

# Negative Curvature and Equality Constrained Optimization

Richard H. Byrd<sup>1</sup>   Frank E. Curtis<sup>2</sup>   Jorge Nocedal<sup>2</sup>

<sup>1</sup>University of Colorado at Boulder

<sup>2</sup>Northwestern University

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# Outline

## Inexact SQP Method for Equality Constrained Optimization

Algorithm Review

Negative Curvature Case

## Unconstrained Optimization

Angle Condition

Verifying the Angle Condition

## Constrained Optimization

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## Problem Formulation

Nonlinear program with equality constraints

$$\begin{aligned} \min_{x \in \mathbb{R}^n} f(x) \\ \text{s.t. } c(x) = 0 \end{aligned}$$

Sequential Quadratic Programming (SQP)

$$\begin{aligned} \min_{d \in \mathbb{R}^n} f_k + g_k^T d + \frac{1}{2} d^T W_k d \\ \text{s.t. } c_k + A_k d = 0 \end{aligned}$$

Step can be obtained via primal-dual system

$$\begin{bmatrix} W_k & A_k^T \\ A_k & 0 \end{bmatrix} \begin{bmatrix} d_k \\ \delta_k \end{bmatrix} = - \begin{bmatrix} g_k + A_k^T \lambda_k \\ c_k \end{bmatrix}$$

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## Line Search SQP Method

- ▶ Apply an iterative solver to the primal-dual system

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until a stopping condition is satisfied<sup>1</sup>

- ▶ Set the penalty parameter  $\pi$  to ensure descent on the penalty function

$$\phi_\pi(x) = f(x) + \pi \|c(x)\|$$

- ▶ Perform a backtracking line search to find  $\alpha_k$  satisfying the Armijo condition

$$\phi_{\pi_k}(x_k + \alpha_k d_k) \leq \phi_{\pi_k}(x_k) + \eta \alpha_k D\phi_{\pi_k}(d_k)$$

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<sup>1</sup>(Byrd, Curtis, Nocedal, 2007)

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## Stopping Conditions

Inexactness determined by reductions in  $\phi_\pi$

$$\text{mred}_\pi(d) = -g_k^T d - \frac{\omega(d)}{2} d^T W_k d + \pi(\|c_k\| - \|r_k\|)$$

An accepted step  $(d_k, \delta_k)$  must satisfy

$$\text{mred}_{\pi_k}(d_k) \geq \sigma \pi_k \max\{\|c_k\|, \|r_k\|\} \quad (1)$$

for a given constant  $0 < \sigma < 1$  and appropriate  $\pi_k$

- ▶ Stopping Condition I: (1) satisfied for  $\pi_k = \pi_{k-1}$
- ▶ Stopping Condition II:  $\|r_k\| \leq \epsilon \|c_k\|$  for  $0 < \epsilon < 1$  and

$$\pi_k \geq \frac{g_k^T d_k + \frac{\omega_k}{2} d_k^T W_k d_k}{(1 - \sigma)(\|c_k\| - \|r_k\|)}$$

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## Assumptions for Global Convergence

Global convergence is guaranteed if

$$Z_k^T W_k Z_k \succ 0$$

where  $Z_k$  is a basis for the null space of  $A_k$  (i.e.,  $A_k Z_k = 0$ ),  
which is known to hold if the primal-dual matrix

$$\begin{bmatrix} W_k & A_k^T \\ A_k & 0 \end{bmatrix}$$

has  $n$  positive and  $m$  negative eigenvalues

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## Step Decomposition

Step can be decomposed into a tangential step  $u_k$ , lying in the null space of  $A_k$ , and a normal step  $v_k$ , lying in the range space of  $A_k^T$

$$d_k = u_k + v_k, \quad \text{where} \quad \|d_k\|^2 = \|u_k\|^2 + \|v_k\|^2$$

We claim that if Stopping Condition I or II is satisfied

▶ ... and

$$\theta \|u_k\|^2 \leq \|v_k\|^2$$

then step is acceptable

▶ ... and

$$\theta \|u_k\|^2 \leq d_k^T W_k d_k$$

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## Observing a Bounded Tangential Step

Observe

$$\begin{aligned}\|v_k\| &\geq \|A_k v_k\| / \|A_k\| \\ &= \|A_k d_k\| / \|A_k\|\end{aligned}$$

and so

$$\theta \|d_k\|^2 \leq \|A_k d_k\|^2 / \|A_k\|^2$$

implies

$$\theta \|u_k\|^2 \leq \|v_k\|^2$$

## Observing Negative Curvature

Observe

$$\begin{aligned}\|u_k\|^2 &= \|d_k\|^2 - \|v_k\|^2 \\ &\leq \|d_k\|^2 - \|A_k d_k\|^2 / \|A_k\|^2\end{aligned}$$

and so

$$\theta (\|d_k\|^2 - \|A_k d_k\|^2 / \|A_k\|^2) \leq d_k^T W_k d_k$$

implies

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## Preliminary Algorithm

Apply an iterative solver to the primal-dual system

$$\begin{bmatrix} W_k & A_k^T \\ A_k & 0 \end{bmatrix} \begin{bmatrix} d_k \\ \delta_k \end{bmatrix} = - \begin{bmatrix} g_k + A_k^T \lambda_k \\ c_k \end{bmatrix} + \begin{bmatrix} \rho_k \\ r_k \end{bmatrix}$$

If

$$\theta \|d_k\|^2 > \|A_k d_k\|^2 / \|A_k\|^2$$

and  $\theta (\|d_k\|^2 - \|A_k d_k\|^2 / \|A_k\|^2) > d_k^T W_k d_k$

then set  $W_k \leftarrow \tilde{W}_k$  such that

$$\theta (\|d_k\|^2 - \|A_k d_k\|^2 / \|A_k\|^2) \leq d_k^T \tilde{W}_k d_k$$

and continue the iteration

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Unconstrained nonlinear optimization

$$\min_{x \in \mathbb{R}^n} f(x)$$

SQP subproblem

$$\min_{d \in \mathbb{R}^n} f_k + g_k^T d + \frac{1}{2} d^T H_k d$$

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## Applying an iterative solver

Inexact step satisfies

$$H_k d_k = -g_k + \rho_k$$

Line search method converges if the angle condition

$$\frac{-g_k^T d_k}{\|g_k\| \|d_k\|} \geq \theta$$

is satisfied, which can be verified directly

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## Hypothetical situation

Suppose we cannot verify an angle condition directly

$$g_k^T d_k \leq -\theta \|g_k\| \|d_k\|$$

- ▶ Verified indirectly if

$$d_k^T W_k d_k \geq \theta \|d_k\|^2 \quad \text{and} \quad \|\rho_k\| \leq \theta \|g_k\|$$

( $W_k \leftarrow \tilde{W}_k$  in a line search method)

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## Inexact SQP Framework

Recall step computation

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Step quality ensured by Stopping Conditions I and II

- ▶ SC I: descent for  $\phi_\pi$  for current  $\pi$
- ▶ SC II: descent for  $\phi_\pi$  for increased  $\pi$

Step length ensured by problem characteristics

- ▶ ... but properties are lost for indefinite  $Z_k^T W_k Z_k$



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## “Angle Test” for Constrained Optimization

An inexact SQP step is acceptable if it satisfies an “angle test” for the penalty function  $\phi_\pi$

- ▶ Taylor expansion yields

$$D\phi_\pi(d_k) \leq g_k^T d_k - \pi(\|c_k\| - \|r_k\|)$$

- ▶ What is the steepest descent direction? ( $\pi$  not fixed)

“Angle test” cannot be verified directly

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## Sufficient Descent

Step satisfying Stopping Condition I or II is acceptable if

$$D\phi_{\pi}(d_k) \leq -\theta \|d_k\|^2$$

and  $D\phi_{\pi}(d_k) \leq -\theta (\|u_k\|^2 + \|c_k\|)$

which hold if

$$D\phi_{\pi}(d_k) \leq -\theta \|d_k\|^2$$

and  $D\phi_{\pi}(d_k) \leq -\theta (\|d_k\|^2 - \|A_k d_k\|^2 / \|A_k\|^2 + \|c_k\|)$

where  $\pi$  is current (SC I) or increased (bounded) value (SC II)

## Proposed Algorithm

Apply an iterative solver to the primal-dual system until SC I or II is satisfied

- ▶ Accept step if

- ▶ ... tangential step is bounded

$$\theta \|d_k\|^2 \leq \|A_k d_k\|^2 / \|A_k\|^2$$

- ▶ ... or curvature is sufficiently positive

$$\theta (\|d_k\|^2 - \|A_k d_k\|^2 / \|A_k\|^2) \leq d_k^T W_k d_k$$

- ▶ ... or direction is of sufficient descent

$$D\phi_\pi(d_k) \leq -\theta \|d_k\|^2$$

$$\text{and } D\phi_\pi(d_k) \leq -\theta (\|d_k\|^2 - \|A_k d_k\|^2 / \|A_k\|^2 + \|c_k\|)$$

- ▶ If  $\theta \|d_k\|^2 > \|A_k d_k\|^2 / \|A_k\|^2$ , then set  $W_k \leftarrow \tilde{W}_k$  to satisfy

$$\theta (\|d_k\|^2 - \|A_k d_k\|^2 / \|A_k\|^2) \leq d_k^T \tilde{W}_k d_k$$

# Conclusion

We have

- ▶ ... observed that an inexact line search SQP algorithm may fail if negative curvature is present
- ▶ ... proposed a method for modifying  $W_k$  during the application of the iterative solver to ensure global convergence
- ▶ ... proposed techniques for avoiding modifications of  $W_k$



## Final Note on Modifying $W_k$

The Hessian of the Lagrangian has the form

$$W_k = \nabla_{xx}^2 f(x) + \sum_{i=1}^m \lambda^i \nabla_{xx}^2 c^i(x)$$

so we may consider modifications of the form

$$\tilde{W}_k = \nabla_{xx}^2 f(x) + \sum_{i=1}^m \lambda^i \nabla_{xx}^2 c^i(x) + G_k$$

where  $G_k \succeq 0$ , or

$$\tilde{W}_k = \nabla_{xx}^2 f(x) + \sum_{i \in \mathcal{I}} \lambda^i \nabla_{xx}^2 c^i(x)$$

if  $\nabla_{xx}^2 f(x) \succ 0$  is known and  $\mathcal{I} \subseteq \{1, \dots, m\}$

Thanks!