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**THE INTERIOR – POINT METHOD TO DETERMINE THE
SYMMETRY OF THE POLYHEDRAL SETS**

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Abstract

There is a variety of measures of symmetry (or asymmetry) for convex sets that have been studied over the years, see Grünbaum [1] and Minkowski [3]. These measures arise naturally in the complexity theory of interior - point methods. In this work we present a method for computing an approximation of the symmetry and a symmetry point of the polyhedral sets.

Keywords: interior – point method, approximation, convex set, symmetry

1. INTRODUCTION

Given a closed convex set S and a point x , define the symmetry of S about x as follows:

$$sym(x, S) = \max\{\alpha \geq 0 \mid x + \alpha(x - y) \in S, (\forall) y \in S\} \quad (1.1)$$

which intuitively states that $sym(x, S)$ is the largest scalar α such that every point $y \in S$ can be reflected through x by the factor α and still lie in S . The symmetry value of S then is:

$$sym(S) = \max_{x \in S} sym(x, S) \quad (1.2)$$

and x^* is a symmetry point of S if x^* achieves the above supremum (also called a “critical point” in [1],[2] and [3]). S is symmetric if $sym(S) = 1$.

We present a simple example. Let be $a, b \in \mathbb{R}, a < b$ and $S = [a, b]$. We show how we can determinate $sym(x, S), x \in S$ and $sym(S)$. Let be $\alpha \geq 0$ so that $x + \alpha(x - y) \in S$,

$(\forall)y \in S$. Results that $a \leq x + \alpha(x-b) \leq x + \alpha(x-y) \leq x + \alpha(x-a) \leq b$ so $\alpha \leq \frac{a-x}{x-b}$ and $\alpha \leq \frac{b-x}{x-a}$. Then $\alpha \in \left[0, \min\left\{\frac{a-x}{x-b}, \frac{b-x}{x-a}\right\}\right]$. Let be

$$f(x) = \frac{a-x}{x-b} - \frac{b-x}{x-a} = \frac{(b-a)(a+b-2x)}{(x-b)(x-a)}.$$

Results that

$$\text{sym}(x, S) = \min\left\{\frac{a-x}{x-b}, \frac{b-x}{x-a}\right\} = \begin{cases} \frac{a-x}{x-b} & \text{if } x \in \left[a, \frac{a+b}{2}\right] \\ \frac{b-x}{x-a} & \text{if } x \in \left(\frac{a+b}{2}, b\right] \end{cases} \quad (1.3)$$

We will compute $\text{sym}(S) = \max_{x \in S} \text{sym}(x, S)$. Using (1.3), let be $f_1 : \left[a, \frac{a+b}{2}\right] \rightarrow \mathbb{R}$,

$$f_1(x) = \frac{a-x}{x-b} \quad \text{and } f_2 : \left(\frac{a+b}{2}, b\right] \rightarrow \mathbb{R}, \quad f_2(x) = \frac{b-x}{x-a}.$$

It is obvious that

$$0 \leq f_1(x) \leq 1 = f_1\left(\frac{a+b}{2}\right) \quad \text{and} \quad 0 \leq f_2(x) < 1. \quad \text{So } \text{sym}(S) = \max_{x \in S} \text{sym}(x, S) = 1 \quad (S \text{ is$$

symmetric) and $x^* = \frac{a+b}{2}$ is a symmetry point of S .

Symmetric convex sets play an important role in convexity theory. There are many other geometric properties of convex bodies S that are also connected to $\text{sym}(S)$. Notice that $\text{sym}(x, S)$ and $\text{sym}(S)$ are invariant under invertible affine transformation and change in norm. The relevance of $\text{sym}(x, S)$ has been revived in the complexity theory of interior - point methods for convex optimization, see Nesterov and Nemirovskii [4] and Renegar [5].

2. GENERAL PROPERTIES OF $\text{sym}(x, S)$ AND $\text{sym}(S)$

We make the following assumption: S is a convex body, i.e., S is a nonempty closed bounded convex set with a nonempty interior. We assume that S has an interior. Notice that the definition of $\text{sym}(x, S)$ given in (1.1) is equivalent to the following ‘‘set-containment’’ definition:

$$\text{sym}(x, S) = \sup\{\alpha \geq 0 \mid \alpha(x-S) \subseteq (S-x)\} \quad (2.1)$$

The general properties from the $\text{sym}(x, S)$ will be shown without demonstration in the following propositions.

Proposition 2.1 If S is a nonempty closed bounded convex set with a nonempty interior, $\text{sym}(\cdot, S) : S \rightarrow [0, 1]$ is a continuous quasiconcave function.

Proof. See [1]

Proposition 2.2 If S is a nonempty closed bounded convex set with a nonempty interior, a symmetric set centered at the origin, and $\|\cdot\|_S$ denote the norm induced by S . Then,

$$\text{for every } x \in S, \text{sym}(x, S) = \frac{1 - \|x\|_S}{1 + \|x\|_S}.$$

Proof. See [1]

Proposition 2.3 If S is a nonempty closed bounded convex set with a nonempty interior, a symmetric set centered at the origin. Then $\text{sym}(\cdot, S)$ is a logconcave function in S .

Proof. See [1]

Proposition 2.4 Let $S, T \subset \mathbb{R}^n$ be convex bodies, and let be $x \in S$ and $y \in T$. Then:

If $x \in S \cap T$,

$$\text{sym}(x, S \cap T) \geq \min\{\text{sym}(x, S), \text{sym}(x, T)\} \quad (2.2)$$

$$\text{sym}(x + y, S + T) \geq \min(\text{sym}(x, S), \text{sym}(y, T)) \quad (2.3)$$

$$\text{sym}((x, y), S \times T) = \min\{\text{sym}(x, S), \text{sym}(y, T)\} \quad (2.4)$$

Let be $A(\cdot)$ be an affine transformation. Then:

$$\text{sym}(A(x), A(S)) \geq \text{sym}(x, S) \quad (2.5)$$

with equality if $A(\cdot)$ is invertible.

Proof. See [1]

3. COMPUTING A SYMMETRY POINT OF S WHEN S IS POLYHEDRAL

Our interest lies in computing an ε -approximate symmetry point of S , which is a point $x \in S$, that satisfies: $\text{sym}(x, S) \geq (1 - \varepsilon)\text{sym}(S)$. We assume that $S = \{x \in \mathbb{R}^n \mid Ax \leq b, A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m\}$ i.e., S is polyhedral. We present a method for computing an ε -approximate symmetry point of S . The method involves solving $m + 1$ linear programs each of which involves m linear inequalities in n unrestricted variables.

Define the following scalar quantities $\delta_i^*, i = 1, \dots, m$:

$$\delta_i^* = \max_x (-A_i x) \quad (3.1)$$

$$Ax \leq b$$

and notice that $b_i + \delta_i^*$ is the range of $A_i x$ over $x \in S$ if the i^{th} constraint is not strictly redundant on S . We compute $\delta_i^*, i = 1, \dots, m$ by solving m linear programs whose feasible region is exactly S . The following proposition shows that if we know $\delta_i^*, i = 1, \dots, m$, then we are able to compute $\text{sym}(x, S)$ for any $x \in S$.

Proposition 3.1 Let $S = \{x \in \mathbb{R}^n \mid Ax \leq b, A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m\}$ be given. For each $x \in S$,

$$\text{sym}(x, S) = \min_{i=1, \dots, m} \left\{ \frac{b_i - A_i x}{\delta_i^* + A_i x} \right\} \quad (3.2)$$

Proof. Let be $\alpha = \text{sym}(x, S)$ and $\beta = \min_{i=1, \dots, m} \left\{ \frac{b_i - A_i x}{\delta_i^* + A_i x} \right\}$. We will proof that $\alpha = \beta$.

For all $y \in S$, $x + \alpha(x - y) \in S$, so $A(x + \alpha(x - y)) \leq b$ and so $A_i x + \alpha A_i x + \alpha(-A_i y) \leq b_i$, $i = 1, \dots, m$. This implies that $A_i x + \alpha A_i x + \alpha \delta_i^* \leq b_i$ and $\alpha \leq \min_{i=1, \dots, m} \left\{ \frac{b_i - A_i x}{\delta_i^* + A_i x} \right\}$ and so $\alpha \leq \beta$

On the other hand for all $y \in S$ and $i = 1, \dots, m$ we have: $\beta \leq \frac{b_i - A_i x}{\delta_i^* + A_i x}$, for all

$i = 1, \dots, m$, so $b_i - A_i x \geq \beta(A_i x + \delta_i^*) \geq \beta(A_i x - A_i y)$, $i = 1, \dots, m$. Thus $A_i x + \beta A_i x + \beta(-A_i y) \leq b_i$ and so $A_i(x + \beta(x - y)) \leq b$, $i = 1, \dots, m$ which implies that

$\alpha \geq \beta$. Thus $\alpha = \beta$ that means $\text{sym}(x, S) = \min_{i=1, \dots, m} \left\{ \frac{b_i - A_i x}{\delta_i^* + A_i x} \right\}$.

Proposition 3.1 can be used to create another single linear program to compute $\text{sym}(S)$ as follows. Let be $\delta^* = (\delta_1^*, \dots, \delta_m^*)$ and consider the following linear program that uses δ^* in the data:

$$\max_{\theta}(\theta) \tag{3.3}$$

$$Ax + \theta(\delta^* + b) \leq b.$$

Proposition 3.2 Let be (x^*, θ^*) be an optimal solution of the linear program (3.3). Then

$$x^* \text{ is a symmetry point of } S \text{ and } \text{sym}(S) = \frac{\theta^*}{1 - \theta^*}.$$

Proof. Suppose that $(\bar{x}, \bar{\theta})$ is a feasible solution of (3.3). Then $A_i \bar{x} + \bar{\theta}(\delta_i^* + b_i) \leq b_i$, $i = 1, \dots, m$.

Because $\delta_i^* = \max_x(-A_i x)$ and $A_i \bar{x} \leq b_i$ then $\delta_i^* \geq -A_i \bar{x} \geq -b_i$, $i = 1, \dots, m$, so $\delta_i^* + b_i > 0$

and that implies $\bar{\theta} \leq \frac{b_i - A_i \bar{x}}{\delta_i^* + b_i}$, $\frac{1}{\bar{\theta}} \geq \frac{\delta_i^* + b_i}{b_i - A_i \bar{x}}$, $\frac{1}{\bar{\theta}} - 1 \geq \frac{\delta_i^* + b_i}{b_i - A_i \bar{x}} - 1 = \frac{\delta_i^* + A_i \bar{x}}{b_i - A_i \bar{x}}$. We have

$\frac{1 - \bar{\theta}}{\bar{\theta}} \geq \frac{\delta_i^* + A_i \bar{x}}{b_i - A_i \bar{x}}$ and so $\frac{\bar{\theta}}{1 - \bar{\theta}} \leq \frac{b_i - A_i \bar{x}}{\delta_i^* + A_i \bar{x}}$. Then from Proposition 3.1 follows that

$\text{sym}(\bar{x}, S) \geq \frac{\bar{\theta}}{1 - \bar{\theta}}$, which implies that $\text{sym}(S) \geq \frac{\theta^*}{1 - \theta^*}$. The reverse inequality follows analogous.

From the propozitions 3.1 and 3.2 results the following method for computing $\text{sym}(S)$ and a symmetry point x^* :

Step 1 For $i=1, \dots, m$, approximately solve the linear program (3.1), stopping each linear program when a feasible solution \bar{x} is computed for which the duality gap \bar{g} satisfies $\bar{g} \leq \frac{\varepsilon(b_i - A_i \bar{x})}{4.1}$. Set $\bar{\delta}_i = -A_i \bar{x}$.

Step 2 Let be $\bar{\delta} = (\bar{\delta}_1, \dots, \bar{\delta}_m)$. Approximately solve the linear program

$$\begin{aligned} & \max_{\theta} (\theta) \\ & Ax + \theta(\bar{\delta} + b) \leq b \end{aligned} \tag{3.4}$$

stopping when a feasible solution $(\bar{x}, \bar{\theta})$ is computed for which the duality gap \bar{g} satisfies $\bar{\theta} \geq (\bar{\theta} + \bar{g}) \left(1 - \frac{\varepsilon}{4.1}\right)$. Then \bar{x} will be an ε -approximate symmetry point of S and $\frac{\bar{\theta}(1-\varepsilon)}{1-\bar{\theta}} \leq \text{sym}(S) \leq \frac{\bar{\theta}}{1-\bar{\theta}}$.

Notice that this method requires that the LP solver computes primal and dual feasible points (or simply primal feasible points and the duality gap) at each of its iterations; such a requirement is satisfied, for example, by a standard feasible interior - point method.

In order to prove a complexity bound for the method, we will assume that S is bounded and has an interior.

A standard interior - point method for solving (3.1) uses Newton's method to compute successive β -approximate solutions for a decreasing sequence of values of barrier parameter $\mu > 0$. It is well known [6], [7] the following result:

Theorem 1 Suppose that $\beta = \frac{1}{4}$ and that (x^0, s^0, z^0) is a given β -approximate solution for the barrier parameter $\mu^0 > 0$. If $(\bar{x}, \bar{s}, \bar{z})$ is a β -approximate solution for the barrier parameter $\bar{\mu} \in (0, \mu^0)$ then such a solution can be computed in at most $\left[(2 + 4\sqrt{m}) \ln \frac{\mu^0}{\bar{\mu}} \right]$ iterations of Newton method, and the duality gap associated with variables $(\bar{x}, \bar{s}, \bar{z})$ satisfy $\bar{g} \leq \frac{5}{4} m \bar{\mu}$.

Proof. See [6].

Proposition 3.3 Let $\varepsilon \in (0, 0.1)$ be given, set $\bar{\varepsilon} = \frac{\varepsilon}{4.1}$, and suppose that Step 1 of the method is executed. Then $\bar{\delta} = (\bar{\delta}_1, \dots, \bar{\delta}_m)$ satisfies $\delta_i^* - \bar{\varepsilon}(\delta_i^* + b_i) \leq \bar{\delta}_i \leq \delta_i^*$,

$i=1, \dots, m$. Furthermore, for any given $x \in S$, let be $\theta = \min_{i=1, \dots, m} \left\{ \frac{b_i - A_i x}{\delta_i^* + A_i x} \right\}$. Then

$$\frac{\theta}{1-\theta} \left(\frac{1-3\bar{\varepsilon}}{1-\bar{\varepsilon}} \right) \leq \text{sym}(x, S) \leq \frac{\theta}{1-\theta} \tag{3.5}$$

Proof. For a given $i=1, \dots, m$ let \bar{g} denote the duality gap computed in the stopping criterion of Step 1 of the method. Then

$$\delta_i^* \geq \bar{\delta}_i \geq \delta_i^* - \bar{g} \geq \delta_i^* - \bar{\varepsilon}(\delta_i^* + b_i) \quad (3.6)$$

Adding b_i in all members of (3.6) implies that

$$(1 - \bar{\varepsilon})(\delta_i^* + b_i) \leq (\bar{\delta}_i + b_i) \leq (\delta_i^* + b_i) \quad (3.7)$$

For a given $x \in S$ let be $\alpha = \text{sym}(x, S)$ and $\bar{\theta} = \min_{i=1, \dots, m} \left\{ \frac{b_i - A_i x}{\delta_i^* + A_i x} \right\}$. Then from

Proposition 3.1 we have

$$\alpha = \min_{i=1, \dots, m} \left\{ \frac{b_i - A_i x}{\delta_i^* + A_i x} \right\} = \frac{\bar{\theta}}{1 - \bar{\theta}} \quad (3.8)$$

Notice that $\bar{\delta}_i \leq \delta_i^*$ for all i , whereby $\theta \geq \bar{\theta}$, which implies that $\alpha = \frac{\bar{\theta}}{1 - \bar{\theta}} \leq \frac{\theta}{1 - \theta}$.

We also see from (3.8) that $0 \leq \bar{\theta} \leq 0.5$. Next notice that (3.6) implies that $\bar{\theta} \geq \theta(1 - \bar{\varepsilon})$. Therefore

$$\begin{aligned} \alpha &= \frac{\bar{\theta}}{1 - \bar{\theta}} \geq \frac{\theta(1 - \bar{\varepsilon})}{1 - \bar{\theta}} = \frac{\theta(1 - \bar{\varepsilon})}{1 - \theta} \frac{1 - \theta}{1 - \bar{\theta}} = \frac{\theta(1 - \bar{\varepsilon})}{1 - \theta} \left(1 + \frac{\bar{\theta} - \theta}{1 - \bar{\theta}} \right) \geq \frac{\theta(1 - \bar{\varepsilon})}{1 - \theta} \left(1 + \frac{\bar{\theta} - \frac{1}{1 - \bar{\varepsilon}} \bar{\theta}}{1 - \bar{\theta}} \right) = \\ &= \frac{\theta(1 - \bar{\varepsilon})}{1 - \theta} \left(1 + \frac{\bar{\theta} - \frac{\bar{\theta}}{1 - \bar{\varepsilon}}}{1 - \bar{\theta}} \right) \geq \frac{\theta(1 - \bar{\varepsilon})}{1 - \theta} \left(1 - \frac{\bar{\varepsilon}}{1 - \bar{\varepsilon}} \right) \geq \frac{\theta}{1 - \theta} \left(1 - \frac{2\bar{\varepsilon}}{1 - \bar{\varepsilon}} \right) = \frac{\theta}{1 - \theta} \frac{1 - 3\bar{\varepsilon}}{1 - \bar{\varepsilon}}. \end{aligned}$$

Proposition 3.4 Let be $\varepsilon \in (0, 0.1)$ be given, set $\bar{\varepsilon} = \frac{\varepsilon}{4.1}$, and suppose that Step 1 of the method is executed, with output $(\bar{x}, \bar{\theta})$. Then

$$\text{sym}(\bar{x}, S) \geq \text{sym}(S) \frac{1 - 5\bar{\varepsilon}}{1 - \bar{\varepsilon}} \geq (1 - \varepsilon) \text{sym}(S) \quad (3.9)$$

Proof. Let θ^* denote the optimal objective value of (3.3), and notice that $\bar{\delta} \leq \delta^*$ implies that $\theta^* \geq \bar{\theta}$. Let \bar{g} be computed in Step 2 of the method. It follows from the stopping criterion in Step 2 that

$$\bar{\theta} \geq (\bar{\theta} + \bar{g})(1 - \bar{\varepsilon}) \geq \theta^*(1 - \bar{\varepsilon}) \geq \bar{\theta}^*(1 - \bar{\varepsilon}) \quad (3.10)$$

From Proposition 3.3 we have

$$\begin{aligned} \text{sym}(\bar{x}, S) &\geq \frac{\bar{\theta}}{1 - \bar{\theta}} \frac{1 - 3\bar{\varepsilon}}{1 - \bar{\varepsilon}} \geq \frac{\bar{\theta}^*}{1 - \bar{\theta}^*} \frac{1 - \bar{\varepsilon}}{1 - \bar{\varepsilon}} \frac{1 - 3\bar{\varepsilon}}{1 - \bar{\varepsilon}} = \frac{\bar{\theta}^*(1 - \bar{\varepsilon})}{1 - \bar{\theta}^*} \frac{1 - 3\bar{\varepsilon}}{1 - \bar{\varepsilon}} \frac{1 - \bar{\theta}^*}{1 - \bar{\theta}^*(1 - \bar{\varepsilon})} \geq \\ &\geq \text{sym}(S)(1 - \bar{\varepsilon}) \frac{1 - 3\bar{\varepsilon}}{1 - \bar{\varepsilon}} \frac{1/2}{1 - 1/2 + (1/2)\bar{\varepsilon}} = \text{sym}(S)(1 - \bar{\varepsilon}) \frac{1 - 3\bar{\varepsilon}}{1 - \bar{\varepsilon}} \frac{1}{1 + \bar{\varepsilon}} \geq \text{sym}(S) \frac{1 - 5\bar{\varepsilon}}{1 - \bar{\varepsilon}} \geq (1 - \varepsilon) \text{sym}(S) \end{aligned}$$

Proposition 3.5 Let $\varepsilon \in (0,0.1)$ be given and set $\bar{\varepsilon} = \frac{\varepsilon}{4.1}$. Suppose that x^a is a $\beta = \frac{1}{8}$ -approximate analytic center of S . Then starting with x^a , the stopping criterion of each linear program in Step 1 of method will be reached in no more than $\left[(2 + 4\sqrt{m}) \ln \frac{42m}{\varepsilon} \right]$

iterations of Newton's method.

Proof. Step 1 of method is used to approximately solve each of the linear programs (3.1) for $i=1, \dots, m$. Let us fix a given i . We will apply to (3.1) a standard feasible path-following interior - point method. A triplet (x, s, z) together with a path parameter μ is a β -approximate solution for μ for the linear program (3.1) if the following system is satisfied

$$\begin{cases} Ax + s = b, s > 0 \\ A^T z = -A_i \\ \left\| \frac{1}{\mu} Sz - e \right\| \leq \beta \end{cases} \quad (3.11)$$

Now let x^a denote the given $\beta = \frac{1}{8}$ -approximate analytic center of the system $Ax \leq b$.

Then there exists (or it is easy to compute) multipliers z^a together with slacks $s^a > 0$ that satisfy the following system:

$$\begin{cases} Ax^a + s^a = b \\ A^T z^a = 0 \\ \|S^a z^a - e\| \leq \frac{1}{8} \end{cases} \quad (3.12)$$

Define:

$$(x^0, s^0, z^0, \mu^0) = (x^a, s^a, 8s_i^a z - e^i, 8s_i^a) \quad (3.13)$$

where e^i is the i^{th} unit vector in R^m . It is then straightforward to show that (3.13) is an

$\frac{1}{4}$ -approximate solution of (3.11) for the parameter μ^0 , so we can start the interior - point method with (3.13). We next bound the value of the parameter μ when the stopping criterion is achieved. Let $(\bar{x}, \bar{s}, \bar{z}, \bar{\mu})$ denote the values of (x, s, z, μ) when the algorithm stops. To keep the analysis simple, we assume that the stopping criterion is met

exactly. We therefore have that: $\frac{5}{4} m \bar{\mu} \geq \bar{g} = \bar{\varepsilon} (b_i - A_i \bar{x}) = \bar{\varepsilon} \bar{s}_i$ which leads to the ratio

$$\text{bound: } \frac{\mu^0}{\mu} \leq \frac{8ms_i^a}{(4/5)\bar{\varepsilon}\bar{s}_i}.$$

However, noting that:

$\bar{s}_i = b_i - A_i \bar{x} \geq b_i + \delta_i^* - \bar{g} = b_i + \delta_i^* - \bar{\varepsilon} \bar{s}_i \geq b_i - A_i x^a - \bar{\varepsilon} \bar{s}_i = \bar{s}_i - \bar{\varepsilon} \bar{s}_i$, we obtain
 $s_i^a \leq (1 + \bar{\varepsilon}) \bar{s}_i$, and substituting this into the ratio bound yields: $\frac{\mu^0}{\mu} \leq \frac{10m(1 + \bar{\varepsilon})}{\bar{\varepsilon}} \leq \frac{42m}{\varepsilon}$
 so $\ln \frac{\mu^0}{\mu} \leq \ln \frac{42m}{\varepsilon}$ and so $(2 + 4\sqrt{m}) \ln \frac{\mu^0}{\mu} \leq (2 + 4\sqrt{m}) \ln \frac{42m}{\varepsilon}$, using $\varepsilon \leq 0.1$, $\bar{\varepsilon} = \frac{\varepsilon}{4.1}$
 and Theorem 1.

Proposition 3.6 Let $\varepsilon \in (0, 0.1)$ be given, $m \geq 3$ and set $\bar{\varepsilon} = \frac{\varepsilon}{4.1}$. Suppose that x^a is an

$\beta = \frac{1}{8}$ -approximate analytic center of S . Then starting with x^a , the stopping criterion of each linear program in Step 2 of method will be reached in no more than $\left\lceil (2 + 4\sqrt{m}) \ln \frac{6m}{\varepsilon} \right\rceil$ iterations of Newton's method.

Proof. The proof is analogous with proposition 3.6.

Proposition 3.7 Let $\varepsilon \in (0, 0.1)$ be given and set $\bar{\varepsilon} = \frac{\varepsilon}{4.1}$. Suppose that x^a is an $\beta = \frac{1}{8}$ -

approximate analytic center of S . Then starting with x^a and using a standard feasible interior - point method to solve each of the linear programs in Steps 1 and 2, the method will compute an ε -approximate symmetry point of S in no more than $m \left\lceil (2 + 4\sqrt{m}) \ln \frac{42m}{\varepsilon} \right\rceil + \left\lceil (2 + 4\sqrt{m}) \ln \frac{6m}{\varepsilon} \right\rceil$ total iterations of Newton's method.

Proof. The propositions 3.3 and 3.4 show that the method indeed computes an ε -approximate symmetry point of S . From the propositions 3.5 and 3.6 it follows that the total number of Newton steps computed by the method is no more than $m \left\lceil (2 + 4\sqrt{m}) \ln \frac{42m}{\varepsilon} \right\rceil + \left\lceil (2 + 4\sqrt{m}) \ln \frac{6m}{\varepsilon} \right\rceil$ since $m \geq n + 1 \geq 3$ and $\varepsilon \in (0, 0.1)$.

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