and an easy induction yields

$$\lambda_i^k = \frac{\|\nabla J_{u_k}\|^2}{\|\nabla J_{u_i}\|^2}, \quad 0 \le i \le k - 1.$$

Consequently, using $(*_3)$ we have

$$d_{k} = \sum_{i=0}^{k-1} \frac{\|\nabla J_{u_{k}}\|^{2}}{\|\nabla J_{u_{i}}\|^{2}} \nabla J_{u_{i}} + \nabla J_{u_{k}}$$

$$= \nabla J_{u_{k}} + \frac{\|\nabla J_{u_{k}}\|^{2}}{\|\nabla J_{u_{k-1}}\|^{2}} \left(\sum_{i=0}^{k-2} \frac{\|\nabla J_{u_{k-1}}\|^{2}}{\|\nabla J_{u_{i}}\|^{2}} \nabla J_{u_{i}} + \nabla J_{u_{k-1}}\right)$$

$$= \nabla J_{u_{k}} + \frac{\|\nabla J_{u_{k}}\|^{2}}{\|\nabla J_{u_{k-1}}\|^{2}} d_{k-1},$$

which concludes the proof.

It remains to compute ρ_k , which is the solution of the line search

$$J(u_k - \rho_k d_k) = \inf_{\rho \in \mathbb{R}} J(u_k - \rho d_k).$$

Since J is a quadratic functional, a basic computation left to the reader shows that the function to be minimized is

$$\rho \mapsto \frac{\rho^2}{2} \langle Ad_k, d_k \rangle - \rho \langle \nabla J_{u_k}, d_k \rangle + J(u_k),$$

whose minimum is obtained when its derivative is zero, that is,

$$\rho_k = \frac{\langle \nabla J_{u_k}, d_k \rangle}{\langle Ad_k, d_k \rangle}.$$
 (*5)

In summary, the conjugate gradient method finds the minimum u of the elliptic quadratic functional

$$J(v) = \frac{1}{2} \langle Av, v \rangle - \langle b, v \rangle$$

by computing the sequence of vectors $u_1, d_1, \ldots, u_{k-1}, d_{k-1}, u_k$, starting from any vector u_0 , with

$$d_0 = \nabla J_{u_0}.$$

If $\nabla J_{u_0} = 0$, then the algorithm terminates with $u = u_0$. Otherwise, for $k \geq 0$, assuming that $\nabla J_{u_i} \neq 0$ for $i = 1, \ldots, k$, compute

$$\begin{cases}
\rho_{k} = \frac{\langle \nabla J_{u_{k}}, d_{k} \rangle}{\langle A d_{k}, d_{k} \rangle} \\
u_{k+1} = u_{k} - \rho_{k} d_{k} \\
d_{k+1} = \nabla J_{u_{k+1}} + \frac{\|\nabla J_{u_{k+1}}\|^{2}}{\|\nabla J_{u_{k}}\|^{2}} d_{k}.
\end{cases}$$