The Lack of Positive Definiteness in the Hessian in Constrained Optimization\(^1\)

by

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Technical Report 83-17, October 1983.

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Abstract

The use of the DFP or the BFGS secant updates requires the Hessian at the solution to be positive definite. The second order sufficiency conditions insure the positive definiteness only in a subspace of $\mathbb{R}^n$. Conditions are given so we can safely update with either update. A new class of algorithms is proposed which generate a sequence $\{z_t\}$ converging 2-step $q$-superlinearly. We also propose two specific algorithms. One that converges $q$-superlinearly if the Hessian is positive definite in $\mathbb{R}^n$ and it converges 2-step $q$-superlinearly if the Hessian is positive definite only in a subspace. The second one generates a sequence converging 1-step $q$-superlinearly. While the former costs one extra gradient evaluation the latter costs one extra gradient evaluation and one extra function evaluation on the constraints.

Key words: Constrained Optimization, Convergence Theory, Quasi-Newton Methods, Rate of Convergence, Multiplier Methods.
1. INTRODUCTION

This paper considers the following equality constrained minimization problem:

\[ \begin{align*}
\text{minimize} & \quad f(x) \\
\text{subject to} & \quad g(x) = 0
\end{align*} \tag{1.1} \]

where \( f: \mathbb{R}^n \to \mathbb{R} \) and \( g: \mathbb{R}^n \to \mathbb{R}^m \). Let \( g = (g_1, \ldots, g_m)^t \).

We define the augmented Lagrangian \( L: \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}_+ \to \mathbb{R} \)

\[ L(x, \lambda, c) = f(x) + g(x)^t \lambda + \frac{(c/2)g(x)^t g(x)}{2}. \]

For \( c \) equal to zero, the augmented Lagrangian reduces to the Lagrangian function which we denote

\[ l(x, \lambda) = f(x) + g(x)^t \lambda. \]

If \( x_\ast \in \mathbb{R}^n \) is such that \( \nabla g(x_\ast) \) is full rank, then a necessary condition for \( x_\ast \) to be a solution of (1.1) is that there exists \( \lambda_\ast \) such that

\[ \begin{align*}
\nabla_x L(x_\ast, \lambda_\ast, c) & = 0 \\
g(x_\ast) & = 0,
\end{align*} \tag{1.2} \]

and \( \lambda_\ast \) is unique. It may be noted that the constant \( c \) does not affect condition (1.2), therefore the constant \( c \) will have the value zero unless it is specified otherwise. Let \( \{z_i\} \) be a sequence which approximate \( x_\ast \).

To simplify the notation let

\[ \begin{align*}
\nabla g(x_i) & = \nabla g_i, \text{ and } \nabla g(x_\ast) = \nabla g_* \\
A_i & = \nabla^2 L(x_i, \lambda_\ast, c) \\
A_* & = \nabla^2 L(x_\ast, \lambda_\ast)
\end{align*} \]

Further, let

\[ M(z) = \{ y \in \mathbb{R}^n : \nabla g(x)^t y = 0 \} \]

and \( N_\ast = M(z_\ast) \) and \( N_i = M(z_i) \). All through the paper we will be working with the following
assumptions:

A1. The functions f, and g have second derivatives which are Holder continuous of order $p \in [0,1]$ in a neighborhood $\Omega$ of $x^*$.

A2. The solution $x^*$ is a nonsingular point of problem (1.1), i.e.

\[(1) \nabla g(x^*) \text{ has full rank.} \]

One of the most successful methods for solving problem (1.1) is the Diagonalized Quasi-Newton Multiplier Method (DQMM) as defined in Tapia [18].

For $k=0,1,2,...$

\[
\begin{align*}
\lambda_{k+1} &= U(x_k, \lambda_k, B_k) \quad (1.3.a) \\
B_{k+1} &= -\nabla f(x_k, \lambda_{k+1}) \quad (1.3.b) \\
y_k &= \nabla f(x_k + s_k, \lambda_{k+1}) - \nabla f(x_k, \lambda_{k+1}) \quad (1.3.c) \\
B_{k+1} &= B(s_k, y_k, B_k) \quad (1.3.d) \\
x_{k+1} &= x_k + s_k \quad (1.3.e)
\end{align*}
\]

where $U$ is a multiplier update formula [18], and $B$ is a secant update formula [4]. Fontecilla-Steihaug-Tapia [10] shows that under the assumptions stated above and the nonsingularity of $A$, we can get local $q$-superlinear convergence of the sequence $\{x_k\}$ if in (1.3.a) we use the Newton multiplier update formula and in (1.3.d) we use the Broyden or the PSB least change secant updates. In case the DFP or the BFGS least change secant updates are used in (1.3.d) the positive definiteness of the Hessian $A$, is required.

Our assumptions guarantee that the Hessian $A$, is positive definite in the subspace $N$, Therefore, it is not obvious whether we can keep the same rate of convergence. However, numerical experiments given by Bertocchi-Cavalli-Spedicato [1], and Tapia [18] show that we can safely use the DFP/BFGS secant updates with the Newton multiplier update when the Hessian $A$, is positive definite only in $N$.

Few theoretical, and practical algorithms have been given in this area. Powell [16] was the first one who attacked this problem by adapting the BFGS in such a way that it maintains the posi-
tive definiteness throughout the process. Assuming local q-linear convergence on $x_k$, Powell gives a sufficient condition to obtain 2-step q-superlinear convergence on $x_k$, but he does not show that his modified BFGS satisfies that condition. Instead, he could only get R-superlinear convergence.

Coleman and Conn [5] give a new algorithm based on the DQMM idea updating the multipliers with the Projection multiplier update. They have to construct an orthonormal basis $(Z_t)$ for the tangent space of the constraints that will be used as a projection operator. They need to project the step, and the difference in gradients in order to work with a projected DFP/BFGS secant updates. They prove that the sequence $\{x_t\}$ converges to $x$, 2-step q-superlinearly.

Our work differs greatly on theirs. However, we will prove under what conditions Powell’s sufficient condition for 2-step q-superlinearity is satisfied as well as giving a new class of algorithms that are 2-step q-superlinear convergent without using any projection, or projecting only the step. The algorithm given by Coleman and Conn can be viewed as a particular case of this class.

In this paper, we use the general convergence theory developed by Fontecilla-Steihau-Tapia [10] for the DQMM in order to construct a new class of algorithms, called 2-step algorithms, that satisfy the characterization of q-superlinear convergence of the sequence $\{x_t\}$.

In Section 2, a new result on the theory of secant updates is given. We consider this result to be our main contribution to this area. We prove that the DFP/BFGS maintains all the properties found by the Broyden-Dennis-More theory when the Hessian is positive definite only in a subspace of $R^n$ as long as the step remains in the subspace corresponding to the current iterate, i.e. $A$, being positive definite in $N$, we just need the step to be in $N$. Using this result in Section 3, we construct a new class of algorithms that will satisfy the two sufficient conditions to obtain q-superlinear convergence. First the current step is in $N$, and also we satisfy the linearized constraints property

$$g_t + \nabla g_t x_t = 0$$

which is fundamental for q-superlinearity. In Section 4, we prove that the algorithms given in Section 3 generate a sequence $\{x_t\}$ that converges to $x$, 2-step q-superlinearly. Some of them are proved to be equivalent to be using the DQMM with the Newton multiplier update formula. In
Section 5, we give our main contribution to the area of constrained optimization by finally constructing an algorithm that take advantage of the positive definiteness of the Hessian $A_\ast$. This algorithm is characterized by the fact that if $A_\ast$ is positive definite on the whole space (i.e. $\langle A_\ast s_i, s_i \rangle > 0$ for all $k$) then it will converge $q$-superlinearly to $z$, the reason being it is the DQMM with the Newton multiplier update formula, and if $A_\ast$ is positive definite in $N_\ast$ (i.e. $\langle A_\ast s_k, s_k \rangle \leq 0$ for some $k$) then we switch to a 2-step algorithm that will be at least 2-step $q$-superlinear convergent. Moreover, the switching from one algorithm to the other costs just an extra gradient evaluation.

Definitions and General Results.

In the following, two norms will be needed. $\|\cdot\|_F$ will denote the matrix Frobenius norm, and $\|\cdot\|$ will denote either the $l_2$ norm or its induced matrix norm, for $\mathbb{R}^n$ as well as for $\mathbb{R}^m$.

Definition 1.1: Consider $U: \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^m$. We say that the multiplier update formula $U$ is $x$-dominated if for all $B \in \mathbb{R}^n \times \mathbb{R}^m$ there exists an open neighborhood $N_2$ containing $(x_\ast, \lambda, \mu, B)$, and a positive constant $\phi$ such that for all $(z, \lambda, \mu) \in N_2$, and for all $\phi \in U(x, \lambda, \mu, B)$

$$|\nabla f(\lambda_\ast - \lambda)| \leq \phi |z - z_\ast|$$

(1.4)

From A1 we know that for a fixed $c \geq 0$ there exists $\gamma \geq 0$ such that

$$|\nabla^2 L(z, \lambda, \mu) - \nabla^2 L(z_\ast, \lambda, \mu)| \leq \gamma |z - z_\ast|^p.$$  

(1.5)

for all $z \in \Omega$. Where $\Omega$ and $p$ are as in A1. The next two lemmas, which will be used throughout the paper can be found in Dennis and Schnabel [8].

Lemma 1.2: Let $F: \mathbb{R}^n \rightarrow \mathbb{R}^m$ be continuously differentiable in the open convex set $D \subset \mathbb{R}^n$ containing $x_\ast$. Assume $F'$ is Holder continuous of order $p \in (0,1]$ in $D$, and $F' (z_\ast)^{-1}$ exists. Then there exist constants $\epsilon > 0$, $\rho > 0$ such that

$$\frac{1}{\rho} |v - u| \leq |F(v) - F(u)| \leq \rho |v - u|$$

(1.6)

for all $u, v \in D$ for which $\max \{|v-x_\ast|,|u-x_\ast|\} \leq \epsilon.$
Lemma 1.3: Let $F$ satisfy the same conditions of Lemma 1.1. Then for any $u, v \in D$ there exists a positive constant $K$ such that

$$|F(v) - F(u) - F'(x_0)(v - u)| \leq K\|v - u\|,$$

where $F'(x_0)$ is the Fréchet derivative of $F$ at $x_0$. The following result is from Fontecilla-Steihaug-Tapia [10].

Lemma 1.4: Assume A1-A2. For any $c > 0$ there exist positive constants $K_3$, $K_4$, and $\epsilon > 0$ such that for any $\lambda \in \mathbb{R}^n$, and $\sigma(z, z_+)$ we have

$$|\nabla_j L(z_+ \lambda, c) - \nabla_j L(z, \lambda, c) - A_j (z_+ - z)| \leq K_3 \|z - z_+\| + K_4 \|\lambda - \lambda_+\| |z_+ - z|$$

where $\sigma(z, z_+) = \max \{\|z - z_+\|, \|z_+ - z_+\|\}$.

Definition 1.5: Let $\{z_k\}$ be any sequence which converges to $z$. Given continuous real-valued functions $\mathcal{g}$ and $\mathcal{h}$ we write

$$\mathcal{g}(z_k) = o(\mathcal{h}(z_k)) \text{ as } k \to \infty$$

if

$$\lim_{k \to \infty} \sup_{z \in \mathcal{B}} \frac{\mathcal{g}(z_k)}{\mathcal{h}(z_k)} = 0.$$ 

All throughout the paper we will be using the DFP or the BFGS secant updates given by

$$B_{+}^{DFP} = B + \frac{(y - B_s)y^t + y(y - B_s)t}{y's} - \frac{s'(y - B_s)yy^t}{(y's)^2}, \quad \text{and}$$

$$B_{+}^{BFGS} = B + \frac{yy^t}{y's} - \frac{(B_s)(B_s)^t}{s'B_s}. \quad (1.8)$$

For ease the notation of those secant updates which depend on the step $s$, and the difference on gradients $y$ we will denote

$$B_{+} = DFP/BFGS(s, y),$$

where $y = \nabla_j L(x + s, \lambda_+) - \nabla_j L(x, \lambda_+).$

Let $\mathcal{C}$ be such that $A_{+}^t$ is positive definite.
2. PROPERTIES OF THE DQMM.

We will follow the theory developed by Broyden, Dennis and More [4] for the DFP (1.8) and the corresponding theory develop by Stachurski [17] for the BFGS (1.9). Their results can be summarized in the following lemma.

Lemma 2.1: Let M be a symmetric nonsingular matrix of order n such that

\[ |My - M^{-1}s| \leq \beta |M^{-1}s| \]  (2.1)

for some \( \beta \in (0, \frac{1}{3}) \) and vectors y and s in \( \mathbb{R}^n \) with \( s \neq 0 \). Then \( y^T s > 0 \) and \( B_+ \) is well defined by the DFP/BFGS(s,y). Moreover, there exist positive constant \( \alpha_0, \alpha_1, \) and \( \alpha_2 \) such that for any symmetric matrix A of order n

\[ ||B_+ - A||_M \leq [(1 - \alpha_0 \beta^2)^{1/2} + \alpha_1 \frac{|My - M^{-1}s|}{|M^{-1}s|} ||B - A||_M \]

\[ + \alpha_2 \frac{|y - As|}{|M^{-1}s|} \]  (2.2)

where \( ||Q||_M = ||MQM||_F \), \( \alpha_3 \in (0,1) \), and

\[ \theta = \begin{cases} \frac{|MB - A|s}{||B - A||_M |M^{-1}s|} & \text{for } B \neq A \\ 0 & \text{otherwise} \end{cases} \]  (2.3)

For the remainder of the paper we will also assume the following.

A3. The multiplier update is x-dominated.

In order to satisfy (2.1) the Hessian we are approximating must be positive definite. This is not case here as our assumptions indicate. The Hessian \( A_+ \) is positive definite only in \( N_+ \). Hence, we will not be able to satisfy (2.2) unless we find a positive definite matrix A and a matrix M satisfying (2.1). The following theorem gives the answer to this problem.

For given \( z, s \in \mathbb{R}^n \) and \( \lambda_+ \in \mathbb{R}^n \) define
\[ y = \nabla_x l(x + s, \lambda_+) - \nabla_x l(x, \lambda_+). \]

**Theorem 2.2:** There exists a symmetric and positive definite matrix \( A \) such that for \( x \)-dominated multiplier update formulas there exist an open neighborhood \( N_1 \) containing \((x_*, \lambda_*, A)\), and nonnegative constants \( \alpha_0, \alpha_1, \) and \( \alpha_2 \) such that for all \((x, \lambda_+, B) \in N_1 \) if \( s \in N(x) \) then \( B_+ = DFP/BFGS(s, y) \) satisfies

\[
\|B_+ - A\|_M \leq [(1 - \alpha_0 \rho^2)^{1/2} + \alpha_1 \sigma(x, x + s)] \|B - A\|_M + \alpha_2 \sigma(x, x + s).
\]  

(2.4)

**Proof:** We will prove that (2.1) is satisfied. Consider

\[
|MY - M^{-1}| \leq |M^{-1}| |y - M^{-2}|. 
\]  

(2.5)

Since \( A_{\tilde{s}} \) is a symmetric positive definite matrix there exists a symmetric nonsingular matrix \( M \) such that

\[ A_{\tilde{s}} = M^{-2} \]

Using the definition of \( A_{\tilde{s}} \) we get

\[
|y - M^{-2}| = |y - A_{\tilde{s}}| = |y - A_{\tilde{s}} - \nabla g, \nabla g|.
\]

Since \( s \in N(x) \) we get

\[
|y - M^{-2}| \leq |y - A_{\tilde{s}}| + \tilde{c} \|\nabla g\| \|\nabla g - \nabla g\| \|s\|.
\]

From A1 there exists \( K_1 \) such that

\[
|y - M^{-2}| \leq |y - A_{\tilde{s}}| + K_1 |z - z_d| \|s\|. 
\]  

(2.6)

Using Lemma 1.6 there exist positive constant \( K_2 \) and \( K_3 \) so that

\[
|y - A_{\tilde{s}}| \leq |K_2 \sigma(z, z + s)| + K_3 |\lambda_+ - \lambda_+| \|s\|.
\]  

(2.7)

Since A3 we get

\[
|y - A_{\tilde{s}}| \leq K_4 \sigma(z, z + s) \|s\| 
\]  

(2.8)

for some positive \( K_4 \). Combining (2.5), (2.6), (2.7), and (2.8) there exists a positive constant \( K_6 \) such that

\[
|MY - M^{-1}| \leq K_6 \sigma(z, z + s) |M^{-1}| \|s\| 
\]  

(2.9)

with \( K_6 = |M^{-1}| [K_4 + K_1 |M|] \). Using the techniques of Broyden, Dennis and More [4] we have the following. By Lemma 1.4 there is an \( \epsilon > 0 \) and \( \rho > 0 \) such that (1.6) holds if \( \sigma(z, z + s) \leq \epsilon \). Set
\[ N_3 = \{ B \in R^{n \times n} : (A_3^T)^{-1} || B - A_3^T || < 1/2 \} \]

\[ N_4 = \{ z \in R^n : || x - z \| < \frac{\epsilon}{2} \text{ and } 2(|| A_3^T || \| \phi + \rho \| || x - z_\d || < \frac{\epsilon}{2} \} \]

and

\[ N_5 = \{ \lambda \in R^n : \| \nabla g(x, \lambda +) - \lambda \| \leq \phi \| x - z_\d \| \}. \]

Then \( N' = N_4 \times N_5 \times N_8 \) is a neighbourhood of \((z_\ast, \lambda_\ast, A_3^T)\) and if \((z, \lambda, B) \in N'\), then by the Banach perturbation Lemma the matrix \( B \) is nonsingular and

\[ || B^{-1} || \leq 2 || (A_3^T)^{-1} ||. \]

Using equation \((1.6)\) and \( A3 \) we get

\[
|s| = |B^{-1}\nabla L(x, \lambda_\ast)| \leq \\
\leq |B^{-1}| |\nabla L(x, \lambda_\ast) - \nabla L(x_\ast, \lambda_\ast)| + |B^{-1}| |\nabla L(x_\ast, \lambda_\ast) - \nabla L(x_\ast, \lambda_\ast)| \\
\leq \rho |B^{-1}| |x - x_\d| + \phi |B^{-1}| |x - x_\d| \\
\leq 2 ||(A_3^T)^{-1}|| \| \phi + \rho \| |x - x_\d| < \frac{\epsilon}{2}
\]

and therefore

\[ |x + s - z \d| \leq |s| + |z - z_\d| < \epsilon. \]

Hence, from \((2.9)\) we have that \((2.1)\) always holds and we obtain

\[ || B_\ast - A_\ast^T ||_M \leq \left[ 1 - \alpha_\ast \beta_\ast \right]^{1/2} + \alpha_\ast \sigma(\alpha_\ast x + s) || B - A_\ast^T ||_M + \alpha_\ast \sigma(\alpha_\ast x + s) \]

which implies \((2.4)\) with \( A \equiv A_\ast^T \)

Q.E.D.

Note that although \((2.4)\) is relative to \( A_\ast^T \), the difference in gradients used (i.e. \( y \)) does not depend on \( z \). In this point leans all the theory that we are about to develop. Before stating the following theorem we need to clarify the point \( s = 0 \). Having the multiplier update \( x \)-dominated and assuming convergence then we have that \( s = 0 \) if and only if \( x = x_\ast \). Therefore, throughout the paper we will have \( s \neq 0 \).

Now the question is obvious, can we find \( x \)-dominated multiplier updates that make the step \( s \) to be in \( N(x) \)? The answer is given by the following result.
Theorem 2.3: Let $s$ be a vector in $\mathbb{R}^n$ such that

$$B s = - \nabla J(x, \lambda_+)$$

for some $\lambda_+ \in \mathbb{R}^m$. Then $s \in N(x)$ if and only if $\lambda_+$ is given by

$$\lambda_+ = - (\nabla g' B^{-1} \nabla g)^{-1} \nabla g' B^{-1} \nabla f. \quad (2.10)$$

Moreover, the multiplier update (2.10) is $x$-dominated.

Proof: Consider $s = - B^{-1} \nabla J(x, \lambda_+)$. Then

$$\nabla g' s = - \nabla g' B^{-1} \nabla f - \nabla g' B^{-1} \nabla g \lambda_+ \quad (2.11)$$

Substituting (2.10) in (2.11) we obtain that $\nabla g' s = 0$ hence, $s \in N(x)$. Conversely, we equal to zero (2.11) and we get (2.10). To prove (2.10) is $x$-dominated we use the techniques of Fontecilla, Steihaug and Tapia [10]. It is straightforward to prove that

$$|\nabla g (\lambda_+ - \lambda_0)| \leq |P_B^t| A_\delta^t \|x - z_t\|$$

with $P_B^t = B^{-1} \nabla g (\nabla g B^{-1} \nabla g)^{-1} \nabla g$. Therefore, (2.10) is $x$-dominated with

$$\phi = |P_B^t| A_\delta. \quad (2.12)$$

Q.E.D.

We will call (2.10) the null-space multiplier update.

Define $P(x) = I - \nabla g(x)(\nabla g(x)^t \nabla g(x))^{-1} \nabla g(x)^t$ as the orthogonal projection onto $N(x)$ and let $P_t = P(z_t)$ and $P_* = P(z_0)$.

Theorem 2.4: Let the sequences $\{z_t\}$ and $\{\lambda_t\}$ be generated by the DQMM with (1.3.a) given by (2.10). Then if

$$\sum_{t=0}^{\infty} |z_t - x_t| \leq + \infty \quad (2.13)$$

then

$$\lim_{t \to \infty} \frac{|P_t(B_t - A_t)x_t|}{|x_t|} = 0. \quad (2.14)$$

Proof: It is a direct consequence from Theorem (2.2). Using the same techniques than Broyden, Dennis and More [4] relation (2.4) together with (2.13) yield
\[
\lim_{i \to \infty} \theta_i = 0
\]

where \( \theta_i = \frac{|M(B_i - A_i^*)s_i|}{||B_i - A_i^*||_d MF^{-1}s_i} \). Hence,

\[
\lim_{i \to \infty} \frac{|(B_i - A_i^*)s_i|}{|s_i|} = 0
\]

since \( |P_d| = 1 \) we get

\[
|P_d(B_i - A_i^*)s_i| = |P_d(B_i - A_i^*)s_i| \leq |(B_i - A_i^*)s_i|
\]

and since \( \lim_{i \to \infty} P_i = P \), we obtain (2.14).

Q.E.D.

There are other multiplier updates which are \( \lambda \)-dominated. For those multiplier updates which due to Theorem 2.3 do not satisfy that the step \( \lambda \) is in \( M(x) \) we have the following result.

**Theorem 2.5:** Let the sequences \( \{z_i\} \) and \( \{\lambda_i\} \) be generated by the DQMM with (1.3.e) given by \( z_{i+1} = z_i + P_i s_i \). If (2.13) holds then

\[
\lim_{i \to \infty} \frac{|P_d(B_i - A_i^*)P_i s_i|}{|s_i|} = 0.
\]

**Proof:** Assume \( P_i s_i \neq 0 \). Let \( w_i = P_i s_i \). Since \( z_{i+1} = z_i + w_i \) and \( |P_i s_i| \leq |s_i| \) then Theorem 2.2 gives us the bounded deterioration (1.4.b). Assuming (2.13), (2.4) yields

\[
\lim_{i \to \infty} \frac{|(B_i - A_i^*)w_i|}{|w_i|} = 0
\]

since \( |w_i| \leq |s_i| \) we get (2.15).

If \( P_i s_i = 0 \) then directly (2.15) holds.

Q.E.D.

Note that Powell's sufficient condition, i.e. (2.15), for having 2-step q-superlinear convergence is satisfied. Having conditions (2.14) and (2.15) using the DFP or the BFGS secant updates assuming that the Hessian is positive definite only in \( N_i \) is the first step to get q-superlinear convergence of the sequence \( \{z_i\} \) in the DQMM. Is a fact that we also need to satisfy condition (2.13).
3. PROPOSED ALGORITHMS

In spite of the lack of positive definiteness on \( A \), Section 2 gives us a sufficient condition to be satisfied by the step we are using to update the DFP/BFGS in order to get relations (2.4) and (2.14). Following Fontecilla-Steihaug-Tapia [10] two conditions are necessary to obtain q-superlinear convergence of the DQMM. They are

\[
\lim_{t \to -\infty} \frac{|P_t(B_t - A)s_t|}{|s_t|} = 0 \tag{3.1}
\]

\[
\lim_{t \to -\infty} \frac{|\nabla g_{k+1}^t|}{|s_t|} = 0. \tag{3.2}
\]

We know that if the step we are using to update the DFP/BFGS is in \( N_t \) then (3.1) holds. On the other hand (3.2) holds if our algorithm satisfy the linearized constraints property, i.e.

\[ g_t + \nabla g_t^t s_t = 0. \tag{3.3} \]

The most natural way to satisfy (3.3) is having the step in the following form

\[ s_t = -\nabla g_t^t g_t \tag{3.4} \]

where \( \nabla g_t^t \) is a right inverse of \( \nabla g_t^t \) that is given by

\[ \nabla g_t^t = Q \nabla \hat{g}_t^t (\nabla \hat{g}_t^t Q \nabla \hat{g}_t)^{-1} \tag{3.5} \]

for an \( n \times n \) matrix \( Q \) such that \( \nabla g_t^t Q \nabla g_t \) is nonsingular. The most natural consideration for the step \( s_t \) to be in \( N_t \) as well as to satisfy (3.3) is to consider steps of the form

\[ s_t = w_t + v_t \tag{3.6} \]

where \( w_t \in N_t \) and it will be used to update the DFP/BFGS, and \( v_t \) satisfies (3.4). We obtain the general form of the algorithms proposed, called 2-step algorithms.

2-step algorithms.

Given \( z_0, \lambda_z \), and \( B_\nu \).

For \( k = 0,1,2,... \)
\( \lambda_{k+1} = U(x_k, \lambda_k, B_k) \) \hspace{1cm} (3.7.a)

\( B_k h_k = -\nabla J(x_k, \lambda_{k+1}) \) \hspace{1cm} (3.7.b)

\( w_k = P_k h_k \) \hspace{1cm} (3.7.c)

\( y_k = \nabla J(x_k + w_k, \lambda_{k+1}) - \nabla J(x_k, \lambda_{k+1}) \) \hspace{1cm} (3.7.d)

\( B_{k+1} = \text{DFP/BFGS}(w_k, y_k) \) \hspace{1cm} (3.7.e)

\( v_k = -\nabla g_k^T g_k \) \hspace{1cm} (3.7.f)

\( x_{k+1} = z_k + w_k + v_k \) \hspace{1cm} (3.7.g)

We point out that for the null-space multiplier update formula step (3.7.c) is unnecessary since \( h_t \in N_t \). If \( w_t = 0 \) in (3.7.c) we go to (3.7.f). There are two natural choices for the matrices \( Q \) in (3.5), \( Q = I \), and \( Q = B_t^{-1} \) which give the following

\[ \nabla g_t^T = -\nabla g_t (\nabla g_t^T \nabla g_t)^{-1} \] \hspace{1cm} (3.8.a)

\[ \nabla g_t^T = -B_t^{-1} \nabla g_t (\nabla g_t^T B_t^{-1} \nabla g_t)^{-1}. \] \hspace{1cm} (3.8.b)

With these two choices for step (3.7.f) and using the null-space multiplier update formula we get the following algorithms.

**ALGI**

For \( k = 0, 1, 2, \ldots \)

\( \lambda_{k+1} = - (\nabla g_t^T B_t^{-1} \nabla g_t)^{-1} \nabla g_t^T B_t^{-1} \nabla J_k \)

\( B_{k+1} w_k = -\nabla J(x_k, \lambda_{k+1}) \)

\( y_k = \nabla J(x_k + w_k, \lambda_{k+1}) - \nabla J(x_k, \lambda_{k+1}) \)

\( B_{k+1} = \text{DFP/BFGS}(w_k, y_k) \)

\( v_k = -\nabla g_t (\nabla g_t^T \nabla g_t)^{-1} g_t \)

\( x_{k+1} = x_k + w_k + v_k \)
ALG2
For $k=0,1,2,...$

$$
\lambda_{k+1} = - (\nabla g' B_t^{-1} \nabla g_t)^{-1} \nabla g' B_t^{-1} \nabla f_t
$$

$$
B_{k} w_k = - \nabla l(x_k, \lambda_{k+1})
$$

$$
y_k = \nabla l(x_k + w_k, \lambda_{k+1}) - \nabla l(x_k, \lambda_{k+1})
$$

$$
B_{k+1} = \text{DFP/BFGS}(w_k, y_k)
$$

$$
v_k = - B_t^{-1} \nabla g_t (\nabla g' B_t^{-1} \nabla g_t)^{-1} g_t
$$

$$
z_{k+1} = z_k + w_k + v_k
$$

Those two algorithms have the following properties. From Theorem 3.1 the multiplier update formula is $x$-dominated. Further, consider $v_k = w_k + v_k$. Since either $P_x g_k = w_k$ for ALG1, or $P_x g_k = w_k$ for ALG2 then there exists a positive constant $K_e$ such that

$$
|w_d| \leq K_e |s_d|. \quad (3.11)
$$

In either case from Theorem 2.3 $w_k \in N_b$, and therefore we have relation (2.4) and assuming (2.13) as in Theorem 2.4 we can prove, since (3.11) holds that

$$
\lim_{k \to \infty} \frac{|P_d (B_k - A_d) w_k|}{|s_d|} = 0. \quad (3.12)
$$

Moreover, since $w_k \in N_b$ the step $s_k$ satisfies (3.3). We thus have all the ingredients to get $q$-superlinear convergence.

We have two other multiplier updates that are $x$-dominated. They are the Projection update

$$
\lambda_{k+1} = - (\nabla g' \nabla g_t)^{-1} \nabla g' \nabla f_t \quad (3.13)
$$

and the Newton’s update

$$
\lambda_{k+1} = (\nabla g' B_t^{-1} \nabla g_t)^{-1} (g_k - \nabla g' B_t^{-1} \nabla f_t). \quad (3.14)
$$

From Theorem 2.3 those multiplier updates will not generate a step $w_k$ in $N_b$, hence the need of projecting the step. With this idea we get the following algorithms.
**ALG1**
For k=0,1,2, ...

\[ \lambda_{k+1} = - (\nabla g_i^t \nabla g_i)^{-1} \nabla g_i \nabla f_i \]

\[ B_k h_k = - \nabla f(x_k, \lambda_{k+1}) \]

\[ w_k = P_{B_k} h_k \]

\[ y_k = \nabla f(x_k + w_k, \lambda_{k+1}) - \nabla f(x_k, \lambda_{k+1}) \]

\[ B_{k+1} = \text{DFP/BFGS}(w_k, y_k) \]

\[ v_k = - \nabla g_i (\nabla g_i^t \nabla g_i)^{-1} g_k \]

\[ x_{k+1} = x_k + w_k + v_k \]

**ALG4**
For k=0,1,2, ...

\[ \lambda_{k+1} = - (\nabla g_i^t \nabla g_i)^{-1} \nabla g_i \nabla f_i \]

\[ B_k h_k = - \nabla f(x_k, \lambda_{k+1}) \]

\[ w_k = P_{B_k} h_k \]

\[ y_k = \nabla f(x_k + w_k, \lambda_{k+1}) - \nabla f(x_k, \lambda_{k+1}) \]

\[ B_{k+1} = \text{DFP/BFGS}(w_k, y_k) \]

\[ v_k = - B_i^{-1} \nabla g_i (\nabla g_i^t B_i^{-1} \nabla g_i)^{-1} g_k \]

\[ x_{k+1} = x_k + w_k + v_k \]

Where \( P_{B_k} = I - B_k^{-1} \nabla g_i (\nabla g_i^t B_k^{-1} \nabla g_i)^{-1} \nabla g_i \) is a projection operator onto the tangent space of the constraints.
\textit{ALG5}

For \( k=0,1,2, \ldots \)

\[ \lambda_{k+1} = (\nabla g^T B_k^{-1} \nabla g_k)^{-1}(g_k - \nabla g^T B_k^{-1} \nabla f_k) \]

\[ B_k h_k = - \nabla f(x_k, \lambda_{k+1}) \]

\[ w_k = P_{\lambda_k} h_k \]

\[ y_k = \nabla f(x_k + w_k, \lambda_{k+1}) - \nabla f(x_k, \lambda_{k+1}) \]

\[ B_{k+1} = \text{DFP/BFGS}(w_k, y_k) \]

\[ v_k = - \nabla g^T \nabla g_k^{-1} g_k \]

\[ z_{k+1} = z_k + w_k + v_k \]

\textit{ALG6}

For \( k=0,1,2, \ldots \)

\[ \lambda_{k+1} = (\nabla g^T B_k^{-1} \nabla g_k)^{-1}(g_k - \nabla g^T B_k^{-1} \nabla f_k) \]

\[ B_k h_k = - \nabla f(x_k, \lambda_{k+1}) \]

\[ w_k = P_{\lambda_k} h_k \]

\[ y_k = \nabla f(x_k + w_k, \lambda_{k+1}) - \nabla f(x_k, \lambda_{k+1}) \]

\[ B_{k+1} = \text{DFP/BFGS}(w_k, y_k) \]

\[ v_k = - B_k^{-1} \nabla g^T \nabla g_k^{-1} g_k \]

\[ z_{k+1} = z_k + w_k + v_k \]

The reasons for projecting the step \( h_k \) in ALG3 and ALG4 with \( P_{\lambda_k} \) instead of \( P_\lambda \) is seen in the next two theorems. For ALG2, ALG4 and ALG5 we obtain the following result.

\textbf{Theorem 3.1:} Let the step \( s_k \) from ALG2, ALG4 or ALG5 satisfy

\[ B_k s_k = - \nabla f(x_k, \mu). \]  \hspace{1cm} (3.15)

for some \( \mu \) in \( \mathbb{R}^m \). Then \( \mu \) is the Newton multiplier update formula (3.14).

\textbf{Proof:} From ALG2 we have that

\[ B_k w_k = - \nabla f_k + \nabla g^T (\nabla g^T B_k^{-1} \nabla g_k)^{-1} \nabla g^T B_k^{-1} \nabla f_k \]

and we also have
Recall

\[ B_k v_k = - \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} g_k. \]

Using (3.14) we get then (3.15). For ALG4 we get

\[ B_k h_k = - \nabla f_k - \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} \nabla g_k \nabla f_k \]

\[ w_k = P_B h_k \]

\[ v_k = - B_k^{-1} \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} g_k \]

Since \( P_B B_k^{-1} \nabla g_k = 0 \) we obtain

\[ w_k = - P_B B_k^{-1} \nabla f_k \]

Summing \( B_k v_k \) on both sides of this equation we get our desired result. From ALG5 we get

\[ B_k h_k = - \nabla f_k - \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} (g_k - \nabla g_k (B_k^{-1} \nabla f_k)) \]

\[ w_k = P_B h_k \]

\[ v_k = - \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} g_k. \]

Doing some algebra on the first equation we get

\[ h_k = - P_B B_k^{-1} \nabla f_k - B_k^{-1} \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} g_k. \]

Now projecting with \( P_h \) and since \( P_h P_B = P_B \)

\[ w_k = P_h h_k = - P_B B_k^{-1} \nabla f_k - P_B B_k^{-1} \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} g_k \]

so

\[ w_k = - P_B B_k^{-1} \nabla f_k - B_k^{-1} \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} g_k + \nabla g_k (\nabla g_k (B_k^{-1} \nabla g_k))^{-1} g_k \]

\[ w_k = h_k - v_k. \]

Therefore,

\[ h_k = w_k + v_k. \]

Q.E.D.

This result is important because it tells us that the DQMM with the Newton update formula and
ALG2/ALG4/ALG5 only differ slightly on the matrices $B_i$'s and although they do not generate the same iterates, asymptotically they will. This fact will be prove in section 5. For the rest of the algorithms we get the following.

**Theorem 3.2:** Let the step $s_i$ from ALG1, ALG3 or ALG6 satisfy (3.15) for some $\mu$ in $\mathbb{R}^n$. Then

$$s_i = -B_i^t \nabla \phi(x_k, \lambda_k^{N+1}) \pm (\nabla g_k^+ - \nabla g_k^-)g_k$$

(3.16)

where $\lambda_k^N$ is the Newton multiplier update formula (3.14).

**Proof:** For ALG1 we have

$$B_i w_1 = -\nabla f + \nabla g_i (\nabla g_i B_i^t \nabla g_i)^{-1} \nabla g_i B_i^t \nabla f_i$$

and

$$B_i v_1 = -B_i \nabla g_i (\nabla g_i \nabla g_i)^{-1} g_i.$$

Then we get

$$B_i s_1 = -\nabla \phi(x_k, \lambda_k^N) + B_k (\nabla g_k^+ - \nabla g_k^-)g_k$$

which implies (3.16). Algorithm ALG3 yields

$$w_1 = P_{B_i} h_1 = -B_i^t \nabla f_1 + B_i^t \nabla g_i (\nabla g_i B_i^t \nabla g_i)^{-1} \nabla g_i^t \nabla f_1$$

since $P_{B_i} B_i^t \nabla g_i = 0$ we get

$$w_1 = -B_i^t \nabla f_1 + B_i^t \nabla g_i (\nabla g_i B_i^t \nabla g_i)^{-1} \nabla g_i B_i^t \nabla f_1$$

which yields (3.16). For ALG6

$$h_1 = -P_{B_i} B_i^t \nabla f_1 + \nabla g_i^t g_i$$

hence

$$w_1 = -P_{B_i} B_i^t \nabla f_1 + \nabla g_i^t g_i - \nabla g_i^t g_i.$$ 

Therefore after adding $w_1$ we get (3.16).

Q.E.D.
4. CONVERGENCE PROPERTIES

In this section we will prove the convergence properties share by the 2-step algorithms of Section 2.

Theorem 4.1: Under assumptions A1 thru A2. Assume the sequence \( \{ z_t \} \) is given by either ALG2, ALG4 or ALG5. Then for any \( r \in (0, 1) \) there exist positive constants \( \epsilon, \delta \) such that if

\[
|z_t - z_0| \leq \epsilon \quad \text{and} \quad |B_t - A_t^*| \leq \delta
\]

the sequence \( \{ z_t \} \) is well defined and converges to \( z \), with

\[
|z_{t+1} - z_t| \leq r |z_t - z_t|
\]

Moreover, the sequences \( \{ |B_t| \} \) and \( \{ |B_{t+1}| \} \) are bounded.

Proof: By the equivalence of norms in \( R^{n \times n} \) we have that for any \( A \in R^{n \times n} \) there exist \( \mu, \eta > 0 \) such that

\[
\mu \| A \| \leq |A| \leq \eta \| A \|
\]

Let \( r \in (0, 1) \), and choose \( \epsilon, \delta \) so small that for

\[
\beta \geq |(A_t^*)^{-1}|
\]

we have

\[
r \geq \frac{\beta}{(1 - 2 \beta \eta \delta)} \left( K_1 \epsilon_2^2 + K_2 \epsilon_1 \phi + 2 \eta \delta \psi + \epsilon_3 \right),
\]

and

\[
(2 \alpha_1 \delta + \alpha_2) \frac{\epsilon_2^2}{1 - r^2} \leq \delta.
\]

Now select \( \delta \), small enough so that \( |B - A_t^*| < \delta \) whenever \( |B - A_t^*| < \delta_t \). If necessary further restrict \( \epsilon, \delta \), so that \( (z, z_+ \lambda, B) \in N_1, (z_+ \lambda, B) \in N_2 \) whenever \( |B - A_t^*| < 2 \eta \delta \), and max \( \{ |z - z_0|, |z_+ - z_0| \} < \epsilon, \)
Let \(|B_s - A\tilde{\alpha}^k| < \delta_r\), \(|z_s - z_d| < \epsilon_n\) from the Banach Perturbation Lemma [15]

\[
|A\tilde{\alpha}^{-1}| \|B_s - A\tilde{\alpha}^k\| \leq \beta \eta \|B_s - A\tilde{\alpha}^k\| < \eta \beta \delta < 2 \eta \beta \delta < 1;
\]

hence \(B_s^{-1}\) exists, and there exists \(\psi > 0\) such that

\[
|B_s^{-1}| \leq \frac{\beta}{1 - 2 \beta \eta \delta}, \quad \text{and} \quad \psi \geq |V_{B_s}^-|.
\]

where \(V_{B_s}^- = |(I - \nabla g_s^t\nabla g_s B_s^{-1}\nabla g_s)^{-1}\nabla g_B B_s^{-1}|\). Furthermore,

\[
|P_d(B_s - A\tilde{\alpha})| = |P_d(B_s - A\tilde{\alpha})| \leq |(B_s - A\tilde{\alpha})| < 2 \eta \delta.
\]

We have

\[
z_1 = z_s - B_s^{-1}\nabla J(x_s, \lambda_1)
\]

thus from standard arguments

\[
z_1 - z_s = B_s^{-1}(\nabla J(x_s, \lambda_1) - \nabla x^l(x_0, \lambda_1) - A_s(x_s - x_0))
+ B_s^{-1}(\nabla J(x_s, \lambda_1)) - \nabla x^l(x_s, \lambda_1))
+ (I - B_s^{-1}A_s)(z_s - z_d).
\]

Now, taking norms and using the triangle inequality

\[
|z_1 - z_d| \leq |B_s^{-1}| |\nabla J(x_s, \lambda_1) - \nabla x^l(x_0, \lambda_1) - A_s(x_s - x_0)|
+ |B_s^{-1}| |(B_s - A_s)(z_s - z_d) - \nabla g_s(\lambda_1 - \lambda_d)|
\]

Using the fact that for the Newton multiplier update formula we have for all \(k\)

\[
\nabla g_s(\lambda_{k+1} - \lambda_d) = \nabla g_s(\nabla g_s B_s^{-1}\nabla g_s)^{-1}\nabla g_s B_s^{-1}(B_s - A_s)(z_s - z_d) + \epsilon_k(z_k - z_d)
\]

(4.1)

where \(\epsilon_k = K_1|z_k - z_d|\) we obtain

\[
|z_1 - z_d| \leq |B_s^{-1}| |\nabla J(x_s, \lambda_1) - \nabla x^l(x_0, \lambda_1) - A_s(x_s - x_0)|
+ |B_s^{-1}| |(I - \nabla g_s(\nabla g_s B_s^{-1}\nabla g_s)^{-1}\nabla g_s B_s^{-1}(B_s - A_s)(z_s - z_d))|
+ \epsilon_k|z_k - z_d|.
\]

Since \(V_{B_s}^- = V_{B_s^*}^-\), we get
\[ |z_1 - z| \leq |B_{r_1}'| |\nabla J(x_0, \lambda_1) - \nabla_x l(x_0, \lambda_1) - A_0 (x_0 - x_0)| + |B_{r_1}'| |V_{\theta_1}||P_d(B_\alpha - A_\alpha)(z_1 - z_1)| + \epsilon_d |z_1 - z_1|. \]

Hence
\[ |z_1 - z| \leq |B_{r_1}'| |\nabla J(x_0, \lambda_1) - \nabla_x l(x_0, \lambda_1) - A_0 (x_0 - x_0)| + |B_{r_1}'| |V_{\theta_1}||P_d(B_\alpha - A_\alpha)| + \epsilon_d |z_1 - z_1|. \]

Therefore,
\[ |z_1 - z| \leq |B_{r_1}'| |K_1 \epsilon_1^2 + K_2 \epsilon_2 \epsilon + 2 \eta \delta \psi + \epsilon_d|z_1 - z| \]

The bound on \( B_{r_1} \), and the condition on \( r \) yield
\[ |z_1 - z| \leq r |z_1 - z|. \]

Now by induction, assume for \( k=0,1, \ldots, m-1 \)
\[ \|B_k - A_{k+1}\| \leq 2 \delta, \quad \text{and} \quad |z_{k+1} - z_k| \leq r |z_k - z_k|. \]

From (1.3.b) we have
\[ \|B_{k+1} - A_{k+1}\| \leq \|B_k - A_{k+1}\| \leq 2 \alpha \epsilon_\Phi r^{k+1} + \alpha_\sigma \epsilon_\sigma r^{k+1} \]

summing both sides from \( k=0 \) to \( m-1 \) we obtain
\[ \|B_m - A_{k+1}\| \leq \|B_0 - A_{k+1}\| + (2 \alpha \delta + \alpha_\sigma) \frac{\epsilon_\Phi}{1 - r} \leq 2 \delta \]

so \( B_m - A_{k+1} \leq 2 \eta \delta \), and \( |P_d(B_m - A_\alpha)| \leq 2 \eta \delta. \)

Using the Banach Perturbation Lemma \( B_m \) exists, and \( |B_m| \leq \frac{\beta}{1 - 2 \beta \eta \delta}. \)

We complete the induction by observing that for \( m = 0 \)
\[ |z_{m+1} - z| \leq |B_{r_1}'| |K_1 \epsilon_1^2 + K_2 \epsilon_2 \epsilon + 2 \eta \delta \psi + \epsilon_d|. \]

The bound on \( B_{r_1} \), and the condition on \( r \) yield
\[ |z_{m+1} - z| \leq r |z_m - z|. \]

Notice that the sequence \( \{|B_{r_1}'|\} \) is always bounded by \( \frac{\beta}{1 - 2 \beta \eta \delta} \), and for all \( m \) we have that
\[ |B_m| \leq 2 \eta \delta + |A_0^2|. \]

Q.E.D.

For the rest of the 2-step algorithms we will prove that the sequence \( \{z_i\} \) verifies

\[ |z_{i+1} - z_i| \leq r |z_{i-1} - z_i| \tag{4.2} \]

for some \( r \in (0,1) \). Note that (4.13) is 2-step q-linear convergence and it implies (2.13).

**Theorem 4.2:** Assume \( A1 \) thru \( A2 \). Let \( \{x_i\} \) be generated by ALG1, ALG3, or ALG6. Then for any \( r \in (0,1) \) there exist positive constants \( \epsilon, \delta \) such that if

\[ |z_0 - x_0| \leq \epsilon \quad \text{and} \quad |B_0 - A_0^2| \leq \delta \]

the sequence \( \{z_i\} \) is well defined and converges to \( x \), with

\[ |z_{i+1} - z_i| \leq r |z_{i-1} - z_i|. \]

Moreover, the sequences \( \{|B_i|\} \) and \( \{|B_i^1|\} \) are bounded.

**Proof:** Choose \( r \in (0,1) \). By the equivalence of norms for any matrix \( A \in \mathbb{R}^{n \times n} \) there exist positive constants \( \mu, \eta \) such that

\[ \mu ||A|| \leq |A| \leq \eta ||A||. \]

Choose \( \epsilon, \delta \) so small that for

\[ \beta \geq |(A_0^2)^{-1}| \]

we have

\[ 2\eta \beta \delta \leq 1 \quad \frac{(2\alpha_1 \delta + \alpha_2) - \epsilon^2}{1 - r^2} \leq \delta \]

\[ r > K_{10} \frac{\beta}{1 - 2\eta \beta \delta} + K_{11} \epsilon + K_{12} \epsilon + 2\beta \eta \delta + \epsilon_1 + K_{13} \epsilon. \]

Now select \( \delta, \epsilon \) small enough so that \( ||B_k - A_0^2|| < \delta \) whenever \( |B_k - A_0^2| < \delta \). If necessary further restrict \( \epsilon, \delta \), so that \( (z, z_{\lambda(B)} \in N_1 \), \( (z, z_{\lambda(B)} \in N_2 \) whenever \( |B_k - A_0^2| < 2\eta \delta \) and \( \sigma(z, z_{\lambda(B)}) < \epsilon_1 \).

Let \( |B_k - A_0^2| < \delta \), and \( |z_k - x_k| < \epsilon \), from the Banach Perturbation Lemma we have

\[ |(A_0^2)^{-1}||B_k - A_0^2| \leq \beta \eta ||B_k - A_0^2|| < \beta \eta \delta < 2\beta \eta \delta < 1 \]

then \( B_0^1 \) exists and
Furthermore, 

$$|B^i_1| \leq \frac{\psi}{1 - 2\psi \delta}.$$ 

Using the techniques of Theorem 2.2 we get that $|z_1 - z_\phi| < \epsilon$ and then with (1.4.b) 

$$\|B_i - A_i\| < 2\delta$$ 

and so 

$$|P_i(B_i - A_i)| \leq 2\eta \delta, \quad |B^i_1| \leq \frac{\beta}{1 - 2\beta \eta \delta}, \quad \text{and} \quad \psi \geq |V_{B^i_1}|.$$ 

From (3.16) we get 

$$|z_2 - z_\phi| \leq |B^i_1| |\nabla_1 (x_1, \lambda_2) - \nabla_1 (x_1, \lambda_2) - A_1 (x_1 - x_\phi)|$$ 

$$+ |B^i_1| |(B_i - A_i)(z_1 - z_\phi) - \nabla_1 \lambda_2 - \lambda_2|$$ 

$$+ |\nabla_1 \phi_1 - \nabla_1 \phi_2||z_1 - z_\phi|$$ 

From (3.3) and (4.1) 

$$|z_2 - z_\phi| \leq |B^i_1| |\nabla_1 (x_1, \lambda_2) - \nabla_1 (x_1, \lambda_2) - A_1 (x_1 - x_\phi)|$$ 

$$+ |B^i_1| |V^i_1(B_i - A_i)| + \epsilon_\delta |z_1 - z_\phi|$$ 

$$+ |\nabla_1 \phi_1 - \nabla_1 \phi_2||z_1 - z_\phi - \nabla_1 \phi_2(z_1 - z_\phi)|$$ 

Using Taylor's Theorem on the last term of the right hand side 

$$|\phi_1 - \phi - \nabla_1 \phi_2(z_1 - z_\phi)| \leq K_8 |z_1 - z_\phi|.$$ 

for some positive $K_8$. Now 

$$|\nabla_1 \phi_1 - \nabla_1 \phi_2||\phi_1 - \phi - \nabla_1 \phi_2(z_1 - z_\phi)| \leq K_8 |z_1 - z_\phi|^2$$ 

$$\leq \epsilon_\delta K_8 |z_1 - z_\phi|^2.$$ 

We get 

$$|z_2 - z_\phi| \leq |B^i_1| |K_1 \epsilon_\phi^i + K_2 \epsilon_\phi^i + 2\beta \eta \delta \phi + \epsilon_\delta| |z_1 - z_\phi| + K_8 \epsilon_\phi |z_1 - z_\phi|.$$ 

Since $|z_1 - z_\phi| \leq K_{10} |z_2 - z_\phi|$ we get 

$$|z_2 - z_\phi| \leq [K_8 |B^i_1| (K_1 \epsilon_\phi^i + K_2 \epsilon_\phi^i + 2\beta \eta \delta \phi + \epsilon_\delta) + K_8 \epsilon_\phi |z_1 - z_\phi|.$$ 

The bound on $|B^i_1|$ and the condition on $\phi$ give 

$$|z_2 - z_\phi| \leq r |z_2 - z_\phi|.$$ 

Now by way of induction assume for $k=1, \ldots, m-1$
From (1.4.b)

\[ \| B_k - A^\hat{u} \| \leq 2\delta \text{ and } |z_{k+1} - x| \leq r |z_{k} - x| \]

so

\[ \| B_{k+1} - A^\hat{u} \| - \| B_k - A^\hat{u} \| \leq 2\alpha_1 \delta r^{\frac{r}{2}} + \alpha_2 \varepsilon r^{\frac{r}{2}} \]

therefore, \( B_{m}^{-1} \) exists

\[ |P_{m}(B_m - A)\| \leq 2\eta \delta \quad \text{and} \quad |B_m\| \leq \frac{\psi}{1 - 2\varepsilon \eta \delta} \]

As for \( m = 0 \) we get

\[ |z_{m+1} - z| \leq r |z_{m} - z| . \]

The sequence \( \{ B_1^{-1} \} \) is always bounded by \( \frac{\beta}{1 - 2\beta \eta \delta} \), and for all \( k \) we have that

\[ |B_k| \leq 2\eta \delta + |A^\hat{u}| \]

Q.E.D.

For the rest of the section assume the following.

\textbf{A4.} The iterates \( z_k \in \Omega \) and \( \lim_{k \to \infty} z_k = z^* \).

\textbf{Theorem 4.3:} Assume A1 thru A4. Let the sequence \( \{ z_k \} \) be generated by the 2-step algorithms.

Then if

\[ \lim_{k \to \infty} \frac{|P_k(B_k - A)w_k|}{|w_k|} = 0 \quad (4.3) \]

then the sequence \( \{ z_k \} \) converges to \( z^* \) 2-step q-superlinearly, i.e.

\[ \lim_{k \to \infty} \frac{|z_{k+1} - z|}{|z_{k} - z|} = 0 \quad (4.4) \]

\textbf{Proof:} Following Theorem 4.4 from Fontecilla-Steinhaug-Tapia [10] we have that

\[ |z_{k+1} - z| \leq |P_k(B_k - A)s_k| + K_{11} |\nabla g_{s+k}| + o(|s_k|) . \quad (4.5) \]

From the q-linearity and (3.16) there exists a positive constant \( K_{12} \) such that
Dividing (4.5) by \( |z_{k-1} - z| \) and using (4.6) we have

\[
\frac{|z_{k+1} - z|}{|z_{k-1} - z|} \leq K_{12} \frac{|P_d(B_k - A_d) s_k|}{|s_k|} + K_{13} \frac{|\nabla g g_{k+1}|}{|s_k|} + o(|s_d|).
\]

Since (3.3) is always satisfied the last two terms of the right hand side are \( o(|s_k|) \). Therefore,

\[
\frac{|z_{k+1} - z|}{|z_{k-1} - z|} \leq K_{12} \frac{|P_d(B_k - A_d) s_k|}{|s_k|} + o(|s_d|).
\]

Using (4.6) we get

\[
|s_{k-1}| \leq K_{14} |z_{k-1} - z|.
\]

Since \( s_k = w_k + v_k \) and \( v_k \) is either (3.8.a) or (3.8.b) we have either \( P_B s_k = w_k \) or \( P_B^\perp s_k = w_k \) which imply

\[
|w_k| \leq K_{15} |s_k|.
\]

Therefore,

\[
\frac{|z_{k+1} - z|}{|z_{k-1} - z|} \leq K_{16} \frac{|P_d(B_k - A_d) w_k|}{|w_k|} + K_{17} \frac{|\nabla g g_k|}{|s_{k-1}|} + o(|s_d|).
\]

Now from (3.3) we have that \( g_k = o(|s_{k-1}|) \). Therefore, taking limits on (4.8) and using (4.3) we get our desired result.

Q.E.D.

We can now summarized our results.

**Theorem 4.4:** Assume A1 thru A4. The sequence \( \{x_i\} \) generated by the 2-step algorithms converges to \( z \), 2-step q-superlinearly.

**Proof:** It is a direct consequence of Theorem 2.4 since for all the 2-step algorithms \( w_i \in N_k \) and (2.13) is always satisfied.

Q.E.D.
5. MODIFIED DIAGONALIZED QUASI-NEWTON ALGORITHMS

In this section we modify the DQMM to construct two new algorithms each one of them generating a sequence \( \{x_k\} \) converging 1-step q-superlinearly when the Hessian is not positive definite. The first one is a combination of the DQMM using Newton's update formula and a 2-step algorithm, specifically ALG2. The second one is constructed using the idea developed by Coleman and Conn [5] and also by Gabay [11]. The former costs one extra gradient evaluation over the DQMM whereas the latest costs one extra gradient evaluation and one extra function evaluation on the constraints.

The Modified Diagonalized Quasi-Newton Method

From Theorem 3.1 the step given by the DQMM using Newton's update formula is of the form

\[
s_k = w_k + v_k
\]

with \( w_k \in N_k \) and \( v_k \) given by (3.8.b). Noticing that \( v_k = o(\|s_k\|) \) as was proved in Section 4 we can say that asymptotically both algorithms are equivalent. Moreover, after few iterations on the DQMM we will be using \( w_k \) instead of \( s_k \) and therefore, the reason why we never had any trouble updating with the DFP/BFGS when the Hessian is positive definite only in \( N_\ast \).

Updating with the DFP/BFGS the inner product \( y^t s \) can be negative or equal to zero in the first few iterations. In order to handle this problem we proposed the following algorithm.

M.D.Q.N.

For \( k = 0, 1, 2, \ldots \)

\[
\beta_{k+1} = (\nabla^2 g_k^t \nabla^2 g_k)^{-1} g_k \quad \text{(5.1.a)}
\]

\[
\mu_{k+1} = - (\nabla^2 g_k^t \nabla^2 g_k)^{-1} \nabla^2 g_k^t \nabla f_k \quad \text{(5.1.b)}
\]

\[
\lambda_{k+1} = \beta_{k+1} + \mu_{k+1} \quad \text{(5.1.c)}
\]

\[
B_k w_k = - \nabla f(x_k, \mu_{k+1}) \quad \text{(5.1.d)}
\]
$B_{k+1} u_{k} = -\nabla g_2 \theta_{k+1}$

$s_{k} = w + u_{k}$

$y_{k} = \nabla J(x_k + s_k, \lambda_{k+1}) - \nabla J(x_k, \lambda_{k+1})$

If $y_{k}' s_{k} > 0$ then

$B_{k+1} = DFP/BFGS(w_{k}, y_{k})$

else

$\overline{y}_{k} = \nabla J(x_k + w_k, \lambda_{k+1}) - \nabla J(x_k, \lambda_{k+1})$

$B_{k+1} = DFP/BFGS(w_{k}, \overline{y}_{k})$

end if.

$x_{k+1} = x_k + s_k$

(5.1.e)

(5.1.f)

(5.1.g)

(5.1.h)

(5.1.i)

(5.1.j)

(5.1.k)

Notice that without steps (5.1.i) and (5.1.j) the MDQMM is nothing but the DQMM with the Newton multiplier update formula. Furthermore, the extra gradient evaluation is made only when it is strictly necessary. We obtain the following result.

**Theorem 5.1:** Let the sequence $\{z_{k}\}$ be generated by the M.D.Q.N. algorithm. If

$|z_{k} - z_{k}'| < \epsilon$ and $|B_{k} - \tilde{A}_{k}| < \delta$

then $\{z_{k}\}$ converges to $z_{*}$ q-superlinearly if $A_{*}$ is positive definite and 2-step q-superlinearly if $A_{*}$ is positive definite only in $N_{*}$.

**Proof:** In Fontecilla-Steinhaug-Tapia [10] it was proved that if the Hessian $A_{*}$ is positive definite in the whole space then the DQMM with the Newton's update formula is q-superlinear convergent in $z_{k}$. If $A_{*}$ is positive definite only in $N_{*}$ then Theorem 4.4 gives the desired result.

Q.E.D.

**The Improved Diagonalized Quasi-Newton Method**

The main difficulty to implement the MDQN is that we do not know when to switch algorithms. The Hessian $A_{*}$ may not be positive definite and we may still have $y_{k}' s_{k} > 0$. We construct an algorithm that does not have this inconvenience. The idea was given by the Coleman and Conn [5]
algorithm although they were not able to prove 1-step q-superlinear convergence. At same time the same idea was given by Gabay [11] but the proof of q-superlinearity was incomplete. The algorithm is a modification on the 2-step algorithms ALG1/ALG2.

I.D.Q.N.

For \( k = 0,1,2, \ldots \)

\[
\begin{align*}
\lambda_{k+1} &= -(\nabla g_1^T_i \nabla g_1)_i \nabla g_1^T_i \nabla f_i \quad \text{(5.2.a)} \\
B_k w_k &= - \nabla J(x_k, \lambda_{k+1}) \quad \text{(5.2.b)} \\
y_k &= \nabla J(x_k + w_k, \lambda_{k+1}) - \nabla J(x_k, \lambda_{k+1}) \quad \text{(5.2.c)} \\
B_{k+1} &= \text{DFP/BFGS}(w_k, y_k) \quad \text{(5.2.d)} \\
v_t &= - \nabla g_1^T g(z_t + w_t) \quad \text{(5.2.e)} \\
x_{t+1} &= z_t + w_t + v_t \quad \text{(5.2.f)}
\end{align*}
\]

The only difference with ALG1/ALG2 is step (5.2.f) where we are doing one extra function evaluation on the constraints. With this extra function evaluation we are able to prove that the sequence \( \{z_t + w_t\} \) converges 1-step q-superlinearly.

Before stating the theorem we need to clarify certain points. We are assuming A1, A2, and A4; moreover, we know that the sequence \( \{z_t\} \) converges 2-step q-superlinearly. Therefore, since \( \tilde{x}_t = z_t + w_t \) we have

\[
|\tilde{x}_t - z_t| \leq |z_t - x_t| + |w_t| \quad \text{(5.3)}
\]

since \( w_t \to 0 \) and \( z_t \to z \), we have convergence of the sequence \( \{\tilde{x}_t\} \). We also need to point out that \( w_t \in N_t \) hence we have

\[
\lim_{{k \to \infty}} \frac{|P_t(B_k - A_t)w_t|}{|w_t|} = 0 \quad \text{(5.4)}
\]

Let us recall from Fontecilla, Steihaug and Tapia [10] that the operator \( H_c \) defined by

\[
H_c(z) = P_t \nabla J(x, \lambda_z) + c \nabla g_1 g(x)
\]

satisfy \( H_c(z) = 0 \) and \( H (z) \) is nonsingular. We will use the following notation
\[ y_t = \rho(z_t) \]

**Theorem 5.2:** Assume \( A1 \) thru \( A4 \). Then the sequence \( \{z_t\} \) generated by the IDQN algorithm converges \( q \)-superlinearly to \( z^* \), i.e.

\[
\lim_{t \to \infty} \frac{|z_{t+1} - z^*|}{|z_t - z^*|} = 0.
\]  

**Proof:** Let us recall that our system can be written as

\[ P_d(B_t + \nabla^d l(x_k, \lambda_{k+1})) = 0. \]

Consider now

\[
-P_v \nabla_j l(\tilde{x}_{k+1}, \lambda_*) = (P_k - P_*) \nabla_x l(\tilde{x}_{k+1}, \lambda_*) - P_k \left[ \nabla_x l(\tilde{x}_{k+1}, \lambda_*) - \nabla_x l(x_k, \lambda_*) - \lambda_* w_k \right]
\]

\[ + P_d(B_t - A_*)w_t. \]

Using the same techniques as in Fontecilla, Steihaug and Tapia [10] we get

\[
-P_v \nabla_j l(\tilde{x}_{k+1}, \lambda_*) = (P_k - P_*) \left[ \nabla_x l(\tilde{x}_{k+1}, \lambda_*) - \nabla_x l(x_k, \lambda_*) \right]
\]

\[ - P_d \left[ \nabla_d l(\tilde{x}_{k+1}, \lambda_*) - \nabla_d l(x_k, \lambda_*) - \lambda_* w_k \right]
\]

\[ + P_d(B_t - A_*)w_t - c \nabla g_{\kappa_{k+1}}. \]

Taking norms, using the triangle inequality, and standard arguments on the left hand side there exist positive constants \( K_1, K_2, K_3 \) such that

\[
|\tilde{z}_{k+1} - z^*| \leq K_1|P_k - P_d||\tilde{z}_{k+1} - z_t| + K_2|w_t|^2
\]

\[ + |P_d(B_t - A_*)w_t| + K_3|\tilde{z}_{k+1}|. \]  

(5.6)

We have that \( |\tilde{z}_{k+1} - z^*| \leq |w_t| + |z_t - z^*| \). The relation

\[
w_t = - B_t^{-1} \nabla_d l(x_k, \lambda_{k+1}) = - B_t^{-1} \left[ \nabla_x l(x_k, \lambda_{k+1}) - \nabla_x l(x_*, \lambda_*) \right] - B_t^{-1} \nabla g_\kappa (\lambda_{k+1} - \lambda_*)
\]

together with the fact that the multiplier update is \( x \)-dominated yield

\[ |w_t| \leq K_4|z_t - z^*| \]  

(5.7)

for some positive constant \( K_4 \). Using the fact that \( \lim_{k \to \infty} P_k = P_* \) we get with (5.7) in (5.6)
for a positive constant $K$. We now need to get an estimate on the last term of the right hand side. Since $\nabla g^i w_k = 0$ we can write $\tilde{y}_{t+1}$ as

$$\tilde{y}_{t+1} = \tilde{y}_{t+1} - g_t - \nabla g^i w_k + g_t$$

so we get

$$|\tilde{y}_{t+1}| \leq K_0 |w_k|^2 + |g_t| \tag{5.8}$$

but we also have $g_t = g_t - \tilde{y}_t - \nabla g^i_{t-1} v_{t-1}$ and $v_{t-1} = \tilde{y}_t - \tilde{z}_t$. Therefore,

$$|g_t| \leq K_7|\tilde{z}_t - \tilde{z}_d|^2. \tag{5.9}$$

Now (5.8) and (5.9) yield

$$|\tilde{y}_{t+1} - z_d| \leq K_0|\tilde{z}_t - z_d|^2 + |P_d(B_k - A_d) w_k| + K_8|\tilde{z}_t - \tilde{z}_d|. \tag{5.10}$$

Furthermore, $\tilde{z}_t = \tilde{z}_t + v_{t-1} = \tilde{z}_t - \nabla g^i_{t-1} \tilde{y}_k$ hence

$$|\tilde{z}_t - z_d| \leq K_0|\tilde{z}_t - z_d|$$

and

$$|\tilde{z}_t - z_d| \leq K_0|\tilde{z}_t - z_d|.$$

Using those two inequalities in (5.10) we get

$$|\tilde{y}_{t+1} - z_d| \leq K_{11}|\tilde{z}_t - z_d|^2 + |P_d(B_k - A_d) w_k|. \tag{5.11}$$

Since

$$\frac{1}{|\tilde{z}_t - z_d|} \leq \frac{K_0}{|\tilde{z}_t - z_d|} \leq \frac{K_0 K_4}{|w_k|}$$

dividing by $|\tilde{z}_t - z_d|$ (5.11) yields

$$\frac{|\tilde{y}_{t+1} - z_d|}{|\tilde{z}_t - z_d|} \leq K_{11}|\tilde{z}_t - z_d| + K_{12} \frac{|P_d(B_k - A_d) w_k|}{|w_k|}.$$

Therefore the sequence $\{z_k\}$ converges q-superlinearly to $z$, if the second term on the right hand side goes to zero, which is true since $w_k \in N_k$.

Q.E.D.
8. CONCLUSIONS

We have proposed a modification of the Diagonalized Quasi-Newton Multiplier Method when it is used with the Newton’s multiplier update formula and the matrices are updated with the DFP/BFGS secant updates. In case the Hessian is positive definite it was proved in Fontecilla-Steihaug-Tapia [10] that the method generates a sequence \( \{ z_t \} \) which converges to \( z \), 1-step \( q \)-superlinearly. Assuming this time that the Hessian is positive definite only in the null space of \( \nabla g_i^j \), we were able to construct a new class of algorithms called 2-step algorithms which generate a sequence \( \{ z_t \} \) that converges 2-step \( q \)-superlinearly to \( z \). The algorithms cost one extra gradient evaluation over the standard DQMM. We also proposed two algorithms. The Modified diagonalized quasi-Newton method which is a combination of the DQMM with a 2-step algorithm. The main feature of this algorithm can be seen in the following situation. Suppose we are using the DQMM and suddenly we are unable to update the BFGS or the DFP, for instance if \( y_i^j s_i^j \leq 0 \), then we shift to a modified DQMM which guarantees that the rate of convergence is at worst 2-step \( q \)-superlinear. The price we pay for the shifting is one extra gradient evaluation.

This latest modification has the following drawback. It may be that the inner product \( y_i^j s_i^j \) is strictly positive during the whole process and the Hessian may not be positive definite. Therefore the need to find other ways of detecting whether we need to shift to a 2-step algorithm or keep using the DQMM. In order to overcome this difficulty we also proposed an algorithm, the Improved diagonalized quasi-Newton method, which guarantees the convergence of a sequence 1-step \( q \)-superlinearly even when the Hessian is not positive definite. This algorithm is the only one to our knowledge that share these features. It costs one extra gradient evaluation and one extra function evaluation on the constraints over the DQMM.

We feel that all the proposed algorithms need some testing. At the same time we think that what we have developed constitutes a good start towards finding global convergent algorithms.
Acknowledgment

This work constitutes a portion of the author's doctoral thesis under the supervision of Professors Richard Tapia and Trond Steihaug in the Department of Mathematical Sciences, Rice University, Houston, Texas. The author is also indebted to Professor J.E. Dennis for making numerous helpful suggestions.
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