

MultiPrecisionArrays.jl: A Julia package for iterative refinement

C. T. Kelley ¹

¹ North Carolina State University, Raleigh NC, USA

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: [Open Journals](#) 

Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#)).

Summary

[MultiPrecisionArrays.jl](#), (Kelley, 2024b) provides data structures and solvers for several variations of iterative refinement (IR). IR can speed up an LU matrix factorization for solving linear systems of equations by factoring a low precision copy of the matrix and using that low precision factorization in an iteration to solve the system. For example, if high precision is double and low precision is single, then the factorization time is cut in half. The additional storage cost is the low precision copy, so IR is at time vs storage trade off. IR has a long history and a good account of the classical theory is in (Higham, 1996).

Statement of need

The solution of linear systems of equations is a ubiquitous task in computational science and engineering. A common method for dense systems is Gaussian elimination done via an LU factorization, (Higham, 1996). Iterative refinement is a way to reduce the factorization time at the cost of additional storage. [MultiPrecisionArrays.jl](#) enables IR with a simple interface in Julia (Bezanson et al., 2017) with an IR factorization object that one uses in the same way as the one for LU. The package offers several variants of IR, both classical (Higham, 1996; Wilkinson, 1948), and some from the recent literature (Amestoy et al., 2024; Carson & Higham, 2017).

Algorithm

This package will make solving dense systems of linear equations faster by using the LU factorization and IR. While other factorizations can be used in IR, the package is limited to LU for now. A very generic description of this for solving a linear system $Ax = b$ in a high (working) precision is

IR(A, b)

- $x = 0$
- $r = b$
- Factor $A = LU$ in a lower precision
- While $\|r\|$ is too large
 - $d = (LU)^{-1}r$
 - $x = x + d$
 - $r = b - Ax$
- end

36 ▪ end

37 In Julia, a code to do this would solve the linear system $Ax = b$ in the working precision, say
 38 double, by using a factorization in a lower (factorization) precision, say single, within a residual
 39 correction iteration. This means that one would need to allocate storage for a copy of A in
 40 the factorization precision and factor that copy.

41 The multiprecision factorization `mplu` makes the low precision copy of the matrix, factors that
 42 copy, and allocates some storage for the iteration. The original matrix and the low precision
 43 factorization are stored in a factorization object that you can use with `\`.

44 IR is a perfect example of a storage/time trade off. To solve a linear system $Ax = b$ in R^N
 45 with IR, one incurs the storage penalty of making a low precision copy of A and reaps the
 46 benefit of only having to factor the low precision copy.

47 Installation

48 The standard way to install a package is to type `import Pkg; Pkg.add("MultiPrecisionArrays")`
 49 at the Julia prompt. One can run the unit tests with `Pkg.test("MultiPrecisionArrays")`.
 50 After installation, type using `MultiPrecisionArrays` when you want to use the functions in
 51 the package.

52 There are only two direct dependencies outside of the Julia standard libraries. The factorization
 53 in half precision (Float16) uses [OhMyThreads.jl](#). The GMRES and Bi-CGSTAB solvers for
 54 Krylov-IR methods are taken from [SIAMFANL.jl](#) ([Kelley, 2022c](#)).

55 A Few Subtleties

56 Within the algorithm one has to determine what the line $d = (LU)^{-1}r$ means. Does one
 57 cast r into the lower precision before the solve or not? If one casts r into the lower precision,
 58 then the solve is done entirely in the factorization precision. If, however, r remains in the
 59 working precision, then the LU factors are promoted to the working precision on the fly. This
 60 makes little difference if TW is double and TF is single and there is a modest performance
 61 benefit to downcasting r into single. Therefore that is the default behavior in that case. If
 62 TF is half precision, Float16, then it is best to do the interprecision transfers on the fly and
 63 if one is using one of the Krylov-IR algorithms ([Amestoy et al., 2024](#)) then one must do the
 64 interprecision transfers on the fly and not downcast r .

65 There are two half precision (16 bit) formats. Julia has native support for IEEE 16 bit floats
 66 (Float16). A second format (BFloat16) has a larger exponent field and a smaller significand
 67 (mantissa), thereby trading precision for range. In fact, the exponent field in BFloat is the
 68 same size (8 bits) as that for single precision (Float32). The significand, however, is only 8
 69 bits. Compare this to the size of the exponent fields for Float16 (11 bits) and single (24 bits).
 70 The size of the significand means that you can get in real trouble with half precision in either
 71 format and that IR is more likely to fail to converge. GMRES-IR can mitigate the convergence
 72 problems ([Amestoy et al., 2024](#)) by using the low-precision solve as a preconditioner. We
 73 support both GMRES ([Saad & Schultz, 1986](#)) and BiCGSTAB ([Vorst, 1992](#)) as solvers for
 74 Krylov-IR methods. One should also know that LAPACK and the BLAS do not yet support
 75 half precision arrays, so working in Float16 will be slower than using Float64.

76 The classic algorithm from ([Wilkinson, 1948](#)) and its recent extension ([Carson & Higham, 2017](#))
 77 evaluate the residual in a higher precision than the working precision. This can give
 78 improved accuracy for ill-conditioned problems at a cost of the interprecision transfers in the
 79 residual computation. This needs to be implemented with some care and ([Demmel et al., 2006](#))
 80 has an excellent account of the details.

81 **MultiPrecisionArrays.jl** provides infrastructure to manage these things and we refer the reader
82 to (Kelley, 2024b) for the details.

83 Projects using MultiPrecisionArrays.jl.

84 This package was motivated by the use of low-precision factorizations in Newton's method
85 (Kelley, 2022a, 2022c) and the interface between a preliminary version of this package and the
86 solvers from (Kelley, 2022c, 2022b) was reported in (Kelley, 2023). That paper used a three
87 precision form of IR (TF=half, TW=single, nonlinear residual computed in double) and required
88 direct use of multiprecision constructors that we do not export in **MultiPrecisionArrays.jl**.
89 We will fully support the application to nonlinear solvers in a future version. We give a
90 detailed account of interprecision transfers in (Kelley, 2024a) and use **MultiPrecisionArrays.jl**
91 to generate the table in that paper.

92 Other Julia Packages for IR

93 The package **IterativeRefinement.jl** is an implementation of the IR method from (J.Dongarra
94 et al., 1983). It has not been updated in four years.

95 The unregistered package **ltref.jl** implements IR and the GMRES-IR method from (Amestoy et
96 al., 2024) and was used to obtain the numerical results in that paper. It does not provide the
97 data structures for preallocation that we do and does not seem to have been updated lately.

98 Acknowledgements

99 This work was partially supported by Department of Energy grant DE-NA003967. Any opinions,
100 findings, and conclusions or recommendations expressed in this material are those of the author
101 and do not necessarily reflect the views of the United States Department of Energy.

102 References

- 103 Amestoy, P., Buttari, A., Higham, N. J., L'Excellent, J.-Y., Mary, T., & Vieublé, B. (2024).
104 Five-precision GMRES-based iterative refinement. *SIAM Journal on Matrix Analysis and*
105 *Applications*, 45(1), 529–552. <https://doi.org/10.1137/23M1549079>
- 106 Bezanson, J., Edelman, A., Karpinski, S., & Shah, V. B. (2017). Julia: A fresh approach to
107 numerical computing. *SIAM Review*, 59, 65–98. <https://doi.org/10.1137/141000671>
- 108 Carson, E., & Higham, N. J. (2017). A new analysis of iterative refinement and its application
109 of accurate solution of ill-conditioned sparse linear systems. *SIAM Journal on Scientific*
110 *Computing*, 39(6), A2834–A2856. <https://doi.org/10.1137/17M1122918>
- 111 Demmel, J., Hida, Y., & Kahan, W. (2006). Error bounds from extra-precise iterative refinement.
112 *ACM Trans. Math. Soft.*, 325–351. <https://doi.org/10.1145/1141885.1141894>
- 113 Higham, N. J. (1996). *Accuracy and stability of numerical algorithms* (p. xxviii+688). Society
114 for Industrial; Applied Mathematics. <https://doi.org/10.1137/1.9780898718027>
- 115 J.Dongarra, J., B.Moler, C., & H.Wilkinson, J. (1983). Improving the accuracy of computed
116 eigenvalues and eigenvectors. *SIAM Journal on Numerical Analysis*, 20, 23–45. <https://doi.org/10.1137/0720002>
- 117
118 Kelley, C. T. (2022a). Newton's method in mixed precision. *SIAM Review*, 64, 191–211.
119 <https://doi.org/10.1137/20M1342902>

- 120 Kelley, C. T. (2022b). *SIAMFANLEquations.jl*. <https://github.com/ctkelley/SIAMFANLEquations.jl>. <https://doi.org/10.5281/zenodo.4284807>
- 122 Kelley, C. T. (2022c). *Solving Nonlinear Equations with Iterative Methods: Solvers and*
123 *Examples in Julia*. SIAM, Philadelphia. <https://doi.org/10.1137/1.9781611977271>
- 124 Kelley, C. T. (2023). *Newton's method in three precisions*. [https://doi.org/10.48550/arXiv.](https://doi.org/10.48550/arXiv.2307.16051)
125 [2307.16051](https://doi.org/10.48550/arXiv.2307.16051)
- 126 Kelley, C. T. (2024a). *Interprecision transfers in iterative refinement*. [https://arxiv.org/abs/](https://arxiv.org/abs/2407.00827)
127 [2407.00827](https://arxiv.org/abs/2407.00827)
- 128 Kelley, C. T. (2024b). *Using MultiPrecisionArrays.jl: Iterative refinement in Julia*. [https://](https://doi.org/10.48550/arXiv.2311.14616)
129 doi.org/10.48550/arXiv.2311.14616
- 130 Saad, Y., & Schultz, M. H. (1986). GMRES a generalized minimal residual algorithm for
131 solving nonsymmetric linear systems. *SIAM J. Sci. Stat. Comp.*, 7, 856–869. [https://](https://doi.org/10.1137/0907058)
132 doi.org/10.1137/0907058
- 133 Vorst, H. A. van der. (1992). Bi-CGSTAB: A fast and smoothly converging variant to Bi-CG
134 for the solution of nonsymmetric systems. *SIAM J. Sci. Stat. Comp.*, 13, 631–644.
135 <https://doi.org/10.1137/0913035>
- 136 Wilkinson, J. H. (1948). *Progress report on the automatic computing engine* (No.
137 MA/17/1024). Mathematics Division, Department of Scientific; Industrial Research,
138 National Physical Laboratory, Teddington, UK. [http://www.alanturing.net/turing_archive/](http://www.alanturing.net/turing_archive/archive/I/I10/I10.php)
139 [archive/I/I10/I10.php](http://www.alanturing.net/turing_archive/archive/I/I10/I10.php)