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# SEARCH FOR AN EXTREMUM USING THE STEEPEST DESCENT METHOD UNDER THE CONDITIONS OF EXPERIMENTAL ERRORS 

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#### Abstract

One of the spread first level methods of optimum search is learned by the steepest descent method in conditions when there are mistakes in the experiment. The steepest descent method is investigated and is successfully applied in situations, when, there are no mistakes of experiment. However, in real situations the used means of measurement always have determined errors owing to what the appropriate meanings of the response receives with mistakes. The model of the steepest descent algorithm in created, when the length of the step does not depend on the meaning of the purpose functioning. Stepping process realization algorithm and program provision in MathCAD, computer mathematic, system is designed. The realization outcome mistakes for different meaning are presented, the step movement of the optimum dot direction is shown according to function meaning and argument meaning as well. The amount needed for the tactics necessary to approach the minimum is established, the quake amplitude in the surrounding of different level experiment mistakes at the optimum search efficiency in different step conditions.


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Introduction. The steepest descent algorithm (in the vicinity of the value of the function argument) is an alternative procedure for the purpose of moving in the direction of the minimum from a given point to the lowest value. Such a direction is the opposite direction given by the gradient vector of the optimization function under the conditions of experimental error.

$$
\Delta f(x)=\left[\frac{\partial f}{\partial x_{1}}, \frac{\partial f}{\partial x_{2}}, \ldots, \frac{\partial f}{\partial x_{n}}\right]^{y}
$$

The general formula of the steepest descent method for finding the argument $\mathrm{x}(\mathrm{k}+1)$ with value $\mathrm{x}(\mathrm{k})$ on the k -step is as follows:

$$
x^{k+1}=x^{k}+\lambda^{k}+x^{k}
$$

Where $\mathrm{x}(\mathrm{k})$ is a unit of length vector at a point $\mathrm{x}(\mathrm{k})$ defined in the opposite direction of the gradient.

$$
S^{k}=-\frac{\nabla f\left(x^{k}\right)}{\left\|\nabla f\left(x^{k}\right)\right\|}
$$

$\left\|\nabla f\left(x^{k}\right)\right\|$ is $\nabla f\left(x^{k}\right)$ The length of the gradient vector

$$
\left\|\nabla f\left(x^{k}\right)\right\|=+\sqrt{\left(\frac{\partial f\left(x_{1}^{k}\right.}{\partial x_{1}}\right)^{2}+\left(\frac{\partial f\left(x_{2}^{k}\right)}{\partial x_{2}}\right)^{2}+\cdots+\left(\frac{\partial f\left(x_{n}^{k}\right)}{\partial x_{n}}\right)^{2}} .
$$

$\lambda^{k}$ Gradient procedure step.

If the step is constant and does not depend on the minimization function, then there will be a constant oscillation in the vicinity of the maximum, the amplitude of which will depend on the value of and the shape of the minimization function. One way to perfect a method with a constant step without the existing complication of the algorithm is to use a step whose magnitude decreases according to the iterative process, i.e. depends on the k step. Such an attitude can be expressed in several different formulas:

$$
\begin{gathered}
\lambda^{k}=\frac{a}{b+k^{\beta}} \\
\lambda^{k}=d \cdot b^{\alpha}
\end{gathered}
$$

Where $\mathrm{a}, \mathrm{b}, \beta, \alpha$ are "positive constants".
The algorithm for this modification reduces and suppresses the oscillation around the extremum when $k \rightarrow \infty$ but, at the same time, the algorithm has a downside if the extremum of the function has a small gradient. Then the step $\lambda^{k}$ precedes the reduction already away from the extreme. Therefore the extreme approach can be reduced quite significantly or a much larger number of iterations may be required, making it necessary to determine the step according to the specific function [1].


Fig.1. Concave quadratic function
Consider a concave quadratic function $f(x, y)=x^{2}+\mu \cdot y^{2}$ (Fig. 1). Its inclination is determined by the parameter: when $\mu=1$, the function $\mathrm{f}(\mathrm{x}, \mathrm{y})$ is a circular parabola, when $\mu>1$ - The paraboloid becomes elliptical, stretching along the x -axis; And when $\mu<1$ - Stretched towards the axis.

Materials and Methods. We carried out the software implementation of the fastest climbing algorithm in the mathematical software Mathcad system. To implement the algorithm, we defined the formulas and parameters to be calculated by the gradient method: vmax $=20$ maximum number of iterations; $\mathrm{v}=0 \ldots$ vmax - range of iteration change, $\mathrm{x} 0=2$ - initial value of the argument $\mathrm{x} ; \mathrm{y} 0=-1 \quad$ the initial value of the argument y ; $\mathrm{f} 0=\mathrm{f}(\mathrm{x} 0, \mathrm{y} 0)$ - the significance of the optimization function at the starting points; $\lambda 0=0.3$ - the initial value of the step, $\mathrm{q}_{\mathrm{x}}(\mathrm{x} . \mathrm{y})=2 * \mathrm{x}$ - with respect to the private derivative of the objective function $\mathrm{x} ; \mathrm{q} \mathrm{x}(\mathrm{x}, \mathrm{y})=2 \mu \mathrm{y}$ - with respect to the private derivative of the objective function y .

Vector length $L(x . y)=\sqrt{g_{-} x(x, y)^{2}+g_{-} y(x, y)^{2}}$
$\mathrm{s}_{-} \mathrm{x}(\mathrm{x}, \mathrm{y})$ and $\mathrm{s}_{-} \mathrm{y}(\mathrm{x}, \mathrm{y})$ planes on the $\mathrm{x} . \mathrm{y}$ axis in the opposite direction of the gradient vector

$$
S_{-} x(x, y)=\frac{-g_{-} x(x . y)}{L(x, y)} ; \quad S_{-} y(x, y)=\frac{-g_{-} y(x, y)}{L(x, y)} .
$$

Step determination parameters

$$
\begin{aligned}
\alpha:=1 ; \quad \beta & :=1 ; \quad \gamma:=0 \\
\operatorname{Step}(\mathrm{v}) & :=\frac{\alpha \cdot \lambda 0}{\beta+\gamma \cdot \mathrm{v}} \\
\lambda(\mathrm{x}, \mathrm{y}) & :=\operatorname{Step}(\mathrm{v})
\end{aligned}
$$

Vector initial values of the gradient procedure

$$
\left[\begin{array}{c}
x_{0} \\
y_{0} \\
f f_{0}
\end{array}\right]=\left[\begin{array}{c}
x 0 \\
y 0 \\
f(x 0, y 0)
\end{array}\right]
$$

Formula for changing vector components during a gradient procedure

$$
\left[\begin{array}{c}
x_{v+1} \\
Y_{v+1} \\
f f_{v+1}
\end{array}\right]=\left[\begin{array}{c}
x_{v}+\lambda\left(x_{v}, Y_{v}\right) \cdot S_{-} X\left(x_{v}, Y_{v}\right) \\
Y_{v}+\lambda\left(X_{v}, Y_{v}\right) \cdot S_{-} X\left(X_{v}, Y_{v}\right) \\
f\left(x_{v}+\lambda\left(X_{v}, Y_{v}\right) \cdot S_{-} X\left(X_{v}, Y_{v}\right) Y_{v}+\lambda\left(x_{v}, Y_{v}\right) \cdot S_{-} Y\left(X_{v}, Y_{y}\right)\right.
\end{array}\right]
$$

With the initial value of the parameter, self-oscillation starts from the seventh measure (Fig.2)
Based on the obtained value, we can determine how many step became necessary to approximate the minimum, With the initial value of the parameter, self-oscillation starts from the seventh step (Fig.2)

$$
\sqrt{(0,122+0,147)^{2}(0,061+0,073)^{2}}=0,301 .
$$

The average value of the objective function at these coordinates is equal to 0.023 (as the result shows, the step length matches the value of the amplitude $\lambda=0.3$ )


As can be seen from Fig. 3, at least in the vicinity there is a self-oscillation. If the paraboid is a circular ( $\mu=1$ ), then the amplitude with respect to both variables will be equal. Under error conditions [2] we implemented the algorithm $\mu$ different ( $\mu=0,25 ; 0,5 ; 0,75 ; 1 ; 1,25 ; 1,50 ; 1,75$ ) and the initial step $\lambda(\lambda=0,1 ; 0,2)$ for different values, the results obtained are given in the table

Table 1. Research Results.

| $\mu=1 ; \lambda=0,1$ |  |  |  |  | $\mu=1 ; \lambda=0,2$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Interaction N | X | Y | Mean value of the function | Interaction N | X | Y | Mean value of the function |
| 0 | 11 | 0.032 | -0.016 | 10.014 | 22 | 0.032 | -0.016 | 10.0025 |
|  |  | -0.147 | 0.07 |  |  | -0.057 | 0.029 |  |
| 10\% | 14 | -0.154 | 0.077 | 10.067 | 26 | -0.12 | 0.06 | 9.862 |
|  |  | 0.062 | -0.031 |  |  | -0.012 | 0.0061 |  |
| 20\% | 14 | -0.161 | 0.08 | 10.1225 | 26 | -0.038 | 0.019 | 10.029 |
|  |  | 0.091 | -0.046 |  |  | 0.061 | -0.03 |  |
| $\mu=1.25 ; \lambda=0.2$ |  |  |  |  | $\mu=1,25 ; \lambda=0.2$ |  |  |  |
|  | Interaction N | X | Y | Mean value of the function | Interaction N | X | Y | Mean value of the function |
| 0 | 24 | 0.044 | -0.011 | 10.0025 | 11 | 0.047 | 0.00011 | 10.0125 |
|  |  | -0.052 | 0.018 |  |  | -0.153 | $0.00051$ |  |
| 10\% | 27 | 0.05 | -0.057 | 9.93 | 14 | -0.152 | 0.055 | 10.057 |
|  |  | 0.0076 | 0.025 |  |  | 0.068 | -0.045 |  |
| 20\% | 28 | 0.096 | 0.0064 | 9.701 | 14 | -0.143 | 0.091 | 10.124 |
|  |  | 0.047 | 0.0023 |  |  | 0.079 | -0.085 |  |

Continuation of table 1.

| $\mu=1,5 ; \lambda=0,1$ |  |  |  |  | $\mu=1,5 ; \lambda=0.2$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Interaction N | X | Y | Mean value of the function | Interaction N | X | Y | Mean value of the function |
| 0 | 23 | -0.038 | 0.0019 | 10.0025 | 17 | 0.0021 | 0.072 | 10.0167 |
|  |  | 0.062 | 0.0057 |  |  | -0.0016 | -0.128 |  |
| 10\% | 29 | $0.0038$ | 0.025 | 9.842 | 15 | 0.098 | 0.0092 | 10.146 |
|  |  | 0.0039 | -0.05 |  |  | 0.077 | -0.0115 |  |
| 20\% | 29 | -0.039 | -0.004 | 9.67 | 16 | 0.00334 | 0.034 | 10.23 |
|  |  | 0.033 | 0.0073 |  |  | -0.0098 | 0.166 |  |
| $\mu=1.75 ; \lambda=0.1$ |  |  |  |  | $\mu=1.75 ; \lambda=0.2$ |  |  |  |
|  | Interaction N | X | Y | Mean value of the function | Interaction N | X | Y | Mean value of the function |
| 0 | 23 | -0.019 | 0.00039 | 10.0025 | 16 | -0.00712 | -0.108 | 10.0175 |
|  |  | 0.081 | -0.0032 |  |  | 0.00043 | 0.092 |  |
| 10\% | 29 | -0.023 | -0.031 | 9.84 | 15 | 0.095 | 0.079 | 10.153 |
|  |  | 0.011 | 0.049 |  |  | -0.00542 | -0.067 |  |
| 20\% | 27 | 0.032 | 0.00254 | 9.862 | 15 | 0.152 | -0.019 | 10.292 |
|  |  | -0.067 | -0.011 |  |  | -0.0018 | 0.014 |  |



Fig. 4.


Fig. 5.

Conclusions. Graphical images are constructed according to the results of the table for visuals (as shown in Fig. 5, when the step length $\lambda=0.2$, the effect of the errors on the value of the objective function is significant at $\xi=20 \%$. Ranges from 10.096 to 10.284 For the values $\mu=1.75$ and $\mu=0.75$, the distance to the extreme point averages 0.28 , a relatively efficient search $\mu=0.25, \mu=1.25$, and $\mu=$ 1 In this case, the mean deviation is 0.12 , the reduction in efficiency is noteworthy for $\mu=0.5$ for the value as shown in the figure. -Times are decreasing. When the step length $\lambda=0,1$ (Fig. 4), then the largest deviation from the minimum point is equal to 0.33 and this is fixed $\mu=0,25 ; \mu=1.25$; And for $\mu=1$ values. Search efficiency $\mu=0.5$ is relatively effective; for the values of $\mu=0.75$ and $\mu=1.75$

Interestingly, autocorrelation under error conditions, for the value $\mu=1$, i.e. when the function is a circular paraboloid, starts relatively quickly. However, a more effective search value than $\mu$ value has already been achieved for this iteration than $\mu$ for other values.

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