Automatic Superlinear Self-Scaling VM-algorithm

Abbas Y. Al-Bayati  Maha S. Al-Salih

College of Computers Sciences & Mathematics
University of Mosul

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Abstract
In this paper, a new self-scaling VM-algorithm for unconstrained non-linear optimization is investigated. Some theoretical and experimental results are given on the scaling technique, which guarantee the Superlinear of the new proposed algorithm.
1. Introduction

Conjugate Gradient (CG) methods were first used to solve the general unconstrained problem by Fletcher and Reeves [14]. Their algorithm (or simple variants) is still frequently used, especially for problems with a large number of variables since they require only a few vectors of length n to be stored.

Given a symmetric positive definite matrix G, the finite set of non-null vectors \{d_1, d_2, \ldots, d_k\} are said to form a conjugate set if

\[ d_i^T G d_j = 0 \quad \text{for all } i \neq j \]

An important class of quasi-Newton methods for solving the unconstrained optimization problem, [13]

\[
\min_{x \in \mathbb{R}^n} f(x),
\]

was proposed by [7]. It consists of iterations of the form

\[ x_{k+1} = x_k + \lambda_k d_k, \quad k \geq 1, \]

where

\[ d_k = -B_k^{-1} g_k \]

Here \( \lambda_k \) is a step length parameter satisfies the Wolfe conditions with exact line search strategy, i.e.

\[
f(x_k + \lambda_k d_k) \leq f(x_k) + \alpha \lambda_k g_k^T d_k \]

\[
g(x_k + \lambda_k d_k)^T d_k \geq \beta g_k^T d_k
\]

for \( 0 < \alpha < \frac{1}{2} \) and \( \alpha < \beta < 1 \), and \( g_k \) denotes the gradient of \( f \) at \( x_k \).

The Hessian approximation \( B_k \) is updated by means of the formula

\[
B_{k+1} = B_k - \frac{B_k s_k s_k^T B_k}{s_k^T B_k s_k} + \frac{y_k y_k^T}{y_k^T s_k} + \phi_k (s_k^T B_k s_k) v_k v_k^T,
\]

where \( \phi \) is a scalar, \( y_k = g_{k+1} - g_k \), \( s_k = x_{k+1} - x_k \) and

\[
v_k = \begin{bmatrix} y_k - B_k s_k \\ y_k^T s_k - s_k^T B_k s_k \end{bmatrix}
\]

The choice of the parameter \( \phi_k \) is important, since it can greatly affect the performance of the methods. The BFGS method corresponds to \( \phi_k = 0 \).
Variable metric (VM) methods were originally proposed by Davidon [11]. Subsequently, many authors have extended the theory and practice,[12] for a survey. The search direction in a VM- method is the solution of the system of equations:

\[ d_k = -H_k g_k \]

where the matrix \( H_k \) is an approximation to \( G_k^{-1} \), the inverse Hessian of the function \( f(x) \). and:

\[ v_k^T G_k v_k \equiv v_k^T y_k \]

This relationship is exact if the non-linear function \( f \) is exactly equal \( q \). The new approximation for the inverse Hessian \( H_{k+1} \) is chosen to ensure that

\[ H_{k+1} y_k = \xi_k v_k \]

where \( \xi_k \) is a scalar; generally for the quasi-Newton (QN) method \( \xi_k = 1 \) and hence (3.15) reduces to

\[ H_{k+1} y_k = v_k \] (called the QN-condition)

And

\[ H_{k+1} = H_k + C_k \]

The matrix \( C_k \) is therefore, the update to \( H_k \).

For the next iteration \( B_{k+1} \) is updated by Al-Bayati’s VM-update, i.e.

\[ B_{k+1} = B_k - \frac{B_k s_k s_k^T B_k}{s_k^T B_k s_k} + \frac{s_k y_k}{(s_k y_k)^2} y_k^T y_k \] \hspace{1cm} (8)

See [1] for more details and properties of this algorithm.

**Algorithm 1.1:** [6]

1. For a starting point \( x_1 \) and non singular matrix \( V_1 \); set \( k = 1 \).
2. Terminate if \( \| g_{k+1} \| < \varepsilon \), \( \varepsilon \) is a small positive real number.
3. Compute
\[ d_k = -V_k^T V_k^{-1} g_k \]

\[ x_{k+1} = x_k + \lambda_k d_k \]

\( \lambda_k \) is computed by exact line search.

(4) Update \( V_k \) using Al-Bayati, 1991 VM-update.

\[ W_k = V_k - \frac{V_k s_k s_k^T V_k}{s_k^T V_k s_k} + \frac{s_k^T V_k y_k}{(y_k^T s_k)^2} \cdot y_k y_k^T \]

(5) Compute the scaling parameter \( \sigma_k \geq 0 \) and \( \mu_k > 0 \) such that \( \sigma_k \leq \mu_k \). If \( w_i \) represents the column of \( W_k \) put \( C_k = \text{diag} \{ c_1, c_2, \ldots, c_n \} \) where

\[
c_i = \begin{cases} 
\sigma_k & \text{if } \|w_i\| < \sigma_k \\
\mu_k & \text{if } \|w_i\| > \mu_k \\
\zeta_k & \text{otherwise}
\end{cases}
\]

Where \( \zeta_k = \frac{y_k^T V_k y_k}{y_k^T s_k} \)

(9)

(6) Set \( V_{k+1} = W_k C_k \)

(7) set \( k = k +1 \) and go to step (1)

Note that:

1- In the above algorithm

\[
B_1 = V_1 V_1^T \\
B_k = V_k V_k^T \\
= W_{k-1} C_{k-1}^2 W_{k-1}^T \quad k > 1
\]

and the update is performed directly on \( V_k \).

2. Basic Results for Super Linear Convergence

First we define the following quantities to be used in this section:

\[ \overline{B}_k = G_{s^2} B_k G_{s^2} \]

\[ \overline{W}_k = G_{s^2} W_k \]

\[ \overline{s}_k = \frac{1}{G_{s^2}} s_k \]

\[ \overline{y}_k = \frac{1}{G_{s^2}} y_k \]

(11)

(12)
\[ \bar{M}_k = \frac{y_k^T y_k}{y_k^T s_k} \quad \text{and} \quad \bar{m}_k = \frac{\bar{y}_k^T \bar{s}_k}{\bar{s}_k^T \bar{s}_k} \tag{13} \]

\[ q_k = \frac{s_k^T B_k s_k}{s_k^T s_k} \quad \text{and} \quad \cos \bar{\theta}_k = \frac{\bar{s}_k^T B_k \bar{s}_k}{\| \bar{s}_k \| \| B_k \| \| \bar{s}_k \|} \tag{14} \]

where \( G_* \) is the Hessian of \( f \) at the minimizer \( x_* \).

The limiting behavior of \( q_k \) and \( \cos \bar{\theta}_k \) is enough to characterize the asymptotic rate of convergence of a sequence of iterates \( \{x_k\} \) generated by a quasi-Newton algorithm. Their result which can be seen as a restatement of the,[12] characterization, is reproduced in the following lemma.

**Lemma (2.1):**

Suppose that the sequence of iterates \( \{x_k\} \) is generated by algorithm (1.1) using some positive definite sequence\( \{B_k\} \), and that \( \lambda_k = 1 \) whenever this value satisfies Wolfe conditions (4)-(5). If \( x_k \to x_* \) then the following two conditions are equivalent:

(i) The steplength \( \lambda_k = 1 \) satisfies conditions (4)-(5) for all large \( k \) and the rate of convergence is superlinear.

(ii) \( \lim_{k \to \infty} \cos \bar{\theta}_k = \lim_{k \to \infty} q_k = 1 \) \( \tag{15} \)

**Proof:** Proof of this lemma can be found in [9]. The next theorem specifies conditions on the scaling parameters \( \sigma_k \) and \( \eta_k \) that allow \( q_k \) and \( \cos \bar{\theta}_k \), produced by Algorithm 1.1, to exhibit the desirable limiting behavior of Lemma 2.1. Such conditions involve the following quantities:

\[ \gamma_k = \sum_{i=1}^{d} \left( (\ln \left\| G_i \cdot \bar{w}_i \right\| \bar{w}_i^T - \left\| G_i \cdot \bar{w}_i \right\|^2 \bar{w}_i ) - (\ln \left\| G_i \cdot \bar{w}_i \right\| \bar{w}_i^T - \sigma_k \left\| G_i \cdot \bar{w}_i \right\|^2 \bar{w}_i \right) \right) \]

\[ \mu_k = \sum_{i=1}^{d} \left( (\ln \left\| G_i \cdot \bar{w}_i \right\| \bar{w}_i^T - \left\| G_i \cdot \bar{w}_i \right\|^2 \bar{w}_i ) - (\ln \left\| G_i \cdot \bar{w}_i \right\| \bar{w}_i^T - \eta_k \left\| G_i \cdot \bar{w}_i \right\|^2 \bar{w}_i \right) \right) \]

\[ \gamma_k \geq \mu_k \]

\[ \sum_{i=1}^{d} \left( (\ln \left\| G_i \cdot \bar{w}_i \right\| \bar{w}_i^T - \left\| G_i \cdot \bar{w}_i \right\|^2 \bar{w}_i ) - (\ln \left\| G_i \cdot \bar{w}_i \right\| \bar{w}_i^T - \sigma_k \left\| G_i \cdot \bar{w}_i \right\|^2 \bar{w}_i \right) \right) \]...

and

\[ \mu_k \geq \gamma_k \]

\[ \sum_{i=1}^{d} \left( (\ln \left\| G_i \cdot \bar{w}_i \right\| \bar{w}_i^T - \left\| G_i \cdot \bar{w}_i \right\|^2 \bar{w}_i ) - (\ln \left\| G_i \cdot \bar{w}_i \right\| \bar{w}_i^T - \eta_k \left\| G_i \cdot \bar{w}_i \right\|^2 \bar{w}_i \right) \right) \]...

and

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\[
\phi_k = \sum_{i=1}^k \left( \ln \left| G_i \right|^2 \| w_i \| - \ln \left| G_i \right|^2 \| w_i \| \right) - \sum_{i=1}^k \left( \ln \zeta_i^2 \| w_i \| - \zeta_i^2 \| w_i \| \right) \quad \ldots (17a)
\]

and whether they sum finitely or not. Note that \( \gamma_k \) and \( \mu_k \) need not be positive. Recall that the sets \( I_k \) and \( J_k \) defined by:

\[
I_k = \{ i \in [1, n] : \| w_i \| < \sigma_k \}
\]

and

\[
J_k = \{ i \in [1, n] : \| w_i \| > \mu_k \}
\]

contain the indices of the columns that are scaled down at iteration \( k \).

We are now ready to state the theorem.

**Theorem 2.1:**

For the quadratic function \( f \), \( x_1 \), \( B_1 \), \( \sigma_k \) and \( \eta_k \) satisfy the assumptions in theorem 1.1. In addition, assume that \( G \) is Lipschitz continuous at \( x^* \). Let \( \{ x_k \} \rightarrow x^* \) be generated by Algorithm 1.1; then if

\[
\sum_{k=1}^\infty \gamma_k < \infty \quad (18)
\]

\[
\sum_{k=1}^\infty \mu_k < \infty \quad (19)
\]

\[
\sum_{k=1}^\infty \phi_k < \infty \quad (19a)
\]

the iterates converge superlinearly (for the case of non-quadratic functions, see [2] and [3].

**Proof:** Let \( \psi(B) = \text{tr}(B) - \ln(\det(B)) \) then,

\[
\text{Tr}(A\bar{C}A^T) = \text{tr}(AA^T) + \text{tr}[(C-I)A^TA]
\]

and from (11), we have

\[
\psi(B_{k+1}) = \text{tr}(G_i^2 W_k C_k^2 W_k^T G_i^2) - \ln(\det(G_i^2 W_k C_k^2 W_k^T G_i^2))
\]

\[
= \text{tr}(\tilde{W}_k C_k^2 \tilde{W}_k^T) - \ln(\det(\tilde{W}_k \tilde{W}_k^T)) - \ln(\det(C_k^2))
\]

\[
= \psi(\tilde{W}_k \tilde{W}_k^T) + \sum_{i=1}^n \left(c_i^2 - 1\right)\| G_i^2 W_i \|^2 - \ln c_i^2
\]

Then by the definition (9) of \( c_i \),
\[
\psi (\tilde{B}_{k+1}) = \psi (\tilde{W}_k W_k^T) + \sum_{i \in J_k} \left[ \frac{\sigma_k^2}{\| W_i \|^2} \right] G_i \cdot \frac{1}{2} \| W_i \|^2 - \ln \frac{\sigma_k^2}{\| W_i \|^2} \\
+ \sum_{i \in J_k} \left[ \frac{\eta_k^2}{\| W_i \|^2} \right] G_i \cdot \frac{1}{2} \| W_i \|^2 - \ln \frac{\eta_k^2}{\| W_i \|^2} \\
+ \sum_{i \in J_k} \left[ \frac{\zeta_k^2}{\| W_i \|^2} \right] G_i \cdot \frac{1}{2} \| W_i \|^2 - \ln \frac{\zeta_k^2}{\| W_i \|^2} \\
= \psi (\tilde{W}_k W_k^T) + \sum_{i \in J_k} \left[ \frac{\sigma_k^2}{\| W_i \|^2} \right] G_i \cdot \frac{1}{2} \| W_i \|^2 - \| G_i \cdot \frac{1}{2} W_i \|^2 \\
- \ln \sigma_k^2 \frac{\| G_i \cdot \frac{1}{2} W_i \|^2}{\| W_i \|^2} + \ln \| G_i \cdot \frac{1}{2} W_i \|^2 \\
+ \sum_{i \in J_k} \left[ \frac{\eta_k^2}{\| W_i \|^2} \right] G_i \cdot \frac{1}{2} \| W_i \|^2 - \| G_i \cdot \frac{1}{2} W_i \|^2 \\
- \ln \eta_k^2 \frac{\| G_i \cdot \frac{1}{2} W_i \|^2}{\| W_i \|^2} + \ln \| G_i \cdot \frac{1}{2} W_i \|^2 \\
+ \sum_{i \in J_k} \left[ \frac{\zeta_k^2}{\| W_i \|^2} \right] G_i \cdot \frac{1}{2} \| W_i \|^2 - \| G_i \cdot \frac{1}{2} W_i \|^2 \\
- \ln \zeta_k^2 \frac{\| G_i \cdot \frac{1}{2} W_i \|^2}{\| W_i \|^2} + \ln \| G_i \cdot \frac{1}{2} W_i \|^2 \\
= \psi (\tilde{W}_k W_k^T) + \gamma_k + \mu_k + \phi_k \\
\tag{20}
\]

Since \( \tilde{W}_k W_k^T \) is the matrix obtained by updating \( B_k \) using the [1] formula, which is invariant under the transformation (11) – (14), we have:

\[
\psi (\tilde{W}_k W_k^T) = \psi (\tilde{B}_k) + (\tilde{M}_k - \ln \tilde{m}_k - 1) \\
+ (1 - \frac{\tilde{q}_k}{\cos^2 \theta_k}) + \ln \frac{\tilde{q}_k}{\cos^2 \theta_k} + \ln \cos \theta_k \tag{21}
\]
Therefore, using (21) in (20), we have:
\[
\psi(\tilde{B}_{k+1}) = \psi(\tilde{B}_k) + (\tilde{M}_k - \ln \tilde{m}_k - 1) + (1 - \frac{q_k}{\cos^2 \theta_k} + \frac{\bar{q}_k}{\cos^2 \tilde{\theta}_k}) + \ln \cos^2 \tilde{\theta}_k + \gamma_k + \mu_k + \phi_j
\]
\[
= \psi(\tilde{B}_k) + \sum_{j=1}^{k} (\tilde{M}_j - \ln \tilde{m}_j - 1) + \sum_{j=1}^{k} (1 - \frac{q_k}{\cos^2 \theta_k} + \frac{\bar{q}_k}{\cos^2 \tilde{\theta}_k}) + \sum_{j=1}^{k} \gamma_j + \sum_{j=1}^{k} \mu_j + \sum_{j=1}^{k} \phi_j
\]
\[
\frac{\sum_{j=1}^{k} (\tilde{M}_j - \ln \tilde{m}_j - 1)}{k} < \infty
\]

Now by the following theorem due to [10].

**Theorem 1.1:**

Let \( x_1 \) be a starting point for which \( f \) satisfies eq.(12) and let \( B_1 \) be a positive definite starting Hessian approximation. Let \( \{x_k\} \) be generated by the new proposed algorithm with \( \sigma_k \) and \( \mu_k \) satisfying eq.(18) and for any \( \rho \in (0, 1) \exists \) a constant \( \beta_1 \) for any \( k > 1 \) the relation \( \cos \theta_j \geq \beta_1 \) holds for at least \( [P_k] \) values of \( j \in [1, k] \).

We know that the iterates converge to \( x^* \) r-linearly. Using this and the Lipschitz continuity of \( G \) at \( x^* \), it is not difficult to show, see [9] that:

\[
\sum_{j=1}^{k} (\tilde{M}_j - \ln \tilde{m}_j - 1) < \infty
\]

Moreover, the hypothesis of the theorem guarantees that the last two summations in (22) are bounded above. Therefore, in order for \( \psi(\tilde{B}_{k+1}) \) to remain positive as \( k \rightarrow \infty \), the sum of the nonpositive terms in the square brackets must also be bounded. This can only be true if:

\[
\lim_{k \rightarrow \infty} (1 - \frac{q_k}{\cos^2 \theta_k} + \frac{\bar{q}_k}{\cos^2 \tilde{\theta}_k}) = \lim_{k \rightarrow \infty} \ln \cos^2 \tilde{\theta}_k = 0
\]

Which implies that both \( \bar{q}_k \) and \( \cos^2 \tilde{\theta}_k \rightarrow 1 \). Hence, superlinear convergence follows from Lemma (2.1) #.

Now we describe a specific and modified implementation of algorithm 1.1 and make use of the theory developed so far to show that it is superlinearly convergent for strictly convex objective functions.

**New Algorithm:**

Step (0) Choose \( x_1 \) and a nonsingular and lower matrix \( V_1 \); set \( k = 1 \).

Step (1) Terminate if a stopping criterion is satisfied.
Step (2) Find an orthogonal matrix $Q_k$ such that $L_k = V_k Q_k$ is a lower triangular.
Compute:
\[ d_k = -L_k^{-T} L_k^{-1} g_k, \]
\[ x_{k+1} = x_k + \lambda_k d_k \]
Where $\lambda_k$ is a steplength that satisfies the Wolfe conditions (The stepsize $\lambda_k = 1$ is always tried first and is accepted if admissible).

Compute:
\[ s_k = x_{k+1} - x_k \]
\[ y_k = g_{k+1} - g_k \]

Step (3) Perform the following steps to update $L_k$ to $W_k$ so that $W_k \, W_k^T$ become Al-Bayati update of $L_k \, L_k^T$ as defined in (8):

(3.1) Compute $r_k =  L_k^T s_k$

(3.2) Find an orthogonal and lower matrix $\Omega_k$ such that $\|r\|_2 / r_{kk} e_{kk} = \Omega_k$

(3.3) Construct $W_k = \{w_1^k, w_2^k, \ldots, w_n^k\}$, where $w_i^k$ is given by
\[ w_i^k = \begin{cases} \frac{y_k^T y_k}{y_k^T s_k} s_k, & i = 1 \\ L_k \, \Omega_k \, e_i, & i = 2, 3, \ldots, n \end{cases} \]

Step (4) Compute the scaling parameters:
If $k = 1$, $\sigma_i^2 = \eta_i^2 = \frac{y_i^T y_i}{s_i^2}$$\zeta_i^2$

Otherwise, $\sigma_k^2 = \frac{1}{n} \left[ (n - |I_{k-1}|) \sigma_{k-1}^2 + \sum_{i \in I_{k-1}} \|W_i^{k-1}\|^2 \right]$
where $I_{k-1} = \{i \in [1, n]: \|W_i^{k-1}\| < \sigma_{k-1}\}$,
And $\eta_k^2 = \frac{1}{n} \left[ (n - |J_{k-1}|) \eta_{k-1}^2 + \sum_{i \in J_{k-1}} \|W_i^{k-1}\|^2 \right]$
where $J_{k-1} = \{i \in [1, n]: \|W_i^{k-1}\| > \eta_{k-1}\}$
Construct $C_k = \text{diagonal}(c_1, c_2, \ldots, c_n)$ where $c_i$ is given by:
\[
\begin{align*}
\mathbf{c}_i &= \begin{cases} 
\frac{\sigma_k}{\|W_i^k\|} & \text{if } \|W_i^k\| < \sigma_k \\
\frac{\eta_k}{\|W_i^k\|} & \text{if } \|W_i^k\| > \eta_k \\
\frac{\zeta_k}{\|W_i^k\|} & \text{otherwise}
\end{cases} \\
\text{Where } y_k^T V_k y_k & \text{ and } y_k^T s_k
\end{align*}
\]

Compute: \( \gamma_{k+1} = W_k C_k \)

Step (5) Set \( k = k + 1 \) and go to step (1).

3. Numerical Results

In order to assess the value of this new technique, numerical tests on twenty test functions were carried out for unconstraint optimization problems. As a standard for the purpose of comparison, the test functions, (from general literature) were solved using two different VM-algorithms.

(i) The standard BFGS algorithm.
(ii) The new proposed algorithm (which it has been proved to be superlinear convergent algorithm).

All the numerical results were presented in tables (1)-(2). All the algorithms terminate whenever \( \|g_{k+1}\| < 1 \times 10^{-5} \) and the two algorithms use exactly the same line search strategy, namely, the cubic fitting technique directly adapted from that published by [8].

Analysis of the two tables shows that the new proposed VM-algorithm is superior to the standard BFGS algorithm. The superiority of the new algorithm is clear for high dimensionality test problems because of the automatic scaling strategy.
Table (1): Comparison of the new algorithm with the standard BFGS for $2 \leq n \leq 10$.

<table>
<thead>
<tr>
<th>Test Function</th>
<th>N</th>
<th>New algorithm</th>
<th>Standard BFGS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>NOI</td>
<td>NOF</td>
</tr>
<tr>
<td>OSP</td>
<td>2</td>
<td>4</td>
<td>24</td>
</tr>
<tr>
<td>Helical</td>
<td>3</td>
<td>22</td>
<td>60</td>
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<tr>
<td>Cubic</td>
<td>4</td>
<td>7</td>
<td>34</td>
</tr>
<tr>
<td>Rosen</td>
<td>4</td>
<td>12</td>
<td>41</td>
</tr>
<tr>
<td>Powell</td>
<td>4</td>
<td>16</td>
<td>72</td>
</tr>
<tr>
<td>Wood</td>
<td>4</td>
<td>20</td>
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</tr>
<tr>
<td>NON</td>
<td>4</td>
<td>26</td>
<td>87</td>
</tr>
<tr>
<td>Miele</td>
<td>4</td>
<td>23</td>
<td>79</td>
</tr>
<tr>
<td>OSP</td>
<td>10</td>
<td>17</td>
<td>79</td>
</tr>
<tr>
<td>Full</td>
<td>10</td>
<td>9</td>
<td>19</td>
</tr>
<tr>
<td>Total</td>
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<td>567</td>
</tr>
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Percentage improvement of the new algorithm compared with the standard BFGS algorithm

<table>
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<th></th>
<th>New % NOI</th>
<th>BFGS % NOI</th>
</tr>
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<tbody>
<tr>
<td>New</td>
<td>100</td>
<td>124.358</td>
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<tr>
<td>BFGS</td>
<td>100</td>
<td>120.282</td>
</tr>
</tbody>
</table>

Table (2): Comparison of the new algorithm with the standard BFGS for $100 < n < 900$.

<table>
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<th>N</th>
<th>New algorithm</th>
<th>Standard BFGS</th>
</tr>
</thead>
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<td></td>
<td></td>
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<td>NOF</td>
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</tr>
<tr>
<td>Miele</td>
<td>900</td>
<td>31</td>
<td>93</td>
</tr>
</tbody>
</table>
| Total         | 595 | 1715| 966 | 2869

49
Percentage improvement of the new algorithm compared to standard BFGS algorithm

<table>
<thead>
<tr>
<th></th>
<th>100 % NOI</th>
<th>100 % NOF</th>
</tr>
</thead>
<tbody>
<tr>
<td>New</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BFGS</td>
<td>162.352</td>
<td>167.288</td>
</tr>
</tbody>
</table>

4. Final Remarks and Conclusions

We have described in this paper the conditions under which new automatic self-scaling algorithms based on the direct form of [1] VM-Update can be proved to be superlinearly convergent. Also some sort of numerical experiments have been done to know the effectiveness of the new proposed algorithm.

It is also possible to describe another similar algorithm based on the inverse scaled-BFGS algorithm. A column scaling algorithm which was proposed by [15] may be modified and implemented with this family of algorithms.

However, values of $\sigma_k$, $\mu_k$ selected in the new algorithm are arbitrary. It might occasionally be better to increase $\sigma_k$ and to decrease $\mu_k$. In any case, the theory developed in this paper will prove to be useful for analyzing the super linear convergence of this algorithm.

Finally this, idea may be extended to constrained optimization problems, see [5] for more details and for non-quadratic models see [4].
REFERENCES


