MocoExtendProblem: Interface Between OpenSim and MATLAB for Rapidly Prototyping Direct Collocation Goals

Aravind Sundararajan [1][¶], **Varun Joshi**[2], **Brian Umberger**[2], **and Matthew O'Neill**[1]

1 Department of Anatomy, Midwestern University, Glendale Arizona, USA **2** School of Kinesiology, University of Michigan, Ann Arbor, Michigan, USA ¶ Corresponding author

Summary

MocoExtendProblem (MEP) is a more convenient MATLAB framework for prototyping and developing direct collocation goals for OpenSim Moco. MEP features several tools for testing and prototyping and using novel MocoGoals without resorting to rebuilding all of opensim or generating an .omoco file from C++ and loading the problem into MATLAB. Instead, users can structure their custom goals, build these with the visual studio and the MEX compiler and add them to existing MATLAB scripts.

This repository features:

- A set of C++ and MATLAB scripts and models for prototyping and testing custom goals.
- a build.m script that compiles goals in the custom_goals or custom_goals45 and procedurally constructs the c++/MATLAB and compiles the MEX interface.
- Compatibility with OpenSIm 4.2-4.4 and 4.5.
- The ability to include MEP as a submodule, build, and use valid custom goals.
- Custom goals previously developed in our labs are in the custom_goals directory.

Statement of need

OpenSim is an open-source software platform for biomechanical modeling and simulation (Seth, 2018). The platform enables researchers and healthcare professionals to investigate how biological and non-biological structures respond to different loads, postures and activities. It has been used to study a wide range of biomechanical problems, such as the mechanics of walking and running (Falisse et al., 2019), the impact of injury or disease on movement (Johnson, 2022), and the effectiveness of rehabilitation exercises (Spomer et al., 2023).

Direct collocation is a numerical optimization method used in dynamic systems and control engineering. It involves representing the system dynamics as a set of algebraic equations, which are then discretized over time, and solved as a nonlinear optimization problem to obtain the optimal control inputs. The method aims to find a numerical solution that satisfies the system constraints and optimizes a performance measure. Optimization paradigms like direct collocation have begun to play a critical role in expanding our understanding of biological locomotion through the in-silico testing of novel therapies and predictive capabilities.

Within OpenSim is the software toolkit Moco (Dembia, 2021), which employs direct collocation with IPOPT (i.e. optimization software; Wächter & Biegler (2006)) in order to solve trajectory optimization problems that could range from tracking experimental motion capture data for

solving generalized coordinates, actuator controls, and kinetics to fully predictive simulations. Moco employs CasADi (Andersson et al., 2018) to transform MocoProblem consisting of control goals and constraints into sets of matrices for nonlinear optimization. While direct collocation is powerful and OpenSim can be used to generate a broad range of dynamically-consistent simulations, it can be daunting for some users to modify and rebuild novel direct collocation goals.

We developed MEP so researchers, clinicians, and students without experience compiling C++ can still write and test custom goals. By contrast, OpenSim's interfaces for MATLAB are developed using SWIG, as opposed to MEX, which can be daunting for even seasoned biomechanists. Running build.m will compile custom goals developed and placed in the custom_goals directory, or if using OpenSim 4.5, MEP will search the custom_goals45. This distinction for pre- and post- 4.5 MEP is to handle where scaling arguments are moved to the abstract MocoGoal.

No further modifications to CMakeLists.txt are required; however cmake and msbuild.exe from Visual Studio 2019 or higher needs to be added to the system PATH. build.m will procedurally construct both extend_problem.m and ExtendProblem.cpp by parsing the header files of the discovered goals within the custom_goals directory. Both ExtendProblem.cpp and extend_problem.m generate bindings to instantiate custom goals placed in the custom_goals directory. Custom Goals will be compiled with VS2019+ and then MATLAB's MEX compiler is used to compile the MEX function. ExtendProblem.cpp leverages the C++ library mexplus (Yamaguchi, 2018) to gain access to MEX entry points entry and exit points through C++ macros.

To incorporate extend_problem goals into an existing script, a C-style pointer to the instantiated MocoProblem is passed as a constructor argument to the extend_problem.m class that wraps the MEP MEX. Class methods of extend_problem.m (Figure 1; blue) are then used to add custom goals to the MocoProblem.

```
MocoExtendProblem
├── bin
│   └── RelWithDebInfo
│       ├── ExtendProblem.cpp
│       ├── extend_problem.m
│       └── extendProblem.mexw64
├── build
├── custom_goals or custom_goals45
│   └── MocoExampleGoal
│       ├── MocoExampleGoal.cpp
│       ├── MocoExampleGoal.h
│       ├── osimMocoExampleGoalDLL.h
│       ├── RegisterTypes_osimMocoExampleGoal.cpp
│       └── RegisterTypes_osimMocoExampleGoal.h
├── test
├── utils
│   ├── build_extend_class.m
│   ├── construct_goal_tree.m
│   ├── cpp_end.m
│   ├── cpp_start.m
│   ├── generate_content.m
│   ├── generate_content45.m
│   ├── get_goal_names.m
│   ├── get_setter_functions.m
│   ├── mex_end.m
│   ├── mex_start.m
│   ├── wrap_end.m
│   └── wrap_start.m
└── build.m
```

Figure 1: MEP Framework organization. The end user runs the build.m script (orange) that subsequently calls methods in the utils folder (red) which are tasked with reading the custom_goals and custom_goals45 folder (green) and procedurally construct the mex and the interface class that calls the mex (blue). Each custom goal (green) is essentially handled as its own compiled plugin.

66 To create a new goal with MEP:

67   1. copy one of the goals in the custom_goals folder.

68   2. rename all files to that of your custom goal's name.
69   3. regex replace (or by hand) mentions of the original copied goal name to that of your
70   goal's name in each of the 5 files, being careful to also modify the include guards in the
71   dll and register types header files.
72   4. Reimplement initializeOnModelImpl, calcIntegrandImpl, calcGoalImpl such that they
73   describe your custom goal.

74 In order to run a new custom goal, obtain the C-style pointer from OpenSim's existing SWIG
75 interface and pass this as a constructor argument to extend_problem.

```
cptr = uint64(problem.getCPtr(problem));
ep = extend_problem(cptr);
ep.addMocoCustomGoal('custom_goal',weight,power,divide_by_distance);
```

76 This paradigm has implications for OpenSim and MATLAB developers beyond the scope of
77 just incorporating novel MocoGoals; these same tools can be used to develop other tools or
78 expand other classes and easily incorporate them into existing MATLAB-OpenSim scripts. We
79 have posted all tools, instructions and simulation results related to this project on GitHub and
80 SimTK.org/MEP.

Showcases

82 To demonstrate the utility of this framework, we utilized a two-dimensional (2-D) full-body
83 human musculoskeletal model operated through the MATLAB-OpenSim API to simulate
84 a half walking gait cycle (Denton & Umberger, 2023). The base code uses Moco's built-
85 in MocoControlEffortGoal and MocoAverageSpeedGoal to generate tracking and predictive
86 simulations of a dynamically-consistent walking step that minimizes the sum of the squared
87 control effort, at an average speed of 1.3 m s-1. Additionally each objective function has an
88 implicit acceleration minimization and auxiliary derivative cost term which help to smooth
89 model kinetics and remove transient oscillations in ground reaction forces.

90 Since Moco lacks any built-in gait stability goals, we developed three custom stability goals
91 using MEP to prototype and compile into a new extend_problem class that adds these to an
92 existing MocoProblem. The first is a base of support (BOS) criterion in which the center
93 of mass is optimized to lay between the average of the two mass centers for the calcaneus
94 projected to the ground reference frame, the second is a zero-moment-point goal (ZMP)
95 criterion that assumes the model is an inverted pendulum and the center of mass tracks the
96 computed zero-tilting moment location, and the third is a marker acceleration minimization
97 goal (ACCmarker) that minimizes the explicit accelerations of the marker's station location.

98 MEP's build.m was used to generate an extendproblem.cpp and extend_problem.m class which
99 wraps the custom goal to create a new, multi-objective function based on the sum of squared
100 control effort + stability criteria, such that:

$$J_{BOS} = W_1 EFF^2 + W_2 ACC_{smoothing} + W_3 BOS \tag{1}$$

$$J_{zmp} = W_1 EFF^2 + W_2 ACC_{smoothing} + W_3 ZMP \tag{2}$$

$$J_{acc} = W_1 EFF^2 + W_2 ACC_{smoothing} + W_3 ACC_{marker} \tag{3}$$

101 The results of each multi-objective predictive simulation, in which the stability criterion was
102 compiled using MEP, is shown against the results from a tracking simulation Figure 2. The
103 tracking simulation objective cost was a weighted sum of the tracking error (i.e. squared sum

104 of simulation from experimental kinematic and ground reaction force data) and sum of the
105 squared control efforts.
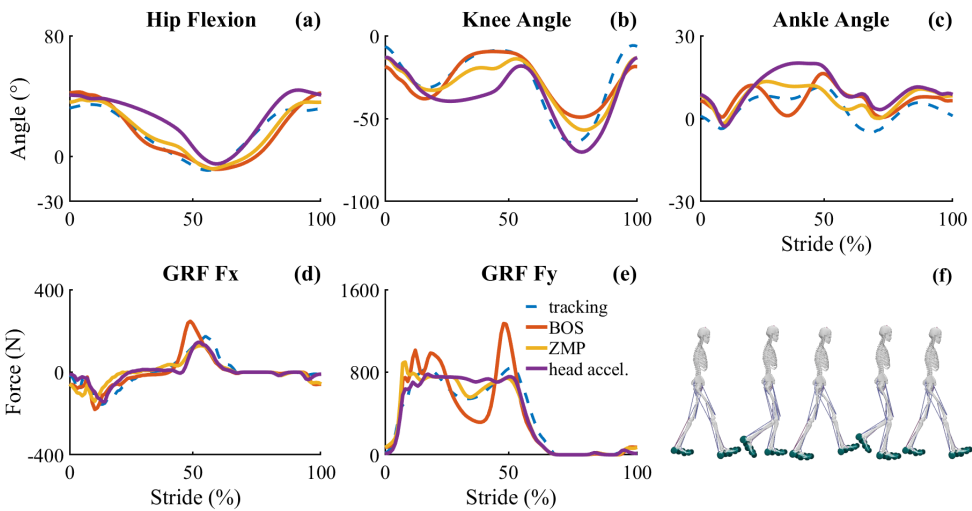
Figure 2: Sagittal plane hip, knee and ankle angles (a-c), vertical and A-P ground reaction forces (d-e), the 11 degree-of-freedom, 18 muscle sagittal plane human walking model used for tracking and predictive simulations (f).

Table 1: Objective cost and term breakdown for three predictive simulations using MEP.

	Objective cost	Effort cost	Smoothing cost	Stability cost
J_{BOS}	3.048285	2.234377	0.008309	0.795659
J_{ZMP}	3.384394	2.679968	0.008816	0.686290
J_{accel}	3.814449	3.680096	0.010208	0.114528

106 MEP is being used in ongoing research (e.g. Varun Joshi (2023); Aravind Sundararajan (2023))
107 of locomotor performance in humans and other animals. For validating MEP's results, after
108 solving each optimal control problem, a test is done to verify if the output MocoSolution
109 numerically equals an output reference of the same problem and weights to within a tolerance
110 based on the model's assembly error tolerance.

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References

114 Andersson, J. A. E., Gillis, J., Horn, G., Rawlings, J. B., & Diehl, M. (2018). CasADi: A software
115   framework for nonlinear optimization and optimal control. *Mathematical Programming*
116   *Computation*, *11*, 1–36. https://api.semanticscholar.org/CorpusID:53559074

117 Aravind Sundararajan, U. B., Larson SG. (2023). Optimal control simulations of 3-d walking in
118   humans and bipedal chimpanzee. In *Proceedings of The American Society of Biomechanics*.
119   Proceedings of The American Society of Biomechanics.

120 Dembia, N. A. A. F., Christopher L. AND Bianco. (2021). OpenSim moco: Musculoskeletal
121   optimal control. *PLOS Computational Biology*, *16*(12), 1–21. https://doi.org/10.1371/
122   journal.pcbi.1008493

123 Denton, A. N., & Umberger, B. R. (2023). Computational performance of musculoskeletal
124   simulation in OpenSim moco using parallel computing. *International Journal for Numerical*
125   *Methods in Biomedical Engineering*, *39*(12), e3777. https://doi.org/https://doi.org/10.
126   1002/cnm.3777

127 Falisse, A., Serrancolí, G., Dembia, C. L., Gillis, J., Jonkers, I., & De Groote, F. (2019). Rapid
128   predictive simulations with complex musculoskeletal models suggest that diverse healthy
129   and pathological human gaits can emerge from similar control strategies. *Journal of The*
130   *Royal Society Interface*, *16*(157), 20190402. https://doi.org/10.1098/rsif.2019.0402

131 Johnson, N. A. A. F., Russell T. AND Bianco. (2022). Patterns of asymmetry and energy cost
132   generated from predictive simulations of hemiparetic gait. *PLOS Computational Biology*,
133   *18*(9), 1–26. https://doi.org/10.1371/journal.pcbi.1010466

134 Seth, J. L. A. U., Ajay AND Hicks. (2018). OpenSim: Simulating musculoskeletal dynamics
135   and neuromuscular control to study human and animal movement. *PLOS Computational*
136   *Biology*, *14*(7), 1–20. https://doi.org/10.1371/journal.pcbi.1006223

137 Spomer, A., Conner, B., Schwartz, M., Lerner, Z., & Steele, K. (2023). Audiovisual biofeedback
138   amplifies plantarflexor adaptation during walking among children with cerebral palsy. *Journal*
139   *of NeuroEngineering and Rehabilitation*, *20*. https://doi.org/10.1186/s12984-023-01279-5

140 Varun Joshi, B. U., Kathryn Boyer. (2023). Optimal control gait simulations of older adults
141   predict foot placement trends not captured by reflex-based models. In *North American*
142   *Congress on Biomechanics*. North American Congress on Biomechanics.

143 Wächter, A., & Biegler, L. T. (2006). On the implementation of an interior-point filter
144   line-search algorithm for large-scale nonlinear programming. *Mathematical Programming*,
145   *106*, 25–57. https://api.semanticscholar.org/CorpusID:14183894

146 Yamaguchi, K. (2018). Mexplus. In *GitHub repository*. GitHub. https://github.com/kyamagu/
147   mexplus