# A SMOOTHING METHOD FOR ABSOLUTE VALUE EQUATION BASED ON A NEW SMOOTHING FUNCTION 

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#### Abstract

In this paper, firstly, we propose a new smoothing function which approximates the absolute value function. Secondly, using this function, we recast the absolute value equation (AVE) as a smoothing system, and then apply a smoothing Newton method to solving the system of equations. Under some assumptions, we get that the algorithm is globally and locally quadratically convergent. Finally, we report the numerical results.


Keywords: Absolute value equation, Smoothing function, Smoothing algorithm

1. Introduction. The absolute value equation (AVE) (Rohn [1]) is to find a point $x \in$ $I R^{n}$ such that

$$
\begin{equation*}
A x+B|x|=b, \tag{1}
\end{equation*}
$$

where $A \in I R^{n \times n}, B \in I R^{n \times n}, b \in I R^{n}$ and $|\cdot|$ means absolute value. A special form of (1) is

$$
\begin{equation*}
A x-|x|=b . \tag{2}
\end{equation*}
$$

The equation of (1) or (2) has attracted much attention in the literature, for example, Mangasarian [2, 3, 4, 5, 6], Rohn [7, 8, 9, 10], Prokopyev [11], Mangasarian and Meyer [12], Jiang and Zhang [13], Caccetta et al. [14].

The papers mentioned above talk about issues as below:

- The existence of the solution;
- How to convert AVE to LCP;
- Solvability of the AVE and the number of solutions;
- The numerical algorithms for the AVE.

Jiang and Zhang [13] firstly considered the function $\phi_{p}(\mu, a)=\sqrt[p]{|a|^{p}+|\mu|^{p}}$, which approximates the absolute value $|a|$, and then presented smoothing Newton method and got good numerical results. Inspired by this idea, we construct a smoothing function $\varphi_{p}(\mu, a)$ to approximate $|a|$. Compared with the function $\phi_{p}$ in [13], our function $\varphi_{p}$ is a piecewise function. For any fixed $\mu>0$, from calculating the distance of two functions, we find that

$$
\begin{aligned}
& \min _{a \in I R}\left\{\phi_{p}(\mu, a)-|a|\right\}>0, \min _{a \in \mathbb{R}}\left\{\varphi_{p}(\mu, a)-|a|\right\}=0, \\
& \max _{a \in \mathbb{R}}\left\{\phi_{p}(\mu, a)-|a|\right\}=\mu, \max _{a \in \mathbb{R}}\left\{\varphi_{p}(\mu, a)-|a|\right\}<\mu .
\end{aligned}
$$

In fact, the mathematical structures of functions $\phi_{p}$ and $\varphi_{p}$ indicate that

$$
\phi_{p}(\mu, a)>\varphi_{p}(\mu, a)>|a| .
$$

From all the above, we see that $\varphi_{p}$ is the one which best approximates the function $|a|$. Then, we reformulate $\operatorname{AVE}(1)$ as a smoothing equation. Like [13], we also use the smoothing-type method to solve the problem AVE (1). Furthermore, we obtain the
same convergence results with [13], which has the global and local quadratic convergence properties. At the end of this paper, we provide some numerical experiments.
2. A Smoothing Function and Its Properties. For any $p \in[2,+\infty)$, define the function $\varphi_{p}: R_{+} \times R \rightarrow R$ by

$$
\varphi_{p}(\mu, t)= \begin{cases}t & t \geq \mu  \tag{3}\\ 2^{\frac{p-1}{p}} \sqrt[p]{|t|^{p}+\mu^{p}}-\mu & -\mu<t<\mu \\ -t & t \leq-\mu\end{cases}
$$

This function is different from the function $\phi_{p}(\mu, a)=\sqrt[p]{|a|^{p}+|\mu|^{p}}$ used in [13]. Our function $\varphi_{p}$ possesses the following properties.
Lemma 2.1. Let $\varphi_{p}$ be defined as in (3). Then,
(i) $\varphi_{p}$ is continuously differentiable on $I R_{++} \times I R$.
(ii) $\left|\varphi_{p}(\mu, t)-|t|\right|<4 \mu$.

Proof: (i) First, we verify that

$$
\begin{gathered}
\frac{\partial \varphi_{p}(\mu, t)}{\partial \mu}= \begin{cases}0 & t \geq \mu \\
2^{\frac{p-1}{p}} \mu^{p-1}\left(|t|^{p}+\mu^{p}\right)^{\frac{1-p}{p}}-1 & -\mu<t<\mu \\
0 & t \leq-\mu\end{cases} \\
\frac{\partial \varphi_{p}(\mu, t)}{\partial t}= \begin{cases}1 & t \geq \mu \\
2^{\frac{p-1}{p}} \operatorname{sgn}(t)|t|^{p-1}\left(|t|^{p}+\mu^{p}\right)^{\frac{1-p}{p}} & -\mu<t<\mu \\
-1 & t \leq-\mu\end{cases}
\end{gathered}
$$

Then, it is clear to see that $\lim _{t \rightarrow \mu} \frac{\partial \varphi_{p}(\mu, t)}{\partial t}=1$ and $\lim _{t \rightarrow-\mu} \frac{\partial \varphi_{p}(\mu, t)}{\partial t}=-1$, because

$$
\lim _{t \rightarrow \mu^{+}} \frac{\partial \varphi_{p}(\mu, t)}{\partial t}=1, \quad \lim _{t \rightarrow \mu^{-}} \frac{\partial \varphi_{p}(\mu, t)}{\partial t}=\lim _{t \rightarrow \mu^{-}} 2^{\frac{p-1}{p}}|t|^{p-1}\left(|t|^{p}+\mu^{p}\right)^{\frac{1-p}{p}}=1
$$

and

$$
\lim _{t \rightarrow-\mu^{-}} \frac{\partial \varphi_{p}(\mu, t)}{\partial t}=-1, \quad \lim _{t \rightarrow-\mu^{+}} \frac{\partial \varphi_{p}(\mu, t)}{\partial t}=\lim _{t \rightarrow-\mu^{+}} 2^{\frac{p-1}{p}} \operatorname{sgn}(t)|t|^{p-1}\left(|t|^{p}+\mu^{p}\right)^{\frac{1-p}{p}}=-1
$$

Hence, $\frac{\partial \varphi_{p}(\mu, t)}{\partial t}$ is continuous.
Similarly, we have

$$
\lim _{t \rightarrow \mu^{+}} \frac{\partial \varphi_{p}(\mu, t)}{\partial \mu}=\lim _{t \rightarrow \mu^{-}} \frac{\partial \varphi_{p}(\mu, t)}{\partial \mu}=0
$$

and

$$
\lim _{t \rightarrow-\mu^{+}} \frac{\partial \varphi_{p}(\mu, t)}{\partial \mu}=\lim _{t \rightarrow-\mu^{-}} \frac{\partial \varphi_{p}(\mu, t)}{\partial \mu}=0 .
$$

Hence, $\frac{\partial \varphi_{p}(\mu, t)}{\partial \mu}$ is continuous.
The analysis mentioned above implies that $\varphi_{p}$ is continuously differentiable at point $(\mu, t) \in I R_{++} \times I R$.
(ii) By a routine computation, we obtain that

$$
\left|\varphi_{p}(\mu, t)-|t|\right|= \begin{cases}0 & t \geq \mu \\ \left|2^{\frac{p-1}{p}} \sqrt[p]{|t|^{p}+\mu^{p}}-\mu-|t|\right| & -\mu<t<\mu \\ 0 & t \leq-\mu\end{cases}
$$

Since $p \geq 2$ and $|t|<\mu$, we know

$$
\left|2^{\frac{p-1}{p}} \sqrt[p]{|t|^{p}+\mu^{p}}-\mu-|t|\right| \leq 2^{\frac{p-1}{p}} \sqrt[p]{|t|^{p}+\mu^{p}}+\mu+|t|<4 \mu .
$$

Therefore, we obtain

$$
\left|\varphi_{p}(\mu, t)-|t|\right|<4 \mu
$$



Figure 1. $\mu=0.1, p=2$


Figure 2. $\mu=0.1, p=4$
From figures, we find that $\varphi_{p}$ will be close to $|x|$ when $\mu \downarrow 0$. In fact, for any $\mu>0$, we obtain

$$
\lim _{|t| \rightarrow \infty}\left|\varphi_{p}(\mu, t)-|t|\right|=0, \quad \lim _{|t| \rightarrow \infty}\left|\phi_{p}(\mu, t)-|t|\right|=0
$$

and

$$
\begin{aligned}
& \max _{t \in \mathbb{R}}\left|\varphi_{p}(\mu, t)-|t|\right|=\left|\varphi_{p}(\mu, 0)\right|=\left|2^{\frac{p-1}{p}} \sqrt[p]{\mu^{p}}-\mu\right|=\left(2^{\frac{p-1}{p}}-1\right) \mu, \\
& \max _{t \in I R}\left|\phi_{p}(\mu, t)-|t|\right|=\left|\phi_{p}(\mu, 0)\right|=\mu .
\end{aligned}
$$

As $p \in[2,+\infty), \sqrt{2}<2^{\frac{p-1}{p}}<2$, this gives that $\left(2^{\frac{p-1}{p}}-1\right) \mu<\mu$. The above expressions indicate that $\varphi_{p}$ is the function which best approximates the function $|t|$.

For any $p \geq 2$, let

$$
\begin{equation*}
\psi_{p}(\mu, x)=\left(\varphi_{p}\left(\mu, x_{1}\right), \cdots, \varphi_{p}\left(\mu, x_{n}\right)\right)^{T}, \quad \forall(\mu, x) \in I R_{+} \times I R^{n} . \tag{4}
\end{equation*}
$$



Figure 3. $\mu=0.01, p=2$


Figure 4. $\mu=0.01, p=4$
Define the function $G_{p}: I R_{+} \times I R^{n} \rightarrow I R^{n+1}$ by

$$
\begin{equation*}
G_{p}(\mu, x)=\binom{\mu}{A x+B \psi_{p}(\mu, x)-b} . \tag{5}
\end{equation*}
$$

Lemma 2.2. Let $\psi_{p}(\mu, x)$ be defined by (4). Then
(i) $\psi_{p}(\mu, x)$ is a regular smoothing function of $|x|$.
(ii) For $p=2, \psi_{p}(\mu, x)$ approximates $|x|$ quadratically.

Proof: (i) According Lemma 2.1 (ii), we find that

$$
\left\|\psi_{p}(\mu, x)-|x|\right\| \leq\left|\varphi_{p}\left(\mu, x_{1}\right)-\left|x_{1}\right|\right|+\cdots+\left|\varphi_{p}\left(\mu, x_{n}\right)-\left|x_{n}\right|\right|<4 n \mu .
$$

(ii) From Lemma 2.6 (ii) in [14], part (ii) is clear.

Lemma 2.3. Let $G_{p}(\mu, x)$ be defined by (5). Then
(i) $G_{p}(\mu, x)=0 \Leftrightarrow x$ solves AVE (1).
(ii) $G_{p}$ is continuously differentiable on $I R_{++} \times I R^{n}$ with

$$
G_{p}^{\prime}(\mu, x)=\left(\begin{array}{cc}
1 & 0 \\
B \frac{\partial \psi_{p}(\mu, x)}{\partial \mu} & A+B \frac{\partial \psi_{p}(\mu, x)}{\partial x}
\end{array}\right),
$$

where

$$
\begin{aligned}
& \frac{\partial \psi_{p}(\mu, x)}{\partial \mu}=\left(\frac{\partial \varphi_{p}\left(\mu, x_{1}\right)}{\partial \mu}, \cdots, \frac{\partial \varphi_{p}\left(\mu, x_{n}\right)}{\partial \mu}\right)^{T} \\
& \frac{\partial \psi_{p}(\mu, x)}{\partial x}=\operatorname{diag}\left(\frac{\partial \varphi_{p}\left(\mu, x_{1}\right)}{\partial x_{1}}, \cdots, \frac{\partial \varphi_{p}\left(\mu, x_{n}\right)}{\partial x_{n}}\right)
\end{aligned}
$$

Proof: To prove the result (i), we recall the AVE (1) and Lemma 2.2 (i). Therefore, part (i) holds. In addition, part (ii) is straightforward.

Now, we state the following assumption.
Assumption 2.1. The minimal singular value of the matrix $A$ is strictly greater than the maximal singular value of the matrix $B$.

Lemma 2.4. ([13]) The AVE (1) is uniquely solvable for any $b \in I R^{n}$ if Assumption 2.1 is satisfied.
3. The Smoothing Algorithm and Its Convergence Properties. In this section, instead of solving the AVE (1), one may solve $G_{p}(\mu, x)=0$. Hence, we focus on the smoothing algorithm discussed in [13]. By making $\mu \downarrow 0$, a solution of AVE (1) can be founded.

## Algorithm

Step 0. Choose $\sigma, \delta \in(0,1), p \in[2,+\infty), \mu_{0}>0, x^{0} \in I R^{n}$. Set $z^{0}=\left(\mu_{0}, x^{0}\right)$. Let $e^{0}=(1,0) \in I R \times I R^{n}$. Select $\beta>1$ such that $\min \left\{1,\left\|G_{p}\left(z^{0}\right)\right\|\right\} \leq \sqrt{\beta \mu_{0}}$. Set $k=0$.

Step 1. If $\left\|G_{p}\left(z^{k}\right)\right\|=0$, stop. Otherwise, compute $\gamma_{k}=\min \left\{1,\left\|G_{p}\left(z^{k}\right)\right\|\right\}$.
Step 2. Get $\triangle z^{k}=\left(\triangle \mu_{k}, \Delta x^{k}\right)$ by

$$
\begin{equation*}
G_{p}^{\prime}\left(z^{k}\right) \triangle z^{k}=-G_{p}\left(z^{k}\right)+\frac{1}{\beta} \gamma_{k}^{2} e^{0} \tag{6}
\end{equation*}
$$

Step 3. Set $\alpha_{k}$ to be the maximum of the values $1, \delta, \delta^{2}, \cdots$ satisfying

$$
\begin{equation*}
\left\|G_{p}\left(z^{k}+\alpha_{k} \triangle z^{k}\right)\right\| \leq\left[1-\sigma\left(1-\frac{1}{\beta}\right) \alpha_{k}\right]\left\|G_{p}\left(z^{k}\right)\right\| . \tag{7}
\end{equation*}
$$

Step 4. Let $z^{k+1}=\left(\mu_{k+1}, x^{k+1}\right)=z^{k}+\alpha_{k} \triangle z^{k}$. Replace $k=k+1$ and go to Step 1.
According to Assumption 2.1, following the same arguments as in [13], it is obvious that the convergence properties of our algorithm are similar to that in [13]. Therefore, we omit the proof.

Theorem 3.1. Let $p \in[2,+\infty)$ and Assumption 2.1 be satisfied. Suppose that the sequence $\left\{z^{k}\right\}$ is generated by our algorithm with $z^{*}=\left(\mu_{*}, x^{*}\right)$ being an accumulation point. Then, we have
(i) $\lim _{k \rightarrow \infty} z^{k}=z^{*}$.
(ii) $\left\|z^{k+1}-z^{*}\right\|=O\left(\left\|z^{k}-z^{*}\right\|^{2}\right)$ and $\mu_{k+1}=O\left(\mu_{k}^{2}\right)$.
4. Numerical Results. In what follows, we report our numerical results for solving AVE (1) with the smoothing function chosen as the $\varphi_{p}$ and $\phi_{p}$ respectively. Our codes are finished by MATLAB. During the testing, we set the parameters in our algorithm as $\sigma=0.0001, \delta=0.2, \mu_{0}=0.0001$. The error tolerance is $\varepsilon=1.0 e-6$. The algorithm was terminated once $\left\|H\left(z^{k}\right)\right\|<\varepsilon$ or $\left|\left\|H\left(z^{k}\right)\right\|-\left\|H\left(z^{k+1}\right)\right\|\right|<\varepsilon$.

The testing problem: First, choose randomly $A \in I R^{200 \times 200}$ and $B \in I R^{200 \times 200}$ from $[-10,10]$. Second, let $[U, S, V]=\operatorname{svd}(A)$. If $\min \{S(i, i): 1 \leq i \leq n\}=0$, then
$A=V(S+0.01 I) V$, where $I$ is the identity matrix. Third, set $A=\frac{\lambda_{\max }\left(B^{T} B\right)+0.01}{\lambda_{\min }\left(A^{T} A\right)} A$. Finally, choose randomly $u \in I R^{200}$ from $[-1,1]$, and then let $b=A u+B|u|$.

Three cases of the starting point $x^{0}$ were considered. (i) Random $x^{0}$ from $[-1,1]$. (ii) $x^{0}=(1,1, \cdots, 1)^{T}$. (iii) $x^{0}=(0,0, \cdots, 0)^{T}$.

In our experiments, we select $p=2,3,4,5,6,7,8$ and every case is implemented ten times. Tables 1 and 2 contain our results. In our tables, Max, Min, It, T, Va and Fa

Table 1. Iterations for function $\varphi_{p}$

| $p$ |  | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Case (i) | Max | 4 | 7 | 4 | 4 | 4 | 4 | 4 |
|  | Min | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
|  | It | 3.1 | 3.5 | 3.1 | 3.3 | 3.1 | 3.1 | 3.1 |
|  | T | 0.0134 | 0.0174 | 0.0152 | 0.0155 | 0.0152 | 0.0146 | 0.0152 |
|  | Va | 7.85E-07 | $1.01 \mathrm{E}-06$ | $1.83 \mathrm{E}-07$ | $9.01 \mathrm{E}-07$ | $3.79 \mathrm{E}-07$ | $3.54 \mathrm{E}-07$ | $5.26 \mathrm{E}-07$ |
|  | Fa | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Case (ii) | Max | 4 | 4 | 4 | 10 | 4 | 4 | 4 |
|  | Min | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
|  | It | 3.2 | 3.1 | 3.4 | 3.9 | 3.1 | 3.1 | 3.1 |
|  | T | 0.0130 | 0.0146 | 0.0159 | 0.0182 | 0.0151 | 0.0141 | 0.0144 |
|  | Va | 6.35E-07 | $2.57 \mathrm{E}-07$ | 8.27E-07 | 9.68E-06 | $3.37 \mathrm{E}-07$ | $3.22 \mathrm{E}-07$ | $2.59 \mathrm{E}-07$ |
|  | Fa | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Case (iii) | Max | 4 | 5 | 4 | 10 | 4 | 3 | 11 |
|  | Min | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
|  | It | 3.2 | 3.3 | 3.2 | 4 | 3.1 | 3 | 4 |
|  | T | 0.0131 | 0.0180 | 0.0152 | 0.0191 | 0.0148 | 0.0141 | 0.0185 |
|  | Va | 6.95E-07 | 7.05E-07 | $2.36 \mathrm{E}-06$ | 6.76E-06 | $1.14 \mathrm{E}-06$ | $2.04 \mathrm{E}-07$ | $2.75 \mathrm{E}-06$ |
|  | Fa | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

Table 2. Iterations for function $\phi_{p}$

| $p$ |  | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Case (i) | Max | 11 | 8 | 5 | 15 | 4 |  | 5 |
|  | Min | 6 | 4 | 3 | 3 | 3 | 3 | 3 |
|  | It | 9.7 | 4.9 | 3.7 | 4.9 | 3.2 | 3.1 | 3.4 |
|  | T | 0.0375 | 0.0156 | 0.0166 | 0.0159 | 0.0147 | 0.0110 | 0.0164 |
|  | Va | $2.45 \mathrm{E}-07$ | 2.80E-07 | 6.14E-06 | $1.72 \mathrm{E}-06$ | 4.19E-07 | 4.13E-07 | $1.54 \mathrm{E}-06$ |
|  | Fa | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Case (ii) | Max | 11 | 8 | 6 | 4 | 4 | 5 | 8 |
|  | Min | 5 | 4 | 3 | 3 | 3 | 3 | 3 |
|  | It | 8.2 | 5.6 | 4 | 3.3 | 3.3 | 3.3 | 3.6 |
|  | T | 0.0208 | 0.0237 | 0.0137 | 0.0112 | 0.0113 | 0.0115 | 0.0123 |
|  | Va | $4.62 \mathrm{E}-07$ | 9.89E-07 | 1.28E-06 | $4.89 \mathrm{E}-07$ | $4.66 \mathrm{E}-07$ | $3.66 \mathrm{E}-07$ | $3.34 \mathrm{E}-06$ |
|  | Fa | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Case (iii) | Max | 12 | 6 | 5 | 7 | 6 | 4 | 4 |
|  | Min | 4 | 4 | 3 | 3 | 3 | 3 | 3 |
|  | It | 7.2 | 4.3 | 3.8 | 4 | 3.7 | 3.2 | 3.4 |
|  | T | 0.0184 | 0.0138 | 0.0125 | 0.0138 | 0.0123 | 0.0117 | 0.0114 |
|  | Va | $4.32 \mathrm{E}-07$ | 1.93E-07 | 1.03E-06 | $7.49 \mathrm{E}-07$ | $1.80 \mathrm{E}-06$ | $2.61 \mathrm{E}-07$ | $4.60 \mathrm{E}-07$ |
|  | Fa | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

mean the maximal number of iterations, the minimal number of iterations, the average value of the iterations, the average value of the CPU time in seconds, the average value of $\left\|H\left(z^{k}\right)\right\|$ when algorithm stops and the total number of algorithm fails, respectively.

From Tables 1 and 2, we see that the numerical performance based on our function $\varphi_{p}$ is better when $p=2$ and $p=3$. On the whole, our function can solve the testing problems in few iterations and little CPU time. Therefore, the smoothing method based on the function $\varphi_{p}$ is effective for solving AVE.
5. Conclusions. In this paper, we discuss a new smoothing function. By using this function, we reformulate the AVE as a smoothing system. Then, we apply a smoothing Newton algorithm to solving it. We find that $\varphi_{p}$ is the one which best approximates the function $|t|$, and it is also the best when the numerical results are taken into account. Therefore, for future work, comparison with other types of algorithms is desirable.

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## REFERENCES

[1] J. Rohn, A theorem of the alternatives for the equation $A x+B|x|=b$, Linear and Multilinear Algebra, vol.52, pp.421-426, 2004.
[2] O. L. Mangasarian, Absolute value programming, Computational Optimization and Applications, vol.36, pp.43-53, 2007.
[3] O. L. Mangasarian, Absolute value equation solution via dual complementarity, Optimization Letters, vol.7, pp.625-630, 2013.
[4] O. L. Mangasarian, Absolute value equation solution via linear programming, Journal of Optimization Theory and Applications, vol.161, pp.870-876, 2014.
[5] O. L. Mangasarian, Primal-dual bilinear programming solution of the absolute value equation, $O p$ timization Letters, vol.6, pp.1527-1533, 2012.
[6] O. L. Mangasarian, A hybrid algorithm for solving the absolute value equation, Optimization Letters, vol.9, pp.1469-1474, 2015.
[7] J. Rohn, On unique solvability of the absolute value equation, Optimization Letters, vol.3, pp.603606, 2009.
[8] J. Rohn, A residual existence theorem for linear equations, Optimization Letters, vol.4, pp.287-292, 2010.
[9] J. Rohn, An algorithm for computing all solutions of an absolute value equation, Optimization Letters, vol.6, pp.851-856, 2012.
[10] J. Rohn, An algorithm for solving the absolute value equation, Electronic Journal of Linear Algebra, vol.18, pp.589-599, 2009.
[11] O. A. Prokopyev, On equivalent reformulations for absolute value equations, Computational Optimization and Applications, vol.44, pp.363-372, 2009.
[12] O. L. Mangasarian and R. R. Meyer, Absolute value equations, Linear Algebra and Its Applications, vol.419, pp.359-367, 2006.
[13] X. Q. Jiang and Y. Zhang, A smoothing-type algorithm for absolute value equations, Journal of Industrial and Management Optimization, vol.9, pp.789-798, 2013.
[14] L. Caccetta, B. Qu and G. L. Zhou, A globally and quadratically convergent method for absolute value equations, Computational Optimization and Applications, vol.48, pp.45-58, 2011.

