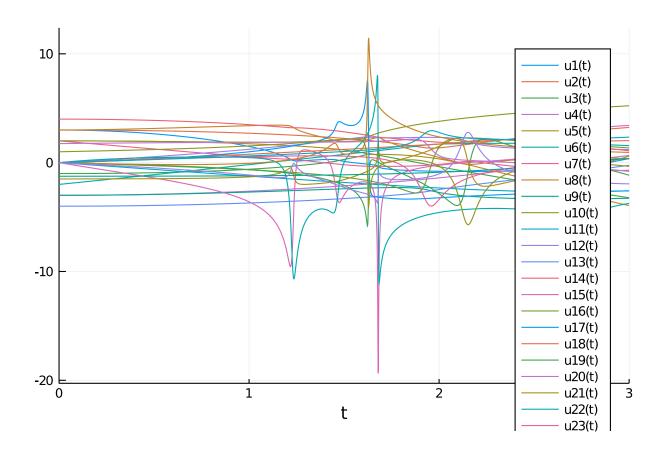
Pleiades Work-Precision Diagrams

Chris Rackauckas

July 4, 2020

```
using OrdinaryDiffEq, ODE, ODEInterfaceDiffEq, LSODA, Sundials, DiffEqDevTools
f = (du,u,p,t) \rightarrow begin
 @inbounds begin
 x = view(u, 1:7)
  y = view(u, 8:14) # y
  v = view(u, 15:21) # x'
  w = view(u, 22:28) # y'
  du[1:7] = v
  du[8:14] = w
  for i in 15:28
    du[i] = zero(u[1])
  for i=1:7, j=1:7
    if i != j
      r = ((x[i]-x[j])^2 + (y[i] - y[j])^2)^(3/2)
      du[14+i] += j*(x[j] - x[i])/r
      du[21+i] += j*(y[j] - y[i])/r
  end
  end
end
prob =
ODEProblem(f,[3.0,3.0,-1.0,-3.0,2.0,-2.0,2.0,3.0,-3.0,2.0,0,0,-4.0,4.0,0,0,0,0,0,1.75,-1.5,0,0,0,-1.28
abstols = 1.0 . / 10.0 .^{(6:9)}
reltols = 1.0 ./ 10.0 .^{(3:6)};
using Plots; gr()
Plots.GRBackend()
sol = solve(prob, Vern8(), abstol=1/10^12, reltol=1/10^10, maxiters=1000000)
test_sol = TestSolution(sol);
```

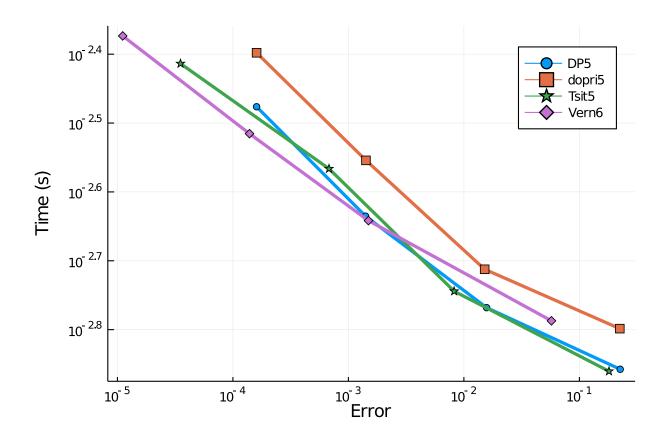
plot(sol)



0.1 Low Order

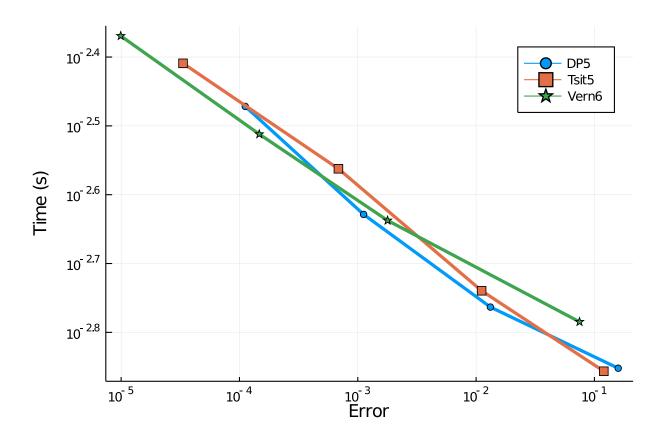
#setups = [Dict(:alg=>ode45())]

ODE.jl had to be discarded. The error estimate is off since it throws errors and aborts and so that artificially lowers the error the time is serverly diminished.



0.1.1 Interpolation

WorkPrecisionSet(prob,abstols,reltols,setups;appxsol=test_sol,numruns=100,maxiters=10000,error_estimate plot(wp)



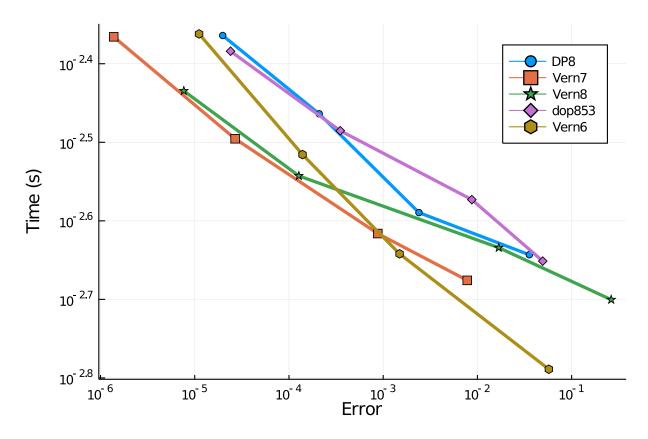
0.2 Higher Order

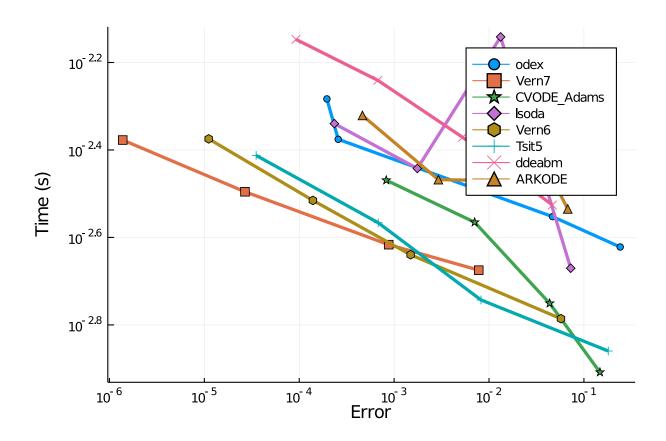
#wp =

plot(wp)

#setups = [Dict(:alg=>ode78())]

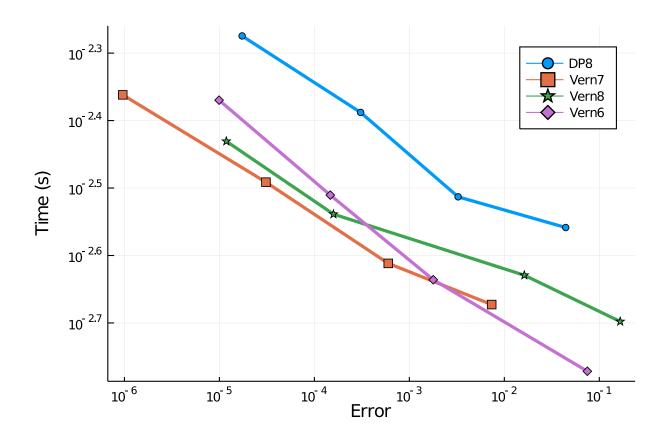
Once again ODE.jl had to be discarded since it errors.





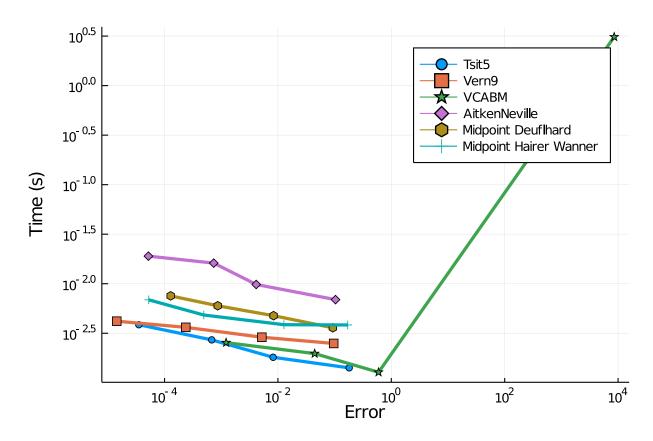
0.2.1 Interpolations

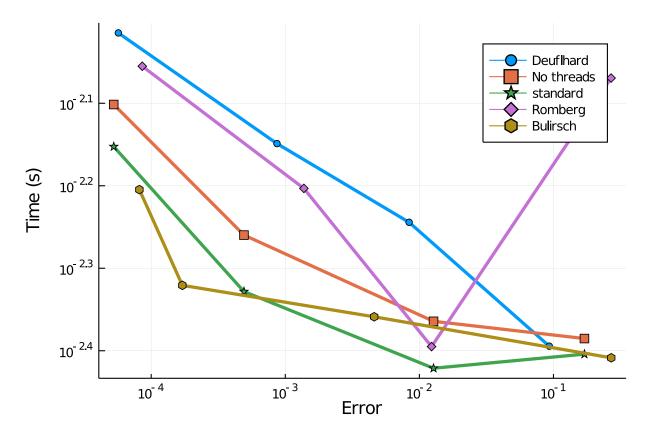
WorkPrecisionSet(prob,abstols,reltols,setups;appxsol=test_sol,numruns=100,maxiters=1000,error_estimate
plot(wp)

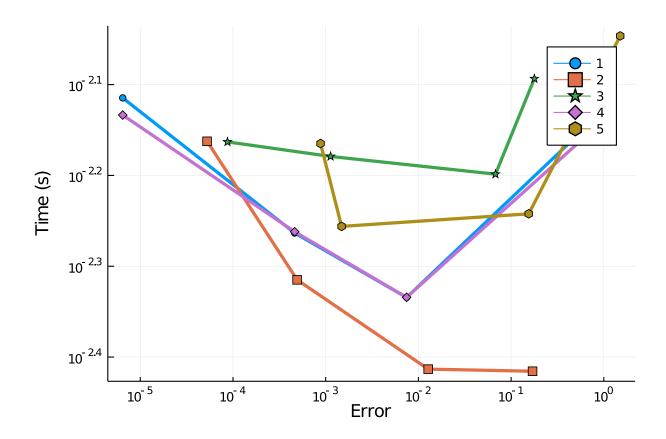


0.3 Comparison with Non-RK methods

Now let's test Tsit5 and Vern9 against parallel extrapolation methods and an Adams-Bashforth-Moulton:







0.4 Conclusion

One big conclusion is that, once again, the ODE.jl algorithms fail to run on difficult problems. Its minimum timestep is essentially machine epsilon, and so this shows some fatal flaws in its timestepping algorithm. The OrdinaryDiffEq.jl algorithms come out as faster in each case than the ODEInterface algorithms. Overall, the Verner methods have a really good showing once again. The CVODE_Adams method does really well here when the tolerances are higher.

```
using DiffEqBenchmarks
DiffEqBenchmarks.bench_footer(WEAVE_ARGS[:folder],WEAVE_ARGS[:file])
```

0.5 Appendix

These benchmarks are a part of the DiffEqBenchmarks.jl repository, found at: https://github.com/JuliaDenchmarks.jl repository,

```
using DiffEqBenchmarks
DiffEqBenchmarks.weave_file("NonStiffODE","Pleiades_wpd.jmd")
```

Computer Information:

```
Julia Version 1.4.2
Commit 44fa15b150* (2020-05-23 18:35 UTC)
Platform Info:
```

```
OS: Linux (x86_64-pc-linux-gnu)
CPU: Intel(R) Core(TM) i7-9700K CPU @ 3.60GHz
WORD_SIZE: 64
LIBM: libopenlibm
LLVM: libLLVM-8.0.1 (ORCJIT, skylake)
Environment:
   JULIA_DEPOT_PATH = /builds/JuliaGPU/DiffEqBenchmarks.jl/.julia
   JULIA_CUDA_MEMORY_LIMIT = 2147483648
   JULIA_PROJECT = @.
   JULIA_NUM_THREADS = 4
```

Package Information:

```
Status: `/builds/JuliaGPU/DiffEqBenchmarks.jl/benchmarks/NonStiffODE/Project.toml`
[f3b72e0c-5b89-59e1-b016-84e28bfd966d] DiffEqDevTools 2.22.0
[7f56f5a3-f504-529b-bc02-0b1fe5e64312] LSODA 0.6.1
[c030b06c-0b6d-57c2-b091-7029874bd033] ODE 2.8.0
[54ca160b-1b9f-5127-a996-1867f4bc2a2c] ODEInterface 0.4.6
[09606e27-ecf5-54fc-bb29-004bd9f985bf] ODEInterfaceDiffEq 3.7.0
[1dea7af3-3e70-54e6-95c3-0bf5283fa5ed] OrdinaryDiffEq 5.41.0
[65888b18-ceab-5e60-b2b9-181511a3b968] ParameterizedFunctions 5.3.0
[91a5bcdd-55d7-5caf-9e0b-520d859cae80] Plots 1.5.2
[c3572dad-4567-51f8-b174-8c6c989267f4] Sundials 4.2.5
[9a3f8284-a2c9-5f02-9a11-845980a1fd5c] Random
```