# ON A SECOND-ORDER STEP-SIZE ALGORITHM| 

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#### Abstract

In this paper we present a modification of the second-order step-size algorithm. This modification is based on the so called "forcing functions". It is proved that this modified algorithm is well-defined. It is also proved that every point of accumulation of the sequence generated by this algorithm is a second-order point of the nonlinear programming problem. Two different convergence proofs are given having in mind two interpretations of the presented algorithm.


Keywords: Forcing function, step-size algorithm, second-order conditions.

## 1. INTRODUCTION

We are concerned with the following problem of the unconstrained optimization:

$$
\begin{equation*}
\min \{\varphi(x) \mid x \in D\} \tag{1}
\end{equation*}
$$

where $\varphi: D \subset R^{n} \rightarrow R$ is a twicecontinuously differentiable function on an open set $D$. We consider iterative algorithms to find an optimal solution to problem (1) generating sequences of points $\left\{x_{k}\right\}$ of the following form:

$$
\begin{align*}
& x_{k+1}=x_{k}+\alpha_{k} s_{k}+\beta_{k} d_{k}, \quad k=0,1, \ldots,  \tag{2}\\
& s_{k}, d_{k} \neq 0, \quad\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle \leq 0, \tag{3}
\end{align*}
$$

and the steps $\alpha_{k}$ and $\beta_{k}$ are defined by a particular step-size algorithm.

[^0]Before we present the modified algorithm, we shall define the original secondorder step-size algorithm.

The original Mc Cormick-Armijo's second order step-size algorithm [4] defines $\alpha_{k}$ in the following way: $\alpha_{k}>0$ is a number satisfying

$$
\alpha_{k}=2^{-i(k)},
$$

where $i(k)$ is the smallest integer from $i=0,1, \ldots$, such that

$$
x_{k+1}=x_{k}+2^{-i(k)} s_{k}+2^{\frac{-i(k)}{2}} d_{k} \in D
$$

and

$$
\varphi\left(x_{k}\right)-\varphi\left(x_{k+1}\right) \geq \gamma\left[-\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle-\frac{1}{2}\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle\right] 2^{-i(k)}
$$

where $0<\gamma<1$ is a preassigned constant, $H(x)$ - the Hessian matrix of the function $\varphi$ at $x, s_{k}, d_{k}$-direction vectors satisfying relations (3).

We begin with the definition which we need in the following text.
Definition (See[5]). A mapping $\sigma:[0, \infty) \rightarrow[0, \infty$ ) is a forcing function if for any sequence $\left\{t_{k}\right\} \subset[0, \infty)$

$$
\lim _{k \rightarrow \infty} \sigma\left(t_{k}\right)=0 \quad \text { implies } \quad \lim _{k \rightarrow \infty} t_{k}=0
$$

and $\sigma(t)>0$ for $t>0$.
(The concept of the forcing function was introduced first by Elkin in [3].)

## 2. A MODIFICATION OF THE SECOND-ORDER STEP-SIZE ALGORITHM

The modified algorithm defines $\alpha_{k}$ in the following way: $\alpha_{k}>0$ is a number satisfying

$$
\alpha_{k}=q^{-i(k)}, \quad q>1
$$

where $i(k)$ is the smallest integer from $i=0,1, \ldots$, such that

$$
\begin{equation*}
x_{k+1}=x_{k}+q^{-i(k)} s_{k}+q^{\frac{-i(k)}{2}} d_{k} \in D \tag{4}
\end{equation*}
$$

and

$$
\begin{equation*}
\varphi\left(x_{k}\right)-\varphi\left(x_{k+1}\right) \geq q^{-i(k)}\left[\sigma_{1}\left(-\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle\right)+\sigma_{2}\left(-\frac{1}{2}\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle\right)\right] \tag{5}
\end{equation*}
$$

where $\sigma_{1}:[0, \infty) \rightarrow[0, \infty)$ and $\sigma_{2}:[0, \infty) \rightarrow[0, \infty)$ are the forcing functions such that $\delta_{1} t \leq \sigma_{1}(t) \leq \bar{\delta}_{1} t, \quad \delta_{2} t \leq \sigma_{2}(t) \leq \bar{\delta}_{2} t \quad 0<\delta_{1}<\bar{\delta}_{1}<1, \quad 0<\delta_{2}<\bar{\delta}_{2}<1 \quad$ and $s_{k}, d_{k} \quad$ are the direction vectors satisfying (3) and $\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle \leq 0$.

In order to have a finite value $i(k)$, it is sufficient that $s_{k}$ and $d_{k}$ satisfy (3) and, in addition, that

$$
\begin{equation*}
\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle<0 \text { whenever } \nabla \varphi\left(x_{k}\right) \neq 0 \tag{6~A}
\end{equation*}
$$

and

$$
\begin{equation*}
\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle<0 \quad \text { whenever } \nabla \varphi\left(x_{k}\right)=0 \tag{6B}
\end{equation*}
$$

Now we shall prove the first convergence theorem.
Theorem 1. Let $\varphi: D \subset R^{n} \rightarrow R$ be a twicecontinuously differentiable function on the open set $D$. Let the sequence $\left\{x_{k}\right\}$ be defined by relations (2), (3), (4),(5),(6A) and (6B). Let $\bar{x}$ be a point of accumulation of $\left\{x_{k}\right\}$ and $K_{1}$ a set of indices such that $x_{k} \rightarrow \bar{x}$ for $k \in K_{1}$.

Assume that:

1. the sequences $\left\{s_{k}\right\}$ and $\left\{d_{k}\right\}$ are uniformly bounded;
2. $\quad-\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle \geq \mu_{k}\left(\left\|\nabla \varphi\left(x_{k}\right)\right\|\right), \quad k \in K_{1}$, where $\mu_{k}:[0, \infty) \rightarrow[0, \infty), \quad k \in K_{1}$ are forcing functions;
3. there exists a value $\beta>0$ such that

$$
-\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle \geq \beta\left\langle H\left(x_{k}\right) e_{k}^{\min }, e_{k}^{\min }\right\rangle
$$

where $e_{k}^{\min }$ is an eigenvector of $H\left(x_{k}\right)$ associated with its minimum eigenvalue.
Then $\bar{x}$ is a stationary point, that is

$$
\nabla \varphi(\bar{x})=0
$$

and $H(\bar{x})$ is a positive semidefinite matrix with at least one eigenvalue equal to zero.
Proof: There are two cases to consider.
a) The integers $\{i(k)\}$ for $k \in K_{1}$ are uniformly bounded from above by some value I.
Because of the descent property it follows that all points of the accumulation have the same function value and

$$
\begin{aligned}
& (0 \geq) \varphi\left(x_{0}\right)-\varphi(\bar{x})=\sum_{k \in K_{1}}\left[\varphi\left(x_{k}\right)-\varphi\left(x_{k+1}\right)\right] \geq \\
& \geq \sum_{k \in K_{1}} q^{-i(k)}\left[\sigma_{1}\left(-\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle\right)+\sigma_{2}\left(-\frac{1}{2}\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle\right)\right] \geq \\
& \geq q^{-I} \delta \sum_{k \in K_{1}}\left[-\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle-\frac{1}{2}\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle\right], \quad\left(\delta=\max \left\{\delta_{1}, \delta_{2}\right\}\right)
\end{aligned}
$$

$$
\geq q^{-I} \delta \sum_{k \in K_{1}}\left[\mu_{k}\left(\left\|\nabla \varphi\left(x_{k}\right)\right\|\right)+\frac{1}{2} \beta\left\langle H\left(x_{k}\right) e_{k}^{\min }, e_{k}^{\min }\right\rangle\right]
$$

Since $\varphi(\bar{x})$ is finite and since each term in the brackets is greater than, or equal to zero for each $k \in K_{1}$, it follows that $\mu_{k}\left(\nabla \varphi\left(x_{k}\right)\right) \rightarrow 0 \Rightarrow\left\|\nabla \varphi\left(x_{k}\right)\right\| \rightarrow 0$ (according to the definition of forcing functions) $\Rightarrow \nabla \varphi(\bar{x})=0$ and that $\left\langle H(\bar{x}) \bar{e}_{\min }, \bar{e}_{\min }\right\rangle=0$, where $\bar{e}_{\min }$ is some accumulation point of $\left\{e_{k}^{\min }\right\}$ for $k \in K_{1}$.
b) There is a subset $K_{2} \subset K_{1}$ such that $\lim _{k \rightarrow \infty} i(k)=\infty$.

Because of the definition of $i(k)$, then either

$$
x_{k}+q^{-i(k)+1} s_{k}+q^{\frac{-i(k)+1}{2}} d_{k} \notin D
$$

or

$$
\begin{align*}
& \varphi\left(x_{k}\right)-\varphi\left(x_{k}+q^{-i(k)+1} s_{k}+q^{\frac{-i(k)+1}{2}} d_{k}\right)<  \tag{7}\\
& <q^{-i(k)+1}\left[\sigma_{1}\left(-\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle\right)+\sigma_{2}\left(-\frac{1}{2}\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle\right)\right]
\end{align*}
$$

If the former condition held infinitely often, then because

$$
x_{k}+q^{-i(k)+1} s_{k}+q^{\frac{-i(k)+1}{2}} d_{k} \rightarrow \bar{x}, \quad k \in K_{2}
$$

it would follow that $\bar{x}$ is on the boundary of $D$. Since $D$ is an open set, $\bar{x} \notin D$, it contradicts the theorem hypothesis. Therefore, without the loss of generality (7) can be considered to hold for all $k \in K_{2}$.

Since $\varphi \in C^{2}$, and since the sequences $\left\{s_{k}\right\}$ and $\left\{d_{k}\right\}$ are assumed to be uniformly bounded, the left -hand side of inequality (7) can be written as

$$
\begin{aligned}
& -q^{-i(k)+1}\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle-q^{\frac{-i(k)+1}{2}}\left\langle\nabla \varphi\left(x_{k}\right), d_{k}\right\rangle- \\
& -\frac{1}{2}\left\langle H\left(x_{k}\right)\left(q^{-i(k)+1} s_{k}+q^{\frac{-i(k)+1}{2}} d_{k}\right), q^{-i(k)+1} s_{k}+q^{\frac{-i(k)+1}{2}} d_{k}\right\rangle-o\left(q^{-i(k)+1}\right)< \\
& <q^{-i(k)+1}\left[\sigma_{1}\left(-\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle\right)+\sigma_{2}\left(-\frac{1}{2}\right)\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle\right]< \\
& <q^{-i(k)+1}\left[-\bar{\delta}_{1}\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle-\bar{\delta}_{2} \cdot \frac{1}{2}\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle\right]
\end{aligned}
$$

Combining terms and incorporating a term where appropriate into $o\left(q^{-i(k)+1}\right)$ yields (using the fact that $-\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle \geq 0$ ):

$$
o\left(q^{-i(k)+1}\right)>q^{-i(k)+1}\left[\left(-1+\bar{\delta}_{1}\right)\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle-\left(-\bar{\delta}_{2}+1\right) \frac{1}{2}\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle\right]
$$

Using the theorem hypothesis 3 we obtain
$o\left(q^{-i(k)+1}\right)>q^{-i(k)+1}\left[\left(-1+\bar{\delta}_{1}\right)\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle+\left(-\bar{\delta}_{2}+1\right) \frac{\beta}{2}\left\langle H\left(x_{k}\right) e_{k}^{\min }, e_{k}^{\min }\right\rangle\right]$.
Dividing by $q^{-i(k)+1}$ yields

$\geq\left(1-\bar{\delta}_{1}\right) \mu_{k}\left(\left\|\nabla \varphi\left(x_{k}\right)\right\|\right)+\frac{-\bar{\delta}_{2}+1}{2} \cdot \beta \cdot\left\langle H\left(x_{k}\right) e_{k}^{\min }, e_{k}^{\min }\right\rangle$.
Since each term is, according to the assumptions, greater than or equal to zero, taking the limit as $k \rightarrow \infty$ for $k \in K_{2}$ yields

$$
\mu_{k}\left(\left\|\nabla \varphi\left(x_{k}\right)\right\|\right) \rightarrow 0 \Rightarrow\left\|\nabla \varphi\left(x_{k}\right)\right\| \rightarrow 0 \Rightarrow \nabla \varphi(\bar{x})=0
$$

and

$$
\left\langle H\left(x_{k}\right) e_{k}^{\min }, e_{k}^{\min }\right\rangle \rightarrow\left\langle H(\bar{x}) \bar{e}_{\min }, \bar{e}_{\min }\right\rangle=0
$$

To prove the second convergence theorem we shall follow Y. Amaya [1]. Namely, we are going to show that the trajectory

$$
\begin{equation*}
f\left(t, x_{k}\right)=x_{k}+t^{2} s_{k}+t d_{k} \tag{8}
\end{equation*}
$$

proposed by the presented algorithm (i.e. satisfying the relations (2), (3), (4), (5), (6A) and (6B)) and

$$
\begin{align*}
& \left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle<0  \tag{9}\\
& \left\langle\nabla \varphi\left(x_{k}\right), d_{k}\right\rangle \leq 0
\end{align*}
$$

and

$$
\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle=0
$$

if $H\left(x_{k}\right)$ is positive semidefinite, and

$$
\begin{align*}
& \left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle \leq 0  \tag{10}\\
& \left\langle\nabla \varphi\left(x_{k}\right), d_{k}\right\rangle \leq 0
\end{align*}
$$

and

$$
\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle<0
$$

if $H\left(x_{k}\right)$ is not positive semidefinite, has the properties set out in Amaya's paper.
Firstly, we shall briefly present Amaya's algorithm [1].

Let $\varphi: D \subset R^{n} \rightarrow R$ be a twicecontinuously differentiable function on the open set $D$ (i.e. $\varphi \in C^{2}$ ) which we want to minimize, and $h: R^{+} \times D \rightarrow R^{n}$ is a function such that, for all $x \in D, h(0, x)=x$. We suppose that for every $x \in D, h(t, x)$ is $C^{2}$ for $t \geq 0$.

Given $x \in D$, the function $h(t, k)$ describes a trajectory in $D \subset R^{n}$ originating at $x$. The minimizing algorithm defines a sequence $\left\{x_{k}\right\}$ in the following way:

$$
x_{k+1}=\left\{\begin{array}{lll}
x_{k} & \text { if } & x_{k} \in M,  \tag{11}\\
h\left(t_{k}, x_{k}\right) & \text { if } & x_{k} \notin M,
\end{array}\right.
$$

where $M=\left\{x \in D \mid \nabla \varphi(x)=0\right.$ and $\left.\langle H(x) p, p\rangle \geq 0, p \in R^{n}\right\}$.
For $x \in D$, we define the $C^{2}$ - class function $f_{x}: R^{+} \rightarrow R^{n}$ by

$$
f_{x}(t)=\varphi[h(t, x)], t \in R^{+} .
$$

This function is shown to satisfy

$$
\begin{aligned}
& f_{x_{k}}^{\prime}(0)=\left\langle\nabla \varphi\left(x_{k}\right), \dot{h}\left(0, x_{k}\right)\right\rangle \quad \text { and } \\
& f_{x_{k}}^{\prime \prime}(0)=\left\langle H\left(x_{k}\right) \dot{h}\left(0, x_{k}\right), \dot{h}\left(0, x_{k}\right)+\left\langle\nabla \varphi\left(x_{k}\right), \ddot{h}\left(0, x_{k}\right)\right\rangle\right\rangle,
\end{aligned}
$$

where $\dot{h}$ and $\ddot{h}$ denote respectively the first and second derivatives of $h$ with respect to $t$.

The following assumptions are made:
A1. $L=\left\{x \in D \mid \varphi(x) \leq \varphi\left(x_{0}\right)\right\}$ is bounded;
A2. $f_{x}^{\prime}(0) \leq 0$ for all $x \notin M$;
A3. if $x \notin M$ and $f_{x}^{\prime}(0)=0$, then $f_{x}^{\prime \prime}(0)<0$.
Amaya in Theorem 3.1 in [1] proves the convergence of a subsequence of points of $\left\{x_{k}\right\}$ defined by (11) to $\bar{x} \in M$, provided that $\varphi \in C^{2}$ and that assumptions A1, A2, A3 hold.

Now we can present the second convergence theorem for the modified Mc Cormick-Armijo's algoritm.

Theorem 2. Under assumptions A1, A2 and A3 every point of accumulation $\bar{x}$ of the sequence $\left\{x_{k}\right\}$ generated by the modified McCormick-Armijo's algorithm and additionally, satisfying (9) and (10) belongs to $M$, that is, the second-order necessary conditions are satisfied at $\bar{x}$.

Proof: Let us suppose that $x_{k} \notin M$ for $k=0,1,2, \ldots$. From the choice of $t_{k}=\alpha_{k}$ by relations (2), (3), (4), (5), (6A) and (6B) we have that $f_{x_{k}}\left(t_{k}\right) \leq f_{x_{k}}(0)$, i.e. the sequence $\left\{\varphi\left(x_{k}\right)\right\}$ is decreasing; hence $\left\{x_{k}\right\} \subset L$. Due to the assumption A1, the sequence $\left\{x_{k}\right\}$ has a point of accumulation $\bar{x}$.

For the trajectory (8) we have:

$$
\begin{aligned}
& f_{x_{k}}^{\prime}(0)=\left\langle\nabla \varphi\left(x_{k}\right), \dot{h}\left(0, x_{k}\right)\right\rangle, \quad \dot{h}\left(0, x_{k}\right)=d_{k}, \\
& f_{x_{k}}^{\prime \prime}(0)=\left\langle H\left(x_{k}\right) \dot{h}\left(0, x_{k}\right), \dot{h}\left(0, x_{k}\right)+\left\langle\nabla \varphi\left(x_{k}\right), \ddot{h}\left(0, x_{k}\right)\right\rangle\right\rangle, \quad \ddot{h}\left(0, x_{k}\right)=s_{k}, \quad \text { i.e. } \\
& f_{x_{k}}^{\prime}(0)=\left\langle\nabla \varphi\left(x_{k}\right), d_{k}\right\rangle, \\
& f_{x_{k}}^{\prime \prime}(0)=\left\langle H\left(x_{k}\right) d_{k}, d_{k}\right\rangle+\left\langle\nabla \varphi\left(x_{k}\right), s_{k}\right\rangle .
\end{aligned}
$$

From (6A) it follows that the assumption A2 holds. Let us examine the assumption A3. Assuming $f_{x_{k}}^{\prime}(0)=0$, we have two cases:
a) if $H\left(x_{k}\right)$ is positive semidefinite, by applying (9) to the relation (11), we obtain $f_{x_{k}}^{\prime \prime}(0)<0 ;$
b) if $H\left(x_{k}\right)$ is not positive semidefinite, by applying (10) to the relation (11), we obtain

$$
f_{x_{k}}^{\prime \prime}(0)<0 .
$$

Following Amaya's proof of theorem 3.1 in [1] we conclude that $\bar{x} \in M$.

## 3. CONCLUSION

Because of general assumptions on the objective function $\varphi$, the modified algorithm can be used for solving a wide class of unconstrained optimization problems. Also, the choice of forcing functions $\sigma_{1}(t)$ and $\sigma_{2}(t)$, with the property $\delta_{1} t \leq \sigma_{1}(t) \leq \bar{\delta}_{1} t, \delta_{2} t \leq \sigma_{2}(t) \leq \bar{\delta}_{2} t, 0<\delta_{1}<\bar{\delta}_{1}<1,0<\delta_{2}<\bar{\delta}_{2}<1$ is wide.

Finally, this modified algorithm can be used for solving constrained optimization problems (see [2]) when constraints are adequately considered.

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[^0]:    * This research was supported by Science Fund of Serbia, grant number 04M03, through Institute of Mathematics, SANU. AMS Mathematics Subject Classification (1991): 90C30

