

PDE-constrained optimization with Alya

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Discrete adjoint method (reduced gradient)

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- Adding gradient calculation

- Adding optimization service

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PDE-constrained optimization

$$\begin{array}{ll} \underset{(u,d) \in \mathcal{U} \times \mathcal{D}}{\text{minimize}} & \mathcal{J}(u, d) \\ \text{subject to} & \mathcal{R}(u, d) = 0 \end{array} \quad (\text{PDECO})$$

with

- \mathcal{U} and \mathcal{D} assumed to be appropriate Hilbert functional spaces.
- $\mathcal{J} : \mathcal{U} \times \mathcal{D} \rightarrow \mathbb{R}$ the cost functional and $\mathcal{R} : \mathcal{U} \times \mathcal{D} \rightarrow \mathcal{U}$ the constraint operator, which is a PDE defined in a domain $\Omega \subset \mathbb{K}^n$ ($\mathbb{K} \in \{\mathbb{R}, \mathbb{C}\}$ and $n \in \{1, 2, 3\}$).
- $u \in \mathcal{U}$ is the solution of the PDE.
- $d \in \mathcal{D}$ is the model or design parameter function which acts as an input of the PDE.

Examples

- Shape optimization in computational fluid dynamics.
- Material inversion in geophysics.
- Data assimilation in weather prediction modeling.
- Structural optimization of stressed systems.
- Control of chemical processes.
- Bio-engineering techniques in cancer treatment.
- Option pricing in computational finance.
- ...



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Discrete adjoint method (reduced gradient)

Domain discretization + FEM:

$$\mathcal{R}(u, d) = 0 \quad \Leftrightarrow \quad \underbrace{\mathbf{A}(d)\mathbf{u} = \mathbf{b}(d)}_{\mathbf{R}(\mathbf{u}, d)=0}$$

Discrete version of (PDECO):

$$\begin{array}{ll} \underset{(\mathbf{u}, \mathbf{d}) \in \mathbb{K}^{n_u} \times \mathbb{R}^{n_d}}{\text{minimize}} & J(\mathbf{u}, \mathbf{d}) \\ \text{subject to} & \mathbf{R}(\mathbf{u}, \mathbf{d}) = \mathbf{0} \end{array} \quad (\text{D-PDECO})$$

Reduced version of (D-PDECO):

$$\underset{\mathbf{d} \in \mathbb{R}^{n_d}}{\text{minimize}} \quad j(\mathbf{d}) := J(\underbrace{\mathbf{u}(\mathbf{d})}_{\mathbf{A}(\mathbf{d})^{-1}\mathbf{b}(\mathbf{d})}, \mathbf{d}) \quad (\text{R-D-PDECO})$$

Discrete adjoint method (reduced gradient)

Calculation of $\nabla_{\mathbf{d}}j(\mathbf{d})$:

0. Set initial value of \mathbf{d} .
1. $\mathbf{u} \leftarrow \mathbf{R}(\mathbf{u}, \mathbf{d}) = \mathbf{0}$ (*forward problem*).
2. Calculate $\nabla_{\mathbf{u}}J(\mathbf{u}, \mathbf{d})$ and $\nabla_{\mathbf{u}}\mathbf{R}(\mathbf{u}, \mathbf{d})^1$.
3. $\boldsymbol{\lambda} \leftarrow \nabla_{\mathbf{u}}\mathbf{R}(\mathbf{u}, \mathbf{d})^T \boldsymbol{\lambda} = \nabla_{\mathbf{u}}J(\mathbf{u}, \mathbf{d})^T$ (*adjoint problem*).
4. Calculate $\nabla_{\mathbf{d}}J(\mathbf{u}, \mathbf{d})$ and $\nabla_{\mathbf{d}}\mathbf{R}(\mathbf{u}, \mathbf{d})^1$.
5. $\nabla_{\mathbf{d}}j(\mathbf{d}) = -\boldsymbol{\lambda}^T \nabla_{\mathbf{d}}\mathbf{R}(\mathbf{u}, \mathbf{d}) + \nabla_{\mathbf{d}}J(\mathbf{u}, \mathbf{d})$.

¹Using automatic differentiation, finite differences or taking derivatives *by hand*

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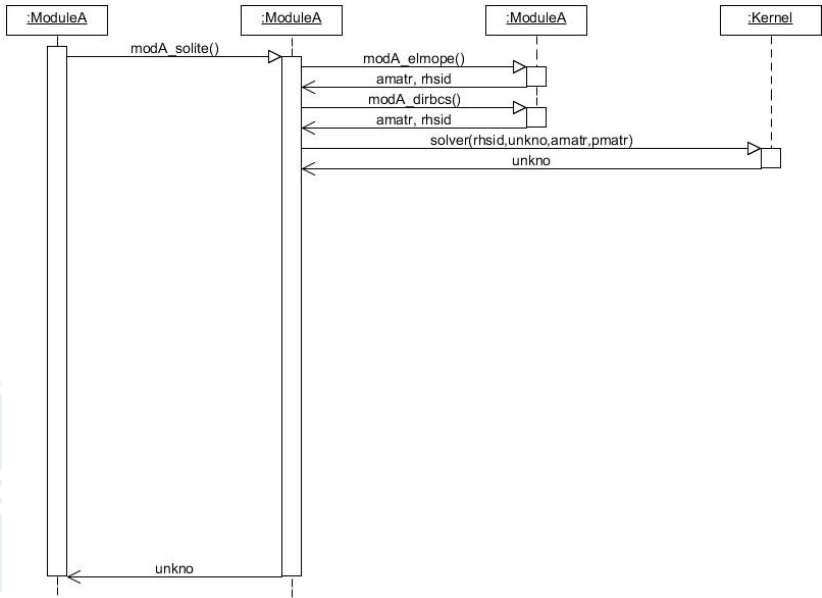


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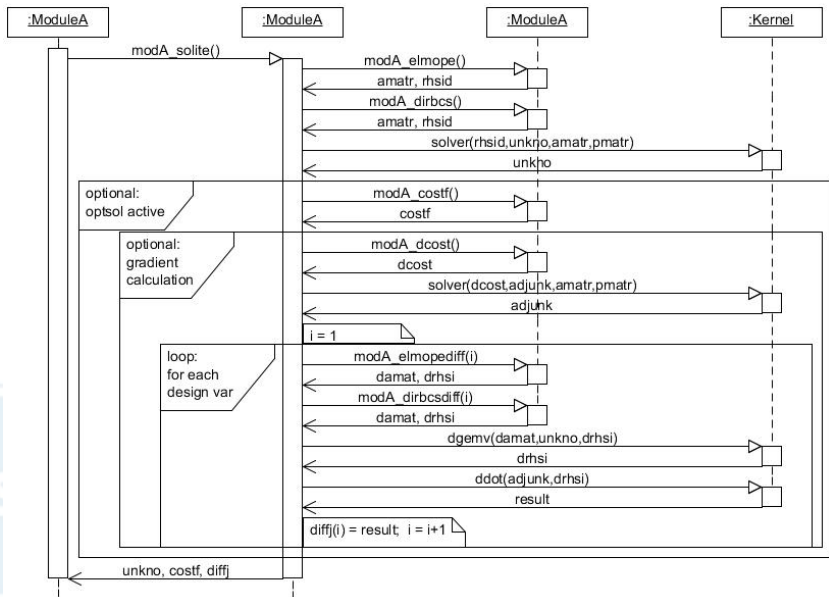
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modA_solite.f90



modA_solite.f90 + gradient calculation



modA_solite.f90 + gradient calculation

- `modA_costf`: for each slave, calculate $j(\mathbf{d}) := J(\mathbf{u}(\mathbf{d}), \mathbf{d})$, then apply `MPI_AllReduce`, and store it in scalar variable `costf`.
- `modA_dcost`: for each slave, calculate $\nabla_{\mathbf{u}} J(\mathbf{u}, \mathbf{d})$ and store it in (distributed) vector variable `dcost` (same size as `rhsid`).
- `modA_elmopediff(i)`: for each slave, assemble $\frac{\partial \mathbf{A}(\mathbf{d})}{\partial \mathbf{d}_i}$ and $\frac{\partial \mathbf{b}(\mathbf{d})}{\partial \mathbf{d}_i}$, and store them in (distributed) vector variables `damat` and `drhsi`.
- `modA_dirbcsdiff(i)`: for each slave, apply $\frac{\partial}{\partial \mathbf{d}_i}$ in b.c.'s and update `damat` and `drhsi`.
- `dgemv(damat, unkno, drhsi)`: calculates

$$\nabla_{\mathbf{d}} \mathbf{R}(\mathbf{u}, \mathbf{d}) = (\nabla_{\mathbf{d}} \mathbf{A}(\mathbf{d})) \mathbf{u} - \nabla_{\mathbf{d}} \mathbf{b}(\mathbf{d})$$

using the expression `drhsi` \leftarrow `damat` * `unkno` - `drhsi`.

- `ddot(adjunk, drhsi)`: calculates $\frac{\partial j(\mathbf{d})}{\partial \mathbf{d}_i}$ using the expression `result` \leftarrow `adjunk`^T * `drhsi`.

modA_solite.f90 + gradient calculation

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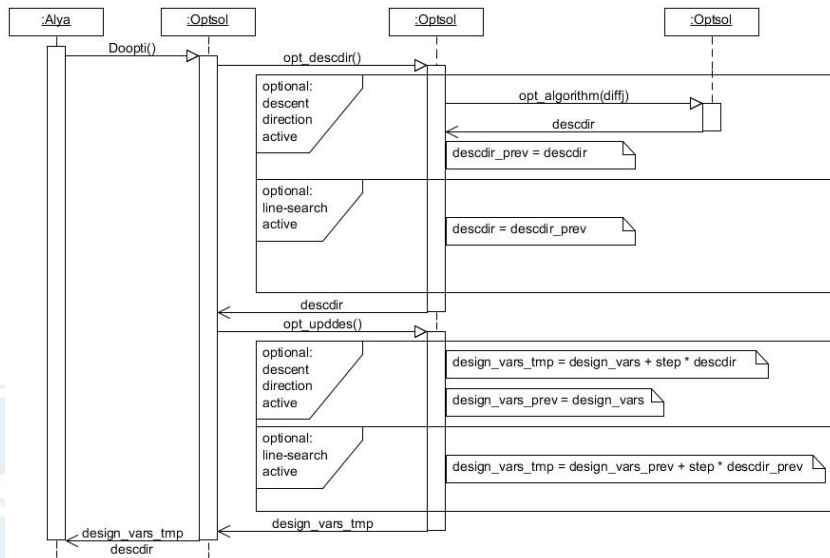
Alya.f90

```
1 program Alya
2
3   call Turnon()
4
5   call Iniunk()
6   call Filter(ITASK_INITIA)
7   call Output(ITASK_INITIA)
8   time: do while (kfl_gotim==1)
9       call Timste()
10      call Begste()
11      block: do while (kfl_goblk==1)
12          coupling: do while (kfl_gocou==1)
13              call Doiter()
14              call Concou()
15          end do coupling
16          call Conblk()
17          call Newmsh(one)
18      end do block
19      call Endste()
20      call Filter(ITASK_ENDTIM)
21      call Output(ITASK_ENDTIM)
22  end do time
23  call Filter(ITASK_ENDRUN)
24  call Output(ITASK_ENDRUN)
25
26
27
28
29   call Turnof()
30 end program Alya
```

Alya.f90 + optimization service

```
1 program Alya
2   call Begopt()      ← Initialization of opti params
3   call Turnon()
4   optimization: do while ( kfl_goopt == 1)
5     call Iniunk()
6     call Filter(ITASK_INITIA)
7     call Output(ITASK_INITIA)
8     time: do while (kfl_gotim==1)
9       call Timste()
10      call Begste()
11      block: do while (kfl_goblk==1)
12        coupling: do while (kfl_gocou==1)
13          call Doiter() ← Assembling, fwd/adj solver and diffj calculation
14          call Concou()
15        end do coupling
16        call Conblk()
17        call Newmsh(one)
18      end do block
19      call Endste()
20      call Filter(ITASK_ENDTIM)
21      call Output(ITASK_ENDTIM)
22    end do time
23    call Filter(ITASK_ENDRUN)
24    call Output(ITASK_ENDRUN)
25    call Doopti() ← Update design variables using grad from Doiter
26    call Endopt() ← Check tolerance and max opti iters
27  end do optimization
28  call Output(ITASK_ENDOPT)
29  call Turnof()
30 end program Alya
```

Doopti.f90



- `opt_descdir`: calculate descent direction and store it in a vector variable `descdir`. If linesearch is active (`kfl_curlin_opt>1`), use desc. direction obtained in the first linesearch iteration.
- `opt_algorithm`: using `diffj` ($\nabla_d j$) obtain descent direction `descdir` using some algorithm (steepest descent, conjugate gradient, quasi-Newton). Currently only steepest descent is programmed.
- `opt_upddes`: update design variables `design_vars` and store the new value in a temporal variable `design_vars_tmp`.

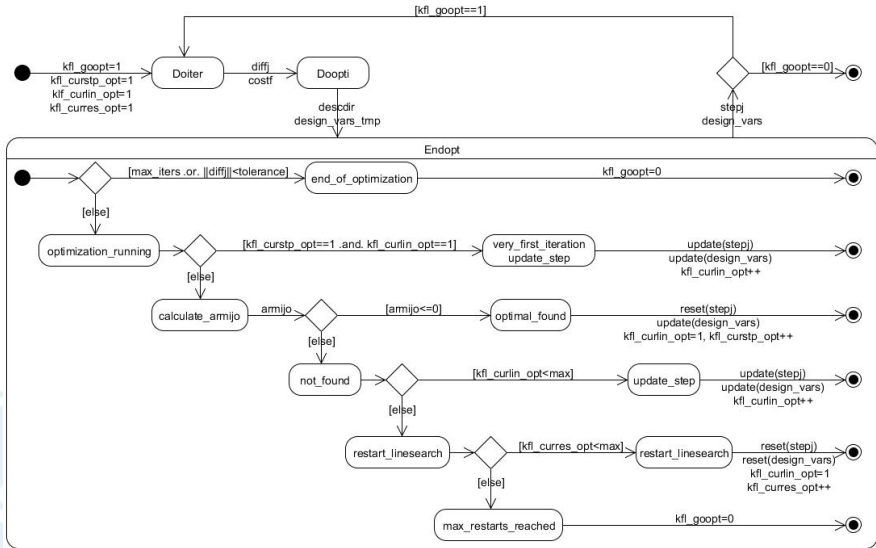
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Endopt.f90



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Inverse 3D Controlled-source Electromagnetism

Secondary potential formulation of Maxwell's equations,

$$\nabla^2 \mathbf{A}_s + i\omega\mu_0\sigma(\mathbf{A}_s + \nabla\phi_s) = -i\omega\mu_0\delta\sigma(\mathbf{A}_p + \nabla\phi_p) \quad (1)$$

$$\nabla \cdot (i\omega\mu_0\sigma(\mathbf{A}_s + \nabla\phi_s)) = -\nabla \cdot (i\omega\mu_0\delta\sigma(\mathbf{A}_p + \nabla\phi_p)) \quad (2)$$

discretized PDE + boundary conditions:

$$\mathbf{K}(\mathbf{d})\mathbf{z} = \mathbf{f}(\mathbf{d}) \quad (3)$$

with $\mathbf{z} = (\mathbf{A}_s^x, \mathbf{A}_s^y, \mathbf{A}_s^z, \phi_s) \in \mathbb{C}^{4n}$

In Alya, module `Helmoz` (developed by Jelena and Vladimir).

Cost function:

$$J(\mathbf{z}, \mathbf{d}) = \overline{(\mathbf{z} - \mathbf{z}^{obs})}^T \mathbf{M}^{obs} (\mathbf{z} - \mathbf{z}^{obs}) \quad (4)$$

Inverse 3D Controlled-source Electromagnetism

- Currently, we have implemented:
 - `hlm_costf`: 2 types
 - `hlm_dcost`: 2 types
 - `hlm_elmopediff`, `hlm_dirbcstdiff`: our design variable is the isotropic electric conductivity tensor (# design vars = number of nodes in the mesh)
 - `hlm_solite`: new features added (multiple shots, optimization in some routines to speed up the exec time, ...)
- We are still in the gradient obtention stage (very difficult).
- After this, when we have a *good* gradient at our disposal, we can calculate a descent direction, linesearch, ...

hlm_solite.f90

```
1 subroutine hlm_solite()  
2  
3     call hlm_matrix()  
4     call solvex(rhsix,unknx,amatx,pmatx)  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29
```

```
end subroutine hlm_solite
```

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hlm_solite.f90 + gradient calculation

```
1  subroutine hlm_solite()
2      shots: do ishot=1,nshot_hlm
3          call hlm_matrix()
4          call solvex(rhsix,unknx,amatx,pmatx)
5          if (kfl_servi(ID.OPTSOL)==1) then
6              if (INOTMASTER) then
7                  call hlm_cstev(delta,shot)
8                  if (kfl_curlin_opt==1) then
9                      call hlm_dcost(delta,shot)
10                 end if
11             end if
12             call pararr('SUM',0_ip,1_ip,costf_shot)
13             if (kfl_curlin_opt==1) then
14                 call hlm_adjvar()
15                 do indvars=1,kfl_ndvars_opt
16                     if (INOTMASTER) then
17                         call hlm_elmopediff(indvars)
18                         call hlm_dirbcddiff(indvars)
19                     end if
20                     call bcsplx2(npoin,4_ip,damat,c_sol,r_sol,unknx,drhsi)
21                     call proptx(npoin,4_ip,aunknx,drhsi,rr)
22                     diffj_shot(indvars) = 2.0_rp * real(rr)
23                 end do
24             end if
25             costf=costf + costf_shot
26             diffj = diffj + diffj_shot
27         end if
28     end do shots
29 end subroutine hlm_solite
```

Thanks for your attention!



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