# On the Regularity of a Trust Region-CG Algorithm for Nonlinear Ill-posed Inverse Problems*

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**Abstract.** In this paper we consider the regularity of the trust region-cg algorithm, when it is applied to nonlinear ill-posed iverse problems. The trust region algorithm can be viewed as a regularization method, but it differs from the traditional regularization method, because no penalty term is need. Thus, the determing of the so-called regularization parameter in a standard regularization method is avoided. Theoretical analysis of the trust region-cg method is presented, convergency and regularity of the trust region algorithm are proved, and numerical tests are also given.
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## 1 Introduction

In scientific and engineering computing, we are often encountered with nonlinear inverse problems. An inverse problem consists of a direct problem and some unknown function(s) or parameters. Inverse problems are usually ill-posed in the sense of J. Hadmard, i.e., at leat one term of the *existence, uniqueness, stability* of the solution is vilated. Particularly we are concerned with the stability, since in many applications the solution does not depend continuously on the unknown quantities and the problem is ill-posed. A typical ill-posed problems is to determine these unknowns given measured, or condaminated data.

We can outline the nonlinear ill-posed problems into an abstract operator equations

$$F(x) = y, \tag{1}$$

where $F : D(F) \subset X \longrightarrow Y$ is a nonlinear mapping, $X$ and $Y$ are both seperable Hilbert spaces. We assume that $F$ is continuous and compact for fixed $x \in D(F)$.

Problem (1) is typically ill-posed in the sense that a solution $x^+$ does not depend continuously on the obervation data $y$. Since in practice only approximate data with some error level

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$\delta$, i.e.,

$$\|y_\delta - y\| \leq \delta \tag{2}$$

are available, problem (1) has to be regularized (see e.g. [3, 7, 23]). Through out this paper we assume that a solution $x^+$ of (1) exists, i.e.

$$F(x^+) = y. \tag{3}$$

Regularization methods are such kind of methods which replace the ill-posed problem with a stabilized problem whose solution depends on a parameter, named as the regularization parameter. The regularized problem is well-posed in the sense of J. Hadamard. For a complete theoretical analysis of such kind of method, please see some well-written books [23, 3, 13, 7, 14, 17].

Certainly the most well-known and most widely used regularization method for nonlinear ill-posed problems is the method of Tikhonov regularization. In which one solves the unconstrained minimization problem

$$\min_{x\in X} J_\alpha[x,y] := \|F(x) - y_\delta\|^2 + \alpha\theta(x). \tag{4}$$

$\alpha > 0$ is the regularization parameter. $\theta(x)$ serves as the stabilizer, i.e., stablizes the minimization process and provides a priori information about the solution.

Replacing $F(x)$ by first order Taylor's expansion, i.e., (4) turns into

$$\min_{\xi\in X} J_\alpha[\xi,y] := \|y_\delta - F(x_k) - F'(x_k)\xi\|^2 + \alpha\theta(\xi). \tag{5}$$

If an approximate solution $\xi_k$ of (5) is computed, we can let $x_{k+1} = x_k + \xi_k$.

Assume that $x_k$ is some approximation of the solution $x^+$, then

$$F(x^+) - F(x_k) = F'(x_k)(x^+ - x_k) + r(x^+;x_k), \tag{6}$$

where $r(x^+;x_k)$ is the Taylor remainder. Denoting $\xi^+ = x^+ - x_k$ and solving for it leads to

$$F'(x_k)\xi^+ = y - F(x_k) - r(x^+;x_k). \tag{7}$$

The above relation can be rewritten as

$$F'(x_k)\xi^+ = y_\delta - F(x_k) + y - y_\delta - r(x^+;x_k). \tag{8}$$

Thus, the linearized problem

$$F'(x_k)\xi = y_\delta - F(x_k) \tag{9}$$

is an approximation to the original problem up to up to an error $err = y_\delta - y + r(x^+;x_k)$ with

$$\|err\| \leq \delta + \|r(x^+;x_k)\|. \tag{10}$$

Clearly (5) is equivalent to applying Tikhonov regularization to problem (9).

**Assumption 1.1** *Assume that after $k$ iterations, $\xi^+ = x^+ - x_k$ satisfies*

$$\|y_\delta - F(x_k) - F'(x_k)\xi^+\| \le \omega \|y_\delta - F(x_k)\|, \ \ 0 < \omega < 1.$$

Apart from the above analysis, we need the following assumption:

**Assumption 1.2** *For a certain ball $\mathcal{B} \subset D(F)$ around the exact solution $x^+$ of (1), and some $1 > d > 0$ let*

$$\|F(x) - F(\hat{x}) - F'(\hat{x})(x - \hat{x})\| \le d\|F(x) - F(\hat{x})\| \tag{11}$$

*for all $x, \ \hat{x} \in \mathcal{B}$.*

This assumption is helpful for analyzing the properties of the trust region algorithm which we presented in this paper.

Recently, optimization methods are becoming popular for solving nonlinear ill-posed inverse problems, for example, Gauss-Newton method ([1, 12]), Broyden's method ([11]), and Levenberg-Marquardt method ([9]), which have been well developed in nonlinear programming.

Trust region method has been used in parameter identification problem and image restoration problem (see [25, 26]) and seems promising. This paper will consider trust region method for nonlinear ill-posed inverse problems.

## 2 A Trust Region-CG Algorithm

Considering the unconstrained optimization problem

$$\min_{x \in X} J[x, y_\delta] := \|F(x) - y_\delta\|^2. \tag{12}$$

We denote by $g(x)$ the gradient of the functional $J$, $Hess(x)$ the approximate Hessian of $J$, i.e.,

$$g(x) = F'(x)^T (F(x) - y_\delta), \ \ Hess(x) = F'(x)^T F'(x).$$

At the $k$-th iteration, a trust region subproblem (TRS) for (12) is

$$\min_{x \in R^n} g_k^T \xi + \frac{1}{2}(Hess_k \xi, \xi) := \psi_k(\xi), \tag{13}$$

$$s.\ t.\ \|\xi\| \le \Delta, \tag{14}$$

where $g_k = g(x_k), \ Hess_k = Hess(x_k)$ and $\Delta > 0$ is the trust region bound. (13)–(14) is solved exactly or inexactly to obtain a trial step $\xi_k$. The ratio

$$r_k = \frac{Ared_k}{Pred_k} \tag{15}$$

is used to decide whether the trial step $\xi_k$ is acceptable and to adjust the trust region bound.

$$Ared_k = J[x_k, y_\delta] - J[x_k + \xi_k, y_\delta] \tag{16}$$

is called the actual reduction in the objective model, and

$$Pred_k = \psi_k(0) - \psi_k(\xi_k) \tag{17}$$

is the predicted reduction. We outline the general trust region algorithm for unconstrained optimization as follows.

**Algorithm 2.1** *(Trust region algorithm for nonlinear ill-posed problem)*

*STEP 1* *Given the initial guess value* $x_1 \in R^n$, $\Delta_1 > 0$, $0 < \tau_3 < \tau_4 < 1 < \tau_1$, $0 \le \tau_0 \le \tau_2 < 1$, $\tau_2 > 0$, $k := 1$;

*STEP 2* *If some stopping rule is satisfied then STOP; Else, solve (13)-(14) giving* $\xi_k$;

*STEP 3* *Compute* $r_k$;

$$x_{k+1} = \begin{cases} x_k & if \quad r_k \le \tau_0, \\ x_k + \xi_k & otherwise; \end{cases} \tag{18}$$

*Choose* $\Delta_{k+1}$ *that satisfies*

$$\Delta_{k+1} = \begin{cases} [\tau_3\|\xi_k\|, \tau_4\Delta_k] & if \quad r_k < \tau_2, \\ [\Delta_k, \tau_1\Delta_k] & otherwise; \end{cases} \tag{19}$$

*STEP 4* *Evaluate* $g_k$ *and* $Hess_k$; *k:=k+1; GOTO STEP 2.*

The constant $\tau_i$ $(i = 0, \cdots, 4)$ can be chosen by users. Typical values are $\tau_0 = 0$, $\tau_1 = 2$, $\tau_2 = \tau_3 = 0.25$, $\tau_4 = 0.5$. For other choices of those constants, please see [4], [5], [15], [19], etc.. The parameter $\tau_0$ is usually zero (see [4], [20]) or a small positive constant (see [2] and [21]). The advantage of using zero $\tau_0$ is that a trial step is accepted whenever the objective function is reduced. Hence it would not throw away a "good point", which is a desirable property especially when the function evaluations are very expensive.

In STEP 2, the stopping rule is based on some kind of so-called discrepancy principle, i.e., once the inequality

$$\|F(x_k) - y_\delta\| \le \tilde{\omega}\delta, \text{ with } \tilde{\omega} > 1$$

is satisfied, no further iteration is needed.

The following lemma is well known (for example, see [16] and [6]):

**Lemma 2.2** *A vector* $\xi^* \in R^n$ *is a solution of (13)-(14) if and only if there exists* $\lambda^* \ge 0$ *such that*

$$(Hess_k + \lambda^* I)\xi^* = -g_k \tag{20}$$

*and that* $Hess_k + \lambda^* I$ *is positive semi-definite,* $\|\xi^*\| \le \Delta$ *and*

$$\lambda^*(\Delta - \|\xi^*\|) = 0. \tag{21}$$

It is shown by Powell [20] that trust region algorithms for (12) is convergent if the trust region step satisfies

$$Pred(\xi) \geq c\|g\| \min\{\Delta, \|g\|/\|Hess\|\} \tag{22}$$

and some other conditions on $Hess$ are satisfied. It is easy to see that

$$\psi(0) - \min_{\|\xi\| \leq \Delta, \xi \in span\{g\}} \psi(s) \geq \frac{1}{2} \quad \|g\| \min\{\Delta, \|g\|/\|Hess\|\}. \tag{23}$$

Therefore it is quite common that in practice the trial step at each iteration of a trust region method is computed by solving the TRS (13)-(14) inexactly. One way to compute an inexact solution of (13)-(14) was the truncated conjugate gradient method proposed by Toint [24] and Steihaug [22] and analyzed by Yuan [30].

The conjugate gradient method for (13) generates a sequence as follows:

$$\xi_{l+1} = \xi_l + \alpha_l d_l, \tag{24}$$

$$d_{l+1} = -g_{l+1}^{\psi} + \beta_l d_l, \tag{25}$$

where $g_l^{\psi} = \nabla\psi_k(\xi_l) = Hess_k\, \xi_l + g_k$ with $g_k = g(x_k) = F'(x_k)^T(F(x_k) - y_\delta)$, $Hess_k = Hess(x_k) = F'(x_k)^T F'(x_k)$ and

$$\alpha_l = -{g_l^{\psi}}^T d_l / d_l^T Hess_k\, d_l, \;\; \beta_l = \|g_{l+1}^{\psi}\|^2 / \|g_l^{\psi}\|^2, \tag{26}$$

with the initial values $\xi_1 = 0, \;\; d_1 = -g_1^{\psi} = -g_k$.

Toint [24] and Steihaug [22] were the first to use the conjugate gradient method to solve the general trust region subproblem (13)-(14). Even without assuming the positive definiteness of $Hess$, we can continue the conjugate gradient method provided that $d_l^T Hess\, d_l$ is positive. If the iterate $\xi_l + \alpha_l d_l$ computed is in the trust region ball, it can be accepted, and the conjugate gradient iterates can be continued to the next iteration. Whenever $d_l^T Hess\, d_l$ is not positive or $\xi_l + \alpha_l d_l$ is outside the trust region, we can take the longest step along $d_l$ within the trust region and terminate the calculations.

**Algorithm 2.3** *(Truncated conjugate gradient method for TRS)*

*STEP 1* *Given* $\xi_1 = 0$, $0 < \tau < 1$, $\epsilon$ *(tolerance)* $> 0$ *and compute* $g_1^{\psi} = \nabla\psi(\xi_1)$, *set* $l := 1, \; d_1 = -g_1^{\psi} = -g_k$;

*STEP 2* *If* $\|A_k \xi_l - \tilde{u}_k\| \leq \tau \|\tilde{u}_k\|$, *stop, output* $\xi^* = \xi_l$;

*Compute* $d_l^T Hess\, d_l$: *if* $d_l^T Hess_k\, d_l \leq 0$ *then goto step 4;*

*Calculate* $\alpha_l$ *by (26).*

*STEP 3* *If* $\|\xi_l + \alpha_l d_l\| \geq \Delta_k$ *then goto step 4;*

*Set* $\xi_{l+1}$ *by (24) and* $g_{l+1}^{\psi} = g_l^{\psi} + \alpha_l Hess_k\, d_l$;

*Compute* $\beta_l$ *by (26) and set* $d_{l+1}$ *by (25);*

*l:=l+1, goto step 2.*

*STEP 4 Compute* $\alpha_l^* \geq 0$ *satisfying* $\|\xi_l + \alpha_l^* d_l\| = \Delta$;

*Set* $\xi^* = \xi_l + \alpha_l^* d_l$, *and stop.*

Note that $\alpha_l^*$ can be computed by choosing the positive root of the quadratic equation in $\alpha$:

$$\|d_l\|^2\alpha^2 + 2(\xi_l, d_l)\alpha + \|\xi_l\|^2 - \Delta_k^2 = 0. \tag{27}$$

Let $\xi^*$ be the inexact solution of (13)-(14) obtained by the above truncated CG method and $\hat{\xi}$ be the exact solution of (13)-(14). Recently Yuan [30] shows that

$$\frac{\psi(0) - \psi(\xi^*)}{\psi(0) - \psi(\hat{\xi})} \geq \frac{1}{2}, \tag{28}$$

which can be written as the following theorem:

**Theorem 2.4** *For any* $\Delta > 0$, $g \in R^n$ *and any positive definite matrix* $Hess \in R^{n\times n}$, *let* $\hat{s}$ *be the global solution of the trust region subproblem (13)-(14), and let* $\xi^*$ *be the solution obtained by the truncated CG method, then*

$$\psi(\xi^*) \leq \frac{1}{2}\psi(\hat{s}). \tag{29}$$

This theorem tells us that the reduction in the approximate model is at least half of the maximum reduction if we use the truncated conjugate gradient method for solving the subproblem (13)-(14).

Applying Algorithm 2.3 to compute the trial step $\xi_k$ in Step 2 of Algorithm 2.1, we obtain a trust region-cg algorithm for nonlinear ill-posed inverse problems. The algorithm consists of two stage iterations: the inner loop and the outer loop. The inner loop is the truncated conjugate gradient method, the outer loop is the trust region method.

To avoid too many inner loop iterations in one out loop iteration, we terminate the inner loop iteration if *itermax* cg steps have been taken, where *itermax* is a given positive number. We also terminate the inner look iteration if a progress in function reduction in the cg step is smaller than $\epsilon$. However, in our numerical tests, this termination rule was not activated.

# 3 Properties of Algorithm 2.3

In this section we give some properties of the truncated conjugate gradient method. The main result is the monotonicity of the iterates.

First, we present an equivalent form of the conjugate gradient method. Denote

$$A_k = F'(x_k),\ u_k = y - F(x_k) - r(x^+; x_k),\ \tilde{u}_k = y_\delta - F(x_k),$$

we have

$$Hess_k = A_k^* A_k,\ g_k = -A_k^* \tilde{u}_k,\ g_l^\psi = A_k^*(A_k \xi_l - \tilde{u}_k),$$

$$
\begin{aligned}
d_{l+1} &= -g_{l+1}^{\psi} + \beta_l d_l = -A_k^*(A_k\xi_{l+1} - \tilde{u}_k) + \beta_l d_l \\
&= -A_k^* A_k \xi_l - \alpha_l A_k^* A_k d_l + A_k^* \tilde{u}_k + \beta_l d_l.
\end{aligned}
$$

If we let $d_l = A_k^* z_l$ provided that such $z_l$ exists, then

$$d_{l+1} = A_k^*(\tilde{u}_k - A_k\xi_l - \alpha_l A_k d_l + \beta_l z_l).$$

Further if we denote $r_l = \tilde{u}_k - A_k\xi_l$, then clearly

$$r_{l+1} = \tilde{u}_k - A_k\xi_{l+1} = r_l - \alpha_l A_k d_l$$

and

$$d_{l+1} = A_k^*(r_l - \alpha_l A_k d_l + \beta_l z_l)$$

hold. We can generate the next search direction by $d_{l+1} = A_k^* z_{l+1}$ with $z_{l+1} = r_l - \alpha_l A_k d_l + \beta_l z_l = r_{l+1} + \beta_l z_l$. Hence, the conjugate gradient iterates can be genereated in the following way:

$$
\begin{aligned}
\xi_{l+1} &= \xi_l + \alpha_l d_l && (30)\\
d_l &= A_k^* z_l && (31)\\
z_{l+1} &= r_{l+1} + \beta_l z_l && (32)\\
r_{l+1} &= r_l - \alpha_l A_k d_l && (33)\\
\alpha_l &= -\frac{{g_l^{\psi}}^T d_l}{d_l^T Hess\, d_l} = \frac{\|A_k^* r_l\|^2}{\|A_k d_l\|^2} && (34)\\
\beta_l &= \frac{\|A_k^* r_{l+1}\|^2}{\|A_k^* r_l\|^2} && (35)\\
\sigma_{l+1} &= 1 + \beta_l \sigma_l && (36)
\end{aligned}
$$

The initial values are $\xi_1 = 0,\ d_1 = -g_k,\ z_1 = r_1,\ r_1 = \tilde{u}_k = y_\delta - F(x_k),\ \sigma_1 = 1$. Here another scalar $\sigma_l$ is added, which will be used for the analysis of the truncated conjugate gradient method.

One tool for the analysis of the truncated conjugate gradient method is the so-called residual polynomials (see [10, 3]). Let $\Pi_l$ be the set of all polynomials of degree $l$ or less, and set

$$\Pi_l^0 := \{p \in \Pi_l : p(0) = 1\}.$$

Then there is an 1-1 relation between elements $\xi \in \mathcal{K}_l(A_k^*\tilde{u}_k; A_k^* A_k)$ and $p \in \Pi_l^0$ via the representation

$$\tilde{u}_k - A_k\xi = p(A_k A_k^*)\tilde{u}_k \tag{37}$$

of the corresponding residual, where $\mathcal{K}_l(A_k^*\tilde{u}_k; A_k^* A_k)$ is the $l$-th Krylov subspace

$$\mathcal{K}_l(A_k^*\tilde{u}_k; A_k^* A_k) = \mathrm{span}\{A_k^*\tilde{u}_k, (A_k^* A_k)A_k^*\tilde{u}_k, \cdots, (A_k^* A_k)^{l-1}A_k^*\tilde{u}_k\}.$$

For simplicity, $p_l \in \Pi_l^0$ denotes the residual polynomial associated with $\xi_l$, the $l$-th CG iterate.

The bilinear form

$$< p, q >:= (p(A_k A_k^*)\tilde{u}_k, q(A_k A_k^*)\tilde{u}_k)$$

defines the inner product for $p,\ q \in \Pi_l$. If $q \in \Pi_{l-1}$ is an arbitrary polynomial of degree $l-1$ then the polynomial $p$ given by $p(\lambda) = p_l(\lambda) + t\lambda q(\lambda)$ belongs to $\Pi_l^0$ for every $t \in R$. Noticing that $p_l$ solves the minimization problem

$$< p, p > \longrightarrow \min \ \text{ for } p \in \Pi_l^0.$$

Hence,

$$< p_l, \lambda q >= \frac{1}{2}\frac{d}{dt} < p, p > |_{t=0} = 0, \text{ for all } q \in \Pi_{l-1}. \tag{38}$$

If we define $q = q_{l-1}$ by $p_l = 1 - \lambda q_{l-1}$, then clearly we have that,

$$< p_l, 1 >=< p_l, p_l >, \tag{39}$$

which will be used for later analysis.

From (30)-(36) and the above definitions, we have that

$$z_l = s_l(A_k A_k^*)\tilde{u}_k,\ s_l(\lambda) := \frac{p_l(\lambda) - p_{l+1}(\lambda)}{\alpha_l \lambda} \in \Pi_l. \tag{40}$$

It was pointed out by [8] that in general $s_l$ does not belong to $\Pi_l^0$. Instead, since the vectors $z_l$ are updated by $z_{l+1} = r_{l+1} + \beta_l z_l$ with $r_{l+1} = \tilde{u}_k - A_k\xi_{l+1}$, it follows from (40) that

$$s_{l+1}(\lambda) = p_{l+1}(\lambda) + \beta_l s_l(\lambda), \tag{41}$$

and hence, $s_l(0)$ and $\sigma_l$ of Algorithm 2.3 share the same recurrence relation (this in fact has been observed by [8]), i.e.,

$$s_l(0) = \sigma_l. \tag{42}$$

With the above analysis, we can now present the monotonicity of the iterates for perturbed right-hand side.

**Theorem 3.1** *Let $\gamma \geq 2,\ l^* \in N$. If Assumption 1.1 holds and if*

$$\|\tilde{u}_k - A_k\xi_l\|^2 + \|\tilde{u}_k - A_k\xi_{l+1}\|^2 > \omega\gamma\frac{\|z_l\|\|\tilde{u}_k\|}{\sigma_l},\ 0 < \omega < 1,\ l = 1, 2, \cdots, l^*, \tag{43}$$

*then $\|\xi^+ - \xi_l\|$ is strictly monotonically decreasing for $l = 1, 2, \cdots, l^*$, and*

$$\|\xi^+\|^2 - \|\xi^+ - \xi_{l^*+1}\|^2 > (\gamma - 2)\omega\|\tilde{u}_k\|\sum_{l=1}^{l^*}\alpha_l\|z_l\|. \tag{44}$$

*Proof.* By induction, we obtain

$$\begin{aligned}
\|\xi^+ - \xi_{l+1}\|^2 &= \|\xi^+ - \xi_l - \alpha_l d_l\|^2 \\
&= \|\xi^+ - \xi_l\|^2 - 2(\xi^+ - \xi_l, \alpha_l A_k^* z_l) + (\alpha_l A_k^* z_l, \alpha_l A_k^* z_l) \\
&= \|\xi^+ - \xi_l\|^2 - \alpha_l(2A_k\xi^+ - 2A_k\xi_l - \alpha_l A_k d_l, z_l) \\
&= \|\xi^+ - \xi_l\|^2 - \alpha_l(\tilde{u}_k - A_k\xi_l, z_l) - \alpha_l(\tilde{u}_k - A_k\xi_{l+1}, z_l) \\
&\quad +2\alpha_l(\tilde{u}_k - A_k\xi^+, z_l).
\end{aligned}$$

From the definitions of $p_l$ and $z_l$, we have

$$\|\xi^+ - \xi_l\|^2 - \|\xi^+ - \xi_{l+1}\|^2 = \alpha_l < p_l, s_l > +\alpha_l < p_{l+1}, s_l > -2\alpha_l < \tilde{u}_k - A_k\xi^+, z_l > .$$

By (42), $s_l(\lambda) = \sigma_l + \lambda q(\lambda)$ for some polynomial $q \in \Pi_{l-1}$, and hence from (38) and (39) we find that

$$\begin{aligned}
&\|\xi^+ - \xi_l\|^2 - \|\xi^+ - \xi_{l+1}\|^2 = \alpha_l\sigma_l(< p_l, 1 > + < p_{l+1}, 1 >) - 2\alpha_l < \tilde{u}_k - A_k\xi^+, z_l > \\
&= \alpha_l\sigma_l(< p_l, p_l > + < p_{l+1}, p_{l+1} >) - 2\alpha_l < \tilde{u}_k - A_k\xi^+, z_l > .
\end{aligned}$$

Since $< p_l, p_l >= \|\tilde{u}_k - A_k\xi_l\|^2$, hence it follows from the above relation and (43) that

$$\|\xi^+ - \xi_l\|^2 - \|\xi^+ - \xi_{l+1}\|^2 > \omega\gamma\alpha_l\|z_l\|\|\tilde{u}_k\| - 2\omega\alpha_l\|\tilde{u}_k\|\|z_l\|, \text{ for all } l = 1, \cdots, l^*. \tag{45}$$

Thus, the monotonicity of $\|\xi^+ - \xi_l\|$ follows from the above inequality and the assumption $\gamma > 2$. Relation (44) follows by taking the sum of (45) for $l = 1, \cdots, l^*$ and observing the fact that $\xi_1 = 0$. Q.E.D

**Remark 3.2** *We have noted that in general $s_l$ will not belong to $\Pi_l^0$, however, $\hat{s}_l := s_l/\sigma_l \in \Pi_l^0$. Hence from the minimization property of the truncated CG we obtain*

$$\|\tilde{u}_k - A_k\xi_{l+1}\| \le \|\tilde{u}_k - A_k\xi_l\| =< p_l, p_l >^{\frac{1}{2}} \le < \hat{s}_l, \hat{s}_l >^{\frac{1}{2}} = \frac{1}{\sigma_l} < s_l, s_l >^{\frac{1}{2}} = \frac{1}{\sigma_l}\|z_l\|. \tag{46}$$

*This together with (43) yield that*

$$\begin{aligned}
2\|\tilde{u}_k - A_k\xi_{l^*}\|^2 &\ge \|\tilde{u}_k - A_k\xi_{l^*}\|^2 + \|\tilde{u}_k - A_k\xi_{l^*+1}\|^2 \\
&> \omega\gamma\frac{\|z_{l^*}\|\|\tilde{u}_k\|}{\sigma_{l^*}} > \omega\gamma\|\tilde{u}_k\|\|\tilde{u}_k - A_k\xi_{l^*}\|,
\end{aligned}$$

*which indicates that*

$$\|\tilde{u}_k - A_k\xi_{l^*}\| \ge \frac{\omega\gamma\|\tilde{u}_k\|}{2} > \omega\|\tilde{u}_k\|.$$

*Since $\|\tilde{u}_k - A_k\xi^+\| \le \omega\|\tilde{u}_k\|$ according to Assumption 1.1, this shows that $l^*$ can not exceed $l_k$, the smallest index of the inner iteration.*

## 4 Convergence of Trust Region-CG for Exact Data

Before presenting the proposition in the following paragraph, we first give an assumption:

**Assumption 4.1** *Assume that in each inner iteration, $\xi_l$ satisfies*

$$\|\tilde{u}_k - A_k\xi_l\| \geq \omega_1\|\tilde{u}_k\|, \text{ with } \omega_1^2 = \gamma\omega \tag{47}$$

*until convergence, where $0 < \omega < \gamma^{-1}$, $\gamma > 2$.*

Assumption 4.1 is closely related with the termination rule of Algorithm 2.3. Where, $\tau$ in STEP 2 serves as the number $\omega_1$ here. Once the opposite inequality of Assumption 4.1 is satisfied, we stop the inner iteration.

**Proposition 4.2** *Suppose that Assumption 4.1 holds. The inequality (47) indicates that (43) is true if $l > 0$. Furthermore, there are only finitely many $l$ for which (47) holds.*

*Proof.* From the Remark 3.2 we know

$$\frac{1}{\sigma_l}\|z_l\| =< \hat{s}_l, \hat{s}_l >^{\frac{1}{2}} .$$

It is proved by [10] that $< \hat{s}_l, \hat{s}_l >$ is strictly monotonically decreasing with $l$, consequently

$$\frac{1}{\sigma_l}\|z_l\| < \frac{1}{\sigma_1}\|z_1\| = \|r_1\| = \|\tilde{u}_k\|.$$

The above inequality together and (47) indicates that (43) is true for $l > 0$. From Remark 3.2, we see that (47) holds for only finitely many indices $l$. Q.E.D

Now assume that $y_\delta = y$, we first prove the monotonicity of the trust region-cg algorithm, i.e., $x_k + \xi_{l_k}$ is a better approximation of $x^+$ than $x_k$. We also assumed that $F(x) = y$ has a solution $x^+ \in \mathcal{B} \subset D(F)$.

**Proposition 4.3** *Assume that Assumptions 1.2 and 4.1 holds, then the iteration error $\|x^+ - x_k\|$ is monotonically decreasing.*

*Proof.* According to Assumption 1.2, (11) holds for $x = x^+$, $\hat{x} = x_k$, i.e.

$$\|y - F(x_k) - F'(x_k)(x^+ - x_k)\| \leq d\|y - F(x_k)\|.$$

Note that $y_\delta = y$, the above expression indicates that Assumption 1.1 is fulfilled with $0 < d < 1$.

Due to Assumption 4.1,

$$\|\tilde{u}_k - A_k\xi_l\|^2 \geq \gamma\omega\|\tilde{u}_k\|^2$$

is satisfied. Hence from Proposition 4.2, the requirement of Theorem 3.1 is fulfilled.

From our notations, we have that $x_{k+1} = x_k + \xi_{l_k}$. Thus, from $\xi^+ = x^+ - x_k$, $\xi^+ - \xi_{l_k} = x^+ - x_{k+1}$ and Theorem 3.1, we see that $\|x^+ - x_{k+1}\| < \|x^+ - x_k\|$. Q.E.D

**Remark 4.4** *Propostion 4.3 also implies two inequalities:*

$$\|u_k\|\|w_k\| < \frac{1}{d(\gamma-2)}(\|x^+ - x_k\|^2 - \|x^+ - x_{k+1}\|^2) \tag{48}$$

*and*

$$\|u_k\|^2 < \frac{\|A_k\|^2}{d(\gamma-2)}(\|x^+ - x_k\|^2 - \|x^+ - x_{k+1}\|^2). \tag{49}$$

(48) is straightforward as $\|u_k - A_k\xi^+\| \leq d\|u_k\|$ with $0 < d < 1$. (49) follows from relations

$$\|u_k\|\|w_k\| > \alpha_1\|u_k\|\|z_1\| = \alpha_1\|u_k\|^2$$

and

$$\alpha_1 = \frac{\|A_k^* r_1\|^2}{\|A_k d_1\|^2} = \frac{\|A_k^* u_k\|^2}{\|A_k A_k^* u_k\|^2} \geq \|A_k\|^{-2}.$$

**Theorem 4.5** *Given the exact data $y_\delta = y$ and suppose that Assumptions 1.2 and 4.1 hold. Then the iterates $\{x_k\}$ generated by Algorithms 2.1 and 2.3 converge to a solution of (1) as $k \to \infty$.*

*Proof.* First we prove that $\{x_k\}$ forms a Cauchy sequence. Let us denote the iteration errors by $e_k = x^+ - x_k$. Given $k, j \in N$ with $k > j$, let $\nu \in \{j, \cdots, k\}$ be chosen in such a way that

$$\|y - F(x_\nu)\| \leq \|y - F(x_i)\|, \; i = j, \cdots, k.$$

Consider now

$$\|e_\nu - e_j\|^2 = \|e_j\|^2 - \|e_\nu\|^2 + 2(e_\nu, e_\nu - e_j). \tag{50}$$

Note that

$$e_j - e_\nu = x_\nu - x_j, \; x_\nu - x_j = \sum_{i=j}^{\nu-1} A_i^* w_i,$$

where $A_i = F'(x_i), \; w_i = \sum_{l=1}^{l_i-1}\alpha_l z_l$. Hence we obtain

$$|(e_\nu, e_\nu - e_j)| = |\sum_{i=1}^{\nu-1}(A_i^* w_i, e_\nu)| \leq \sum_{i=1}^{\nu-1}\|w_i\|\|A_i e_\nu\|.$$

We can estimate that

$$\begin{aligned}
\|A_i e_\nu\| &= \|A_i e_i - A_i(e_\nu - e_i)\| \\
&\leq \|y - F(x_i) - F'(x_i)e_i\| + \|F(x_\nu) - F(x_i) - F'(x_i)(e_\nu - e_i)\| \\
&\quad + \|y - F(x_\nu)\| \\
&\leq d\|y - F(x_i)\| + d\|F(x_\nu) - F(x_i)\| + \|y - F(x_\nu)\| \\
&\leq 2d\|y - F(x_i)\| + (1+d)\|y - F(x_\nu)\| \leq (1+3d)\|y - F(x_i)\|.
\end{aligned}$$

Relation (48) and the above expression give that

$$\begin{aligned} |(e_\nu, e_\nu - e_j)| &\leq (1+3d)\sum_{i=j}^{\nu-1} \|w_i\|\|y - F(x_i)\| \\ &\leq \frac{1+3d}{d(\gamma-2)}(\|x^+ - x_j\|^2 - \|x^+ - x_\nu\|^2), \end{aligned}$$

which, together with (50), yields

$$\|e_\nu - e_j\|^2 \leq C(\|x^+ - x_j\|^2 - \|x^+ - x_\nu\|^2)$$

with $C = \frac{2(1+3d)}{d(\gamma-2)} + 1$ independent of $\nu$, $j$, $k$. Similarly one can obtain

$$\|e_j - e_\nu\|^2 \leq C(\|x^+ - x_\nu\|^2 - \|x^+ - x_j\|^2),$$

hence

$$\begin{aligned} \|x_k - x_j\|^2 &= \|e_j - e_k\|^2 \leq 2(\|e_k - e_\nu\|^2 + \|e_\nu - e_j\|^2) \\ &\leq 2C(\|x^+ - x_j\|^2 - \|x^+ - x_k\|^2). \end{aligned} \tag{51}$$

Therefore, $\{x_k\}$ form a Cauchy sequence because the monotonicity of $\{\|x^+ - x_k\|\}$.

Denote the limit of $x_k$ by $x$. From (49) we know $\sum_{k=1}^{\infty} \|u_k\|^2$ converges, and therefore $F(x_k) \to y$ as $k \to \infty$. This indicates that $x$ is a solution of (1). Q.E.D

# 5 Regularity of the Algorithm for Inexact Data

Now we consider the case where inexact date $y_\delta$ instead of $y$. It is assumed that (2) is satisfied.

Our stopping rule is based on the discrepancy principle, i.e., we terminate the calculations at the smallest iteration index $k_D$ such that the discrepancy inequality

$$\|y_\delta - F(x_k^\delta)\| \leq \tilde{\omega}\delta, \text{ with } \tilde{\omega} > 1 \tag{52}$$

holds.

We denote $x_k^\delta$ the corresponding iterates and consider the regularity of the trust region-cg algorithm.

**Theorem 5.1** *Assume that Assumptions 1.2 and 4.1 hold. Let $x$ be a solution of (1) with $F$ satisfies (11) for some $1 > d > 0$ in a ball $\mathcal{B} \subset D(F)$ around $x$. Let $\tilde{\omega}$ in (52) be chosen that $\tilde{\omega} > \frac{1+d}{1-d}$. Then $\|x - x_k^\delta\|$ is monotonically decreasing. Moreover, Algorithm 2.1 terminates after $k_D < \infty$ iterations.*

*Proof.* We prove that

$$\|x - x_{k+1}^\delta\| \leq \|x - x_k^\delta\| \tag{53}$$

with $x$ a solution of (1).

Using Assumption 1.2, we estimate that

$$\begin{aligned} \|y_\delta - F(x_k^\delta - F'(x_k^\delta)(x - x_k^\delta)\| &\le \delta + \|F(x) - F(x_k^\delta - F'(x_k^\delta)(x - x_k^\delta)\| \\ &\le \delta + d\|y - F(x_k^\delta)\| \\ &\le (1+d)\delta + d\|y_\delta - F(x_k^\delta)\|. \end{aligned}$$

According to the discrepancy principle, $\|y_\delta - F(x_k^\delta)\| > \tilde{\omega}\delta$ as $k < k_D$, hence

$$\delta < \frac{1}{\tilde{\omega}}\|y_\delta - F(x_k^\delta)\|$$

and

$$\|y_\delta - F(x_k^\delta - F'(x_k^\delta)(x - x_k^\delta)\| \le \frac{1+d+\tilde{\omega}}{\tilde{\omega}}\|y_\delta - F(x_k^\delta)\|.$$

By assumption, $0 < (1 + d + \tilde{\omega})/\tilde{\omega} < 1$, hence Assumption 1.1 is fulfilled. Consequently Propostion 4.3 applies and the monotonicity assertion (53) follows as in the proof of Proposition 4.3.

Next we show that there are only finite number of iterations. In fact as the same as in the proof of (49), we have

$$\|y_\delta - F(x_k^\delta)\|^2 < \frac{L}{d(\gamma-2)}(\|x - x_k^\delta\|^2 - \|x - x_{k+1}^\delta\|^2) \tag{54}$$

with $L = \sup\{\|F^{'}(x_k^\delta)\|^2\}$ for all $k < k_D$.

Assume that (53) holds for $x = x^+$. Now taking the sum of (54) for $k = 1, 2, \cdots, k_D - 1$ we obtain

$$(k_D - 1)\tilde{\omega}^2\delta^2 \le \sum_{k=1}^{k_D-1}\|y_\delta - F(x_k^\delta)\|^2 \le \frac{L}{d(\gamma-2)}\|x^+ - x_1\|^2 < \infty.$$

This indicates that $k_D$ is a finite number. Q.E.D

**Theorem 5.2** *Assume that $F(x_k^\delta) \to F(x_k)$ as $\delta \to 0$. If $k \le k_D$ for all $\delta$ sufficiently small, then $x_k^\delta \to x_k$ for $k \le k_D$ as $\delta \to 0$.*

*Proof.* Given sufficiently small number $\epsilon$, we want to prove $\|x_k^\delta - x_k\| \le \epsilon$ as $\delta \to 0$ for $k \le k_D$. We proceed by induction.

Assume that $x_k^\delta \to x_k$ as $\delta \to 0$, and that $k + 1 \le k_D$. Note that

$$x_{k+1} = x_k + \xi_{l_k},\ \ x_{k+1}^\delta = x_k^\delta + \xi_{l_k}^\delta,$$

$$\xi_{l_k} = F(x_k)^* \sum_{i=1}^{l_k-1}\alpha_i z_i,\ \ \xi_{l_k}^\delta = F(x_k^\delta)^* \sum_{i=1}^{l_k-1}\alpha_i^\delta z_i^\delta,$$

we can estimate that

$$\begin{aligned}\|x_{k+1}^\delta - x_{k+1}\| &\leq \|x_k^\delta - x_k\| + \|\xi_{l_k}^\delta - \xi_{l_k}\| \\ &\leq \|x_k^\delta - x_k\| + \|F(x_k^\delta)^* \sum_{i=1}^{l_k-1} (\alpha_i^\delta z_i^\delta - \alpha_i z_i)\| \\ &\quad + \|(F(x_k^\delta)^* - F(x_k)^*) \sum_{i=1}^{l_k-1} \alpha_i z_i\| \\ &\leq \|x_k^\delta - x_k\| + \|F(x_k^\delta)\|(l_k - 1) \max_i \{\|\alpha_i^\delta z_i^\delta - \alpha_i z_i\|\} \\ &\quad + \|F(x_k^\delta) - F(x_k)\|\|\sum_{i=1}^{l_k-1} \alpha_i z_i\| \qquad (55)\end{aligned}$$

By the induction assumption $x_k^\delta \to x_k$, we have that

$$F(x_k^\delta) \to F(x_k).$$

Therefore, it follows that $\alpha_i^\delta \to \alpha_i,\ z_i^\delta \to z_i$. Consequently, it from (55) that $x_{k+1}^\delta \to x_{k+1}$. Q.E.D

**Theorem 5.3** *Assume that $F$ satisfies (11) in some ball $\mathcal{B} \subset D(F)$ and let $y_\delta$, $x_\delta$ as before. Then the iterates $x_k^\delta$ generated by Algorithms 2.1 and 2.3 converge to a solution of (1) as $k \to \infty$ and $\delta \to 0$.*

*Proof.* For simplicity, We use $k(\delta)$ instead of $k_D$ in the following analysis.

From Theorem 4.5 we know that iterates $x_k$ converge to a solution of (1). Combining this fact with Theorem 5.2, we find that the iterates $x_k^\delta$ converge to a solution of (1) for $k \leq k(\delta)$ as $\delta \to 0$.

Now assume that $k(\delta) \to \infty$ as $\delta \to 0$, and denote $x^+$ the limit of the iterates $x_k$, $x^+$ is a solution of (1). It suffieces to consider subsequences $\{k(\delta_n)\}_n$ which are monotinically increasing to infinity as $n \to \infty$ and $\delta_n \to 0$. Without loss of generality, let us consider $k(\delta_m) > k(\delta_n)$ for $m > n$. By the monotonicity of $x_k^\delta$, i.e., Theorem 5.1, we have

$$\|x_{k(\delta_m)}^{\delta_m} - x^+\| \leq \|x_{k(\delta_n)}^{\delta_m} - x^+\| \leq \|x_{k(\delta(n)}^{\delta(m)} - x_k(\delta_n)\| + \|x_{k(\delta_n)} - x^+\|.$$

Given a sufficiently small number $\epsilon > 0$ and for some sufficiently large number $n$, $\|x_{k(\delta_n)} - x^+\| \leq \epsilon/2$ by Theorem 4.5. On the other hand, for sufficiently large number $m$ and fixed $n$, $\|x_{k(\delta(n)}^{\delta(m)} - x_k(\delta_n)\| \leq \epsilon/2$ by Theorem 5.1. This proves that $\|x_{k(\delta_m)}^{\delta_m} - x^+\| \leq \epsilon$ for all $m$ sufficiently large, and thereafter $x_{k(\delta_m)}^{\delta_m} \to x^+$ as $m \to \infty$. Hence, we see that $x_k^\delta \to x^+$ as $k \to \infty$ and $\delta \to 0$. Q.E.D.

# 6 Numerical Test

In this section, we give an example to test our algorithm. The example is the inverse Gravimetry problem (see [23]). We write it as

$$\begin{aligned} & F(x) : X \longrightarrow Y \\ F(x)(t) \;\; = & \int_a^b k(t,s,x(s))ds = y(t),\ t \in [c,d]. \end{aligned} \tag{56}$$

with $k(t,s,x(s)) = \ln \frac{(t-s)^2+H^2}{(t-s)^2+(x(s)-H)^2}$. Clearly the kernel $k$ is defined on the set $\Pi = \{[c,d] \times [a,b] \times R\}$ and $k(t,s,x(s)) \in C^1(\Pi)$. The first derivative $F'(x) : X \longrightarrow Y$ is defined by

$$[F^{'}(x)u](t) = \int_a^b \frac{\partial k}{\partial x}(t,s,x(s))u(s)ds,\ t \in [c,d], \tag{57}$$

where the kernel $\frac{\partial k}{\partial x}(t,s,x(s))$ can be evaluated by

$$\frac{\partial k}{\partial x}(t,s,x(s)) = \frac{2(H-x(s))}{(t-s)^2+(x(s)-H)^2}.$$

$F^{'}(x)$ is compact, since the kernel is square integrable.

Now, we will set up the problem of approximate determination of normal pseudosolution to the equation (56).

For simplicity, two equidistant grids on intervals $[a,b]$ and $[c,d]$ are applied:

$$\Sigma_n(s) = \{s_j : s_j = a + h_s(j-1), j = 1,2,\cdots,n\},\ h_s = \frac{b-a}{n-1},$$
$$\Sigma_m(t) = \{t_i : t_i = c + h_t(i-1), i = 1,2,\cdots,n\},\ h_t = \frac{d-c}{m-1}.$$

In this way, the spaces of all grid functions defined on $\Sigma_n(s)$ and $\Sigma_m(t)$, respectively, are treated as $X_n$ and $Y_m$.

The integral operator $F$ gives rise to an operator $F_{mn} : X_n \longrightarrow Y_m$ by

$$[F_{mn}(x)]_i = \int_a^b k(t_i,s,x(s))ds,\ 1 \le i \le m.$$

Similarly the derivative operator $F^{'}(x)$ yields an $m \times n$ matrix:

$$[F^{'}_{mn}(x)]_{ij} = \int_a^b \frac{\partial k}{\partial x}(t_i,s,x(s))\phi_j(s)ds,\ 1 \le i \le m,\ 1 \le j \le n.$$

Where $\phi_j(s)$ we used is the standard linear basic functions

$$\phi_j(s) = \begin{cases} \frac{s-s_{j-1}}{h},\ if\ s \in [s_{j-1},s_j], \\ \frac{s_{j+1}-s}{h},\ if\ s \in [s_j,s_{j+1}], \\ 0,\ else. \end{cases}$$

In which, $s_j = jh,\ h = \frac{1}{n},\ j = 1,2,\cdots,n.$ The integral can be computed numerically.

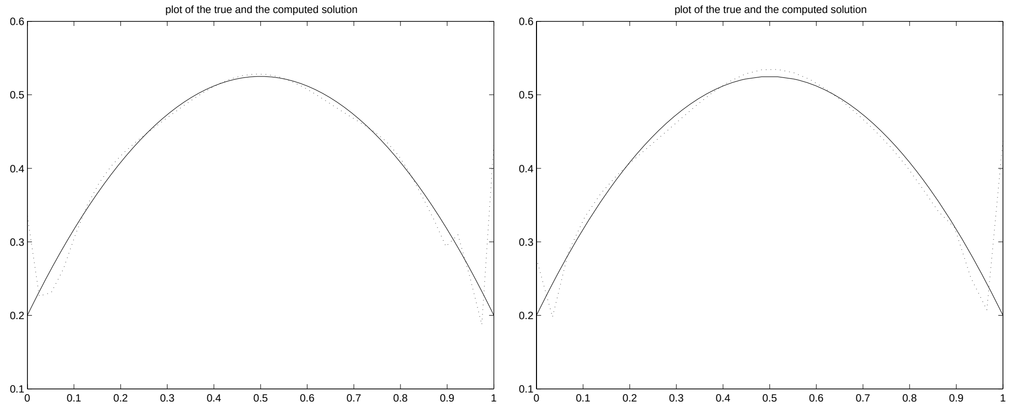


Figure 1: Solution of the inverse problem: nonlinear Fredholm equation

We take $[a, b] = [c, d] = [0, 1]$, $H = 0.1$ and different $m$, $n$ to give a discretization. Our true function is $x_{true}(s) = 1.3s(1-s) + 0.2$, and it is discretized by evaluating it at the points $s_i$ to give the components $x_i$ of $x$. The right-hand side $y$ is generated by integral (56).

The numerical results are shown in figures 1 and 2. In all of these figures, the true solution is denoted by solid line, the approximate solution is denoted by dotted line.

First we choose: $n = 30$, $m = 30$, $\tilde{\omega} = 4.8$, $\tau = 0.8$, $\Delta_0 = 0.1$ with perturbation error level $\delta = 0.01$. The results are shown in the left of Figure 1; It needs 18 inner iterations and 16 outer iterations to generate convergence.

Then we choose $n = 40$, $m = 40$, $\tilde{\omega} = 6.7$, $\tau = 0.8$, $\Delta_0 = 0.1$, with small perturbation $\delta = 0.005$, The results are shown in the right of Figure 1. It needs 20 inner loops and 18 outer loops to generate convergence.

Finally we choose $n = m = 50$, $\Delta_0 = 0.1$ with large perturbation $\delta = 0.05$ and dominant parameter $\tilde{\omega} = 6.8$, $\tau = 0.9$ to give a computation. The results are shown in Figure 2. It needs 7 inner iterations and 10 outer iterations to generate convergence.

**Remark 6.1** *To safeguard Pred is not too small, we choose* $\epsilon = 1.0 \times 10^{-32}$*. If* $Pred \le \epsilon$*, then we regard it as zero and stop the inner iteration. However, this is not activated in our numerical test.*

**Remark 6.2** *In practical applications, the right-hand side is the observation data* $y_\delta$ *which contains noise or error instead of the exact data* $y_{true}$*. To give a reasonable simulation of the observation data, we add Gaussian white noise rand to the right-hand side* $y_{true}$*, i.e.,*

$$y_{noise} = y_{true} + \delta * rand, \tag{58}$$

*where rand is a vector with its components some random numbers in* $[0, 1]$*.*

*Note that* $\delta$ *should not be too small or too large. If* $\delta$ *is too small, according to (58), the noise will not be enough important to give interesting results. However, if* $\delta$ *is too large, the*

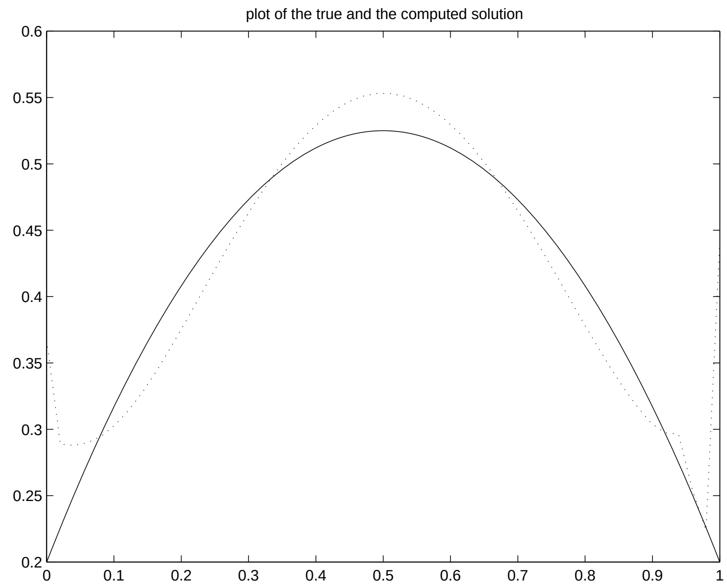


Figure 2: Solution of the inverse problem: nonlinear Fredholm equation

*observation is a poor approximation to the original problem, it will also not enough to give a reasonable results.*

## 7 Conclusion

We have establised the convergence and regularity of the trust region-cg method for nonlinear ill-posed inverse problems. It deserved pointing out that Plato in [18] had establised the regularity property of the conjugate gradient method. Later on, Hanke in [8] had established the regularity of Newon-CG method. All of the methods are stable for solving ill-posed inverse problems.

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