

CS 83

ITERATIVE REFINEMENTS OF
LINEAR LEAST SQUARES SOLUTIONS
BY HOUSEHOLDER TRANSFORMATIONS

BY
Å. BJÖRCK
G. GOLUB

TECHNICAL REPORT NO. CS 83
JANUARY 19, 1968

COMPUTER SCIENCE DEPARTMENT
School of Humanities and Sciences
STANFORD UNIVERSITY



Iterative Refinements of Linear Least Squares Solutions

by Householder Transformations.*

Contributed by A. Björck and G. Golub.**

Theoretical background

, Let A be a given $m \times n$ real matrix with $m > n$ and of rank n and b a given vector. Let A and b be partitioned

$$A = \begin{pmatrix} A_1 \\ A_2 \end{pmatrix} \begin{matrix} m_1 \times n \\ m_2 \times n \end{matrix}, \quad b = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$$

where $m_1 \leq n$ and assume that A_1 has rank m_1 . We wish to determine a vector x subject to the linear constraints

$$A_1 x = b_1$$

such that

$$\|r_2\| = \min., \quad r_2 = b_2 - A_2 x,$$

where $\|\dots\|$ indicates the euclidian norm.

*This work was supported by the Swedish Natural Science Research Council.
**The work of this author was in part supported by NSF and ONR.

Using Lagrange multipliers it is easily shown that the solution satisfies the system of equations

$$\left(\begin{array}{c|c|c} 0 & 0 & A_1 \\ \hline 0 & I & A_2 \\ \hline A_1^T & A_2^T & 0 \end{array} \right) \begin{pmatrix} \lambda \\ r_2 \\ x \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ c \end{pmatrix} \quad (1)$$

where λ is the vector of Lagrange parameters and $c = 0$. For reasons which later will become evident we develop a method for solving (1) which works for an arbitrary vector c .

Let P be a permutation matrix which permutes the columns of A so that

$$AP = \begin{pmatrix} A'_1 \\ A'_2 \end{pmatrix} = \begin{pmatrix} A'_{11} & A'_{12} \\ A'_{21} & A'_{22} \end{pmatrix}$$

where A'_{11} is square and nonsingular. We now determine an orthogonal matrix Q_{11} so that

$$Q_{11}A'_1 = (R_{11} \mid R_{12}), \quad (2)$$

where R_{11} is $m_1 \times m_1$ and upper triangular. Next we put

$$Q_{12} = R_{11}^{-T} A_{21}^T, \quad A_{22} = A'_{22} - Q_{12}^T R_{12} \quad (3)$$

and determine an orthogonal transformation Q_{22} so that

$$Q_{22}^T A_{22} = \begin{pmatrix} R_{22} \\ 0 \end{pmatrix}_{(m-n) \times n} \quad (4)$$

where again R_{22} is upper triangular. Denote by R the $n \times n$ upper triangular matrix

$$R = \left(\begin{array}{c|c} R_{11} & R_{12} \\ \hline 0 & R_{22} \end{array} \right)$$

Then it is easily verified that

$$A_{PR}^{-1} = \left(\begin{array}{c|c} Q_{11} & Q_{12} \\ \hline 0 & Q_{22} \end{array} \right)^T \quad (5)$$

where

$$Q_{22} = (I_{n-m_1} | 0) Q_{22} \quad (6)$$

and I_{n-m_1} is an $(n-m_1) \times (n-m_1)$ unit matrix. Thus if we define the-vectors

$$y = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}_{n-m_1}^{m_1}, \quad d = \begin{pmatrix} d_1 \\ d_2 \end{pmatrix}_{n-m_1}^{m_1}$$

by the relations

$$x = PR^{-1}y \quad , \quad d = PR^{-T}c \quad (7)$$

then (1) can be written

$$\left(\begin{array}{cc|cc} 0 & 0 & Q_{11}^T & 0 \\ 0 & I & Q_{12}^T & \tilde{Q}_{22}^T \\ \hline Q_{11} & Q_{12} & 0 & 0 \\ 0 & \tilde{Q}_{22} & 0 & 0 \end{array} \right) \begin{pmatrix} \lambda \\ r_2 \\ y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ d_1 \\ d_2 \end{pmatrix} \quad (8)$$

Using the orthogonality of Q_{11} and Q_{22} we get the following algorithm for solving (1):

$$y_1 = Q_{11} b_1$$

$$g = Q_{22} (b_2 - Q_{12}^T y_1) = \begin{matrix} g_1 \\ g_2 \end{matrix} \begin{matrix} \}^{(n-m_1)} \\ \}^{(m-u)} \\ 0 \end{matrix}$$

$$y_2 = g_1 - d_2$$

$$r_2 = Q_{22}^T \begin{pmatrix} d_2 \\ g_2 \end{pmatrix}$$

$$\lambda = Q_{11}^T (d_1 - Q_{12} r_2) .$$

Here d is defined from (7) which is also used for computing x .

A very effective method to realize the decompositions (2) and (4) is via Householder transformations [4]. Let $A' = A^{(1)}$, and let $A^{(k+1)}$, $k=1,2,\dots, n, k \neq m_1$ be defined as follows

$$A^{(k+1)} = P^{(k)} A^{(k)}$$

$P^{(k)}$ is a symmetric, orthogonal matrix of the form

$$P^{(k)} = I - \beta_k u^{(k)} u^{(k)T}$$

where the elements of $P^{(k)}$ are derived so that

$$a_{i,k}^{(k+1)} = 0, \quad i = k+1, \dots, m(k),$$

$$m(k) = \begin{cases} m_1, & k < m_1 \\ m, & k > m_1 \end{cases}$$

It follows that

$$A_1^{(m_1)} = (R_{11} \mid R_{12})$$

and if we finally define

$$A^{(m_1+1)} = \left(\begin{array}{c|c} R_{11} & R_{12} \\ \hline 0 & A_{22} \end{array} \right)$$

where A_{22} is computed from (3) then $A^{(n+1)} = \begin{pmatrix} R \\ 0 \end{pmatrix}$

It can be shown cf. [5] that $P^{(k)}$ is generated as follows:

$$\sigma_k = \left(\sum_{i=k}^{m(k)} (a_{ik}^{(k)})^2 \right)^{1/2}$$

$$\beta_k = (\sigma_k (\sigma_k + |a_{kk}^{(k)}|))^{-1}$$

$$u_i^{(k)} = 0 \quad \text{for } i < k, \quad i > m(k)$$

$$u_k^{(k)} = \text{sgn}(a_{kk}^{(k)}) (\sigma_k + |a_{kk}^{(k)}|),$$

$$u_i^{(k)} = a_{ik}^{(k)} \quad \text{for } k < i \leq m(k).$$

The matrix $P^{(k)}$ is not computed explicitly. Rather we note that

$$A^{(k+1)} = (I - \beta_k u^{(k)} u^{(k)T}) A^{(k)} = A^{(k)} - u^{(k)} y_k^T$$

where

$$y_k^T = \beta_k u^{(k)T} A^{(k)}.$$

In computing the vector y_k and $A^{(k+1)}$, one takes advantage of the zero components of $u^{(k)}$.

The permutation of the columns of A to obtain $A' = AP$ is conveniently done at the same time. At the k^{th} stage the column is chosen which will maximize $|a_{kk}^{(k+1)}|$. This will ensure that the matrix R_{11} is non-singular. Let

$$s_j^{(k)} = \sum_{i=k}^{m(k)} (a_{ij}^{(k)})^2, \quad j = k, k+1, \dots, n.$$

Then since $|a_{kk}^{(k+1)}| = \sigma_k$, one should choose that column for which $s_j^{(k)}$ is maximized. After $A^{(k+1)}$, $k \neq m_1$, has been computed, one can compute $s_j^{(k+1)}$ as follows:

$$s_j^{(k+1)} = s_j^{(k)} - (a_{kj}^{(k+1)})^2$$

since the orthogonal transformations leave the column lengths invariant.

Because of the influence of rounding errors the first computed solution may not be sufficiently accurate in an ill-conditioned case. Provided the columns of A are not almost linearly dependent to working accuracy, the solution may be improved by the following iterative procedure. Put

$$B = \begin{pmatrix} 0 & 0 & A_1 \\ \hline 0 & I & A_2 \\ \hline A_1^T & A_2^T & 0 \end{pmatrix}, \quad z = \begin{pmatrix} \lambda \\ \hline r_2 \\ \hline x \end{pmatrix}, \quad h = \begin{pmatrix} b_1 \\ \hline b_2 \\ \hline 0 \end{pmatrix}.$$

and let $z^{(0)} = z$. The s^{th} iteration involves the three steps:

- (i) $f^{(s)} = h - Bz^{(s)}$,
- (ii) $\delta z^{(s)} = B^{-1} f^{(s)}$,
- (iii) $z^{(s+1)} = z^{(s)} + \delta z^{(s)}$.

It is essential that the residuals $f^{(s)}$ are computed using double precision accumulation of inner-products. We then solve for $\delta z^{(s)}$ by the method developed above, using the same decomposition in all iterations. Note that $f^{(s)}$ generally differs from zero also in the last n components, which explains why we did not assume $c=0$ in (1).

It has been shown in [1] that if the iterations 'converge' then for sufficiently large s the accuracy in $(z^{(s)} + \delta z^{(s)})$ will be approximately the same as if double precision had been used throughout without refinement.

Let the number of operations needed for the decomposition resp. one iteration step for a single right hand side be N_d resp. N_s . Then a simple calculation shows that

$$N_d = \left[n^2 \left(m - \frac{n}{3} \right) - m_1 m_2 \left(n - \frac{m_1}{2} \right) \right] \left(1 + O\left(\frac{1}{n}\right) \right) \text{ s.p.}$$

$$N_s = \left[n \left(m - \frac{n}{4} \right) - 2m_1 m_2 \right] \left(1 + O\left(\frac{1}{n}\right) \right) \text{ s.p.} + 2mn \text{ d.p.}$$

where s.p. refers to single precision operations and d.p. to operations performed with double precision accumulation

Applicability

The algorithm least squares solution may be used to compute accurate solutions and residuals to linear least squares problems with or without linear constraints. It may also be used to compute accurate

solutions to systems of linear equations where A is a square matrix and to compute accurate inverses of such matrices. The procedure will fail when A_1 or A modified by rounding errors has rank less than m_1 or n respectively. It will also fail if A is so ill-conditioned that there is no perceptible improvement in the iterative refinement. The matrix A is retained in order to form the residuals. When $m \gg n$ the large storage requirement of this procedure might make it preferable to use instead a double precision version of the Householder decomposition without iterative refinement. Note that in the linear equation case the calculation of residuals may be suppressed by putting $m_1 = m = n$.

Formal parameter list

Input to procedure least squares

m_1	number of linear constraints $m_1 \leq n$.
m	total number of equations
n	number of unknowns $n < m$
a	an $m \times (n+1)$ array having the given matrix as first n columns
p	number of right hand sides
b	an $m \times p$ array containing the given right hand sides
ϵ	the largest number for which $1 + \epsilon = 1$ on the computer
singular	exit used when A_1 or A modified by rounding errors has rank less than m_1 or n respectively
fail	exit used when the iterative refinement fails to improve the solution

Output of procedure least squares

x an $n \times p$ array consisting of the p solution vectors
res an $m_2 \times p$ array consisting of the p residuals vectors

ALGOL Program

```
procedure least squares solution(ml) data: (m,n,a,p,b,eta) failure
      exits: (singular, fail) result: (x, res);
value ml,m,n,p,eta;
integer ml,m,n,p; real eta;
array a,b,x,res; label fail, singular;
comment The array a[l:m,l:n+1] contains in its first n columns the
      given matrix of an overdetermined system of m linear equations
      in n unknowns ( $m \geq n$ ), where the first ml equations
      ( $ml \leq n$ ) are to be strictly satisfied. For the p right
      hand sides given as columns of the array b[l:m,l:p] the
      least squares solution and the residuals are computed and
      stored in the columns of the arrays x[l:n,l:p] and
      res[ml+1:m,l:p] respectively. If rank(a) < n or
      rank(al) < ml the emergency exit singular is used. If the
      iterative refinement fails to improve the solution sufficiently
      the exit fail is used. In either case b and the first n
      columns of a are left intact. The (n+1)st column in
      a is used as temporary storage for the successive right hand
      sides. Eta is the relative machine precision;
```

```

begin integer i,j,l;

array xl[1:n+1], resl[1:m], alpha[1:n], qr[0:m,1:n];

integer array pivot[1:n];

real procedure innerprod(i,m,n,ai,bi,c);

value m,n,c;

real ai,bi,c; integer i,m,n;

begin real sum;

    sum:=-0;

    for i:=m step 1 until n do sum:=sum+aiXbi;

    innerprod:=sum+c

end innerprod;

real procedure innerproddp(i,m,n,ai,bi,c);

value m,n,c

real ai,bi,c; integer i,m,n;

comment This procedure accumulates the sum of products aiXbi

    and adds it to the initial value c in double precision.

    The body of this procedure cannot be expressed in ALGOL.

    begin real s1,s2, (s1,s2):=0,

        for i:=m step 1 until n do

            (s1,s2):=(s1,s2)+aiXbi, comment dbl.pr.acc.

            innerproddp:=((s1,s2)+c) rounded

    end innerproddp;

procedure decompose(ml)data:(m,n,eta) data and result:(qr)

    result: (alpha,pivot) failure exit:(singular);

value ml,m,n,eta;

integer ml,m,n; real eta; array qr, alpha;

```

```

    integer array pivot; label singular;

comment Decompose uses essentially a sequence of elementary orthogonal
transformations  $(I - \beta u u^T)$  to determine a qr-decomposition
of the matrix given in the array qr[1:m,1:n] . The diagonal
elements of the upper triangular matrix r are stored in the
array alpha[1:n], the offdiagonal elements in the upper
right triangular part of qr. The nonzero components of the
vectors u are stored on and below the leading diagonal of
qr. Pivoting is done by choosing at each step the column
with the largest sum of squares to be reduced next. These
interchanges are recorded in the array pivot[1:n] . If at
any stage the sum of squares of the column to be reduced is
exactly equal to zero then the emergency exit singular is
used;

begin integer i,j,jbar,k,mr,s; boolean fsum;
    real beta,sigma,alphak,qrkk,smax,y;array sum[1:n];
    mr:= m; fsum:= true;
    for j:=1 step 1 until n do pivot[j]:=j;
    for k:=1 step 1 until n do
    begin comment k-th hpuseholder transformation;
        if k=m+1 then
            begin fsum:=true; mr:=m end;
            if fsum then
piv:   for j:=k step 1 until n do
            sum[j]:=innerprod(i,k,mr,qr[i,j], qr[i,j], 0);
            sigma:=sum[k]; jbar:=k;

```

```

for j:=k+1 step 1 until n do
  if sigma < sum[j] then
    begin sigma:=sum[j]; jbar:=j end;
  if fsum then smax:=sigma; fsum:=sigma < etaXsmax;
  if fsum then goto piv;
  if jbar ≠ k then
    begin comment column interchange;
      i:=pivot[k]; pivot[k]:=pivot[jbar]; pivot[jbar]:=i;
      sum[jbar]:=sum[k];
      for i:=1 step 1 until m do
        begin sigma:=qr[i,k]; qr[i,k]:=qr[i,jbar];
          qr[i,jbar]:=sigma
        end i
      end column interchange;
      sum[k]:=sigma:=innerprod(i,k,mr,qr[i,k], qr[i,k], 0);
      if sigma = 0 then goto singular;
      grkk:=qr[k,k]; alphak:=alpha[k]:=
      if qrkk < 0 then sqrt(sigma) else -sqrt(sigma);
      qr[k,k]:=qrkk-alphak;
      beta:=qr[0,k]:=alphakXqr[k,k];
      for j:=k+1 step 1 until n do
        begin y:=innerprod(i,k,mr,qr[i,k], qr[i,j], 0)/beta;
          for i:=k step 1 until mr do qr[i,j]:=qr[i,j]+yXqr[i,k];
          sum[j]:=sum[j] - qr[k,j]2
        end j;
      if k=ml then
        for j:=ml+1 step 1 until m do

```

```

    for s:=1 step 1 until n do
    begin mr:= if s>ml then ml else s-1;
        y:="-innerprod(i,l,mr,qr[i,s],qr[j,i],-qr[j,s]);
        qr[j,s]:= if s>ml then y else y/alpha[s]
    end s
    end k-th householder-transformation
end decompose;
procedure accsolve(ml)data:(m,n,a,qr,alpha,pivot,eta) result:(x,res)
    failure exit:(fail);
value ml,m,n,eta;
integer ml,m,n; real eta; array a,qr,alpha,x,res;
integer array pivot; label fail;
comment Accsolve uses the decomposition of a stored in the array
    qr[l:m,l:n] by decompose for the iterative refinement of the
    least squares solution. The right hand side b is given in
    the (n+1)st column of the array a[l:m,l:n+1]. The
    residuals of the augmented system of (m+n) equations are
    computed using the procedure innerproddp which forms accurate
    inner-products. As initial approximation is taken x=r=0,
    and the two first iterations are always executed. The
    iterations are repeated as long as the norm of the correction
    at any stage is less than 1/8 of that at the previous stage
    until the norm of the correction is less than epsilon times
    the norm of the solution. Exit to label fail is made if the
    solution fails to improve sufficiently;

```

```

begin integer i,j,k,s;

    real c,nx,nr,ndx1,ndx2,ndr1,ndr2,eta2;

    array f[1:m], g[1:n];

    procedure householder(p,q,r,m);

    value p,q,r,m; integer p,q,r,m;

    for s:=p step q until r do

    begin :=innerprod(i,s,m,qr[i,s], f[i], 0)/qr[0,s];

        for i:=s step 1 until m do f[i]:=f[i] + cXqr[i,s]

    end householder;

    eta2:=(eta2)2; x[n+1]:=-1;

    comment initial values;

    for j:=1 step 1 until n do x[j]:=g[j]:=0;

    for i:=1 step 1 until m do

    begin res[i]:=0; f[i]:=a[i,n+1] end

    for k:=0,1,k+1 while (64Xndx2 < ndx1  $\wedge$  ndx2 > eta2Xnx) V

    (64Xndr2 < ndr1  $\wedge$  ndr2 > eta2Xnr) do

    begin comment k-th iteration step;

        ndx1:=ndx2; ndr1:=ndr2; ndx2:=ndr2:=0;

        if k  $\neq$  0 then

        begin comment-new residuals;

            for i:=1 step 1 until m do res[i]:=res[i] + f[i];

            for s:=1 step 1 until n do

            begin j:=pivot[s]; x[j]:=x[j] + g[s];

                g[s]:=-innerproddp(i,1,m,a[i,j], res[i], 0);

                g[s]:=-innerprod(i,1,s-1,qr[i,s], g[i], -g[s])/

                alpha [s]

```



```

        end;
        for i:=1 step 1 until m do
            f[i]:=-innerproddp(j,l,n+1,a[i,j], x[j],
                if i > ml then res[i] else 0)
        end new residuals;
        householder(l,l,ml,ml);
        for i:=ml+1 step 1 until m do
            f[i]:=-innerprod(s,l,ml,qr[i,s], f[s], -f[i]);
            householder(ml+1,l,n,m);
            for i:=1 step 1 until n do
                begin c:=f[i]; f[i]:=g[i];
                    g[i]:=if i>ml then c-g[i] else c
                end;
            for s:-n step -1 until 1 do
                begin g[s]:=innerprod(i,s+1,n,qr[s,i], g[i], -g[s])/
                    alpha[s]; ndx2:=ndx2+g[s]2
                end;
            householder(n,-1,ml+1,m);
            for s:=1 step 1 until ml do
                f[s]:=-innerprod(i,ml+1,m,qr[i,s], f[i], -f[s]);
                householder(ml,-1,l,ml);
            for i:=1 step 1 until m do
                ndr2:=ndr2+f[i]2;
            if k = 0 then begin nx:=ndx2; nr:=ndr2 end
        end k-th iteration step;

        if ndr2 > eta2*nr A ndx2 > eta2*nx then goto fail

```

```

    end accsolve;
    for j:=1 step 1 until n do
    for i:=1 step 1 until m do qr[i,j]:=a[i,j];
    decompose(ml,m,n,eta,qr,alpha,pivot,singular);
    for l:=1 step 1 until p do
    begin comment l-th right hand side;
        for i:=1 step 1 until m do a[i,n+1]:=b[i,l];
        accsolve(ml,m,n,a,qr,alpha,pivot,eta,xl,resl,fail);
        for j:=1 step 1 until n do x[j,l]:=xl[j];
        for i:=ml+1 step 1 until m do res[i,l]:=resl[i]
    end l-th right hand side
end least squares;

```

Organizational and Notational Details

The array a containing the original matrix A is transferred to the array qr which serves as storage for $A^{(k)}$. The non-zero components of the vectors $u^{(k)}$ and the derived matrix Q_{12} are stored on and below the leading diagonal of qr . The diagonal elements of R , the reduced matrix, are stored in the array α , and the elements β_k on row number zero in qr .

The column sum of squares, $s_j^{(k)}$, is stored in the array sum . Naturally, the elements of this array are interchanged whenever the columns of $A^{(k+1)}$ are interchanged. The array $pivot$ contains the order in which the columns are selected.

The recursive computation of $s_j^{(k)}$ will fail if A is sufficiently ill-conditioned. To prevent this $s_j^{(k)}$ are recomputed every time the condition

$$\max_{k \leq j \leq n} s_j^{(k)} < \eta \cdot \max_{k' \leq j \leq n} s_j^{(k')}$$

is satisfied, where k' is the last step at which this was done. Since the number of iterations needed is dependent on the right hand side the iterative refinement is executed for one right hand side at a time. During the refinement the current right hand side is transferred to the $(n+1)$ st column of A .

In accsolve the first set of solutions is taken to be null vectors, and the two first iteration steps are always executed. The iteration for the current right hand side is terminated when the conditions (i) and (ii) below are simultaneously satisfied:

$$(i) \quad \|\delta x^{(s)}\|_2 > 0.125 \|\delta x^{(s-1)}\|_2 \text{ or } \|\delta x^{(s)}\|_2 \leq \eta \|x^{(1)}\|_2$$

$$(ii) \quad \|\delta r^{(s)}\|_2 \geq 0.125 \|\delta r^{(s-1)}\|_2 \text{ or } \|\delta r^{(s)}\|_2 \leq \eta \|r^{(1)}\|_2 .$$

If the iteration has been terminated and at the same time

$$\|\delta x^{(s)}\|_2 > 2\eta \|x^{(1)}\|_2 \text{ and } \|\delta r^{(s)}\|_2 > 2\eta \|r^{(1)}\|_2 ,$$

then the exit fail is used.

Both a single precision and a double precision inner product routine are used. On a computer where double precision accumulation of inner products is fast, the double precision routine can be used throughout,

Discussion of Numerical Properties

The procedure has been analyzed in [1] for $m_1 = 0$ under the assumption that all inner-products are accumulated in double precision. (If single precision inner-products are used where possible, the bounds given below for the rate of convergence and the error will increase by a factor less than m .)

Let t_1 and t_2 be the number of binary digits in our single and double precision floating point mantissas. Put

$$\alpha = 32.6 n^{3/2} 2^{-t_1} \kappa(A)$$

where

$$\kappa(A) = \max_{\|x\|_2=1} \|Ax\|_2 / \min_{\|x\|_2=1} \|Ax\|_2 ,$$

and assume that $\alpha < 1$. If the errors made in computing the residuals and in adding the corrections can be neglected, then

$$\begin{pmatrix} \|r-r^{(s)}\|_2 \\ \|A\|_2 \|x-x^{(s)}\|_2 \end{pmatrix} < 14.4 n^{3/2} 2^{-t_1} \rho^{s-1} \begin{pmatrix} \kappa' + \frac{4}{3} & \frac{5}{3} \\ \kappa'(\kappa' + \frac{4}{3}) & \kappa' \frac{5}{3} \end{pmatrix} \begin{pmatrix} \|r\|_2 \\ \|A\|_2 \|x\|_2 \end{pmatrix}$$

where

$$\kappa' = (1-\alpha)^{-1/2} \kappa(A) ,$$

and the "initial rate of convergence" ρ is bounded by

$$\rho < 38.7 n^{3/2} (\kappa' + \frac{1}{2}) 2^{-t_1} .$$

The process 'converges' if $\rho < 1$. Then for sufficiently large s the errors will satisfy

$$\begin{pmatrix} \|r-r^{(s)}\|_2 \\ \|A\|_2 \|x-x^{(s)}\|_2 \end{pmatrix} < (1-\rho)^{-1} K \begin{pmatrix} 1 \\ \kappa' \end{pmatrix} + 2^{-t_1} \begin{pmatrix} \|r\|_2 \\ \|A\|_2 \|x\|_2 \end{pmatrix} ,$$

where-

$$K = 14.4 n^{3/2} 2^{-2t_1} ((\kappa' + \frac{4}{3}) \|r\|_2 + \frac{5}{3} \|A\|_2 \|x\|_2) + \\ 1,022 2^{-t_2} (\kappa' (m+4) \|r\|_2 + (n+5) \|A\|_2 \|x\|_2) .$$

If $t_2 \geq 2t_1$ then the first term in K usually dominates, and $x^{(s)} + \delta x^{(s)}$ will ultimately have t_1 more correct binary digits than $x^{(1)}$. Note however that the process may well converge even if $x^{(1)}$ has relative error greater than 1. To get full benefit of the refinement we ought to have $t_2 \approx 2t_1$, but there is nothing to be gained by taking t_2 much greater than $2t_1$.

Since it is possible to have $x = 0$ or $r = 0$, it is obvious that even when $p < 1$, we cannot guarantee that $x^{(s)}$ or $r^{(s)}$ ultimately will have a small relative error. Let

$$\gamma = (\kappa' + \frac{4}{3}) \frac{\|r\|_2}{\|A\|_2 \|x\|_2}$$

and assume that $\rho < 1/4$ and that the second term in K can be neglected. If

$$\gamma < 1.58 \frac{1}{\rho}$$

then we will ultimately have

$$\|x - x^{(s)}\|_2 < 2.2^{-t_1} \|x\|_2.$$

Similarly if

$$1.61\rho < \gamma$$

then ultimately

$$\|r - r^{(s)}\|_2 < 202^{-t_1} \|r\|_2.$$

Note that $r^{(s)}$ will converge to the exact residual corresponding to the correct solution x . When $\|r\| \ll \|A\| \|x\|$ these may be very different from the residual corresponding to x rounded to single precision. In many cases the later may be the more relevant.

Test Results

The procedure was tested on the CD 3600 (University of Uppsala) which, has $t_1 = 36$ and $t_2 = 84$, with $\eta = 2^{-36} \approx 1.5 \cdot 10^{-11}$. The matrix A consists of the last six columns of the inverse of the 8×8 Hilbert matrix. For $m_1 = 0$ two right hand sides were treated. The: first, b_1 , is chosen so that the system $Ax = b_1$ is compatible i.e. $r = 0$. The second, b_2 , is obtained by adding to b_1 a vector orthogonal to the columns of A , the length of which was adjusted so that

$$(\kappa' + \frac{4}{3}) \frac{\|r\|_2}{\|A\|_2 \|x\|_2} \approx \frac{1}{2} \cdot 10^6.$$

Thus in both cases the exact solution is the same, namely

$$x = (1/3, 1/4, 1/5, 1/6, 1/7, 1/8)^T.$$

Due to the large residuals in the second case however, this system is much more ill-conditioned cf. [1]. For $m_1 = 2$ the same matrix A and the right hand sides b_1 and b_3 was used where b_3 was obtained by changing b_2 in its first two components so that the exact solution x remains the same. Note that all problems are so ill-conditioned that $t_1 > 32$ is required for convergence.

The results for $m_1 = 0$ confirms that the "initial rate of convergence" is independent of the right hand side. In fact (disregarding the first step) the errors in the components of x and r decreases initially with a factor approximately equal to 10^{-3} . For economy of presentation, we have given only the last six components of $r^{(s)}$; the behavior of the other components is exactly analogous. For the right hand side b_1 , $x^{(4)}$ is already correct to working accuracy. The iteration is terminated after the computation of $\delta x^{(5)}$ and $\delta r^{(5)}$ when the condition $\|\delta r^{(5)}\|_2 < \eta \|r^{(1)}\|_2$ is satisfied. For the right hand side b_2 , $x^{(1)}$ is in error by a factor almost equal to 10^3 . The iteration is again terminated after $\delta x^{(5)}$ and $x^{(5)}$ is correct to working accuracy. This accuracy which seems to be more than could be expected is explained by the fact that the residuals $(b_2 - Ax)$ are integers which can be represented exactly in the machine. In fact $r^{(s)}$ exactly equals r for $s \geq 4$ which makes the problem no more ill-conditioned when $s > 4$ than for the r.h.s. b_1 .

The behavior when $m_1 = 2$ is exactly analogous. Note however that the rate of convergence is faster almost by a factor of 10^2 compared to the case $m_1 = 0$. For the right hand sides b_1 and b_3

five respectively four steps of the iteration are executed. For b_1 ,
already $x^{(3)}$ is correct to working accuracy and for b_3 , $x^{(4)}$ is
almost correct.

Example

A				B			
20160	-92400	221760	-288288	152192	-51480	945	8400945
-952560	4658960	-11642400	15567552	-10594584	2882880	-40320	4159680
11430720	-58212000	149688000	-204324120	141261120	-38918880	456120	3256120
-58212000	304920000	-850415000	1109908800	-776936160	216216000	-2236080	-136080
149688000	-800415000	2134440000	-2996753760	2118916800	-594594000	5599440	7279440
-204324120	1109908800	-2996753760	4249941696	-3030051024	856215360	-7495488	-6095488
141261120	-776936160	2118916800	-3030051024	2175421248	-618377760	5105100	6305100
-38918880	216216000	-594594000	856215360	-618377760	176679360	-1389960	-339960

$$x^{(s)}, s=1,2,3,4.$$

$m_1 = 0,$	rhs	b_1				
3.33323	25269 ₁₀ ⁻¹	2.49983	36160 ₁₀ ⁻¹	1.99979	68894 ₁₀ ⁻¹	1.66644
						47493 ₁₀ ⁻¹
3.33333	35247 ₁₀ ⁻¹	2.50000	03124 ₁₀ ⁻¹	2.00000	03809 ₁₀ ⁻¹	1.66666
						70842 ₁₀ ⁻¹
3.33333	33334 ₁₀ ⁻¹	2.50000	00001 ₁₀ ⁻¹	2.00000	00001 ₁₀ ⁻¹	1.66666
						66668 ₁₀ ⁻¹
3.33333	33334 ₁₀ ⁻¹	2.50000	00000 ₁₀ ⁻¹	2.00000	00000 ₁₀ ⁻¹	1.66666
						66667 ₁₀ ⁻¹

				1.42834	14088 ₁₀ ⁻¹	1.24976	82424 ₁₀ ⁻¹
				1.42857	18638 ₁₀ ⁻¹	1.25000	04414 ₁₀ ⁻¹
				1.42857	14287 ₁₀ ⁻¹	1.25000	00001 ₁₀ ⁻¹
				1.42857	14286 ₁₀ ⁻¹	1.25000	00000 ₁₀ ⁻¹

$$r^{(s)}, s=1,2,3,4,5.$$

9.32626	24303 ₁₀ ⁻⁰⁵	2.12487	75112 ₁₀ ⁻⁰⁴	2.46137	01049 ₁₀ ⁻⁰⁴	2.50505	06480 ₁₀ ⁻⁰⁴	2.43935	32104 ₁₀ ⁻⁰⁴	2.33348	99208 ₁₀ ⁻⁰⁴	
5.05114	03416 ₁₀ ⁻⁰⁷	4	58496	31646 ₁₀ ⁻⁰⁸	-2.65944	32257 ₁₀ ⁻⁰⁷	-4.67148	08377 ₁₀ ⁻⁰⁷	-5.95081	64441 ₁₀ ⁻⁰⁷	-6.75178	33458 ₁₀ ⁻⁰⁷
3.65217	71718 ₁₀ ⁻¹¹	-1.25607	41336 ₁₀ ⁻¹⁰	-2.09271	44739 ₁₀ ⁻¹⁰	-2.52288	19034 ₁₀ ⁻¹⁰	-2.73216	93519 ₁₀ ⁻¹⁰	-2.81694	14023 ₁₀ ⁻¹⁰	
1.95300	70174 ₁₀ ⁻¹³	-2.68782	76487 ₁₀ ⁻¹⁴	9.11843	16499 ₁₀ ⁻¹⁴	1.68927	42630 ₁₀ ⁻¹³	2.19246	26557 ₁₀ ⁻¹³	2.51362	10252 ₁₀ ⁻¹³	
4.37027	04750 ₁₀ ⁻¹⁵	-7.43763	51683 ₁₀ ⁻¹⁵	-8.15470	18418 ₁₀ ⁻¹⁵	-8.40092	32237 ₁₀ ⁻¹⁵	-7.77909	61723 ₁₀ ⁻¹⁵	-7.37817	06343 ₁₀ ⁻¹⁵	

m_1	\circ	rhs	b_2	$x^{(s)}$, $s = 1, 2, 3, 4, 5$.	
5.56239	01547	10^{+1}	9.02800	72549	10^{+1}
3.37777	18060	10^{-1}	2.56809	75057	10^{-1}
3.33311	57908	10^{-1}	2.49964	54446	10^{-1}
3.33333	33117	10^{-1}	2.49999	99664	10^{-1}
3.33333	33334	10^{-1}	2.50000	00000	10^{-1}
2.80130	68864	10^{+6}	2.09994	38069	10^{+6}
2.79999	98248	10^{+6}	2.09999	96497	10^{+6}
2.79999	99995	10^{+6}	2.10000	00000	10^{+6}
2.80000	00000	10^{+6}	2.10000	00000	10^{+6}
$m_1 = 2$, rhs	b_1		$x^{(s)}$, $s = 1, 2, 3$.		
3.33325	69325	10^{-1}	1.99981	23581	10^{-1}
3.33333	33323	10^{-1}	2.00000	00002	10^{-1}
3.33333	33334	10^{-1}	2.00000	00000	10^{-1}
2.13646	45736	10^{-03}	1.99172	38410	10^{-03}
-7.38044	15024	10^{-08}	4.80542	04172	10^{-07}
-1.65462	21882	10^{-10}	1.59782	75647	10^{-10}
-4.06743	50023	10^{-14}	4.20185	43185	10^{-14}
-1.48834	27910	10^{-14}	8.33620	08075	10^{-15}
$x^{(s)}$, $s = 1, 2, 3, 4, 5$.			$r^{(s)}$, $s = 1, 2, 3, 4, 5$.		
1.09708	61620	10^{+2}	1.19973	52027	10^{+2}
2.07823	90423	10^{-1}	1.74786	46338	10^{-1}
1.99956	83846	10^{-1}	1.66619	41295	10^{-1}
1.99999	99609	10^{-1}	1.66666	66257	10^{-1}
2.00000	00000	10^{-1}	1.66666	66667	10^{-1}
1.67905	65883	10^{+6}	1.39850	07847	10^{+6}
1.67999	96002	10^{+6}	1.39999	95972	10^{+6}
1.68000	00003	10^{+6}	1.40000	00006	10^{+6}
1.68000	00000	10^{+6}	1.40000	00000	10^{+6}
1.99981	23581	10^{-1}	1.66644	84069	10^{-1}
2.00000	00002	10^{-1}	1.66666	66679	10^{-1}
2.00000	00000	10^{-1}	1.66666	66667	10^{-1}
1.99172	38410	10^{-03}	-3.50968	45825	10^{-03}
4.80542	04172	10^{-07}	1.37349	84350	10^{-07}
1.59782	75647	10^{-10}	1.15019	08106	10^{-10}
4.20185	43185	10^{-14}	4.78313	47444	10^{-14}
8.33620	08075	10^{-15}	1.70696	27914	10^{-14}
1.24798	36748	10^{+2}	1.19815	74912	10^{+6}
1.50905	26268	10^{-1}	1.19999	96122	10^{+6}
1.42807	94663	10^{-1}	1.20000	00007	10^{+6}
1.42857	13875	10^{-1}	1.20000	00000	10^{+6}
1.42857	14286	10^{-1}	1.20000	00000	10^{+6}
1.24975	07088	10^{-1}	1.24975	07088	10^{-1}
1.25000	00030	10^{-1}	1.25000	00030	10^{-1}
1.25000	00000	10^{-1}	1.25000	00000	10^{-1}
-4.21736	74494	10^{-03}	-4.06513	18158	10^{-03}
-6.59523	94825	10^{-07}	-2.95920	01738	10^{-07}
-8.07926	91980	10^{-11}	1.48955	70888	10^{-11}
1.95614	94080	10^{-14}	3.51856	16491	10^{-14}
2.14757	15640	10^{-14}	2.04140	44723	10^{-14}
2.14979	05645	10^{-14}			

$m_1 = 2,$	rhs	b_3	$\bar{x}(s),$	$s = 1, 2, 3, 4.$
5.43942	34352	10^{-1}	7.60691	80418 10^{-1} 8.39395 19792 10^{-1} 8.94072 75252 10^{-4} 9.29507 22442 10^{-4}
3.33414	78920	10^{-1}	2.00211	42052 10^{-1} 1.66917 52116 10^{-1} 1.43134 91136 10^{-1} 1.25295 50085 10^{-4}
3.33333	35241	10^{-1}	2.00000	04828 10^{-1} 1.66666 72353 10^{-1} 1.42857 20546 10^{-1} 1.25000 06600 10^{-4}
3.33333	33334	10^{-1}	2.00000	00001 10^{-1} 1.66666 66668 10^{-1} 1.42857 14287 10^{-1} 1.25000 06001 10^{-4}

$\bar{z}(s),$	$s = 1, 2, 3.$
2.79993	42742 10^{+6} 2.10010 54284 10^{+6} 1.68006 97605 10^{+6} 1.40000 52065 10^{+6} 1.19994 83616 10^{+6} 1.04990 48202 10^{+6}
2.79999	99780 10^{+6} 2.10000 00226 10^{+6} 1.68000 00222 10^{+6} 1.40000 00120 10^{+6} 1.29000 00010 10^{+6} 1.04999 99914 10^{+6}
2.80000	00000 10^{+6} 2.10000 00000 10^{+6} 1.68000 00000 10^{+6} 1.40000 00000 10^{+6} 1.20000 00000 10^{+6} 1.05000 00000 10^{+6}

References

- [1] Björck, Å.: Iterative Refinement of Linear Least Squares
Solutions I. BIT 7(1967), to appear.
- [2] Businger P. and Golub, G. H.: Linear Least Squares Solutions
by Householder Transformations. Num. Math. 7, 269-276 (1965).
- [3] Golub,, G. H.: Numerical Methods for Solving Linear Least Squares
Problems. Num. Math. 7, 206-216 (1965) .
- [4] Householder, A. S.: Unitary Triangularization of a Nonsymmetric
Matrix. Assoc. Comput. Mach. 5, 339-342 (1958).
- [5] Wilkinson, J. H.: Householders Method for Symmetric Matrices.
Num. Math. 4, 354-361 (1962).