير المقيدة

سعد شاكر محمود  
جعفر حمود عيدي  
جنان عادل جاسم

قسم الرياضيات، كلية التربية، الجامعة المستنصرية، بغداد، العراق.

الخلاصة:
عدد محاولات بذلت لتحويل شرط كواسي نيوتن للمثلية غير المقيدة وذلك للحصول على تقارب اسرع مع خواص كاملة (التناظرية والموجبة) لمعكوس المصفوفة هيسين (المشتقة الثانية لدالة الهدف). هناك الكثير من طرق المثلية غير المقيدة التي لا تولد معكوس مصفوفة هيسين موجبة. أحد هذه الطرق هو التحديث التناظري من الرتبة الأولى (النسخة $H$)، حيث أن هذا التحديث يحقق شرط كواسي نيوتن ويضمن خصائص الموجبة لمعكوس مصفوفة هيسين عندما تكون مصفوفة هيسين الابتدائية موجبة. إن الموجبة لمعكوس المصفوفة هيسين مهم لضمان وجود نقطة النهاية الصغرى لدالة الهدف وكذلك للحصول على أصغر قيمة لدالة الهدف.

الكلمات المفتاحية: مصفوفة هيسين، التحديد الموجب، شرط كواسي-نيوتن، التحديث من الرتبة 1 المتماثل (النسخة $H$)، المثلية غير المقيدة.