

# On the Geometry Phase in Model-Based Algorithms for Derivative-Free Optimization

Giovanni Fasano\*

José Luis Morales†

Jorge Nocedal‡

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## Abstract

A numerical study of model-based methods for derivative-free optimization is presented. These methods typically include a geometry phase whose goal is to ensure the adequacy of the interpolation set. The paper studies the performance of an algorithm that dispenses with the geometry phase altogether (and therefore does not attempt to control the position of the interpolation set). Data is presented describing the evolution of the condition number of the interpolation matrix and the accuracy of the gradient estimate. The experiments are performed on smooth unconstrained optimization problems with dimensions ranging between 2 and 15.

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\*Dipartimento di Matematica Applicata, Università Ca' Foscari di Venezia and INSEAN. This author thanks Programma di Ricerca INSEAN 2007-2009.

†Departamento de Matemáticas, Instituto Tecnológico Autónomo de México, México. This author was supported by Asociación Mexicana de Cultura AC and CONACyT-NSF grants 39372-A and 53135.

‡Department of Electrical Engineering and Computer Science, Northwestern University, USA. This author was supported by National Science Foundation grant CCF-0514772 and Department of Energy grant DE-FG02-87ER25047-A004.

# 1 Introduction

Model-based methods have proved to be effective techniques for solving unconstrained optimization problems for which derivatives are not available [13, 2, 3, 4, 14, 9, 19, 1, 6, 12, 5]. Some of these methods construct quadratic models of the objective function by interpolating a set of function values, and compute steps by minimizing the models inside a trust region. For the model to be well defined, the interpolation points must be *poised* [5, 14], meaning that they must be compatible with the interpolation conditions imposed on them. In practice, it is common for the interpolation points to lose poisedness as the iteration progresses, and this is reflected in an increasing ill conditioning in the interpolation system. To prevent difficulties, a *geometry* phase is included in contemporary model-based algorithms; it typically replaces one or more of the interpolation points by other points that are selected with the exclusive goal of improving the position of the interpolation set.

In this paper we consider the effect of dispensing with the geometry phase altogether. We find, to our surprise, that omitting the geometry phase does not seem to harm the efficiency and robustness of our algorithm, which is competitive in our tests with two established model-based algorithms that include a geometry phase. Although high ill conditioning in the interpolation system is observed during the course of the iteration — and the quality of model is often poor at regular intervals — the overall progress achieved by the method appears to be quite satisfactory. The conditioning of the interpolation system grows initially, but then oscillates during much of the run and tends to increase slowly (except possibly very near the solution). We conjecture that a self-correction mechanism may be at play that prevents the conditioning from growing steadily and prevents the algorithm from failing.

The observations made in this paper are based on experiments involving 60 smooth test problems with dimensions ranging between 2 and 15. All the algorithms tested construct quadratic models using  $(n + 1)(n + 2)/2$  interpolation points. Our results are relevant to the design of algorithms because the geometry phase adds substantial complexity to these algorithms.

## 2 A Simple Model-Based Algorithm

We limit our discussion to the unconstrained optimization problem

$$\min_{x \in \mathbb{R}^n} f(x), \tag{2.1}$$

where  $f$  is a scalar-valued function. We consider an algorithm that, at every iteration, approximates the objective function  $f$  by means of a quadratic model  $m_c$ . To define the model, we assume that at the current iterate  $x_c$  we have a set of interpolation points  $Y_c = \{y^1, y^2, \dots, y^q\}$ , with  $y^i \in \mathbb{R}^n$ ,  $i = 1, 2, \dots, q$ , where

$$q = \frac{1}{2}(n + 1)(n + 2). \tag{2.2}$$

We assume that  $x_c$  is an element of this set and that no point in  $Y_c$  has a lower function value than  $x_c$ . We write the quadratic model in the form

$$m_c(x_c + p) = d_c + g_c^T p + \frac{1}{2} p^T G_c p, \tag{2.3}$$

and determine the scalar  $d_c$ , the vector  $g_c \in \mathbb{R}^n$ , and the symmetric matrix  $G_c \in \mathbb{R}^{n \times n}$  by imposing the interpolation conditions

$$m_c(y^\ell) = f(y^\ell), \quad \ell = 1, 2, \dots, q. \tag{2.4}$$

Since there are  $\frac{1}{2}(n+1)(n+2)$  coefficients in the model (2.3), the interpolation conditions (2.4) represent a square system of linear equations in the coefficients  $d_c, g_c, G_c$ . If we choose the interpolation points  $y^1, y^2, \dots, y^q$  so that this system is nonsingular, the model  $m_c$  will be uniquely determined (we follow Conn, Scheinberg and Vicente [5] and say that points with this property are *poised*).

Once  $m_c$  has been formed, we compute a step  $p_c$  by approximately solving the trust-region subproblem

$$\min_p m_c(x_c + p), \quad \text{subject to } \|p\|_2 \leq \Delta_c, \quad (2.5)$$

for some trust-region radius  $\Delta_c > 0$ . The complete algorithm (which is a simplification of the method described in [9]) is specified as follows.

### Algorithm I

Choose the parameters  $\alpha, \beta \in (0, 1)$ ,  $\gamma > 1$ , an initial trust region radius  $\Delta_c > 0$ , and an initial guess  $x_c$ . Select an initial interpolation set  $Y_c = \{y^1, y^2, \dots, y^q\}$  that is poised. (We assume that  $x_c \in Y_c$  and that  $f(x_c) \leq f(y)$  for all  $y \in Y_c$ ).

**Repeat** until a convergence test is satisfied

1. Form the model (2.3) that interpolates the function  $f$  on the interpolation set  $Y_c$ ;
2. Compute  $p_c$  by (approximately) solving subproblem (2.5);
3. Set  $\text{ared}(p_c) = f(x_c) - f(x_c + p_c)$  and  $\text{pred}(p_c) = m_c(x_c) - m_c(x_c + p_c)$ ;
4. Update  $\Delta_c$   
**If**  $\text{ared}(p_c) > \alpha \text{pred}(p_c)$ , set  $\Delta_+ = \gamma \Delta_c$ ;  
**else** set  $\Delta_+ = \beta \Delta_c$ ;
5. Find a point in  $Y_c$  that is farthest from the current iterate (break ties arbitrarily)  
 $y^{\ell_{\text{out}}} = \arg \max_{y \in Y_c} \|y - x_c\|_2$ ;
6. **If**  $f(x_c + p_c) < f(x_c)$  (successful iteration)  
Update the current iterate, and include  $x_c + p_c$  in the interpolation set, discarding  $y^{\ell_{\text{out}}}$   
a.  $x_+ = x_c + p_c$ ;  
b.  $Y_+ = \{x_+\} \cup Y_c \setminus \{y^{\ell_{\text{out}}}\}$ ;  
**else** (unsuccessful iteration)  
If the new trial point is not further from the current iterate than  $y^{\ell_{\text{out}}}$   
admit it to the interpolation set, discarding  $y^{\ell_{\text{out}}}$ ; otherwise, discard the new trial point;  
c.  $x_+ = x_c$ ;  
d.  $Y_+ = \begin{cases} \{x_c + p_c\} \cup Y_c \setminus \{y^{\ell_{\text{out}}}\} & \text{if } \|y^{\ell_{\text{out}}} - x_c\|_2 \geq \|(x_c + p_c) - x_c\|_2 \\ Y_c & \text{otherwise;} \end{cases}$
7.  $x_c \leftarrow x_+$ ,  $Y_c \leftarrow Y_+$ ,  $\Delta_c \leftarrow \Delta_+$ ;

**End**

Note that Algorithm I does not include a geometry phase, i.e., it does not attempt to ensure the poisedness of the interpolation set in any way. We use the method of Moré and Sorensen [10] to compute a solution of the problem (2.5). In our experiments, we set  $\alpha = 0, \beta = .75$  and  $\gamma = 1.5$ .

The initial point  $x_c$  in Algorithm I is selected by the user; the rest of the points in the initial set  $Y_c$  are chosen as the set of vertices and mid-points of the simplex defined by (see [15, 18])

$$y^i = x_c + \Delta_c e_i, \quad i = 1, \dots, n, \quad (2.6)$$

where the initial trust region radius is set to  $\Delta_c = 0.5$ , and  $e_i$  denotes the  $i$ th coordinate vector.

Algorithm I is not as economical as other model-based methods for derivative free optimization because it recomputes the model  $m_c$  at every iteration, which requires forming and factoring the coefficient matrix in the linear system (2.4) afresh at every iteration. This causes the workload of each iteration to be of order  $O(n^6)$ . The linear algebra cost could be reduced to  $O(n^4)$  by expressing the model  $m_c$  using Lagrange polynomials and updating them at every iteration [15]. One could reduce the work even further by implementing the Powell-Frobenius [18, 16, 17] approach that only imposes  $O(n)$  interpolation conditions. However, since the goal of this paper is to study the effect of omitting the geometry phase, we choose to work with the simplest possible algorithm.

### 3 Numerical Tests

We describe the results of numerical tests comparing Algorithm I with the NEWUOA and DFO software packages. NEWUOA implements the Powell-Frobenius method [17, 19] and DFO is a well established code that uses an increasing number of interpolation points until a full set of  $(n+1)(n+2)/2$  is available [2]. Both NEWUOA and DFO include a geometry phase.

In NEWUOA, the number of interpolation points can be chosen between  $2n+1$  and  $\frac{1}{2}(n+1)(n+2)$ ; the remaining degrees of freedom are absorbed by a minimum Frobenius norm update. In our experiments, we use  $\frac{1}{2}(n+1)(n+2)$  interpolation points so that NEWUOA uses the same amount of information as Algorithm I and DFO. (In §3.1 we also report comparisons with the WEDGE software package [9], but that algorithm attempts to control poisonedness of the interpolation set in a different manner than most model-based algorithms.)

Algorithm I uses a monomial basis to define the quadratic interpolant, whereas NEWUOA and DFO employ Lagrange and Newton polynomials, respectively, that yield substantial savings in computation; see [17, 18]. Algorithm I moves the reference point in the definition of the quadratic model at every iteration (it is the current iterate  $x_c$ ), whereas NEWUOA and DFO change the reference point in their bases only a few times throughout the whole iteration. Therefore Algorithm I has a numerical advantage because displacing the reference point limits rounding errors. We do not believe, however, that this fact alters the observations made below.

We tested the three codes on the 60 problems from the CUTER collection listed in Table 1. All problems are unconstrained and the number of variables varies between 2 and 15. Table 1 reports the name of the problem, the number of variables, the number of function evaluations required by the KNITRO package [20] (using second derivatives) and the optimal objective value computed by KNITRO to approximately 14 digits of accuracy. We use the results of KNITRO as a reference for our experiments.

To compare the three algorithms for various levels of accuracy in the solution, we terminated the runs when a prescribed number of correct significant figures in  $f$  was attained, or when a limit of 15,000 function evaluations was reached. We use two levels of accuracy: 3 and 6 significant figures, and we report results where all three algorithms converged to the same objective value. The results are summarized in Figures 1-2 using the logarithmic performance profiles described in [7]; they compare the number of function evaluations needed to achieve the desired accuracy in  $f$ .

name	$n$	fev	$f^*$	name	$n$	fev	$f^*$
allinitu	4	9	5.74438491032034e+00	freuroth	10	11	1.01406407257452e+03
arglinb	10	2	4.63414634146338e+00	genhumps	5	64	9.31205762089110e-33
arglinc	8	2	6.13513513513513e+00	gulf	3	26	5.70816776659866e-29
arwhead	15	7	5.32907051820075e-15	hairy	2	39	2.0000000000000e+01
bard	3	8	8.21487730657899e-03	hatfldd	3	22	6.61511391864778e-08
bdqrtic	10	11	1.82811617535935e+01	hatflde	3	15	4.43440070723924e-07
beale	2	9	1.03537993810258e-30	helix	3	17	1.81767515239766e-28
biggs3	3	11	3.49751055496115e-25	hilberta	10	2	1.51145573593758e-20
biggs6	6	76	5.49981608181981e-16	himmelbf	4	9	3.18571748791125e+02
box2	2	7	3.32822794031215e-23	himmelbg	2	8	1.17043537660229e-27
box3	3	9	1.85236429640516e-20	jensmp	2	10	1.24362182355615e+02
brkmcc	2	4	1.69042679196450e-01	kowosb	4	19	3.07505603849238e-04
brownal	10	8	1.49563496755546e-16	mancino	10	4	1.24143266331958e-19
brownden	4	9	8.58222016263563e+04	maratosb	2	8	-1.00000006249999e+00
chebyquad	8	19	1.75843686283896e-03	mexhat	2	5	-4.0100000000000e-02
chrosen	15	19	1.21589148855346e-19	morebv	10	4	1.85746736253704e-24
craggly	10	15	1.88656589666311e+00	nasty	2	2	1.53409170790554e-72
cube	2	44	5.37959996529976e-25	osborneb	11	21	4.01377362935478e-02
denschnd	3	28	2.15818302178292e-04	palmer1c	8	2	9.75979912629838e-02
denschne	3	22	1.29096866601748e-18	palmer3c	8	2	1.95376385131058e-02
denschnf	2	7	6.51324621983021e-22	palmer5c	6	2	2.12808666605511e+00
dixmaanc	15	14	1.0000000000000e+00	palmer8c	8	2	1.59768063470262e-01
dixmaang	15	28	1.0000000000000e+00	power	10	2	6.03971630559837e-31
dixmaani	15	15	1.0000000000000e+00	rosenbr	2	29	3.74397564313947e-21
dixmaank	15	18	1.0000000000000e+00	sineval	2	68	7.09027697800298e-20
dixon3dq	10	2	2.95822839457879e-31	singular	4	20	6.66638187151797e-12
dqdrtic	10	2	5.91645678915759e-29	sisser	2	20	1.06051492721772e-12
engval1	2	8	0.0000000000000e+00	vardim	10	15	1.59507305257139e-26
engval2	3	21	0.0000000000000e+00	yfitu	3	46	6.66972048929030e-13
expfit	2	9	2.40510593999058e-01	zangwil2	2	2	-1.8200000000000e+01

Table 1: Test Problems

Note that the three algorithms perform similarly in these tests, both in terms of robustness and in terms of number of function evaluations. This is surprising, as we expected Algorithm I to be often slow (or even fail) due to a lack of control in the quality of the model.

Although the overall performance of Algorithm I is quite good, this does not mean that the interpolation points generated during the iteration remain well poised. On the contrary, the interpolation system normally becomes ill-conditioned after only a few iterations; yet the algorithm is able to make steady progress toward the solution. To illustrate the behavior of the algorithm in some detail, in the rest of the paper we provide data about the evolution of the condition number, the quality of the gradient and the rate of success of the iteration.

### 3.1 Conditioning of the Interpolation System

If we define  $d_c = f(x_c)$  in (2.3), we remove one unknown and the interpolation conditions (2.4) can be expressed as the  $(q-1) \times (q-1)$  linear system

$$Mx = b, \tag{3.1}$$

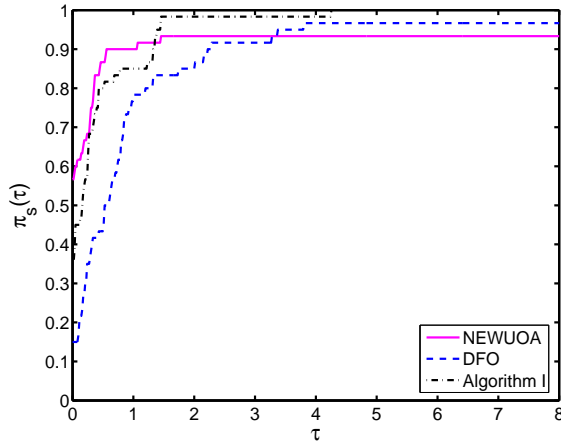


Figure 1: 3 digits of accuracy in final function value.

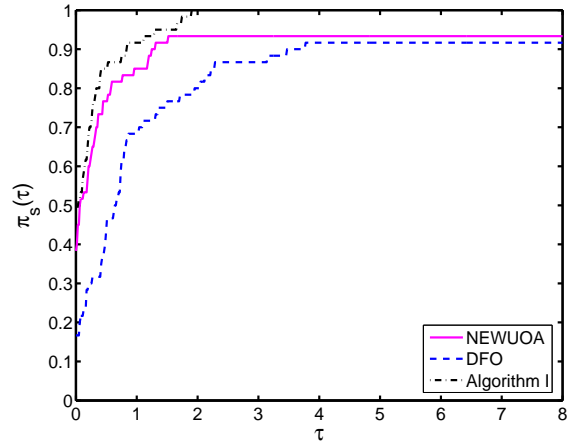


Figure 2: 6 digits of accuracy in final function value.

where  $x$  contains the elements of  $g_c$  and  $G_c$ .  $M$  is a matrix whose  $l$ -th row is given by

$$\left( (s^\ell)^T, \{s_i^\ell s_j^\ell\}_{i < j}, \left\{ \frac{1}{\sqrt{2}} (s_i^\ell)^2 \right\}_{i=1, \dots, n} \right)^T, \quad \ell = 1, \dots, q-1,$$

with  $s^\ell = y^\ell - x_c$ , and the right hand side vector  $b$  is given by [9]

$$b = [f(y^1) - f(x_c), \dots, f(y^{q-1}) - f(x_c)]^T;$$

As discussed by Conn, Scheinberg and Vicente [5], the matrix  $M$  should be scaled because its condition number grows as the interpolation points cluster near  $x_c$  — even if the interpolation set  $Y_c$  is well poised. The appropriate scaling matrix is given by

$$D = \begin{bmatrix} rI_n & 0 \\ 0 & r^2 I_{q-n-1} \end{bmatrix},$$

where  $r$  is the radius of smallest ball centered at  $x_c$  that contains all points in  $Y_c$ .

When computing the model (2.3) in Algorithm I, we replace (3.1) by the scaled system

$$\hat{M}\hat{x} = b, \quad \text{with} \quad \hat{M} = MD, \quad \hat{x} = D^{-1}x. \quad (3.2)$$

In Figures 3—6 we plot the logarithm of the condition number of  $\hat{M}$  as a function of the iteration number, for four representative problems in the test set. A circle indicates that the step gave a reduction in the objective function and a ‘+’, that it did not. The algorithms were terminated when 9 significant digits in  $f$  were obtained so that the complete run can be observed.

Note from these figures that the condition number of  $\hat{M}$  grows rapidly in the first few iterations, but increases only modestly during the rest of the run (except sometimes towards the very end). Observe also that there is a fairly regular oscillation in the condition number. Therefore, there appears to be a self-regulating mechanism that prevents the condition number of  $\hat{M}$  from growing steadily, but we have not been able to provide an analytical explanation for it.

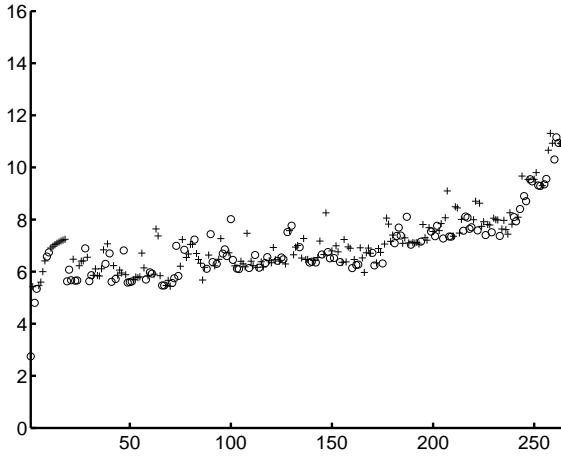


Figure 3:  $\log_{10} \text{cond}(\hat{M})$  vs. number of iterations for problem **arhead**.

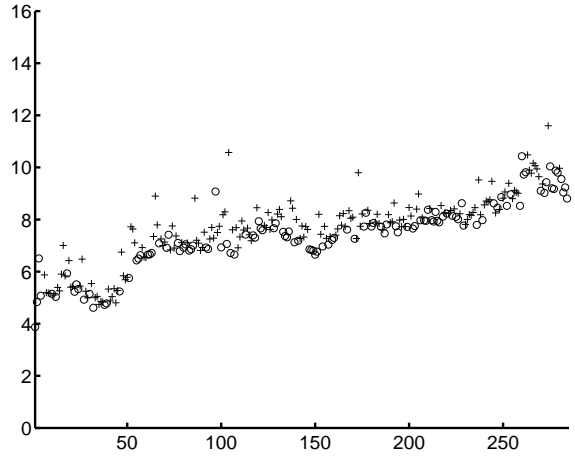


Figure 4:  $\log_{10} \text{cond}(\hat{M})$  vs. number of iterations for problem **brownal**.

An examination of the runs also shows that when a step yields a higher value of the objective function, the trust region is typically reduced, which forces the interpolation points to cluster. After a few unproductive steps, the conditioning of  $\hat{M}$  decreases slightly and the algorithm is able to make progress. Therefore unproductive steps seem to play a role similar to the geometry phase used in other methods, although it exerts a very weak control on the poisedness of the interpolation set.

Let us compare the conditioning of the interpolation systems generated by Algorithm I and by the WEDGE software package [9]. WEDGE implements a model-based method that ensures the poisedness of the interpolation set by including an additional constraint in the step generation subproblem (2.5). Table 2 reports some statistics about the conditioning of the scaled interpolation matrix  $\hat{M}$  for Algorithm I and WEDGE. We compare the two codes on the 60 test problems given in Table 1, using the two levels of accuracy discussed in the previous section.

digits in $f$	3	6	3	6
WEDGE	12	81	12086	17959
Algorithm I	106	177	11609	13447

Table 2: Total number of iterations in which the condition number of  $\hat{M}$  exceeded  $10^{12}$  (first 2 columns) and total number of function evaluations (last 2 columns) to achieve 3 and 6 digits of accuracy in  $f$ .

As expected, WEDGE controls the condition number of the interpolation system better than Algorithm I, and an examination of the results shows that WEDGE produces longer sequences of accepted steps. However, Algorithm I consistently requires a lower number of function evaluations because its successful steps are more productive. Table 2 gives cumulative results; performance profiles [7] would also show a clear advantage of Algorithm I over WEDGE. This was another unexpected finding of our experiments.

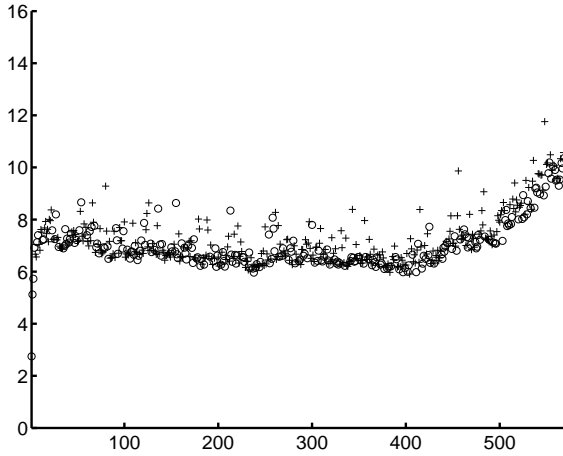


Figure 5:  $\log_{10} \text{cond}(\hat{M})$  vs. number of iterations for problem `dixmaank`.

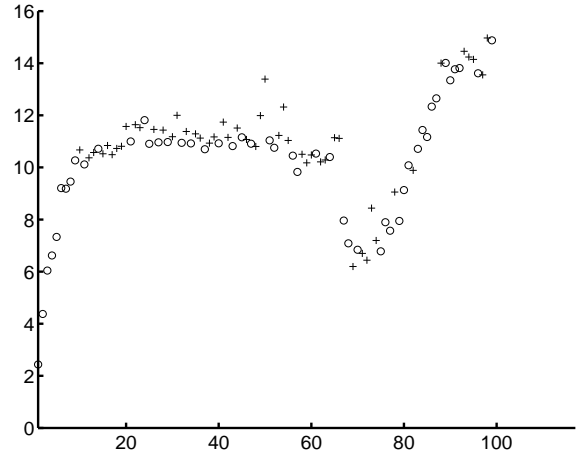


Figure 6:  $\log_{10} \text{cond}(\hat{M})$  vs. number of iterations for problem `mancino`.

It is natural to ask whether the gradient estimates  $g_c$  are highly inaccurate, given that for most iterations of Algorithm I the points in the interpolation set  $Y_c$  are not well poised. The analysis given in [5] indicates that in this case the gradient and Hessian estimates  $g_c, G_c$  in (2.3) can be expected to be poor, but to our knowledge their accuracy has not been reported in the literature. We could try to use the analytical error bounds given in [5], but they depend on unknown Lipschitz constants (and may not always be tight). Therefore we compute the error in the gradient estimate (which plays a more important role than  $G_c$ ) numerically. We compare our estimate  $g_c$  with the exact gradient  $g_c^*$  computed by AMPL [8].

We first test whether  $-g_c$  is a descent direction. Figure 7 plots the cosine of the angle between  $g_c$  and the  $g_c^*$ , i.e.,

$$\cos \theta_c \equiv \frac{g_c^T g_c^*}{\|g_c\|_2 \|g_c^*\|_2},$$

as a function of the iteration number, for problem `arwhead`. Note from this figure that although the estimated gradient  $g_c$  is a descent direction in the majority of the iterations, the descent property is not achieved consistently since  $\cos \theta_c$  changes sign frequently.

We also recorded statistics about the relative error in the gradient,

$$e_c = \|g_c - g_c^*\|_2 / \|g_c^*\|_2.$$

In more than 50% of the iterations of a typical run, this error is greater than 1; often, much greater than 1. These results confirm that poorly poised interpolation points normally lead to highly inaccurate gradient approximations  $g_c$ . This in turn leads to the generation of many unproductive steps. We have observed that between 25% and 50% of the iterations are unsuccessful, in the sense that they produce a function value that is larger than  $f(x_c)$ . This may seem highly inefficient, but model-based methods invoke the geometry phase with a similar frequency.

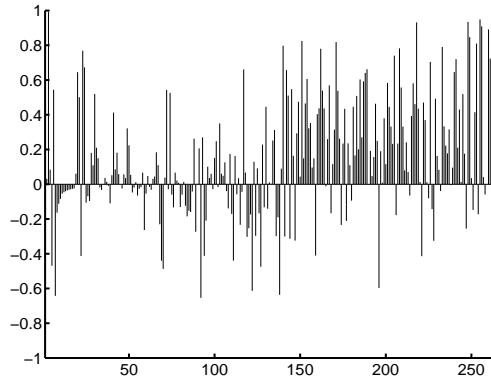


Figure 7:  $\cos \theta_c$  vs. iteration number for problem `arwhead`.

## 4 Final Remarks

The numerical experiments reported in this paper suggest that a model-based algorithm that ignores the position of the interpolation points performs as well as two established methods (`NEWUOA` and `DFO`) that include a geometry phase. Although the interpolation systems become highly ill conditioned during the course of the iteration, this ill conditioning remains at tolerable levels and the algorithm is able to make steady progress toward the solution.

Our experiments suggest that a self-correcting mechanism may be at play: if the interpolation points are close to lying in a low dimensional subspace of  $\mathbb{R}^n$ , then the model becomes accurate enough in that subspace and a point outside of it is generated. This cycle could then be repeated. Although it may not be possible to prove that this cyclic behavior always takes place, it may be possible to show that there is a tendency for it—but this remains an open question.

The test problems used in this study are all smooth unconstrained optimization problems. Moré and Wild [11] study the performance of derivative-free methods on noisy, smooth, and piecewise-smooth problems. They test an implementation of the Nelder-Mead method, a pattern search method, and the model-based method in `NEWUOA`, and report that `NEWUOA` is overall the most effective method—in many cases by a very wide margin. These results and the developments reported by Powell [19] provide new impetus for further development of model based methods. In this paper, we have studied model-based algorithms that use  $(n+1)(n+2)/2$  interpolation points, whereas [11] implements `NEWUOA` with only  $2n+1$  interpolation points. It remains to be seen whether the observations made in this paper apply also in that context. In any case, our results suggest that the role of the geometry phase should be re-examined. Perhaps it may be preferable to employ it only as a method of last resort; not as an integral part of the algorithm. Or it may be desirable to improve the geometry phase so that it exerts better control over the position of the interpolation points and yields faster convergence than the simple algorithm studied in this paper.

Algorithm I has been implemented in `MATLAB` and can be obtained from the authors.

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