A note on the equivalence of Broyden and Block ABS methods

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Abstract

In this paper we are considering a scaled linear system and presenting a result of equivalence between Broyden's Method and Block ABS Method applied to this system. As consequence, we have an alternative proof of finite termination for Broyden's method [6].

keywords. ABS Block Methods, Broyden's Method, Scaled Linear System

1 Introduction

The study about methods for solving linear systems is not new, but the growing emergence of real-world problems formulated under this optics has made these studies focused on practical efficacy and theoretical development of these methods. There are several work about this subject and we recommend [7, 5, 10, 8] and the references therein.

In this paper we are approaching one generalization of ABS methods. This class was proposed to solve determined and undetermined linear systems by J. Abaffy, C. Broyden and E. Spedicato [3], in 1984.

In [2], Abaffy and Spedicato proved that ABS methods (introduced in [3]) when used for *n*-squared systems and by certain choices of parameters have the property that 2 steps of Broyden's method are equivalent to one step of ABS method. Since ABS methods have finite termination, they showed an alternative proof of finite termination for Broyden's methods, complementing the early results proposed by Gay [6] in 1979.

Recently, Adib [4] by considering a scaled version of ABS methods for systems of type:

$$V^T A x = V^T b, (1)$$

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where $V = V_{n \times n}$ is nonsingular, proved that by certain choice of parameters this version of ABS algorithm is related to Broyden's method too. Scaled linear systems appears naturally in ill-conditioned problems so it is a relevant topic in several practical algorithms.

Another important contribution given in [2] is the introduction of Block ABS methods class for solving scaled linear systems. In *i*-step ABS method we find the solution for the i-1 first equations. The Block ABS method is more flexible than ABS method because we can choose many equations to solve in each step. This flexible feature is obtained by segmentation of certain matrix by certain submatrix.

The goal of this paper is to consider the scaled system 1 and show an equivalence between Broyden's algorithm and Block ABS methods. Consequently we are complementing the results given in [4].

2 Background Material

Consider the linear system of equation Ax = b, where $A \in \mathbb{R}^{n \times n}$, $b \in \mathbb{R}^n$ and $x \in \mathbb{R}^n$. Let $g : \mathbb{R}^n \to \mathbb{R}$ defined by g(x) = Ax - b. We begin this section by describing the Broyden's method (Algorithm 1).

Algorithm 1 Broyden's algorithm (see [6])

1: Choose a vector $x_0 \in \mathbb{R}^n$ as an initial guess and $H_0 \in \mathbb{R}^{n \times n}$ as nonsingular matrix 2: for $k = 0, 1, 2, \dots$ do Compute $s_k = -H_k g(x^k)$ 3: Update $x_{k+1} = x_k + s_k$ 4:Compute $c_k = g(x_{k+1}) - g(x_k)$ 5: if $c_k = 0$ then 6: 7: $H_{k+1} = H_k$ 8: else Choose $z_k \in \mathbb{R}^n$ such that $z_k^T c_k = 1$ and $z_k^T H^{-1} s_k \neq 0$ 9: Update $H_{k+1} = H_k + (s_k - H_k y_k) z_k^T$ 10: end if 11: 12: end for

Note that H_k is a nonsingular matrix for all k. Furthermore, considering the difference between $g(x_{k+1})$ and $g(x_k)$, we have:

$$c_k = g(x_{k+1}) - g(x_k) = Ax_{k+1} - b - (Ax_k - b) = As_k = -AH_kg(x_k).$$

Consequently,

$$g(x_{k+1}) = g(x_k) + c_k = g(x_k) - AH_kg(x_k) = (I - AH_k)g(x_k)$$

Let us define $F_k = I - AH_k$ and to present an important property related to this sequence. **Lemma 1.** Let us suppose $k \leq 2n - 1$ odd. Let $c_k \neq 0, z_k^T c_{j-1} \neq 0, j = 1, ..., k, z_0 \in Im(F_0^T), F_0 = I - AH_0 \in \mathbb{R}^{n \times n}$ is nonsingular and $l \leq 2n - 1$ are odd indices. Then there exits a sequence $\{t_l\}$ of linearly independent vectors satisfying

$$t_1^T F_j = 0, \forall j \ge 1,$$

$$t_l^T F_j = t_{l-2}^T, l = 3, 5, 7, \dots, k, \forall j \ge l.$$

Moreover $t_i^T g(x_j) = 0, j = i + 1, i + 2, ..., k$.

Proof. We recommend [9] for a detailed proof.

To elucidate the idea of Block scaled ABS method let us consider the Algorithm 2.

Algorithm 2 Block ABS algorithm (see [2])

Choose a vector y₀ ∈ ℝⁿ as an initial guess, K₀ ∈ ℝ^{n×n}, V = [V₀ V₁...V_r] ∈ ℝ^{n×n} as nonsingular matrix and V_k ∈ ℝ^{n×s_k}, k = 1, ..., r where s₁ + ... + s_r = n
 for k = 0, 1, 2, ..., r do
 Choose Z_k ∈ ℝ^{n×n} and q_k ∈ ℝ^{s_k} such that

$$V_k^T A P_k q_k = V_k^T \overline{g}_k$$
 where

$$P_k = K_k^T Z_k$$
 and $\overline{g}_k = Ay_k - b \in \mathbb{R}^n$

- 4: Update $y_{k+1} = y_k P_k q_k$
- 5: Choose $W_k \in \mathbb{R}^{n \times s_k}$ satisfying $[W_k^T K_k A^T V_k] = I_{s_k \times s_k}$
- 6: Update K_k by

$$K_{k+1} = K_k - K_k A^T V_k W_k^T K_k \in \mathbb{R}^{n \times n}$$

7: end for

By simplicity we are considering $g_k = g(x_k)$. Related to Algorithm 2, we have important properties.

Lemma 2. The following conditions hold:

- *i.* $K_j A^T V_k = 0, \forall k < j;$
- ii. $K_i K_j = K_j K_i = K_j$ if $i \leq j$;
- iii. If A is full rank then

$$rank(K_k A^T V_k | K_k A^T V_{k+1} | \dots | K_k A^T V_r) = n - (s_0 + s_1 + \dots + s_{k-1});$$

iv. If $A \in \mathbb{R}^{n \times n}$ is nonsingular, then

 $K_k A^k V_j, j > k \text{ spans } Im(K_k) \text{ and}$ $A^T V_j, j > k \text{ spans } Kernel(K_k).$

Proof. We recommend [1].

3 Main Result

This section is devoted to show an important relation between Broyden's Algorithm and Block ABS Algorithm. This relationship is formalized by the following theorem.

Theorem 1. Consider Ax = b a linear system where $A \in \mathbb{R}^{n \times n}$ is nonsingular. Let z_k and c_k as defined in Broyden's algorithm satisfying the Lemma 1. Let (x_0, H_0) and (y_0, K_0) initial choices for Algorithm 1 and 2 respectively with $x_0 = y_0$. Then, for $2m_j$ steps of Algorithm 1 it is possible to find Z_j, W_j and V_j such that

$$x_{2m_j} = y_{j+1}$$

where m_i is the number of columns of $\overline{V}_i = [V_0 \ V_1 \dots V_i]$. Consequently,

 $x_{2m_r} = y_{r+1}, where m_r = n.$

Proof. Let $V = (t_1 \ t_3 \dots t_{2n-1})$ with vectors $t'_i s$ linearly independent which satisfy the Lemma 1. The proof will be made using induction arguments on indices of x and y. First, we will show there exist some choices of parameters in Algorithm 2 that obtain:

$$x_{2m_0} = y_1, (2)$$

where m_0 represents the number of columns of $\overline{V_0}$ defined by $V_0 \in \mathbb{R}^{n \times m_0}$. Now, using Algorithm 1 we have

$$x_{p+1} = x_p + s_p \text{ with } s_p = -H_p g_p.$$
(3)

Consequently

$$x_{2m_0} = x_0 - d_1$$
, where $d_1 = \sum_{i=1}^{2m_0 - 1} H_i g_i$. (4)

By step 2 of Algorithm 2 we have

$$y_1 = y_0 - K_0^T Z_0 q_0. (5)$$

So, we need to show that there exist choices for Z_0 , q_0 such that

$$K_0^T Z_0 q_0 = d_1 (6)$$

and

$$V_0^T A K_0 Z_0 q_0 = V_0^T \overline{g}_0. aga{7}$$

The choices to satisfy (6) follow immediately from nonsingularity of K_0 . Thus we need to show that these choices satisfy (7). In this case, we need to prove that

$$V_0^T A d_1 = V_0^T \overline{g}_0$$

In fact,

$$V_0^T A d_1 = V_0^T A \left(\sum_{i=0}^{2m_0 - 1} H_i g_i \right) = \sum_{i=0}^{2m_0 - 1} V_0^T A H_i g_i$$
(8)

or equivalently

$$V_0^T A d_1 = \begin{bmatrix} \sum_{\substack{i=0\\2m_0-1\\m_0-1}}^{2m_0-1} t_1^T A H_i g_i \\ \sum_{i=0}^{2m_0-1} t_3^T A H_i g_i \\ \vdots \\ \sum_{i=0}^{2m_0-1} t_{2m_0-1}^T A H_i g_i \end{bmatrix}$$

Using Lemma 1 we have

$$t_1^T = t_1^T A H_j, \forall j \ge 1,$$
(9)

$$(t_k^T - t_{k-2}^T) = t_k^T A H_j, \forall j \ge k \ge 3,$$
(10)

$$t_k^T g_j = 0, \forall j > k.$$
(11)

:

Consequently,

$$\sum_{i=0}^{2m_0-1} t_1^T A H_i g_i = t_1^T A H_0 g_0 + t_1^T A H_1 g_1 + \sum_{i=2}^{2m_0-1} t_1^T A H_i g_i$$
(12)

$$= t_1^T A H_0 g_0 + t_1^T A H_1 g_1 + \sum_{i=2}^{2m_0 - 1} t_1^T g_i$$
(13)

$$= t_1^T A H_0 g_0 + t_1^T A H_1 g_1. (14)$$

By Algorithm 1 we have that $g_{k+1} = (I - AH_k)g_k$, for all $k \ge 0$. Thus

$$\sum_{i=0}^{2m_0-1} t_1^T A H_i g_i = t_1^T A H_0 g_0 + t_1^T A H_1 (I - A H_0) g_0$$

= $t_1^T A H_0 g_0 + t_1^T (I - A H_0) g_0$
= $t_1^T A H_0 g_0 + t_1^T g_0 - t_1^T A H_0 g_0$
= $t_1^T g_0.$ (15)

For the general case, let's consider $j \leq 2m_0 - 1$ and odd. Therefore

$$\sum_{i=0}^{2m_0-1} t_j^T A H_i g_i = \sum_{i=0}^j t_j^T A H_i g_i + \sum_{\substack{i=j+1\\2m_0-1\\2m_0-1}}^{2m_0-1} t_j^T A H_i g_i$$
$$= \sum_{i=0}^j t_j^T A H_i g_i + \sum_{\substack{i=j+1\\i=j+1}}^{2m_0-1} (t_j^T - t_{j-2}^T) g_i$$
(16)
$$= \sum_{i=0}^j t_j^T A H_i g_i.$$

Using (9) and (10) we have

$$\sum_{i=0}^{j} t_{j}^{T} A H_{i} g_{i} = \sum_{\substack{i=0\\j=2}}^{j-2} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} A H_{j-1} g_{j-1} + t_{j}^{T} A H_{j} g_{j}$$

$$= \sum_{\substack{i=0\\j=2}}^{j-2} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} A H_{j-1} g_{j-1} + t_{j}^{T} g_{j}$$

$$= \sum_{\substack{i=0\\j=2}}^{j-2} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} A H_{j-1} g_{j-1} + t_{j}^{T} g_{j-1} - t_{j}^{T} A H_{j-1} g_{j-1}$$

$$= \sum_{\substack{i=0\\j=2}}^{j-2} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} A H_{j-1} g_{j-1} + t_{j}^{T} g_{j-1} - t_{j}^{T} A H_{j-1} g_{j-1}$$

$$= \sum_{\substack{i=0\\j=2}}^{j-2} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} g_{j-1}.$$
(17)

With similar ideas of (17) we can show that:

$$\sum_{i=0}^{l} t_j^T A H_i g_i + t_j^T g_{l+1} = \sum_{i=0}^{l-1} t_j^T A H_i g_i + t_j^T g_l,$$
(18)

for all $l \leq j$. In fact,

$$\sum_{i=0}^{l} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} g_{l+1} = \sum_{i=0}^{l-1} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} A H_{l} g_{l} + t_{j}^{T} g_{l+1}$$

$$= \sum_{i=0}^{l-1} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} A H_{l} g_{l} + t_{j}^{T} (I - A H_{l}) g_{l}$$

$$= \sum_{i=0}^{l-1} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} A H_{l} g_{l} + t_{j}^{T} g_{l} - t_{j}^{T} A H_{l} g_{l}$$

$$= \sum_{i=0}^{l-1} t_{j}^{T} A H_{i} g_{i} + t_{j}^{T} g_{l}.$$
(19)

Now, using (18) recursively we obtain

$$\sum_{i=0}^{2m_0-1} t_j^T A H_i g_i = t_j^T A H_0 g_0 + t_j^T g_1$$

= $t_j^T A H_0 g_0 + t_j^T (I - A H_0) g_0$
= $t_j^T A H_0 g_0 + t_j^T g_0 - t_j^T A H_0 g_0$
= $t_j^T g_0.$ (20)

Consequently,

$$V_0^T A d_1 = \begin{bmatrix} \sum_{\substack{i=0\\2m_0-1\\2m_0-1\\i=0}}^{2m_0-1} t_1^T A H_i g_i \\ \vdots \\ \sum_{\substack{i=0\\i=0}}^{2m_0-1} t_1^T A H_i g_i \end{bmatrix} = \begin{bmatrix} t_1^T g_0 \\ t_3^T g_0 \\ \vdots \\ t_{2m_0-1}^T g_0 \end{bmatrix} = V_0^T \overline{g}_0,$$

terminating the first part of the induction argument.

Let's assume that

$$x_{2m_k} = y_{k+1}, \forall \quad 1 \le k < r,$$

where m_k represents the number of columns of $\overline{V}_k = [V_0 \ V_1 \dots V_k]$. We will show $x_{2m_r} = y_{r+1}$.

Considering the Algorithm 1, we have

$$x_{2m_r} = x_{2m_{(r-1)}} - d_r$$
, where $d_r = \sum_{i=2m_{(r-1)}}^{2m_r-1} H_i g_i$ (21)

and considering the Algorithm 2, we have

$$y_{r+1} = y_r - K_r^T Z_r q_r.$$
 (22)

We need to show that exist Z_r and q_r such that

$$K_r^T Z_r q_r = d_r, (23)$$

with $V_r^T A K_r^T Z_r q_r = V_r^T \overline{g}_r$. By Lemma 2, we have the equivalence:

$$K_r^T Z_r q_r = d_r \quad \Leftrightarrow \quad d_r \in Im(K_r^T) \Leftrightarrow \quad d_r \perp \{A^T V_0, A^T V_1, \dots A^T V_{r-1}\} \Leftrightarrow \quad d_r \perp A^T V_k, \text{ for all } 0 \le k \le r-1.$$

$$(24)$$

Consequently it is sufficient to show

$$V_k^T A d_r = 0, \text{ for all } 0 \le k \le r - 1.$$

$$\tag{25}$$

Observe that

$$\overline{V_{r-1}}^{T}Ad_{r} = \begin{bmatrix} V_{0}^{T}Ad_{r} \\ V_{1}^{T}Ad_{r} \\ \vdots \\ V_{r-1}^{T}Ad_{r} \end{bmatrix} = \begin{bmatrix} t_{1}^{T}Ad_{r} \\ t_{3}^{T}Ad_{r} \\ \vdots \\ t_{2m_{(r-1)}-1}^{T}Ad_{r} \end{bmatrix}.$$
(26)

Using, again, (9)-(11) we can obtain

$$t_1^T A d_r = t_1^T \left(\sum_{i=2m_{(r-1)}}^{2m_r - 1} H_i g_i \right) = \sum_{i=2m_{(r-1)}}^{2m_r - 1} t_1^T A H_i g_i = \sum_{i=2m_{(r-1)}}^{2m_r - 1} t_1^T g_i = 0$$
(27)

and with similar arguments, for $j \leq 2m_{(r-1)} - 1$ odd we have

$$t_j^T A d_r = t_j^T \left(\sum_{i=2m_{(r-1)}}^{2m_r - 1} H_i g_i \right) = \sum_{i=2m_{(r-1)}}^{2m_r - 1} t_j^T A H_i g_i = \sum_{i=2m_{(r-1)}}^{2m_r - 1} t_j^T g_i = 0.$$
(28)

Thus, from (26), (27) and (28), we conclude (25). We need to prove that the choices of Z_r and q_r satisfy $V_r^T A K_r^T Z_r q_r = V_r^T \overline{g}_r$, or equivalently, $V_r^T A d_r = V_r^T \overline{g}_r$. Considering $V_r = [t_{2m_{(r-1)}+1} \ t_{2m_{(r-1)}+3} \dots t_{2m_r-1}]$ we have

$$V_{r}^{T}Ad_{r} = \begin{bmatrix} t_{2m_{(r-1)}+1}^{T}Ad_{r} \\ t_{2m_{(r-1)}+3}^{T}Ad_{r} \\ \vdots \\ t_{2m_{r}-1}^{T}Ad_{r} \end{bmatrix}.$$
 (29)

Since $d_r = \sum_{i=2m_{(r-1)}}^{2m_r-1} H_i g_i$ we can obtain

$$t_{2m_{(r-1)}+1}^{T}Ad_{r} = t_{2m_{(r-1)}+1}^{T}A\left(\sum_{i=2m_{(r-1)}}^{2m_{r}-1}H_{i}g_{i}\right)$$

$$= \sum_{\substack{i=2m_{(r-1)}\\2m_{(r-1)}+1\\m_{m_{(r-1)}+1}}}^{2m_{(r-1)}+1}AH_{i}g_{i}$$

$$= \sum_{\substack{i=2m_{(r-1)}\\i=2m_{(r-1)}}}^{2m_{(r-1)}+1}t_{2m_{(r-1)}+1}^{T}AH_{i}g_{i} + \sum_{\substack{i=2m_{(r-1)}+2\\i=2m_{(r-1)}+1}}^{2m_{(r-1)}+1}AH_{i}g_{i}.$$
(30)

Note that $2m_{(r-1)} + 1 < 2m_{(r-1)} + 2$ and using Lemma 1 we get from (30) that

$$t_{2m_{(r-1)}+1}^{T}Ad_{r} = \sum_{\substack{i=2m_{(r-1)}\\2m_{(r-1)}+1\\2m_{(r-1)}+1}}^{2m_{(r-1)}+1}t_{2m_{(r-1)}+1}^{T}AH_{i}g_{i} + \sum_{\substack{i=2m_{(r-1)}\\2m_{(r-1)}+1\\2m_{(r-1)}+1}}^{2m_{(r-1)}+1}dH_{i}g_{i}$$

$$= t_{2m_{(r-1)}+1}AH_{2m_{(r-1)}}g_{2m_{(r-1)}} + (t_{2m_{(r-1)}+1} - t_{2m_{(r-1)}-1})g_{2m_{(r-1)}+1}$$

$$= t_{2m_{(r-1)}+1}AH_{2m_{(r-1)}}g_{2m_{(r-1)}} + t_{2m_{(r-1)}+1}(I - AH_{2m_{(r-1)}})g_{2m_{(r-1)}}$$

$$= t_{2m_{(r-1)}+1}g_{2m_{(r-1)}}.$$
(31)

With similar argument given in (16)-(20) we can conclude

$$t_k^T A d_r = t_k^T g_{2m_{(r-1)}}, \text{ for all } 2m_{(r-1)} + 1 \le k \le 2m_r - 1.$$
 (32)

Since $g_{2m_{(r-1)}} = \overline{g}_r$, we obtain

$$V_{r}^{T}Ad_{r} = \begin{bmatrix} t_{2m_{(r-1)}+1}^{T}Ad_{r} \\ t_{2m_{(r-1)}+3}^{T}Ad_{r} \\ \vdots \\ t_{2m_{r}-1}^{T}Ad_{r} \end{bmatrix} = \begin{bmatrix} t_{2m_{(r-1)}+1}^{T}g_{2m_{(r-1)}} \\ t_{2m_{(r-1)}+3}^{T}g_{2m_{(r-1)}} \\ \vdots \\ t_{2m_{r}-1}^{T}g_{2m_{(r-1)}} \end{bmatrix}.$$
(33)

4 Conclusion

This work has the same direction of [4]. However, we consider the Block ABS Method instead of ABS method and we show that 2n steps of Broyden's Method is equivalent to one step of the ABS Block Method, when the block size is n. Since the ABS Block Method has finite termination, we provide another proof for Gay's theorem [6].

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