A fast nonlinear conjugate gradient based method for frictional contact problems

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Delft Institute of Applied Mathematics, TU Delft

2nd Feb., 2015



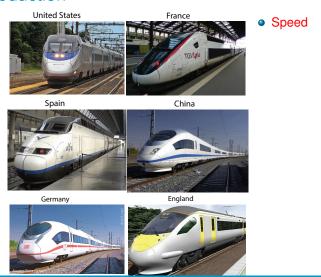
Outline

- Introduction.
- Formulation of frictional contact.
- TangCG algorithm.
- Numerical results of a Cattaneo shift problem.
- Conclusion.











United States Spain



- Speed
- Security (e.g. anti-derailment).



















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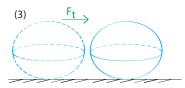


Pressure & Contact area





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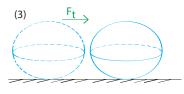


Delft University of Technology





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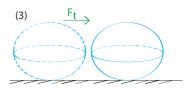


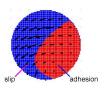






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Frictional stress, adhesion & slip

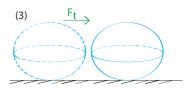


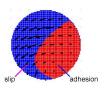






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Kalker's numerical variational form (after discretization):

$$\min_{\mathbf{p}} \ \phi = \frac{1}{2} \mathbf{p}^{T} A \mathbf{p} + \mathbf{w}^{T} \mathbf{p}$$

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We aim at a faster solver.



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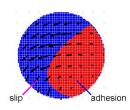
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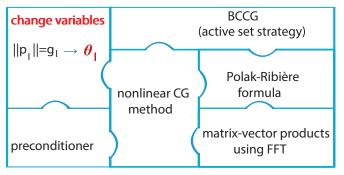
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We solve for **p**, *H* and *S*.



Main components of TangCG:





♠ Change variables in slip area

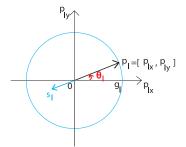
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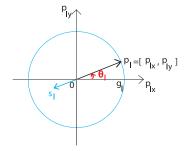
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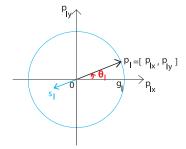
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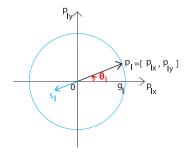
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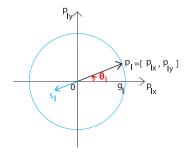
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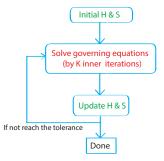


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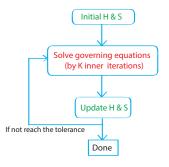
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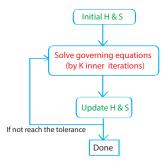


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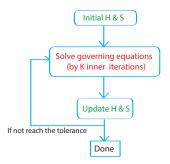
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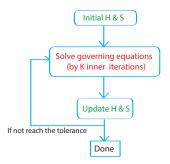
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- Apply the fast Fourier transform (FFT) technique, the complexity is reduced to $O(n \log n)$ from $O(n^2)$.



One iteration on the slip element *I*:

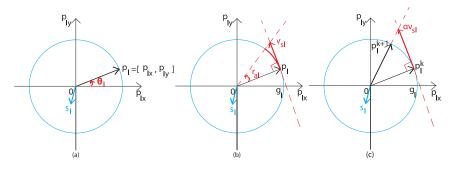


Figure: (a) current iterate. (b) residual and search direction. (c) update.



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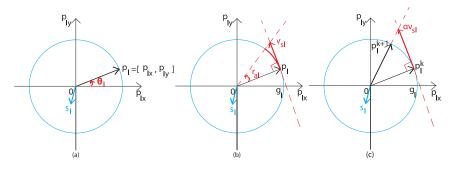


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Numerical results of a Cattaneo shift problem

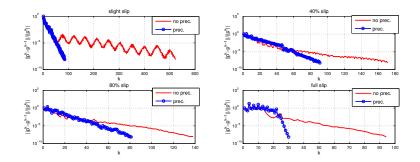
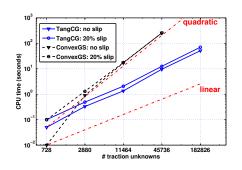
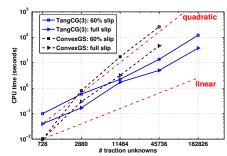


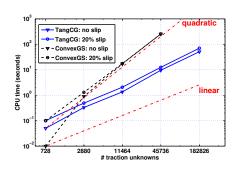
Figure: The convergence behavior of TangCG with and without prec.

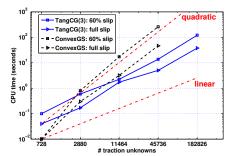






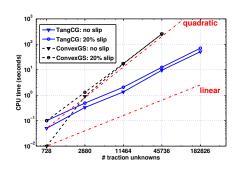


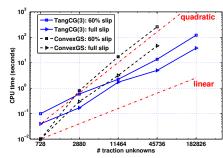




Conclusion about TangCG with prec.:



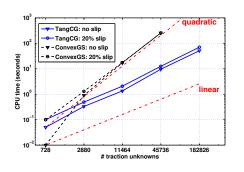


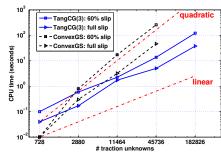


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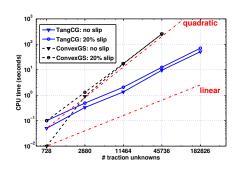


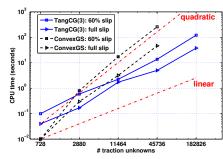
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Thank you for your attention!



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