ANOTHER CONJUGATE GRADIENT ALGORITHM FOR UNCONSTRAINED OPTIMIZATION

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Rezumat. *Se propune şi se analizează un alt algoritm hibrid de gradient conjugat. Parametrul* β_k *se calculează ca o combinaţie convexa a lui* β_k^{HS} *(Hestenes-Stiefel) şi* β_k^{DY} *(Dai-Yuan), adică:* $\beta_k^C = (1-\theta_k)\beta_k^{HS} + \theta_k\beta_k^{DY}$. *Parametrul* θ_k *se calculează astfel încât direcţia corespunzătoare acestui algoritm hibrid de gradient conjugat să fie egală cu direcţia Newton. Algoritmul utilizează condiţiile de căutare liniară Wolfe. Comparaţiile numerice efectuate pe un tren de 750 de funcţii de test, câteva dintre acestea fiind din biblioteca CUTE, arata ca aceasta schemă computaţională surclasează algoritmii de gradient conjugat Hestenes-Stiefel şi Dai-Yuan, precum şi alţi algoritmi de gradient conjugat.*

Abstract. *Another hybrid conjugate gradient algorithm is proposed and analyzed. The parameter* β_k *is computed as a convex combination of* β_k^{HS} *corresponding to Hestenes-Stiefel and* β_k^{DY} *of Dai-Yuan conjugate gradient algorithms, i.e.* $\beta_k^C = (1-\theta_k)\beta_k^{HS} + \theta_k\beta_k^{DY}$. *The parameter* θ_k *is computed in such a way that the direction corresponding to the conjugate gradient algorithm is equating the Newton direction. The algorithm uses the standard Wolfe line search conditions. Numerical comparisons with conjugate gradient algorithms using a set of 750 unconstrained optimization problems, some of them from the CUTE library, show that this hybrid computational scheme outperforms the Hestenes-Stiefel and the Dai-Yuan conjugate gradient algorithms, as well as some other known conjugate gradient algorithms.*

Keywords: unconstrained optimization, hybrid conjugate gradient method, Newton direction, conjugacy condition, numerical comparisons

Introduction.

For solving the nonlinear unconstrained optimization problem

$$\min\left\{ f(x) : x \in R^n \right\}, \tag{1}$$

where $f : R^n \to R$ is a continuously differentiable function, bounded from below, starting from an initial guess $x_0 \in R^n$, a nonlinear conjugate gradient method, generates a sequence $\{x_k\}$ as:

$$x_{k+1} = x_k + \alpha_k d_k, \tag{2}$$

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