# Lecture 4. Tikhonov method for equations with convex functional. Local strict convexity of the Tikhonov functional for non-linear operators. 

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## 1 Tikhonov method for equations with convex functional

Tikhonov scheme allows to construct approximation methods for solution of equation $F(x)=$ 0 not only for special case of operator $F$, when $F=A x-f$.

In this lesson we will analyze more common case when functional $\Phi$ is convex, but not necessary quadratic. As before, we assume that $F=F\left(N_{1}, N_{2}\right)$. If equation have form $A x=f$, then corresponding functional

$$
\Phi(x)=\frac{1}{2}\|A x-f\|_{H_{2}}^{2}
$$

is convex and class of operator equations which we are interested in, is not empty. This class is extension of class $F\left(N_{1}, 0\right)$. Differentiating Tikhonov functional

$$
\Phi_{\alpha}(x)=\frac{1}{2}\|A x-f\|_{H_{2}}^{2}+\frac{1}{2} \alpha\left\|x-x_{0}\right\|_{H_{1}}^{2}
$$

gives as

$$
\Phi_{\alpha}^{\prime}(x)=\Phi^{\prime}(x)+\alpha\left(x-x_{0}\right), x \in H_{1}
$$

Because functional $\Phi$ is convex, we have

$$
\left(\Phi^{\prime}(x)-\Phi^{\prime}(y), x-y\right)_{H_{1}} \geq 0, \forall x, y \in H_{1}
$$

Thus,

$$
\begin{equation*}
\left(\Phi_{\alpha}^{\prime}(x)-\Phi_{\alpha}^{\prime}(y), x-y\right)_{H_{1}} \geq \alpha\|x-y\|_{H_{1}}^{2}, \forall x, y \in H_{1} \tag{1}
\end{equation*}
$$

Equation (2) says that functional $\Phi_{\alpha}$ is strongly convex in $H_{1}$ for $\forall \alpha>0$. from theory of convex optimization is known that in this case exists unique global minimizer of this problem which realizes minimum of functional $\Phi_{\alpha}$ in $H_{1}$.

$$
\begin{equation*}
\Phi_{\alpha}\left(x_{\alpha}\right)=\inf _{x \in H_{1}} \Phi_{\alpha}(x), \alpha>0 \tag{2}
\end{equation*}
$$

In optimization theory there exists a lot of minimization methods for strongly convex functionals. In all algorithms we face out with two difficulties:

- first problem is that there are not convergence estimates of $x_{\alpha}$ to $x^{*}$ when $\alpha \rightarrow 0$.
- second problem is that iterative processes are less effective with reducing of parameter $\alpha$ since these processes requires increasing of optimization iterations when $\alpha \rightarrow 0$.

Let us clarify this on one example when we apply gradient method for minimizing of functional $\Phi_{\alpha}$ :

$$
\begin{equation*}
x_{0} \in H_{1}: x_{n+1}=x_{n}-\gamma \Phi_{\alpha}^{\prime}\left(x_{n}\right), n=0,1, \ldots \tag{3}
\end{equation*}
$$

Because of (3) and necessary minimum condition

$$
\Phi_{\alpha}^{\prime}\left(x_{\alpha}\right)=\Phi^{\prime}\left(x_{\alpha}\right)+\alpha\left(x_{\alpha}-x_{0}\right)=0, n=0,1, \ldots
$$

we have

$$
\begin{align*}
\left\|x_{n+1}-x_{\alpha}\right\|_{H_{1}}^{2} & =\left\|x_{n}-x_{\alpha}-\gamma\left(\Phi_{\alpha}^{\prime}\left(x_{n}\right)-\Phi^{\prime}\left(\alpha\left(x_{\alpha}\right)\right)\right)\right\|_{H_{1}}^{2} \\
& =\left\|x_{n}-x_{\alpha}\right\|_{H_{1}}-2 \gamma\left(\Phi_{\alpha}^{\prime}\left(x_{n}\right)-\Phi_{\alpha}^{\prime}\left(x_{\alpha}\right), x_{n}-x_{\alpha}\right)_{H_{1}}  \tag{4}\\
& +\gamma^{2}\left\|\Phi_{\alpha}^{\prime}\left(x_{n}\right)-\Phi_{\alpha}^{\prime}\left(x_{\alpha}\right)\right\|_{H_{1}}^{2} .
\end{align*}
$$

Remind that

$$
\Phi^{\prime}(x)=F^{*^{\prime}}(x) F(x), \quad x \in H_{1} .
$$

Following estimate takes place

$$
\begin{align*}
\left\|\Phi_{\alpha}^{\prime}\left(x_{n}\right)-\Phi_{\alpha}^{\prime}\left(x_{\alpha}\right)\right\|_{H_{1}}^{2} & \leq \\
& \leq\left\|\Phi^{\prime}\left(x_{n}\right)-\Phi^{\prime}\left(x_{\alpha}\right)\right\|_{H_{1}}+\alpha\left\|x_{n}-x_{\alpha}\right\|_{H_{1}} \\
& \leq\left\|F^{\prime *}\left(x_{n}\right)\right\|_{L\left(H_{1}, H_{2}\right)}\left\|F\left(x_{n}\right)-F\left(x_{\alpha}\right)\right\|_{H_{2}} \\
& +\left\|F^{\prime *}\left(x_{n}\right)-F^{\prime *}\left(x_{\alpha}\right)\right\|_{L\left(H_{2}, H_{1}\right)}\left\|F\left(x_{\alpha}\right)\right\|_{H_{2}}  \tag{5}\\
& +\alpha\left\|x_{n}-x_{\alpha}\right\|_{H_{1}} \\
& \leq\left(N_{1}^{2}+N_{2}\left\|F\left(x_{\alpha}\right)\right\|_{H_{2}}+\alpha\right)\left\|x_{n}-x_{\alpha}\right\|_{H_{1}} .
\end{align*}
$$

By definition of $x_{\alpha}$

$$
\Phi_{\alpha}\left(x_{\alpha}\right)=\frac{1}{2}\left\|F\left(x_{\alpha}\right)\right\|_{H_{2}}^{2}+\frac{\alpha}{2}\left\|x_{\alpha}-x_{0}\right\|_{H_{1}}^{2} \leq \Phi_{\alpha}\left(x_{x_{o}}^{*}-x_{0}\right)_{H_{1}}^{2}
$$

and thus

$$
\begin{equation*}
\left\|F\left(x_{\alpha}\right)\right\|_{H_{2}} \leq \sqrt{\alpha} \Phi_{\alpha}\left(x_{x_{o}}^{*}-x_{0}\right)_{H_{1}} \tag{6}
\end{equation*}
$$

From estimates (5) and (6) follows that

$$
\begin{align*}
\left\|\Phi_{\alpha}^{\prime}\left(x_{n}\right)-\Phi_{\alpha}^{\prime}\left(x_{\alpha}\right)\right\|_{H_{1}}^{2} & \leq L\left\|x_{n}-x_{\alpha}\right\|_{H_{1}}, \\
L & =N_{1}^{2}+N_{2}\left\|x_{x_{0}}^{*}-x_{0}\right\|_{H_{1}} \sqrt{\alpha}+\alpha . \tag{7}
\end{align*}
$$

Substituting estimates (5) and (7) in (4) and using (2) we can get

$$
\begin{equation*}
\left\|x_{n+1}-x_{\alpha}\right\|_{H_{1}}^{2} \leq \sqrt{1-2 \gamma \alpha+\gamma^{2} L^{2}}\left\|x_{n}-x_{\alpha}\right\|_{H_{1}} \tag{8}
\end{equation*}
$$

We see that for $\forall \gamma>0$ in (8) $1-2 \gamma \alpha+\gamma^{2} L^{2}>0$. Value of $\gamma$ we should choose like that expression $1-2 \gamma \alpha+\gamma^{2} L^{2}$ should be small. We can require that

$$
1-2 \gamma \alpha+\gamma^{2} L^{2}<1
$$

For this it is sufficient that following condition should be fullfilled

$$
\begin{equation*}
0<\gamma<\frac{2 \alpha}{L^{2}} \tag{9}
\end{equation*}
$$

In the case that (9) is true we have

$$
\begin{array}{r}
\left\|x_{n}-x_{\alpha}\right\|_{H_{1}}^{2} \leq \sqrt{1-2 \gamma \alpha+\gamma^{2} L^{2}}\left\|x_{0}-x_{\alpha}\right\|_{H_{1}} q^{n}(\alpha),  \tag{10}\\
q(\alpha)=\sqrt{1-2 \gamma \alpha+\gamma^{2} L^{2}}, \quad q(\alpha) \in(0,1) .
\end{array}
$$

From (10) follows that defined by (3) sequence $x_{n}$ converges to $x_{\alpha}$ as geometric progression. Then minimal value its achieved at $\gamma=\alpha L^{-2}$ and corresponding minimal value of $1-$ $2 \gamma \alpha+\gamma^{2} L^{2}$ is equal to $1-\alpha^{2} / L^{2}$. Thus, when $\alpha \rightarrow 0$ then $q(\alpha) \rightarrow 1$ for any choice of $\gamma$ from condition (9). Because of this we need to make more iterations in minimizing of our functional.

### 1.1 Convexity of Tikhonov functional for linear operators

Let $H_{1}$ and $H_{2}$ be two real valued Hilbert spaces. Denote norms in these spaces as $\|\bullet\|_{1}$ and $\|\bullet\|_{2}$. Let the operator $F: H_{1} \rightarrow H_{2}$. Consider a general equation

$$
\begin{equation*}
F(x)=0, x \in H_{1} . \tag{11}
\end{equation*}
$$

An important case of this equation is

$$
\begin{equation*}
F(x)=A x-f, A \in \mathbb{L}\left(H_{1}, H_{2}\right) ; x \in H_{1}, f \in H_{2} . \tag{12}
\end{equation*}
$$

Thus, we will discuss now the linear operator equation

$$
\begin{equation*}
A x=f, x \in H_{1}, A \in \mathbb{L}\left(H_{1}, H_{2}\right), f \in H_{2} . \tag{13}
\end{equation*}
$$

In other words, $A: H_{1} \rightarrow H_{2}$ is a bounded linear operator. In the case of ill-posed problems $A$ is a compact operator. Therefore, a bounded inverse $A^{-1}$ does not exist. Thus, we need to consider the Tikhonov functional $\Phi_{\alpha}$ to approximately solve equation (3), where

$$
\begin{equation*}
\Phi_{\alpha}(x)=\frac{1}{2}\|A x-f\|_{2}^{2}+\frac{\alpha}{2}\left\|x-x_{0}\right\|_{1}^{2} \tag{A}
\end{equation*}
$$

Here $x_{0}$ is a certain a priori chosen vector. In computational practice usually $x_{0}$ is a good approximation for the correct solution.

We now establish the strict convexity of $\Phi_{\alpha}(x)$. This is an important property. Indeed, it is well known that a strictly convex functional can have at most one point of minimum. Now, if $\operatorname{dim} H_{1}<\infty$, then this minimum exists. Indeed, it is clear that

$$
\lim _{\|x\|_{1} \rightarrow \infty} \Phi_{\alpha}(x)=\infty
$$

On the other hand,

$$
\Phi_{\alpha}(0)=\frac{\|f\|_{2}^{2}}{2}+\frac{\alpha\left\|x_{0}\right\|_{1}^{2}}{2}
$$

In other words, $\Phi_{\alpha}(0)$ has a certain bounded value. Hence, by the Weierstrass theorem a minimizer $x_{\alpha}$ of $\Phi_{\alpha}(x)$ exists and by Theorem 1 this minimizer is unique: the uniqueness is because $\Phi_{\alpha}(x)$ is strictly convex.

Definition 1. Let $U \subseteq H_{1}$ be convex set and the operator $G: U \rightarrow H_{2}$ ( $G$ is not necessary linear). The operator $G$ has the Frechet derivative $G^{\prime}(x) \in L\left(H_{1}, H_{2}\right)$ at the point $x \in U$ if the following representation is valid

$$
\begin{equation*}
G(x+h)-G(x)=G^{\prime}(x)(h)+o_{x}\left(\|h\|_{1}\right), \forall h \in H_{1}, \tag{100}
\end{equation*}
$$

where

$$
\begin{equation*}
\lim _{\|h\|_{1} \rightarrow 0} \frac{\left\|o_{x}\left(\|h\|_{1}\right)\right\|_{2}}{\|h\|_{1}}=0 \tag{101}
\end{equation*}
$$

In other words, the difference $G(x+h)-G(x)$ is a linear operator $G^{\prime}(x)(h)$ plus a function, whose norm us much smaller than $\|h\|_{1}$ for sufficiently small $\|h\|_{1}$. This is the full similarity with the conventional definition of the differential.

Furthermore, it follows from (100) and (101) that in order to figure out the Frechet derivative $G^{\prime}(x)(h)$ at the point $x$, one should consider the difference $G(x+h)-G(x)$ and consider the linear, with respect to $h$, part of this difference. So, this part is a good candidate for being the Frechet derivative: do not forget that we also need to prove (101).

Definition. Let $U \subseteq H_{1}$ be convex set and let the functional $\Phi: U \rightarrow \mathbb{R}$ has the Frechet derivative $\Phi^{\prime}(x)$ for all $x \in U$. This functional is called strictly convex on the set $U$ with the strict convexity parameter $\kappa$ if

$$
\begin{equation*}
\Phi(x+y)-\Phi(x)-\Phi^{\prime}(x)(y) \geq \kappa\|y\|_{1}^{2}, \forall x, y \in U \text { such that } x+y \in U \tag{B}
\end{equation*}
$$

Theorem 1. Suppose that the operator $A$ in (13) is linear and bounded. Then the functional $\Phi_{\alpha}$ is strictly convex on the space $H_{1}$ with the strict convexity parameter $\alpha / 2$.

Proof. First, we consider the Frechet derivative $\Phi_{\alpha}^{\prime}(x)$ of the functional $\Phi_{\alpha}(x)$. So, by the above rule, we need to consider the difference $\Phi_{\alpha}(x+h)-\Phi_{\alpha}(x)$, single out its linear part (with respect to h) and prove (101) for the rest. Let $(,)_{1}$ and $(,)_{2}$ be scalar products in $H_{1}$ and $H_{2}$ respectively. Since we have real valued Hilbert spaces, then $(a, b)_{k}=$ $(b, a)_{k}, \forall a, b \in H_{k}, k=1,2$. Hence,

$$
\Phi_{\alpha}(x+h)-\Phi_{\alpha}(x)=\frac{1}{2}(A x+A h, A x+A h)_{2}+\frac{\alpha}{2}(x+h, x+h)_{1}
$$

$$
\begin{gather*}
-\frac{1}{2}(A x, A x)_{2}-\frac{\alpha}{2}(x, x)_{1}  \tag{C}\\
=\left[(A x, A h)_{2}+\alpha(x, h)_{1}\right]+\left[\frac{1}{2}(A h, A h)_{2}+\frac{\alpha}{2}(h, h)_{1}\right] .
\end{gather*}
$$

Since $A$ is bounded operator, than

$$
\left|\frac{1}{2}(A h, A h)_{2}+\frac{\alpha}{2}(h, h)_{1}\right| \leq \frac{1}{2}(\|A\|+\alpha)\|h\|_{1}^{2} .
$$

Hence,

$$
\begin{aligned}
& \lim _{\|h\|_{1} \rightarrow 0} \frac{1}{\|h\|_{1}}\left\{\left[\frac{1}{2}(A h, A h)_{2}+\frac{\alpha}{2}(h, h)_{1}\right]\right\} \\
\leq & \frac{1}{2} \lim _{\|h\|_{1} \rightarrow 0}(\|A\|+\alpha)\|h\|_{1}=0
\end{aligned}
$$

Therefore, it follows from (100), (101) and (C) that

$$
\begin{aligned}
\Phi_{\alpha}^{\prime}(x)(h) & =(A x, A h)_{2}+\alpha(x, h)_{1} \\
\text { or } \Phi_{\alpha}^{\prime}(x)(h) & =\left(\left(A A^{*}+\alpha\right) x, h\right)_{1} .
\end{aligned}
$$

Hence, $\Phi_{\alpha}^{\prime}(x)=\left(A A^{*}+\alpha I\right) x$, where $I$ is the identity operator on $H_{1}$.
Now, we are ready to use (B) to prove the strict convexity of $\Phi_{\alpha}$. We have

$$
\begin{gathered}
\Phi_{\alpha}(x+y)-\Phi_{\alpha}(x)-\Phi_{\alpha}^{\prime}(x)(y) \\
=\frac{1}{2}(A x+A y, A x+A y)_{2}+\frac{\alpha}{2}(x+y, x+y)_{1} \\
-\frac{1}{2}(A x, A x)_{2}-\frac{\alpha}{2}(x, x)_{1}-(A x, A y)_{2}-\alpha(x, y)_{1} \\
=\frac{1}{2}(A y, A y)_{2}+\frac{\alpha}{2}(y, y)_{1} \geq \frac{\alpha}{2}\|y\|_{1}^{2} .
\end{gathered}
$$

We have used here the fact that $(A y, A y)_{2} \geq 0$.

## 2 Existence of minimizer

As before we assume that there exists Frechet derivative of functional $\Phi_{\alpha}(x)$ and $F \in$ $\left(N_{1}, N_{2}\right)$.

We assume that

$$
\begin{equation*}
\left\|F\left(x^{*}\right)\right\| \leq \delta, 0<\delta<1 \tag{14}
\end{equation*}
$$

We also assume that the operator $F$ has the Fechet derivative $F^{\prime}(x)$ for $x \in V_{1}\left(x^{*}\right)=$ $\left\{\left\|x-x^{*}\right\|<1\right\}$ and this derivative is Lipschitz continuous or

$$
\begin{equation*}
\left\|F^{\prime}(x)\right\| \leq N_{1},\left\|F^{\prime}(x)-F^{\prime}(y)\right\|<N_{2}\|x-y\| \tag{15}
\end{equation*}
$$

We now assume that

$$
\begin{align*}
\left\|x_{\text {glob }}-x^{*}\right\| & \leq \delta^{\mu_{1}}, \mu_{1}=\text { const. } \in(0,1)  \tag{16}\\
\alpha & =\delta^{\mu_{2}}, \mu_{2}=\text { const. } \in\left(0, \min \left(\mu_{1}, 2\left(1-\mu_{1}\right)\right)\right) \tag{17}
\end{align*}
$$

Lemma $A$ minimizer $x_{\alpha}$ of the functional $\Phi_{\alpha}(x)$ on the space $H_{1}$ exists for any value of the regularization parameter $\alpha$. For any $r>0$ denote $V_{r}\left(x_{\alpha}\right)=\left\{x \in H_{1}:\left\|x-x_{\alpha}\right\|<r\right\}$. Assume that conditions (16), (17) hold. Then $x_{\text {glob }} \in V_{\sqrt{2} \delta^{\mu_{1}}}\left(x_{\alpha}\right)$ and $x^{*} \in V_{(1+\sqrt{2}) \delta^{\mu_{1}}}\left(x_{\alpha}\right)$. Let $\beta_{1} \in(0,1)$ be any number. Then there exists a sufficiently small number $\delta_{0}=\delta_{0}\left(\mu_{1}, \mu_{2}, \beta_{1}\right) \in$ $(0,1)$ such that if $\delta \in\left(0, \delta_{0}\right)$, then $x^{*}, x_{g l o b} \in V_{\beta_{1} \alpha}\left(x_{\alpha}\right)$.

## Proof.

Since $\operatorname{dim} H<\infty$, then $\lim _{\|x\| \rightarrow \infty} \Phi_{\alpha}(x)=\infty$ implies the existence of a minimizer $x_{\alpha}$.
Since $\Phi_{\alpha}\left(x_{\alpha}\right) \leq \Phi_{\alpha}\left(x^{*}\right)$ then

$$
\begin{equation*}
\Phi_{\alpha}\left(x^{*}\right)=\Phi\left(x^{*}\right)+\frac{\alpha}{2}\left\|x^{*}-x_{g l o b}\right\|=\frac{1}{2}\left\|F\left(x^{*}\right)\right\|^{2}+\frac{\alpha}{2}\left\|x^{*}-x_{g l o b}\right\| \leq \frac{\delta^{2}+\alpha \delta^{2 \mu_{1}}}{2} \tag{18}
\end{equation*}
$$

and then

$$
\begin{equation*}
\Phi_{\alpha}\left(x_{\alpha}\right) \leq \Phi_{\alpha}\left(x^{*}\right)=\frac{\delta^{2}+\alpha \delta^{2 \mu_{1}}}{2} \tag{19}
\end{equation*}
$$

and thus

$$
\begin{equation*}
\Phi_{\alpha}\left(x_{\alpha}\right) \leq \frac{\delta^{2}+\alpha \delta^{2 \mu_{1}}}{2}<\alpha \delta^{2 \mu_{1}} \tag{20}
\end{equation*}
$$

$$
\text { Why } \frac{\delta^{2}+\alpha \delta^{2 \mu_{1}}}{2}<\alpha \delta^{2 \mu_{1}} ?
$$

Since $\alpha=\delta^{\mu_{2}}$, then

$$
\frac{\alpha \delta^{2 \mu_{1}}}{\delta^{2}}=\delta^{\mu_{2}-2\left(1-\mu_{1}\right)}
$$

By (17) $\mu_{2}<2\left(1-\mu_{1}\right)$. Hence $\mu_{2}-2\left(1-\mu_{1}\right)<0$. Hence,

$$
\begin{equation*}
\lim _{\delta \rightarrow 0} \delta^{\mu_{2}-2\left(1-\mu_{1}\right)}=\infty \tag{D}
\end{equation*}
$$

But in Lemma we talk about sufficiently small $\delta_{0}$. Hence, it follows from (D) that if $\delta_{0}$ is sufficiently small, then for $\delta \in\left(0, \delta_{0}\right)$ we have

$$
\frac{\alpha \delta^{2 \mu_{1}}}{\delta^{2}}=\delta^{\mu_{2}-2\left(1-\mu_{1}\right)}>1 \rightarrow \alpha \delta^{2 \mu_{1}}>\delta^{2}
$$

Then, by the definition of $\Phi_{\alpha}\left(x_{\alpha}\right)$ we have

$$
\begin{equation*}
\Phi_{\alpha}\left(x_{\alpha}\right)=\Phi\left(x_{\alpha}\right)+\frac{\alpha}{2}\left\|x_{\alpha}-x_{g l o b}\right\|^{2}=\frac{1}{2}\left\|F\left(x_{\alpha}\right)\right\|^{2}+\frac{\alpha}{2}\left\|x_{\alpha}-x_{g l o b}\right\|^{2}<\alpha \delta^{2 \mu_{1}} \tag{21}
\end{equation*}
$$

It follows from this equation that

$$
\begin{equation*}
\frac{1}{2}\left\|F\left(x_{\alpha}\right)\right\|^{2}<\alpha \delta^{2 \mu_{1}} \tag{22}
\end{equation*}
$$

and

$$
\begin{equation*}
\frac{\alpha}{2}\left\|x_{\alpha}-x_{g l o b}\right\|^{2}<\alpha \delta^{2 \mu_{1}} \tag{23}
\end{equation*}
$$

From the last inequality we get that

$$
\begin{equation*}
\left\|x_{\alpha}-x_{g l o b}\right\|<\sqrt{2} \delta^{\mu_{1}} \tag{24}
\end{equation*}
$$

Using this estimate, we obtain

$$
\begin{align*}
\left\|x_{\alpha}-x_{g l o b}\right\| & \leq\left\|x_{\alpha}-x_{g l o b}\right\|+\left\|x_{0}-x^{*}\right\| \\
& <\sqrt{2} \delta^{\mu_{1}}+\delta^{\mu_{1}}  \tag{25}\\
& =(1+\sqrt{2}) \delta^{\mu_{1}}<\beta_{1} \alpha=\beta_{1} \delta^{\mu_{2}}
\end{align*}
$$

Why $(1+\sqrt{2}) \delta^{\mu_{1}}<\beta_{1} \alpha=\beta_{1} \delta^{\mu_{2}} \boldsymbol{?}$
Since $\mu_{2}<\mu_{1}$, then

$$
\lim _{\delta \rightarrow 0} \frac{\beta_{1} \delta^{\mu_{2}}}{(1+\sqrt{2}) \delta^{\mu_{1}}}=\infty
$$

and $\delta$ is sufficiently small. Thus

$$
\frac{\beta_{1} \delta^{\mu_{2}}}{(1+\sqrt{2}) \delta^{\mu_{1}}}>1
$$

and thus

$$
\beta_{1} \delta^{\mu_{2}}>(1+\sqrt{2}) \delta^{\mu_{1}}
$$

Theorem Assume that conditions (16), (17) hold. Then there exists numbers $\beta_{1}=$ $\beta_{1}\left(N_{1}, N_{2}\right) \in(0,1)$ and $\delta_{1}=\delta_{1}\left(\mu_{1}, \mu_{2}, N_{2}, \beta_{1}\right) \in(0,1)$ depending only on listed parameters such that if $\rho=\beta_{1} \alpha$, then for any $\delta \in\left(0, \delta_{1}\right)$ the functional $J_{\alpha}$ is strictly convex in the neighborhood $V_{\rho}\left(x_{\alpha}\right)$ of the point $x_{\alpha}$ with the strict convexity parameter $\kappa=\alpha / 4$. Furthermore, by Lemma 2.1 points $x_{\text {glob }}, x^{*} \in V_{\rho}\left(x_{\alpha}\right)$.

Proof. Let $\beta_{1} \in(0,1)$ be the number which we will choose below in this proof, $\rho=\beta_{1} \alpha$ and $x, y \in V_{\rho}\left(x_{\alpha}\right)$ be two arbitrary points. By (2.9)

$$
\begin{align*}
\left(J_{\alpha}^{\prime}(x)-J_{\alpha}^{\prime}(y), x-y\right)= & \alpha\|x-y\|^{2}+\left(F^{\prime *}(x) F(x)-F^{\prime *}(y) F(y), x-y\right) \\
= & \alpha\|x-y\|^{2}+\left(F^{\prime *}(x) F(x)-F^{\prime *}(x) F(y), x-y\right)  \tag{26}\\
& +\left(F^{\prime *}(x) F(y)-F^{\prime *}(y) F(y), x-y\right) .
\end{align*}
$$

Denote $A_{1}=\left(F^{*}(x) F(x)-F^{*}(x) F(y), x-y\right), A_{2}=\left(F^{*}(x) F(y)-F^{*}(y) F(y), x-y\right)$ and estimate $A_{1}, A_{2}$ from the below.

Since $A_{1}=A_{1}-\left(F^{* *}(x) F^{\prime}(x)(x-y), x-y\right)+\left(F^{\prime *}(x) F^{\prime}(x)(x-y), x-y\right)$, then we have

$$
\begin{aligned}
A_{1} & =\left(F^{\prime *}(x) F(x)-F^{\prime *}(x) F(y), x-y\right)-\left(F^{\prime *}(x) F^{\prime}(x)(x-y), x-y\right) \\
& +\left(F^{\prime *}(x) F^{\prime}(x)(x-y), x-y\right) \\
& =\left(F^{\prime *}(x)(F(x)-F(y), x-y)-\left(F^{* *}(x) F^{\prime}(x)(x-y), x-y\right)\right. \\
& +\left(F^{\prime *}(x) F^{\prime}(x)(x-y), x-y\right)
\end{aligned}
$$

then using main theorem of calculus

$$
F(x)-F(y)=\int_{0}^{1}\left(F^{\prime}(y+\theta(x-y))\right)(x-y) d \theta
$$

we can rewrite $A_{1}$ as

$$
\begin{aligned}
A_{1}= & \left(F^{\prime *}(x) \int_{0}^{1}\left(F^{\prime}(y+\theta(x-y))-F^{\prime}(x)\right)(x-y) d \theta, x-y\right) \\
& +\left(F^{\prime *}(x) F^{\prime}(x)(x-y), x-y\right)
\end{aligned}
$$

We obtain

$$
\begin{aligned}
&\left|F^{\prime *}(x) \int_{0}^{1}\left[F^{\prime}(y+\theta(x-y))-F^{\prime}(x)\right](x-y) d \theta, x-y\right| \\
& \leq\left\|F^{\prime}(x)\right\| \int_{0}^{1}\left\|\left[F^{\prime}(y+\theta(x-y))-F^{\prime}(x)\right](x-y)\right\| d \theta \cdot\|x-y\| \\
& \leq N_{1} N_{2} \int_{0}^{1}(y+\theta(x-y)-x)(x-y) d \theta \cdot\|x-y\| \\
& \leq \frac{1}{2} N_{1} N_{2}\|x-y\|^{3} \\
& z=\int_{0}^{1}\left[F^{\prime}(y+\theta(x-y))-F^{\prime}(x)\right](x-y) d \theta .
\end{aligned}
$$

Hence,

$$
\left|\left(F^{\prime *}(x) \int_{0}^{1}\left[F^{\prime}(y+\theta(x-y))-F^{\prime}(x)\right](x-y) d \theta, x-y\right)\right|
$$

$$
\begin{gathered}
=\left|\left(F^{\prime *}(x) z, x-y\right)\right| \leq\left\|F^{\prime *}(x)\right\| \cdot\|z\| \cdot\|x-y\| \\
=\left\|F^{\prime}(x)\right\| \cdot\|z\| \cdot\|x-y\|
\end{gathered}
$$

We have used here that for every bounded linear operator $A$ we have $\left\|A^{*}\right\|=\|A\|$.
Also,

$$
\left(F^{\prime *}(x) F^{\prime}(x)(x-y), x-y\right)=\left(F^{\prime}(x)(x-y), F^{\prime}(x)(x-y)\right)_{2}=\left\|F^{\prime}(x)(x-y)\right\|_{2}^{2} \geq 0
$$

Hence, $A_{1} \geq N_{1} N_{2}\|x-y\|^{3} / 2$. Now we estimate $A_{2}$,

$$
\left|A_{2}\right| \leq\|F(y)\|_{2}\left\|F^{\prime}(x)-F^{\prime}(y)\right\|\|x-y\| \leq N_{2}\|x-y\|^{2}\|F(y)\|_{2}
$$

Since

$$
\begin{equation*}
\|F(y)\|_{2} \leq\left\|F(y)-F\left(x_{\alpha}\right)\right\|_{2}+\left\|F\left(x_{\alpha}\right)\right\|_{2} \leq N_{1}\left\|y-x_{\alpha}\right\|+\left\|F\left(x_{\alpha}\right)\right\|_{2}, \tag{27}
\end{equation*}
$$

since

$$
\begin{equation*}
\left\|F(y)-F\left(x_{\alpha}\right)\right\|_{2} \leq\left(\max _{x \in V_{1}\left(x^{*}\right)}\left\|F^{\prime}(x)\right\|\right)\left\|y-x_{\alpha}\right\| \leq N_{1}\left\|y-x_{\alpha}\right\|, \tag{28}
\end{equation*}
$$

then

$$
\begin{equation*}
\left|A_{2}\right| \leq N_{2}\|x-y\|^{2}\left(N_{1}\left\|y-x_{\alpha}\right\|+\left\|F\left(x_{\alpha}\right)\right\|_{2}\right) . \tag{29}
\end{equation*}
$$

By (14), (15) and Lemma $\left\|F\left(x_{\alpha}\right)\right\|_{2} \leq\left\|F\left(x_{\alpha}\right)-F\left(x^{*}\right)\right\|_{2}+\delta \leq \alpha \beta_{1} N_{1}+\delta$.
Hence,

$$
\begin{equation*}
A_{2} \geq-N_{2}\|x-y\|^{2}\left(N_{1}\left\|y-x_{\alpha}\right\|+\alpha \beta_{1} N_{1}+\delta\right) \tag{30}
\end{equation*}
$$

Combining this with (26) and the above estimate for $A_{1}$, we obtain

$$
\begin{gather*}
\left(\Phi_{\alpha}^{\prime}(x)-\Phi_{\alpha}^{\prime}(y), x-y\right) \geq  \tag{31}\\
\|x-y\|^{2}\left[\alpha-\frac{N_{1} N_{2}}{2}\|x-y\|-N_{1} N_{2}\left\|y-x_{\alpha}\right\|-N_{2}\left(N_{1} \alpha \beta_{1}+\delta\right)\right]
\end{gather*}
$$

We have by Lemma

$$
\begin{equation*}
\frac{\|x-y\|}{2}=\frac{\left\|x-x_{\alpha}+x_{\alpha}-y\right\|}{2} \leq \frac{\alpha \beta_{1}+\alpha \beta_{1}}{2}=\alpha \beta_{1} . \tag{32}
\end{equation*}
$$

and thus

$$
\begin{align*}
& N_{1} N_{2} \frac{\|x-y\|}{2}+N_{1} N_{2}\left\|y-x_{\alpha}\right\|+N_{2}\left(N_{1} \alpha \beta_{1}+\delta\right) \\
& \leq \alpha \beta_{1} N_{2} N_{1}+\alpha \beta_{1} N_{2} N_{1}+\alpha \beta_{1} N_{2} N_{1}+N_{2} \delta  \tag{33}\\
& \leq 3 \alpha \beta_{1} N_{2} N_{1}+N_{2} \delta
\end{align*}
$$

Choose $\beta_{1}=\beta_{1}\left(N_{1}, N_{2}\right) \in(0,1)$ such that $3 \beta_{1} N_{2} N_{1} \leq 1 / 4$. Given this $\beta_{1}$, choose $\delta_{1}=$ $\delta_{1}\left(\mu_{1}, \mu_{2}, N_{1}, N_{2}\right) \in(0,1)$ so small that

$$
\begin{equation*}
N_{2} \delta<\delta^{\mu_{2}} / 4=\alpha / 4 \tag{34}
\end{equation*}
$$

and $2 \delta^{\mu_{1}}<\beta_{1} \delta^{\mu_{2}}=\beta_{1} \alpha, \forall \delta \in\left(0, \delta_{1}\right)$. Then we have that $\alpha / 4+\alpha / 4=\alpha / 2$ in (33) and thus from (31) we have $\alpha-\alpha / 2=\alpha / 2$.

