

1 **GeRelion: GPU-enhanced parallel implementation of single particle cryo-EM** 2 **image processing**

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11 **Single particle cryo-EM emerges as a powerful and versatile method to characterize the**
12 **structure and function of macromolecules, revealing the structural details of critical**
13 **molecular machinery inside the cells. RELION is a widely used EM image processing**
14 **software, and most of the recently published single particle cryo-EM structures were**
15 **generated by using RELION. Due to the massive computational loads and the growing**
16 **demands for processing much larger cryo-EM data sets, there is a pressing need to speed**
17 **up image processing. Here we present GeRelion ([https://github.com/gpu-pdl-](https://github.com/gpu-pdl-nudt/GeRelion)**
18 **[nudt/GeRelion](https://github.com/gpu-pdl-nudt/GeRelion)), an efficient parallel implementation of RELION on GPU system. In the**
19 **performance tests using two cryo-EM data sets, GeRelion on 4 or 8 GPU cards**
20 **outperformed RELION on 256 CPU cores, demonstrating dramatically improved speed**
21 **and superb scalability. By greatly accelerating single particle cryo-EM structural analysis,**
22 **GeRelion will facilitate both high resolution structure determination and dissection of**
23 **mixed conformations of dynamic molecular machines.**
24

25 Single particle cryo-EM has become a game-changing technique in structural biology, gaining
26 unprecedented insights into many macromolecular machines in fundamental life processes^{1,2}. By
27 directly imaging the biological samples frozen in buffer solutions, cryo-EM circumvents the
28 need to obtain well-ordered crystals, a major bottleneck in traditional crystallographic methods
29 for high resolution structure determination. Single particle cryo-EM is also capable of
30 computationally separating mixed conformations in a single sample, greatly facilitating the
31 determination of high resolution structures and the analysis of dynamic molecular machines³.

32 In single particle cryo-EM, the molecules embedded in vitreous ice adopt different
33 orientations, and generate various two dimensional (2D) projection images, so called particles. A
34 three dimensional (3D) reconstruction is generated by averaging a large number of particles
35 according to their rotation angles and in-plane shifts. The resolution of 3D reconstruction is
36 gradually improved by iteratively refining the geometric parameters of each particle⁴.
37 Furthermore, sophisticated computation methods enable the selection of the most homogeneous
38 particles to achieve high-resolution 3D reconstructions, as well as the separation of different
39 conformations within one sample. Particularly, RELION implements a Bayesian approach and
40 the maximum a posteriori (MAP) algorithm, and demonstrates outstanding performance in 3D
41 classification and 3D refinement^{5,6}. In fact, most of the recently published single particle cryo-
42 EM structures were generated using RELION. However, the computational cost of RELION is
43 very high, and the enormous computational loads practically limit the number of cryo-EM
44 particles that can be routinely analyzed. With the development of automatic EM data collection
45 and the ever-growing demands for analyzing more particles to achieve higher resolution and to
46 dissect mixed conformations, there is a pressing need to speed up the image processing^{1,7}.

47 To accelerate the computation, many EM software packages, such as SPIDER⁸,
48 FREALIGN⁹, EMAN¹⁰, and RELION⁶, implement parallel computation based on Central
49 Processing Units (CPUs), and the speed increase depends on the number of available CPUs. In
50 the last decade, due to the progress of hardware architecture and high-level programming model,
51 the Graphic Processing Unit (GPU) has been widely used to accelerate time-consuming scientific
52 applications such as medical image processing¹¹, bioinformatics¹² and machine learning¹³.
53 Equipped with thousands of processing units in one processor, modern GPUs provide massive
54 computation power, with significantly higher memory bandwidth than multi-core CPUs. In
55 addition, the performance-price ratio of GPU is usually higher than that of CPU. Thus, GPU
56 offers an attractive alternative for parallel implementation of the computation-intensive EM
57 image processing applications. GPU implementation has been reported for EMAN, FREALIGN,
58 and other programs^{10,14,15}. Despite being extremely popular in the field for several years, the
59 computationally expensive RELION has not been implemented in GPU system, probably due to
60 the challenges to restructure the complicated work flow to map GPU computation. First,
61 RELION uses coarse parallelization, which is not compatible with fine-grained parallelization of
62 GPU. Second, the data structure in RELION is designed for individual images, resulting in
63 discontinuous processing of multiple images. Third, RELION introduces two sampling methods,
64 and the second sampling is sparse and sometimes with uncertainty, which makes it difficult for
65 GPU implementation.

66 Here we present GeRelion, an efficient parallel implementation of RELION using GPU-
67 enhanced system. Our tests on the two single particle cryo-EM data sets demonstrate that
68 GeRelion with 4 or 8 NVIDIA GPUs outperforms RELION running on a modern CPU cluster
69 with 256 CPU cores. GeRelion displays essentially linear scalability up to the 8 GPUs tested in
70 our experiments, indicating great potential for further scaling on larger GPU clusters. In this
71 paper we report the implementation of GeRelion, the results of performance tests, and a detailed
72 procedure of utilizing the GeRelion program. This new parallel implementation on GPU system
73 will significantly improve the efficiency of single particle EM image processing, and enable the
74 routine analysis of much larger data sets, thus facilitating the determination of high resolution
75 cryo-EM structures and the analysis of mixed conformations of dynamic molecular machines.

76

77 **RESULTS**

78 **Profiling of RELION**

79 RELION integrates various function modules for single particle cryo-EM image processing. Our
80 implementation focuses on the two mostly used and computationally intensive functionalities:
81 3D classification and 3D refinement. In order to parallelize RELION on GPU, we first analyzed
82 the RELION program to locate the computation hot spots and identified the computation patterns.

83 The mathematic basis of RELION is Bayesian statistics and the underlying algorithm is
84 expectation-maximization method (details in **Online Methods**)⁶. We analyzed the execution
85 time distribution of RELION, according to the program skeleton of RELION (**Supplementary**
86 **Fig. 1**). The overall computation procedure is divided into three steps: expectation, maximization,
87 and others. The expectation step consists of four major subroutines:
88 `getFourierTransformAndCtfs` (`getImg`), `getAllSquaredDifferences` (`getDiff`),
89 `convertAllSquaredDifferencesToWeights` (`convert`) and `storeWeightedSums` (`store`). The others
90 step includes MPI communication, overhead of data read/write, and certain data processing tasks
91 on the host side such as combining the partial 3D reconstruction files. We first used 8 CPU cores
92 with MPI parallelism to evaluate the execution time distribution of RELION, by running 3D

93 classification of the TRPV1 cryo-EM data set¹⁶. This data set contains 35,645 particles with a
94 size of 256 x 256 pixels. The results show that the most time-consuming step is expectation,
95 occupying over 97% of the total time, while the maximization and others steps take only 0.4%
96 and 2.1%, respectively (**Fig. 1a**). Within the expectation step, the getDiff subroutine, which
97 computes the l2-norm of expectation algorithm, is the slowest part. The same test was carried out
98 for another single particle cryo-EM data set of the RAG complexes¹⁷, which contains 154,984
99 particles with a size of 192 x 192 pixels, resulting in a similar pattern of execution time
100 distribution (**Fig. 1b**).

101 We further evaluated the scalability of RELION with increasing number of CPUs, by
102 testing the total execution time and the time in the expectation step. We carried out 3D
103 classifications using the TRPV1 data set with and without C4 symmetry, and also the RAG data
104 set. The RELION computation speed on the TRPV1 data set increased linearly with up to 64
105 CPUs, but the speed improvement significantly slowed down with more than 64 CPUs (**Fig. 1c**).
106 The limitation of CPU-based speedup was due to the substantially increased time proportions in
107 the maximization and others steps (**Supplementary Fig. 2b**). The overhead of combining the
108 partial 3D reconstruction files seems to be the most significant portion in the others step. The
109 suppression of speedup with more CPUs appeared less severe in the tests on the TRPV1 data set
110 without applying symmetry, and on the RAG data set that contains more than 4 times the
111 particles of the TRPV1 data set (**Fig. 1c**). This is due to the increased computational loads in the
112 slowest expectation step, which partially alleviated the increasing time occupancy in the
113 maximization and others steps (**Supplementary Fig. 2e**). Indeed, for all three tests, the speedup
114 in the expectation step was consistently more linear than that in the overall execution time (**Fig.**
115 **1d**). To remove the extra bottlenecks from the maximization step and certain overheads, which
116 would significantly impact the scaling of RELION computation, we decided to parallelize all the
117 steps on GPU system.

118 Based on the abovementioned tests and careful analysis of RELION program, we classified
119 the RELION computation tasks into three categories: intensive computation, sparse index
120 deduced computation, and global reduction operation. Specific strategies were developed for the
121 parallel implementation of these different tasks on GPU, as detailed in **Online Methods**.

122

123 **Implementation of GeRelion**

124 We have implemented GeRelion, a GPU-enhanced version of RELION, to accelerate the most
125 widely used functionalities: 3D classification and 3D refinement (“auto-refine”). The original
126 RELION codes for data read/write and MPI communication are unmodified, and the flow control
127 of progressive processing in the original RELION is kept.

128 Rich data-level fine-grained parallelism and efficient memory access are two major factors
129 that determine the performance of GPU program. In this work, we designed a four-level parallel
130 model for the single particle cryo-EM image processing to exploit the powerful computational
131 capability of GPU. In the first level, the particle images are divided into a set of pools that are
132 parallelized onto individual GPUs, and the number of pools to be processed simultaneously
133 equals to the number of GPUs (**Fig. 2a**). In the second level, the images within one pool are
134 parallelized onto the stream multi processors of one GPU (**Fig. 2b**). In the third level, the
135 workload for one image in one orientation will be assigned to one thread block of the GPU
136 kernel, and the parallel degree of this level equals the number of orientations to be processed

137 (Fig. 2c). In the fourth level, the processing of one or several pixels is assigned to one thread
138 within each thread block, and all the pixels within one particle image are processed
139 simultaneously (Fig. 2d). In GeRelion, the maximal parallel degree equals $nr_gpus * M * N * K$,
140 where nr_gpus , M , N and K represent the number of GPUs, the number of images within one
141 pool, the number of orientations to be processed, and the pixel number in one particle image,
142 respectively.

143 In order to efficiently map the proposed multi-level parallel model to GPU-based system,
144 we restructured the program in several aspects, as detailed in **Online Methods**. The original deep
145 loops were flattened and partitioned, and data layout was reorganized to fit the architecture of
146 GPU (**Supplementary Fig. 3**). To address the problem of memory limitation on GPU, GeRelion
147 implements an adaptive parallel framework to determine the number of orientations to be
148 processed simultaneously, based on the available memory space. To exploit the data reuse, we
149 enlarged the parallel granularity in the first coarse sampling pass, and designed the lightweight
150 kernels in the second fine sampling to achieve sufficient parallelism. In addition, we parallelized
151 the sparse index computation by compacting the sparse data array to a continuous vector
152 (**Supplementary Fig. 4**), and optimized the global reduction operation with atomic operation
153 strategy.

154 **Performance of GeRelion**

156 To test the performance of GeRelion and compare it with the original RELION, we used two
157 computation systems (system 1 and system 2 in **Table 1**). The unmodified RELION ran on a
158 CPU-only cluster with 256 CPU cores, while GeRelion ran on a GPU-based cluster with 2 nodes,
159 each containing 4 GPUs and 12 CPU cores.

160 We first used the TRPV1 data set to run 3D refinement without or with C4 symmetry, and
161 compared the computation times of RELION and GeRelion. The test results show that the
162 overall computation speed of GeRelion on 4 GPUs is similar to that of RELION on 256 CPU
163 cores, and GeRelion demonstrated a near-linear speedup with up to 8 GPUs, indicating excellent
164 scalability of the implementation (**Fig. 3a, 3c**). The speed enhancement of GeRelion in the total
165 execution time is consistent with that in the expectation step (**Fig. 3a, 3c**), which was in turn
166 contributed by the similar speedup of all four major subroutines in the expectation step (**Fig. 3b,**
167 **3d**). We notice the extra speed increase in the overall execution compared to the expectation step
168 (**Fig. 3a, 3c**), which is due to the significant speedup in the steps of maximization and others
169 (**Table 2, Supplementary Fig. 5**). To prove the computation accuracy of our implementation,
170 we also confirmed that the 3D reconstructions generated by RELION and GeRelion are
171 essentially identical (**Fig. 3e, 3f**).

172 We then compared the performance of GeRelion and RELION in 3D classification. The
173 results are very similar to those from the tests of 3D refinement, showing excellent scalability of
174 GeRelion with increasing number of GPUs (**Fig. 4**). For the TRPV1 data set, GeRelion on 4
175 GPUs outperformed RELION on 256 CPU cores (**Fig. 4a**). Since the scalability of CPU-based
176 RELION is improved with higher computational loads in the expectation step (**Fig. 1c, 1d**), for
177 the RAG data set with significantly more particles, 8 GPUs were needed for GeRelion to outrun
178 the 256 CPU core-powered RELION (**Fig. 4c**). In addition, we also tested the 3D refinement
179 using the RAG data set and the 3D classification using the TRPV1 data set with C4 symmetry.
180 The execution times of all the tests in this work are summarized in **Table 2**. Collectively, our
181 extensive performance tests demonstrate the superb acceleration and scalability of GeRelion.

182

183 **DISCUSSION**

184 RELION is a popular image processing program in the cryo-EM field, and has generated most of
185 the recently published high-resolution single particle cryo-EM structures. However, the Bayesian
186 statistics-based computation in RELION is very costly, and the resulting massive computational
187 loads limit the particle number of routine single particle data sets to well below one million. Due
188 to the widely used automatic data collection and the need to analyze more particles to extract
189 more structural information from a particular biological sample, there is a pressing need to
190 significantly accelerate the image processing programs such as RELION¹.

191 Here we presented GeRelion, an efficient GPU-based parallel implementation of the RELION
192 program. To exploit the powerful computational capability of GPU system, we designed a four-
193 level parallel model and restructure the RELION program to efficiently map this parallel model
194 to GPU system. The resulting GeRelion implementation demonstrates significant speedup in the
195 tests with two cryo-EM data sets, and shows excellent scalability with increasing number of
196 GPUs. To our knowledge, GeRelion represents the first systematic GPU conversion of all the
197 computation steps in the two most widely used RELION functionalities: 3D classification and
198 3D refinement.

199 Our tests show that GeRelion using 4 or 8 GPUs outperforms RELION using 256 modern
200 CPU cores. Thus, to achieve similar computation speed, it is more cost-effective to purchase and
201 maintain a couple GPU nodes than a large CPU cluster. Specifically, one NVIDIA K40m GPU
202 provides 1.43T FLOPS (float-point operations per second) for double precision float, and its
203 price is about \$3,000. In contrast, an Intel Xeon E5-2620 v2 CPU supports up to 100.8G FLOPS,
204 and its price is about \$400 per CPU. When considering the cost of memory and other
205 components of a computer node, the prices for 8 GPUs (2 nodes) and 256 CPU cores (22 nodes)
206 are about \$34,000 and \$67,700, respectively. Practically it is also much easier to build and
207 maintain a couple GPU nodes than a large CPU cluster. Furthermore, regular RELION
208 computation uses double precision float point data, which makes it necessary to use high-end
209 GPUs. The calculation with single precision float point has been implemented in the RELION
210 version 1.4. If the computation with single precision float point can satisfy the requirement of
211 image processing at least under certain circumstances, it will be an optimal choice to use the
212 consumer level GPU at the price range of \$200-600, which is similar to the price of a six-core
213 Intel Xeon CPU.

214 Several aspects of our current GeRelion implementation may be further improved in the
215 future work. First, the parallel degree of the getImg subroutine can be increased. In the current
216 implementation, we only parallelized one pool of images for each kernel invoked, and the default
217 number of 8 is insufficient for GPU. Therefore, we can parallel hundreds or thousands of images
218 in this step and keep the results in GPU memory for the following getDiff subroutine. Second,
219 the maximization step can be optimized for the large particles such as those with a size of 512 or
220 more pixels. Due to the GPU memory limitation, currently it is difficult to execute the Fourier
221 transform function for the very large particles. Third, a hybrid GPU-CPU implementation can be
222 developed to utilize the CPU computation capability, which comes with the GPU system, for
223 further improvement of the computation efficiency. Fourth, the parallel read/write can be
224 improved, which will become particularly important for scaling in much larger GPU clusters.

225 In summary, GeRelion dramatically speeds up the computation-intensive 3D classification
226 and 3D refinement in RELION, and demonstrates a great potential for scaling the speed
227 enhancement on larger GPU clusters. GeRelion will greatly accelerate the processing of much

228 larger single particle cryo-EM data sets, and thereby facilitate high resolution structure
229 determination as well as analysis of mixed conformations in biological samples.

230

231 **METHODS**

232 Methods and any associated references are available in the online version of the paper.

233

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242

243 **AUTHOR CONTRIBUTIONS**

244 M.L. and D.L. conceived the project. D.L. and X. L. supervised the project. H.S. and D.L.
245 designed the overall development of GeRelion. H.S., W.W., X.D and D.L implemented the GPU
246 program. H.S, W.W and M.L designed the test and analyzed the results. M.L, D.L and H.S.
247 wrote the manuscript. All authors read and approved the final manuscript.

248

249 **COMPETING FINANCIAL INTERESTS**

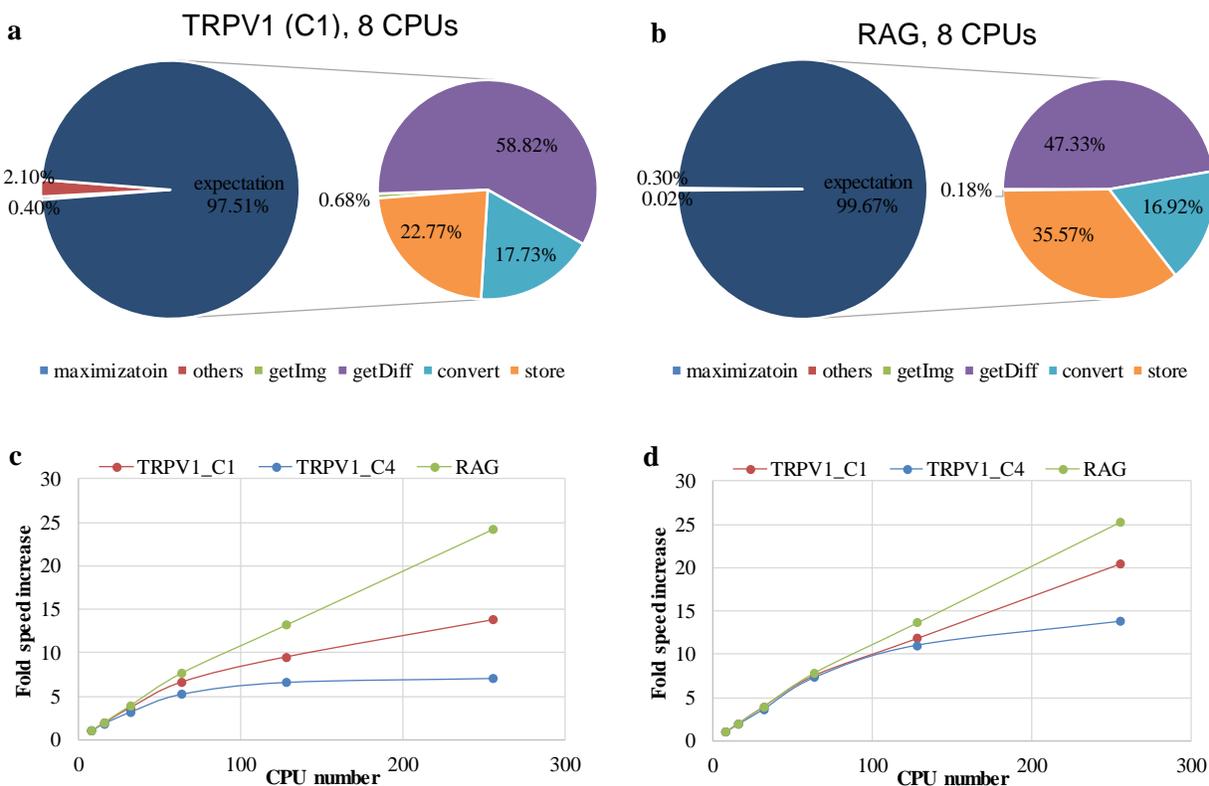
250 The authors declare no competing financial interests.

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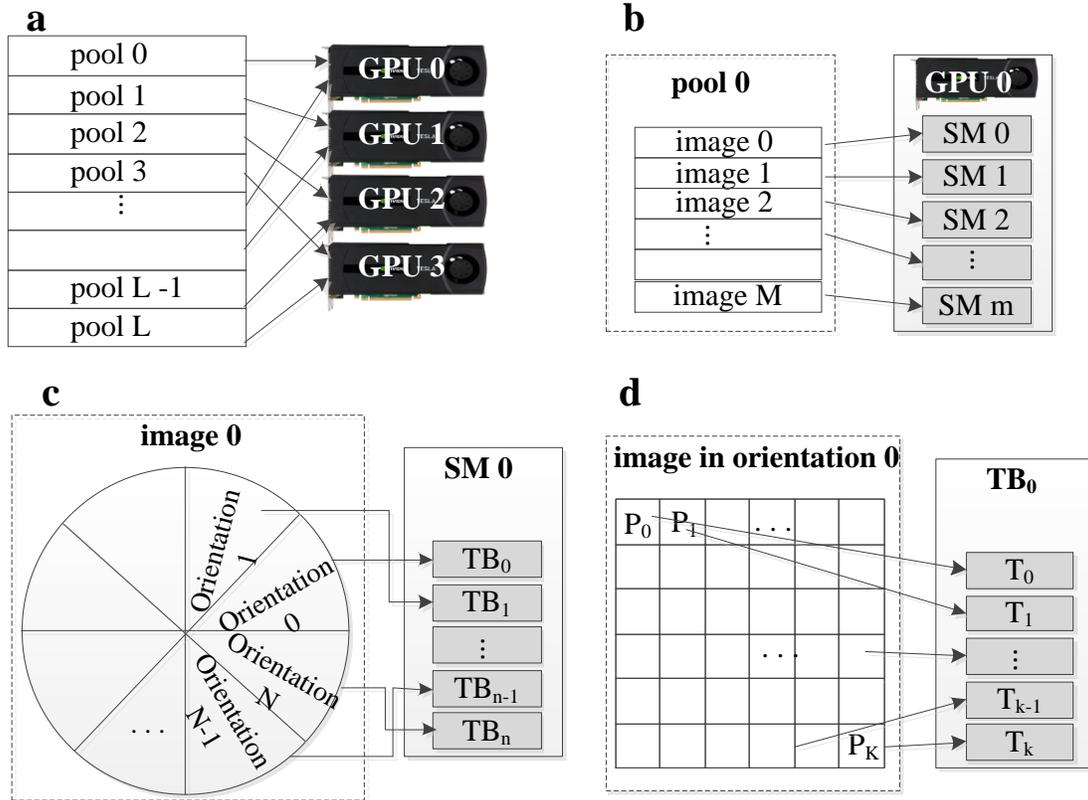
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257 **Figure 1** | Execution time distribution and scalability of RELION. (a) Execution time
 258 distribution of 3D classification of the TRPV1 data set (without symmetry) using 8 CPU cores.
 259 The time distributions for the three steps (expectation, maximization and others) and for the four
 260 major subroutines (getImg, getDiff, convert and store) in the expectation step are shown. (b)
 261 Same as (a), except the 3D classification was carried out for the RAG data set. (c) Speed
 262 enhancement in 3D classifications of the TRPV1 data set, with and without C4 symmetry, and
 263 that of the RAG data set, using 8, 16, 32, 64, 128 and 256 CPU cores. The speeds of 8 CPU cores
 264 were used as the reference to calculate the speed enhancement. (d) Same as (c), except the speed
 265 enhancement is for the expectation step.

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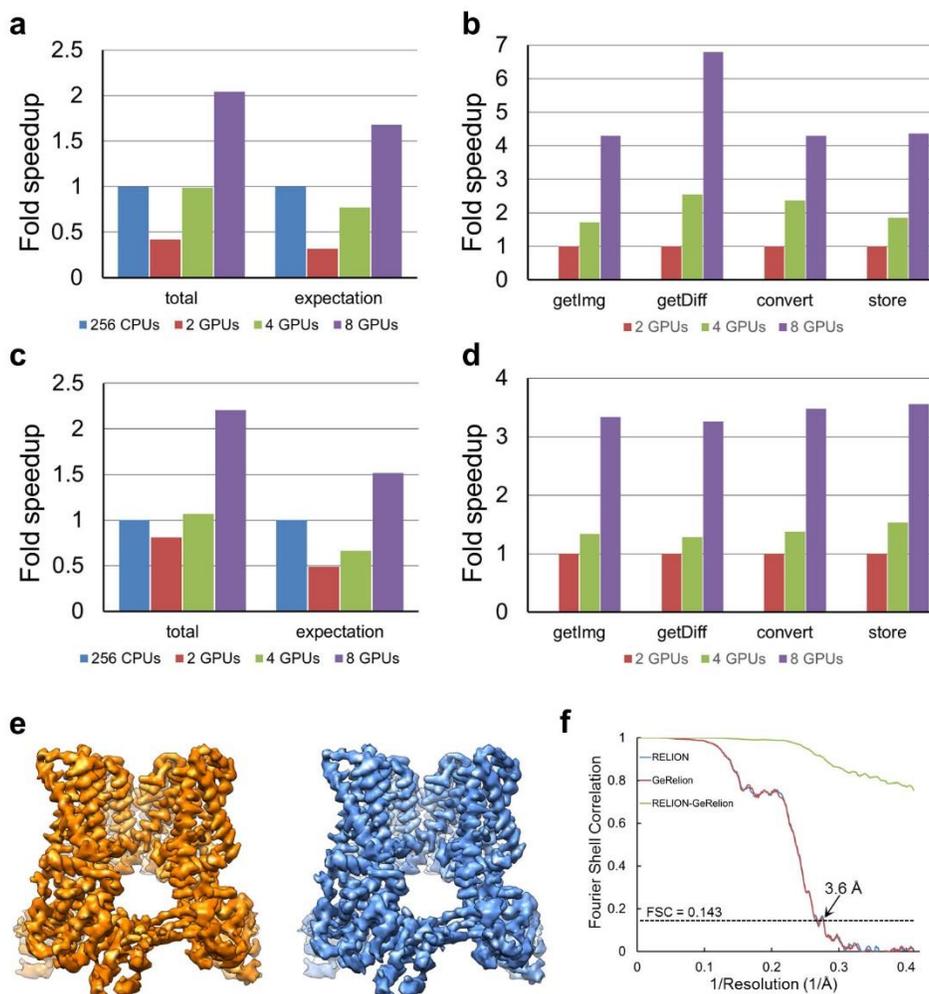
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270 **Figure 2** | Multi-level parallel model of GeRelion. **(a)** Multi-pool parallelization to multiple
 271 GPUs. The particle images are divided into a set of pools. The maximal parallel degree is the
 272 number of GPU: nr_gpus . **(b)** Multi-image parallelization to stream multi processors (SM) of one
 273 GPU. The maximal parallel degree is the number of particle images within the pool: M . **(c)**
 274 Multi-orientation parallelization to thread blocks (TB). The maximal parallel degree is the
 275 number of orientations to be calculated for the particle image: N . **(d)** Multi-pixel parallelization
 276 to threads (T). The maximal parallel degree is the total pixel number within one particle image:
 277 K . Therefore, the maximal overall parallel degree of GeRelion equals $nr_gpus * M * N * K$.
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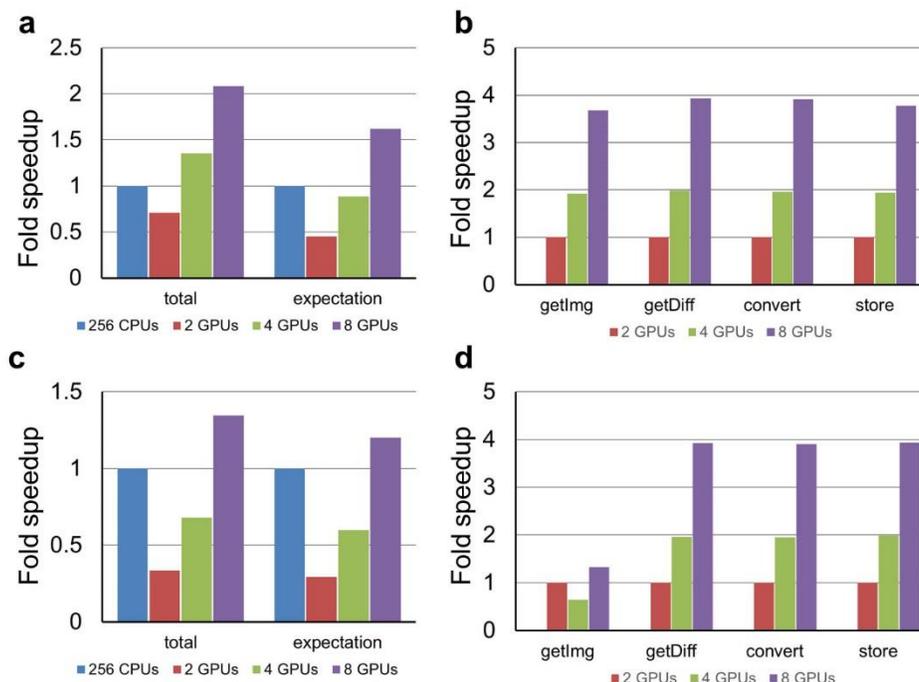


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281 **Figure 3** | Performance of GeRelion in 3D refinement of the TRPV1 cryo-EM data set. (a)
 282 Computation speeds of RELION on 256 CPU cores and GeRelion on 2, 4 and 8 GPUs. The 3D
 283 refinement was carried out without applying symmetry. The speed of RELION was used as the
 284 reference to calculate the speed enhancement of GeRelion. (b) Computation speeds of the four
 285 major subroutines of the expectation step in GeRelion, from the tests in (a). The speeds of
 286 GeRelion on 2 GPUs were used as the reference to calculate the speed enhancement with more
 287 GPUs. (c) Same as (a), except the 3D refinement was carried out with C4 symmetry. (d) Same as
 288 (b), except the 3D refinement was carried out with C4 symmetry. All the corresponding
 289 execution times are listed in **Table 2**. (e) 3D reconstructions of TRPV1 generated by RELION
 290 (left, in orange) and GeRelion (right, in blue). Both maps were filtered at 3.6 Å resolution, and
 291 show essentially identical features. (f) Gold-standard Fourier shell correlation (FSC) curves (in
 292 orange and blue) of the two 3D reconstructions in (e) show excellent overlap, and the FSC curve
 293 between these two reconstructions (in green) shows the FSC values of 0.9 and 0.75 at the 3.6 Å
 294 resolution and Nyquist limit, respectively. These indicate that the two reconstructions generated
 295 by RELION and GeRelion are essentially identical.

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299 **Figure 4** | Performance of GeRelion in 3D classification. (a) Computation speeds of RELION on
300 256 CPU cores and GeRelion on 2, 4 and 8 GPUs, in 3D classification of the TRPV1 data set
301 without symmetry. The speed of RELION was used as the reference to calculate the speed
302 enhancement of GeRelion. (b) Computation speeds of the four major subroutines of the
303 expectation step in GeRelion, from the tests in (a). The speeds of GeRelion on 2 GPUs were
304 used as the reference to calculate the speed enhancement with more GPUs. (c) Computation
305 speeds of RELION on 256 CPU cores and GeRelion on 2, 4 and 8 GPUs, in 3D classification of
306 the RAG data set. The speed of RELION was used as the reference to calculate the speed
307 enhancement of GeRelion. (d) Computation speeds of the four major subroutines of the
308 expectation step in GeRelion, from the tests in (c). The speeds of GeRelion on 2 GPUs were used
309 as the reference to calculate the speed enhancement with more GPUs. All the corresponding
310 execution times are listed in **Table 2**.

311

312 **Table 1** | Computation systems used for the tests.

System 1: CPU cluster	System 2: GPU-based cluster	
CPU	CPU	GPU
Intel E5-2620 v2	Intel E5-2620 v3	NVIDIA K40m
2.10GHz	2.40GHz	0.75GHz
2x6 cores per node	2x6 cores per node	4 GPUs per node
DDR3 1866MHz	DDR4 2133MHz	GDDR 5 3004MHz
128GB per nodes	128 GB per node	
22 nodes	2 nodes	

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316 **Table 2** | Execution time (in minutes) of RELION and GeRelion in auto-refine and 3D
 317 classification of the two single particle cryo-EM data sets.

		total	expecta- tion	Maxi mi- zation	others	get- Img	getDiff	convert	store
TRPV1 auto- refine C1	256 cpus	298.0	221.2	50.0	26.8	1.0	164.2	10.0	26.3
	2 gpus	713.0	698.3	7.0	7.1	51.2	440.8	67.7	129.3
	4 gpus	301.0	287.4	7.7	5.9	29.9	173.3	28.6	70.1
	8 gpus	146.0	131.6	8.8	5.6	11.9	64.9	15.7	29.6
TRPV1 auto- refine C4	256 cpus	203.0	115.9	60.4	26.7	0.9	82.8	3.4	16.4
	2 gpus	251.0	237.3	8.1	5.7	35.9	102.5	25.4	65.6
	4 gpus	190.0	174.6	8.5	7.3	26.9	80.0	18.5	43.0
	8 gpus	92.0	76.4	9.4	6.2	10.8	31.4	7.3	18.5
RAG auto- refine	256 cpus	863.1	773.0	69.0	21.0	34.2	517.7	82.5	203.2
	2 gpus	1697.0	1670.3	4.5	22.3	147.6	619.8	193.0	676.6
	4 gpus	1112.0	1071.9	4.5	22.7	110.6	470.0	140.4	304.7
	8 gpus	639.0	615.8	3.1	20.2	57.2	248.4	72.3	203.8
TRPV1 3D class C1	256 cpus	223.0	136.0	21.2	65.8	0.6	82.8	16.0	18.7
	2 gpus	314.0	302.3	1.3	10.5	9.6	160.4	63.3	64.7
	4 gpus	165.0	153.5	0.8	10.7	5.0	80.7	32.2	33.3
	8 gpus	107.0	84.0	6.5	16.5	2.6	40.7	16.2	17.1
TRPV1 3D class C4	256 cpus	157.0	66.7	20.0	70.3	0.7	25.9	4.1	23.3
	2 gpus	161.0	143.2	1.9	15.8	10.1	56.7	31.1	41.0
	4 gpus	93.0	78.8	1.0	13.2	5.7	31.0	16.6	23.0
	8 gpus	75.0	46.3	6.9	21.8	2.8	15.5	8.2	11.5
RAG 3D class	256 cpus	876.0	748.8	30.9	96.3	1.8	427.5	141.8	127.0
	2 gpus	2482.0	2456.4	1.8	23.9	32.3	1022.4	488.5	844.2
	4 gpus	1285.3	1248.0	1.3	36.1	50.0	521.9	250.2	425.1
	8 gpus	650.7	623.4	2.2	25.2	24.4	260.9	125.3	214.9

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 319 “Total” indicates the total execution time of the whole application, which includes three steps:
 320 “expectation”, “maximization” and “others”. The “expectation” step consists of four major
 321 subroutines: “getImg”, “getDiff”, “convert” and “store”. The computation tasks in the “others”
 322 step include MPI communication, I/O overhead, and certain data processing tasks on the host
 323 side such as combining the partial 3D reconstruction files.

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368 **ONLINE METHODS**

369 **RELION algorithm.** RELION is an open-source software package for single particle cryo-EM
 370 structure determination. Like most of the existing implementations for cryo-EM image
 371 processing, it employs the so-called weak-phase object approximation, leading to the following
 372 linear image formation model in Fourier space.

$$373 \quad X_{ij} = CTF_{ij} \sum_{l=1}^L P_{jl}^{\phi} V_{kl} + N_{ij} \quad (1)$$

374 Where X_{ij} is the j th component, with $j = 1, \dots, J$ of the 2D Fourier transformation X_i of the i th
 375 experimental image, with $i = 1, \dots, N$. CTF_{ij} is the j th component of the contrast transfer
 376 function for the i th image. V_{kl} is the l th component, with $l = 1, \dots, L$, of the 3D Fourier
 377 transformation V_k of the k th of K underlying structures in the data set. All components V_{kl} are
 378 assumed to be independent, zero-mean, and Gaussian distributed with variance τ_{kl}^2 ; P^{ϕ} is a $J \times L$
 379 projecting matrix of elements P_{jl}^{ϕ} , N_{ij} is noise in the complex plane, which is assumed to be
 380 independent, zero-mean, and Gaussian distributed with variance σ_{ij}^2 .

381 The objection of cryo-EM image analysis software RELION is to find the model with
 382 parameter set Θ (including all V_{kl} , σ_{ij}^2 and τ_{kl}^2) that has the highest probability of being the
 383 correct one in the light of both the observed data X and the prior information Y . From the Bayes'
 384 law, this so-called posterior distribution factorizes into two components, shown as equation (2).
 385 Where the likelihood $P(X|\Theta, Y)$ quantifies the probability of observing the data given the model,
 386 and the prior $P(\Theta|Y)$ expresses how likely that model is given the prior information [16]. It
 387 should be noticed that most of the other methods in Fourier domain aimed to only optimize $P(X|$
 388 $\Theta, Y)$.

$$389 \quad P(\Theta|X, Y) \propto P(X|\Theta, Y)P(\Theta|Y) \quad (2)$$

390 As for RELION, prior information is the smoothness hypothesis about cryo-EM
 391 reconstructions, and posterior information is provided by cryo-EM image data set. The deduced
 392 optimization is called maximum a posterior (MAP) estimation. MAP estimation is the most
 393 likely model which gets most out of the data at the Gaussian prerequisite of smoothness.
 394 RELION implements an iterative expectation-maximization algorithm to optimize the MAP
 395 model 2. The iterative algorithm is expressed by formulas 3~7.

$$396 \quad V_{kl}^{(n+1)} = \frac{\sum_{i=1}^N \int_{\phi} \Gamma_{ik\phi}^{(n)} \sum_{j=1}^J P_{jl}^{\phi} \frac{CTF_{ij}^T X_{ij}}{\sigma_{ij}^2} d\phi}{\sum_{i=1}^N \int_{\phi} \Gamma_{ik\phi}^{(n)} \sum_{j=1}^J P_{jl}^{\phi} \frac{CTF_{ij}^2}{\sigma_{ij}^2} d\phi + \frac{1}{\tau_{kl}^2}} \quad (3)$$

$$397 \quad \sigma_{ij}^{2(n+1)} = \frac{1}{2} \times \sum_{k=1}^K \int_{\phi} \Gamma_{ik\phi}^{(n)} |X_{ij} - CTF_{ij} \sum_{j=1}^J P_{jl}^{\phi} V_{kl}^{(n)}|^2 d\phi \quad (4)$$

$$398 \quad \tau_{kl}^{2(n+1)} = \frac{1}{2} \times |V_{kl}^{(n+1)}|^2 \quad (5)$$

$$399 \quad \Gamma_{ik\phi}^{(n)} = \frac{P(X_i|k, \phi, \Theta^{(n)}, Y) P(k, \phi | \Theta^{(n)}, Y)}{\sum_{k'=1}^K \int_{\phi'} P(X_i|k', \phi', \Theta^{(n)}, Y) P(k', \phi' | \Theta^{(n)}, Y) d\phi'} \quad (6)$$

400 where $\Gamma_{ik\phi}^{(n)}$ in equation (6) is the posterior probability of class assignment k and orientation
 401 assignment ϕ for the i th image, given the model at iteration n . The iterative algorithm starts from

402 an initial estimate model of V_k . User controls the number of models K that is to be refined
403 simultaneously. Initial estimations for τ_{kl}^2 and σ_{ij}^2 are calculated from the power spectra of the
404 starting model and individual particles, respectively. Within each iteration, the posterior
405 probability $\Gamma_{ik\phi}^{(n)}$ for all images has to be calculated in all possible orientation and class k . The
406 major computation comes from the calculation of the l_2 -norm in equation (7).

407
408 **Three computation modes of RELION.** According to the computation instructions, we
409 classified the computation tasks of RELION into three categories: the intensive computation, the
410 sparse index computation and the global reduction (**Supplementary Table 1**). In the first
411 sampling of “getDiff”, the l_2 -norm will be calculated for all particle images and reference CTF
412 images in all possible orientations. High resolution structure determination often requires
413 hundreds of thousands, or even millions of particles, and more than a thousand of orientations for
414 the angle search. On top of these, there is another search grid of XY shift. The total computation
415 requirement for “getDiff” will be over PetaFLOPs, the procedure can be considered as
416 computation intensive. In Relion, the process of the second fine sampling is only carried out in
417 the significant orientations determined in the first sampling. An orientation can be consider as
418 significant if the corresponding weight is larger than the threshold value. Compared with the
419 total number of orientations, the number of significant orientations is relative small. The
420 computation pattern is sparse index computation. To calculate weighted sum in the subroutine
421 “store”, the operation of summing all images in formula (3) and the integration $\int_{\phi} \Gamma_{ik\phi}^{(n)}$
422 corresponds to solve the discrete sum in all significant orientations. Both of them refer to the
423 global reduction for all particles and orientations. Similarly, the execution path of “store” also
424 depends on whether the corresponding weight is significant. Due to the sparse feature of weight
425 matrix, the process of “store” is both sparse index and global reduction.

426
427 **Restructuring of RELION for GPU implementation.** In order to efficiently parallelize the
428 RELION computation onto GPU system, we restructured the program in several aspects.

429 **Partition and unroll loops.** The philosophy of GPU programing is unrolling loops to kernels.
430 Generally, a simple kernel is designed based on one or several loops of code segment with the
431 same parallel degree: the size of the loop index. In RELION, the subroutines consist of several
432 layer of loops, the workload within different layer loops correspond to different parallel degrees.
433 For example, the subroutine “getDiff” consists of three layer for loops, the orientation for loop,
434 particle for loop and the translation for loop. The sub-functions of getFref, applyCTFtoFref and
435 calDiff reside in these three layer loops respectively. That means the parallel degrees of them are
436 not the same. These workloads should be parallelized with different GPU kernels. Therefore,
437 we partition the long loops into several short loops, with the key function processed within each
438 loop. Though loop unrolling, we can design kernels for each short loop by mapping workload of
439 different layer loops to multilevel programming model of GPU (**Supplementary Fig. 3**).

440 **Reorganize the data layout.** In the original program, the image data of different particles are
441 stored in separate memory space, which disobeys the continuous access principle of GPU
442 programming. Additionally, in order to save memory space, the operation on-the-fly is adopted
443 for projection and back-projection. In GeRelion, we reorganize the image data by gathering the
444 raw image data of different particles into a large array at the beginning of each iteration. While in

445 the following steps, all input data are generated from the previous kernels on GPU, which avoids
446 the preparation of input for kernels and exploits the locality between producer and consumer.

447 **Build adaptive parallel framework.** Generally, we hope to unroll the entire loop of a
448 function to kernel. In RELION, in order to save memory, the program is designed to traverse
449 loops to process all jobs of the entire orientation. Within each traversing, only one image will be
450 processed. We consider to parallelize the workload of all orientations into one kernel, however,
451 which may lead to out-of-memory error due to numerous orientations and images. In GeRelion,
452 we proposed an adaptive parallel framework to address this problem. We firstly evaluate the
453 maximal memory requirement according to the number of orientations, images and image size.
454 Combining the memory requirement and the free GPU memory, a suitable parallel degree taken
455 orientation as unit can be computed. Through this way, we can use the GPU resource as much as
456 possible and avoid the problem of memory limitation.

457 **Enlarge parallel granularity and increase parallel degree.** According to the profiling of
458 RELION, there are three major computation modes. In GeRelion, we design kernels for
459 different sampling passes. For the first pass, considering that most of the orientations is valid and
460 there is good data locality between the whole XY shift grid, we design a coarse kernel to
461 parallelize the first pass of getDiff by enlarge the parallel granularity. One thread is used to deal
462 with the job of the whole XY shift grid, and the reference image data can be reused for multiple
463 times. For the second sampling, where the significant orientations are very few, in order to
464 exploit enough parallelism, we developed a lightweight kernel by giving priority to parallel
465 degree and using one thread to process only one pixel.

466 **Transform sparse computation into continuous processes.** Although the sparse index
467 computation is difficult and inefficient for GPU, the GPU-based parallelization of the sparse
468 computing is inevitable for achieving high-performance GPU enhanced RELION. On one hand,
469 from the profiling results, the sparse computation occupies a certain proportion of the execution
470 time, especially in 3D classification. On the other hand, if the sparse index computation
471 functions remain on the host side, a lot of intermediate data must be copied back to CPU.
472 However, the data transmission between CPU and GPU is costly. In GeRelion, we transform the
473 sparse computation to continuous process to avoid divergence in GPU kernels. In our
474 implementation, we pick up the significant weights of all particles from the sparse weight matrix
475 into a small continuous vector. In order to keep the consistency of the weight with the
476 corresponding image and orientation, an aux vector is introduced to store the indexes of the
477 weights in the original sparse weight matrix. An example of the weight array and vector in CPU
478 and GPU RELION are shown in **Supplementary Fig. 4**. Generally, the global reduction is done
479 on the host side, even though the overhead of copy back the large weight matrix to CPU is costly
480 and a lock primitive is also needed to ensure the correctness of the program. Due to the possible
481 written conflict when back projecting 2D slices into the 3D Fourier space, we adopt atomic
482 operation to implement global reduction.

483
484 **Performance tests of GeRelion.** We used two single particle cryo-EM data sets to test the
485 performance of GeRelion in 3D classification and 3D refinement (“auto-refine”). Both of the
486 TRPV1 and RAG data sets can be downloaded from the Electron Microscopy Pilot Image
487 Archive (<https://www.ebi.ac.uk/pdbe/emdb/empiar/>). The TRPV1 data set (EMPIAR-10005)

488 contains 35,645 particles with a size of 256 x 256 pixels. For our tests, we only used the particles
489 averaged from all 30 movie frames to generate a map at 3.6 Å resolution. A continued 3D
490 refinement using the particles averaged from the #3-16 movie frames would have improved the
491 resolution to 3.4 Å. The RAG data set (EMPIAR-10049) is a combination of SEC and PC
492 particles, and contains 154,984 particles with a size of 192 x 192 pixels. In the tests of 3D
493 classification, the TRPV1 data is classified into 3 classes, and the RAG data into 6 classes.

494 Currently GeRelion can only support command lines to submit jobs. The commands for
495 running all the GeRelion tests in this work are listed below. “Node01” and “node02” are the
496 hostnames of the two GPU nodes. “Relion_refine_mpi” is the executable file of GeRelion.
497 GeRelion can run on GPU or CPU, by setting the “model” parameter to 1 or 0.

498
499 The command of auto-refine on TRPV1 without symmetry:
500 mpirun --np 9 -N 5 --host node01,node02 relion_refine_mpi --o Refine_OPT_C1/run8 --
501 auto_refine --split_random_halves --i new_DFMerge_20.star --particle_diameter 160 --angpix
502 1.2156 --ref EMD-5778.mrc --firstiter_cc --ini_high 60 --ctf --ctf_corrected_ref --flatten_solvent
503 --zero_mask --oversampling 1 --healpix_order 2 --auto_local_healpix_order 4 --offset_range 5 --
504 offset_step 2 --sym C1 --low_resol_join_halves 40 --norm --scale --j 1 --memory_per_thread 8 --
505 dont_combine_weights_via_disc --mode 1

506
507 The command of auto-refine on TRPV1 with C4 symmetry:
508 mpirun --np 9 -N 5 --host node01,node02 relion_refine_mpi --o Refine_OPT_C1/run8 --
509 auto_refine --split_random_halves --i new_DFMerge_20.star --particle_diameter 160 --angpix
510 1.2156 --ref EMD-5778.mrc --firstiter_cc --ini_high 60 --ctf --ctf_corrected_ref --flatten_solvent
511 --zero_mask --oversampling 1 --healpix_order 2 --auto_local_healpix_order 4 --offset_range 5 --
512 offset_step 2 --sym C4 --low_resol_join_halves 40 --norm --scale --j 1 --memory_per_thread 8 --
513 dont_combine_weights_via_disc --mode 1

514
515 The command of 3D classification on TRPV1 without symmetry:
516 mpirun --np 9 -N 5 --host node01,node02 relion_refine_mpi --o Class3D_OPT/run8 --i
517 allimg.star --particle_diameter 180 --angpix 1.23 --ref 3D_relion_class001_shz-5.dat --
518 firstiter_cc --ini_high 40 --ctf --ctf_corrected_ref --iter 25 --tau2_fudge 4 --K 6 --flatten_solvent
519 --zero_mask --oversampling 1 --healpix_order 2 --offset_range 5 --offset_step 2 --sym C1 --
520 norm --scale --j 1 --memory_per_thread 8 --dont_combine_weights_via_disc --mode 1

521
522 The command of 3D classification on TRPV1 with C4 symmetry:
523 mpirun --np 9 -N 5 --host node01,node02 relion_refine_mpi --o Class3D_OPT/run8 --i
524 allimg.star --particle_diameter 180 --angpix 1.23 --ref 3D_relion_class001_shz-5.dat --
525 firstiter_cc --ini_high 40 --ctf --ctf_corrected_ref --iter 25 --tau2_fudge 4 --K 6 --flatten_solvent
526 --zero_mask --oversampling 1 --healpix_order 2 --offset_range 5 --offset_step 2 --sym C4 --
527 norm --scale --j 1 --memory_per_thread 8 --dont_combine_weights_via_disc --mode 1

528
529 The command of auto-refine on RAG:
530 mpirun --np 9 -N 5 --host node01,node02 relion_refine_mpi --o Refine3D_OPT/run8 --
531 auto_refine --split_random_halves --i particles_autopick_sort_class2d.star --particle_diameter
532 200 --angpix 3.54 --ref 3i3e_lp50A.mrc --firstiter_cc --ini_high 60 --ctf --ctf_corrected_ref --
533 flatten_solvent --zero_mask --oversampling 1 --healpix_order 2 --auto_local_healpix_order 4 --

534 offset_range 4 --offset_step 2 --sym D2 --low_resol_join_halves 40 --norm --scale --j 2 --
535 memory_per_thread 4 --random_seed 1401784870 --dont_combine_weights_via_disc --mode 1

536

537 The command of 3D classification on RAG:

538 mpirun --np 9 -N 5 --host node01,node02 relion_refine_mpi --o Class3D_OPT/run8 --i
539 particles_autopick_sort_class2d.star --particle_diameter 200 --angpix 3.54 --ref 3i3e_lp50A.mrc
540 --firstiter_cc --ini_high 50 --ctf --ctf_corrected_ref --iter 25 --tau2_fudge 2 --K 4 --
541 flatten_solvent --zero_mask --oversampling 1 --healpix_order 2 --offset_range 3 --offset_step 2 -
542 -sym C1 --norm --scale --j 1 --memory_per_thread 4 --dont_combine_weights_via_disc --mode
543 1

544

545 **Code availability.** The GeRelion program is open source and available on github
546 (<https://github.com/gpu-pdl-nudt/GeRelion>).