

Functional a posteriori error estimate for the PBE

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July 4, 2016

Outline

- 1 Derivation of the PBE
- 2 Functional a posteriori error estimate

Derivation

Poisson equation

$$-\nabla \cdot (\epsilon \nabla \phi) = \frac{4\pi}{\epsilon_0} \rho$$

$\rho(x)$ -charge distribution,
 $\epsilon(x)$ -relative dielectric permittivity
 ϵ_0 -dielectric permittivity constant of vacuum

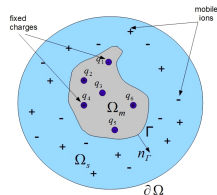
1) molecular region Ω_m

$$\rho_f = \sum_{i=1}^N q_i \delta_{x_i}(x), \quad x_i \in \Omega_m \Rightarrow -\nabla \cdot (\epsilon_m \nabla \phi) = \frac{4\pi}{\epsilon_0} \rho_f$$

2) solvent region Ω_s

$$\rho_s = cq e \frac{q\phi}{kT} - cq e \frac{-q\phi}{kT} = 2cq \sinh \frac{q\phi}{kT} \Rightarrow -\nabla \cdot (\epsilon_s \nabla \phi) = \frac{4\pi}{\epsilon_0} \rho_s$$

Interface conditions $[\phi]_{\Gamma} = 0, \left[\epsilon \frac{\partial \phi}{\partial n} \right]_{\Gamma} = 0$



Combining 1) and 2) with generalized coefficients $\epsilon(x)$ and $c(x)$

$$\left\{ \begin{array}{l} -\nabla \cdot (\epsilon \nabla \phi) = \frac{4\pi}{\epsilon_0} (\rho_f + \rho_s) \\ \phi(\infty) = 0 \\ [\phi]_{\Gamma} = 0 \\ \left[\epsilon \frac{\partial \phi}{\partial n} \right]_{\Gamma} = 0 \end{array} \right.$$

The equation for the dimensionless potential \tilde{u} is:

$$-\nabla \cdot (\epsilon(x) \nabla \tilde{u}) + k^2 \sinh(\tilde{u}) = \sum_{i=1}^N z_i \delta_{x_i}(x)$$

3-term regularization: $\tilde{u} = G + u^h + u \Rightarrow$

$$\left\{ \begin{array}{l} -\nabla \cdot (\epsilon \nabla u) + k^2 \sinh(u) = 0 \\ [u]_{\Gamma} = 0, \quad \left[\epsilon \frac{\partial u}{\partial n} \right]_{\Gamma} = g_{\Gamma} \\ u = g, \quad \text{on } \partial\Omega \end{array} \right. \quad (1)$$

The weak formulation:

Find $u \in H_g^1(\Omega) := \{v \in H^1(\Omega) : v = g \text{ on } \partial\Omega\}$ such that

$$\int_{\Omega} \epsilon \nabla u \cdot \nabla v dx + \int_{\Omega} k^2 \sinh(u) v dx = \int_{\Gamma} g_{\Gamma} v ds, \quad \forall v \in H_0^1(\Omega) \quad (2)$$

This formulation has a unique weak solution $u \in H_g^1(\Omega) \cap L^{\infty}(\Omega)$

Another splitting: $u = u^l + u^n$

Find $u^l \in H_g^1(\Omega)$ such that

$$a(u^l, v) = \langle g_{\Gamma}, v \rangle, \quad \forall v \in H_0^1(\Omega) \quad (3)$$

Find $u^n \in H_0^1(\Omega)$ such that

$$a(u^n, v) + \int_{\Omega} b(x, u^n + u^l) v dx = 0, \quad \forall v \in H_0^1(\Omega) \quad (4)$$

$$a(u, v) = \int_{\Omega} \epsilon \nabla u \cdot \nabla v dx, \quad \begin{aligned} b(x, s) &: \Omega \times \mathbb{R} \rightarrow \mathbb{R} \\ b(x, s) &= k^2(x) \sinh(s) \end{aligned}$$

(3) has a unique solution $u^l \in H_0^1(\Omega) \cap L^\infty(\Omega) \Rightarrow$ (4) also has a unique weak solution $u^n \in H_0^1(\Omega) \cap L^\infty(\Omega)$ which is the unique minimizer of

$$J(v) = \int_{\Omega} \frac{\epsilon}{2} |\nabla v|^2 dx + \int_{\Omega} B(x, v + u^l) dx$$

$$B(x, s) : \Omega \times \mathbb{R} \rightarrow \mathbb{R}, \quad B(x, s) = k^2(x) \cosh(s)$$

Functional a posteriori error estimate for u^n

Notation:

$$V := H_0^1(\Omega), \quad Y := (L_2(\Omega))^3$$

$\Lambda = \nabla : V \rightarrow Y$ is bounded from above and below

$$\Rightarrow \exists \Lambda^* : Y^* \rightarrow V^*$$

$$g(x, \xi) = \frac{\epsilon(x)}{2} \xi \cdot \xi : \Omega \times \mathbb{R}^3 \rightarrow \mathbb{R}$$

$$B(x, s) = k^2(x) \cosh(s) : \Omega \times \mathbb{R} \rightarrow \mathbb{R}$$

$$G : Y \rightarrow \mathbb{R}, \quad G(y) = \int_{\Omega} \frac{\epsilon}{2} |y|^2 dx$$

$$G(\Lambda v) = \int_{\Omega} g(x, \nabla v) dx = \int_{\Omega} \frac{\epsilon(x)}{2} |\nabla v|^2 dx$$

$$F(v) = \int_{\Omega} B(x, v + u') dx = \int_{\Omega} k^2(x) \cosh(v + u') dx$$

$$\left. \begin{array}{l} G(\Lambda v) = \int_{\Omega} g(x, \nabla v) dx = \int_{\Omega} \frac{\epsilon(x)}{2} |\nabla v|^2 dx \\ F(v) = \int_{\Omega} B(x, v + u') dx = \int_{\Omega} k^2(x) \cosh(v + u') dx \end{array} \right\} \Rightarrow J(v) = G(\Lambda v) + F(v)$$

Definition ([1])

A convex functional $J : V \rightarrow \mathbb{R}$ is called uniformly convex if there exists a nonnegative proper and l.s.c functional $\Upsilon : V \rightarrow \mathbb{R} : \Upsilon(v) = 0 \Leftrightarrow v = 0$ such that for all $v_1, v_2 \in V$ the following inequality holds:

$$J\left(\frac{v_1 + v_2}{2}\right) + \Upsilon(v_1 - v_2) \leq \frac{1}{2} (J(v_1) + J(v_2))$$

Definition (Dual functional/ Fenchel conjugate/ convex conjugate)

Let $J : V \rightarrow \mathbb{R}$. The functional $J^* : V^* \rightarrow \mathbb{R}$ defined by

$$J^*(v^*) := \sup_{v \in V} \{\langle v^*, v \rangle - J(v)\}$$

is called the dual functional / Fenchel conjugate functional of J

Definition (Second conjugate)

Let $J : V \rightarrow \mathbb{R}$. The functional $J^{**} : V \rightarrow \mathbb{R}$ defined by

$$J^{**}(v) := \sup_{v^* \in V^*} \{ \langle v^*, v \rangle - J^*(v^*) \}$$

is called the second conjugate functional J

Theorem (Fenchel-Moreau)

If J is a convex, proper ($J : V \rightarrow (-\infty, +\infty]$ and $J \not\equiv +\infty$), l.s.c functional, then $J = J^{**}$

$$J(v) = G(\Lambda v) + F(v) = \sup_{y^* \in Y^*} \{ \langle y^*, \Lambda v \rangle - G^*(y^*) + F(v) \},$$

$G^* : Y^* \rightarrow \mathbb{R}$ is the Fenchel conjugate of G

$L : V \times Y^* \rightarrow \mathbb{R}$ the Lagrangian for J , $L(v, y^*) := \langle y^*, \Lambda v \rangle - G^*(y^*) + F(v)$,

$$\inf_{v \in V} J(v) = \inf_{v \in V} \sup_{y^* \in Y^*} L(v, y^*)$$

$$I^*(y^*) := \inf_{v \in V} L(v, y^*) = -G^*(y^*) + \inf_{v \in V} \{ \langle y^*, \Lambda v \rangle + F(v) \}$$

$$= -G^*(y^*) - \sup \{ \langle -\Lambda^* y^*, v \rangle - F(v) \} = -G^*(y^*) - F^*(-\Lambda^* y^*)$$

Strong duality

Under certain conditions like lower/upper semicontinuity and convexity/concavity on $L(v, y^*)$ with respect to v and y^* respectively, and lower semicontinuity for J and $-I^*$, some coercivity conditions on L , there are $u \in V$ and $p^* \in Y^*$ such that

$$J(u) = \inf_{v \in V} J(v) = \inf_{v \in V} \sup_{y^* \in Y^*} L(v, y^*)$$

$$I^*(p^*) = \sup_{y^* \in Y^*} I^*(y^*) = \sup_{y^* \in Y^*} \inf_{v \in V} L(v, y^*)$$

$$J(u) = I^*(p^*) \text{ (strong duality holds)}$$

J is uniformly convex

$$\begin{aligned} & \frac{1}{2}G(\Lambda v_1) + \frac{1}{2}G(\Lambda v_2) - G\left(\frac{\Lambda(v_1 + v_2)}{2}\right) \\ &= \frac{1}{4} \int_{\Omega} \left(\epsilon |\nabla v_1|^2 + \epsilon |\nabla v_2|^2 - \frac{\epsilon}{2} |\nabla v_1 + \nabla v_2|^2 \right) dx \\ &= \frac{1}{8} \int_{\Omega} \epsilon |\nabla(v_1 - v_2)|^2 dx \end{aligned}$$

$\Rightarrow G$ is uniformly convex with $\mathcal{R}_G(v - u) = \frac{1}{8} \int_{\Omega} \epsilon |\nabla(v - u)|^2 dx$. Therefore J is also uniformly convex with the same forcing functional.

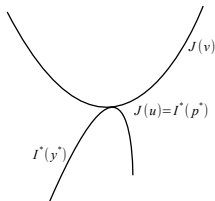
If u is the minimizer of J , by the definition of uniformly convex functional, applied to J and its forcing functional Υ_G [1] \Rightarrow

$$\begin{aligned} \Upsilon_G(v - u) &\leq \frac{1}{2} (J(v) + J(u)) - J\left(\frac{v+u}{2}\right) \leq \frac{1}{2} (J(v) - J(u)) \\ &\leq \frac{1}{2} (J(v) - I^*(y^*)) = \frac{1}{2} (G(\Lambda v) + F(v) + G^*(y^*) + F^*(-\Lambda^* y^*)) \end{aligned}$$

So we get

$$\begin{aligned} \|u - v\|_{H^1(\Omega)} &\sim \Upsilon_G(v - u) \\ &\leq \frac{1}{2} (G(\Lambda v) + F(v) + G^*(y^*) + F^*(-\Lambda^* y^*)) =: M_{\oplus}(v, y^*) \end{aligned}$$

with "=" iff $v = u$ and $y^* = p^* = \epsilon \nabla u$.



Computing $G^*(y^*)$

$$\begin{aligned}
 G^*(y^*) &= \sup_{y \in Y} (\langle y^*, y \rangle - G(y)) \\
 &= \sup_{y \in Y} \int_{\Omega} \left[y^*(x) \cdot y(x) - \frac{\epsilon(x)}{2} y(x) \cdot y(x) \right] dx \\
 &\leq \int_{\Omega} \sup_{\xi \in \mathbb{R}^3} \left\{ y^*(x) \cdot \xi - \frac{\epsilon(x)}{2} \xi \cdot \xi \right\} dx \\
 \xi(x) &\stackrel{=}{=} \frac{1}{\epsilon(x)} y^*(x) \int_{\Omega} \frac{1}{2\epsilon(x)} |y^*(x)|^2 dx
 \end{aligned}$$

Computing $F^*(-\Lambda^* y^*)$

$$\begin{aligned}
 F^*(-\Lambda^* y^*) &= \sup_{w \in H_0^1(\Omega)} [\langle -\Lambda^* y^*, w \rangle - F(w)] = \sup_{w \in H_0^1(\Omega)} [\langle -y^*, \Lambda w \rangle - F(w)] \\
 &= \sup_{w \in H_0^1(\Omega)} \int_{\Omega} [-y^* \cdot \nabla w - B(x, w + u^l)] dx = \quad (\text{if } y^* \in H(\text{div}; \Omega)) \\
 &= \sup_{w \in H_0^1(\Omega)} \int_{\Omega} [\text{div } y^* w - B(x, w + u^l)] dx \\
 &= \sup_{w \in H_0^1(\Omega)} \underbrace{\int_{\Omega} [\text{div } y^*(w + u^l) - B(x, w + u^l)] dx}_{:=I(w)} - \int_{\Omega} \text{div } y^* u^l dx \\
 &\leq \int_{\Omega} \sup_{\xi \in \mathbb{R}} [\text{div } y^*(x) (\xi + u^l(x)) - B(x, \xi + u^l(x))] dx - \int_{\Omega} \text{div } y^*(x) u^l(x) dx \\
 &= \int_{\Omega} [\text{div } y^*(x) (\xi_0(x) + u^l(x)) - B(x, \xi_0(x) + u^l(x))] dx - \int_{\Omega} \text{div } y^*(x) u^l(x) dx
 \end{aligned}$$

$$= I(\xi_0) - \int_{\Omega} \operatorname{div} y^* u' dx$$

where $\xi_0 : \Omega \rightarrow \mathbb{R}$ is computed from the necessary (and sufficient) condition for maximum:

$$\begin{aligned} \frac{d}{d\xi} \left(\operatorname{div} y^*(x) \left(\xi + u'(x) \right) - B \left(x, \xi + u'(x) \right) \right) &= 0 \\ \xi_0(x) &= \operatorname{arcsinh} \left(\frac{\operatorname{div} y^*(x)}{k^2(x)} \right) - u'(x) \\ &= \underbrace{\ln \left(\frac{\operatorname{div} y^*(x)}{k^2(x)} + \sqrt{\left(\frac{\operatorname{div} y^*(x)}{k^2(x)} \right)^2 + 1} \right)}_{\in L^2(\Omega) \forall y^* \in H(\operatorname{div}; \Omega), \text{ because } |\ln(y + \sqrt{y^2 + 1})| \leq |y|, \forall y \in \mathbb{R}} - u'(x) \end{aligned}$$

Is it really true $\sup_{w \in H_0^1(\Omega)} I(w) = I(\xi_0)$? \rightarrow Note that $\xi_0 \notin H_0^1(\Omega)$

Theorem

For any $y^* \in H(\text{div}; \Omega)$ it is true that $\sup_{w \in H_0^1(\Omega)} I(w) = I(\xi_0)$.

Idea of the proof:

- find a suitable sequence $w_n \in H_0^1(\Omega)$ s.t $I(w_n) \rightarrow I(\xi_0)$
- For this, find $\{f_n\} \subset C_0^\infty(\Omega) : f_n(x) \rightarrow f(x) := \frac{\text{div } y^*}{k^2}$ a.e and $\{u'_n\} \subset C_0^\infty(\Omega) : u'_n(x) \rightarrow u'(x)$, a.e, s.t $|f_n(x)| \leq h(x) \in L^2(\Omega)$ and $|u'_n(x)| \leq \|u'\|_{L^\infty(\Omega)} + 2$.
- Then $w_n(x) := \ln \left(f_n(x) + \sqrt{f_n^2(x) + 1} \right) - u'_n(x) \rightarrow \xi_0(x)$, a.e in Ω and $w_n \in C_0^\infty(\Omega) \subset H_0^1(\Omega)$
- $\text{div } y^*(x) (w_n(x) + u'(x)) - B(x, w_n(x) + u'(x)) \rightarrow \text{div } y^*(x)(\xi_0(x) + u'(x)) - B(x, \xi_0(x) + u'(x))$
- (*) Find a dominating summable function for $\text{div } y^*(x) (w_n(x) + u'(x)) - \cosh(x, w_n(x) + u'(x))$ and apply Lebesgue DCT

Thank you for listening!



P. Neittaanmaki, S. Repin.

Reliable Methods for Computer Simulation: Error Control and Posteriori Estimates.

Elsevier, 2004.