

1 **Title:**

2 MitoGeneExtractor: Efficient extraction of mitochondrial genes from next generation
3 sequencing libraries

4 **Running title:**

5 MitoGeneExtractor: mining mitochondrial genes

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13 **Abstract:**

14 Mitochondrial DNA sequences (mtDNA) are often found as byproduct in hybrid enrichment
15 data sets originally created to capture anchored hybrid enrichment (AHE) or ultra-conserved
16 element (UCE) nuclear loci. The mtDNA sequences in these data sets are currently rarely
17 used, even though mitochondrial genes such as COI, ND5, CytB, and 16S are of general
18 interest and often not yet known and deposited in public databases. We developed
19 MitoGeneExtractor to extract mitochondrial genes of interest from genomic libraries. Gene
20 sequences are reconstructed through multiple sequence alignments of sequencing reads to
21 an amino acid reference. We applied MitoGeneExtractor to recently published data created
22 for UCE enrichment and were able to extract complete or nearly complete COI and ND5
23 sequences for a large proportion of the sequencing libraries. MitoGeneExtractor can be used
24 to extract mitochondrial protein coding genes from a wide range of next generation
25 sequencing data sets.

26 **Key words:** Data mining, DNA barcoding, data re-use, mitochondrial genes, COI, ND5

27 **Introduction:**

28 Next generation sequencing (NGS) and high throughput sequencing have become standard
29 tools in biological research and enable the generation of unprecedented amounts of
30 sequencing data (Reuter, Spacek, & Snyder, 2015). Rapidly evolving sequencing technologies
31 and relatively low sequencing costs of ~1,000 USD per genome (30 X coverage on Illumina
32 platforms; [genome.gov/sequencingcostsdata](https://www.genome.gov/sequencingcostsdata); accessed on 03.05.2021) allow researchers to
33 investigate biological processes based not only on one or a few genes. Instead, millions of
34 sequencing reads are generated per run in order to analyze thousands of loci or whole
35 genomes, ranging from individual specimens to entire biological communities. The
36 continuously dropping costs promise the growing exploitation of DNA sequence information
37 in an application-oriented context such as medicine (Lecuit & Eloit, 2015), biomonitoring
38 (Baird & Hajibabaei, 2012) or species conservation (Allendorf, Hohenlohe, & Luikart, 2010).
39 Despite the clear trend towards increased cost-efficiency, generating and analyzing high-
40 throughput sequencing data is still resource demanding with regard to laboratory and
41 computational costs, time and skills.

42 NGS data potentially harbor much more information than is exploited over the course of the
43 initial experiment. Although it is highly important to incorporate genomic complexity in
44 biological studies, researchers might be particularly interested in specific genes. One
45 example is the mitochondrial cytochrome oxidase I subunit (COI) gene, which is the most
46 commonly used molecular marker in animal species identification (Hebert, Cywinska, Ball, &
47 deWaard, 2003) and related fields, despite some limitations (Eberle, Ahrens, Mayer, Niehuis,
48 & Misof, 2020). Fragments of this gene are further used to assess biotic communities in DNA

49 metabarcoding approaches, using either bulk samples of e.g. trapped invertebrates or free
50 environmental DNA (eDNA) from samples such as water or soil (Cordier et al., 2021;
51 Taberlet, Coissac, Pompanon, Brochmann, & Willerslev, 2012). Organellar DNA sequences
52 are generally present in gDNA sequencing libraries due their high abundances in the cell and
53 therefore in gDNA extracts (Bogenhagen & Clayton, 1974; Samuels et al., 2013) and can be
54 found as byproduct in sequence capture/enrichment data sets (Allio et al., 2020; Amaral et
55 al., 2015; Picardi & Pesole, 2012). Often, these organelle related reads are discarded or
56 ignored during bioinformatic processing, potentially wasting this source of data. Studies that
57 have extracted mitochondrial sequences from ultra-conserved genomic loci enrichment
58 (UCE) data or anchored hybrid enrichment data are rare (e.g. Meiklejohn et al. 2014; Pie et
59 al. 2017; Wang et al. 2017; Caparroz et al. 2018), probably due to the lack of conveniently
60 applicable tools.

61 Here, we describe an approach to make use of this sequencing byproduct in order to extend
62 the utility of the constantly growing amount of sequencing data beyond the initial study
63 purpose. By aligning DNA sequencing reads to an amino acid reference sequence (e.g. the
64 COI gene), we are able to reconstruct *in silico* the corresponding COI or other mitochondrial
65 sequences, if the mitogenome is sufficiently represented within the genomic read pool. This
66 is especially important for the generation of sequence information in non-model organisms
67 or taxonomic groups in which sample access can be difficult or even impossible, such as rare
68 or extinct taxa. As such, these sources constitute an important but hitherto untapped
69 contribution to the global DNA barcode databases like the Barcode of Life Data System
70 (BOLD) (Ratnasingham & Hebert, 2007).

71 We selected mitochondrial genes as a case study due to their significance in biological
72 research, because of their usually good representation in sequencing libraries, and since
73 they are typically well conserved and indels are not expected within taxonomic groups.

74 Several tools such as Phyluce (Faircloth, 2016), MITObim (Hahn, Bachmann, & Chevreux,
75 2013), Trimitomics (Plese et al., 2019), MitoZ (Meng, Li, Yang, & Liu, 2019) or Mitofinder
76 (Allio et al., 2020) already exist, which aim to reconstruct and extract *in silico* mitochondrial
77 sequences or even whole mitogenomes from genomic read pools. All the mentioned tools
78 are based on assembly results: for example, MITObim aims to reconstruct whole
79 mitogenomes from genomic NGS data sets, relying on the genome assembler MIRA
80 (Chevreux, Wetter, & Suhai, 1999). Based on an iterative selection of reads matching a
81 current intermediate sequence and an assembly of these currently selected reads, MITObim
82 tries to reconstruct mitochondrial genomic regions starting from a seed sequence (Hahn et
83 al., 2013).

84 The Phyluce pipeline was originally designed to extract UCEs and to subsequently perform
85 phylogenetic analyses with these loci (Faircloth, 2016). Phyluce uses the output of assembly
86 tools such as Trinity (Grabherr et al., 2011) by aligning the produced contigs to a bait (or
87 oligonucleotide probe) reference sequence. Initially designed for standard enrichment baits
88 for UCE loci, Phyluce can in principle be used to extract other loci as well, dependent on the
89 input bait reference. Trimitomics assembles mitochondrial genomes from transcriptomic
90 data (Plese et al., 2019) and MitoFinder is designed to assemble simultaneously both UCE
91 and complementary mtDNA from raw UCE capture libraries (Allio et al., 2020) by using the

92 meta-assembler metaSPAdes (Nurk, Meleshko, Korobeynikov, & Pevzner, 2017) or IDBA
93 (Peng, Leung, Yiu, & Chin, 2010).

94 Assembly guided sequence reconstruction approaches have several drawbacks: i.)
95 assemblies are highly parameter dependent, ii.) the quality of assemblies quickly drops if
96 read coverage values are low (see results of this study). iii.) An assembly process is always
97 computationally intensive, especially for large data sets. This can prevent or at least hamper
98 the fast and efficient sequence reconstruction for hundreds or thousands of individuals/taxa.

99 iv.) Existing approaches rely on reference sequences from a closely related species or at least
100 seeding sequences such as the barcode region. Finally, (v) in the presence of NUMTs (nuclear
101 mitochondrial DNA), a sequence variation is introduced which can prevent a successful
102 assembly of the reads. In preliminary analyses, we have found that MITObim suffers from
103 this problem. Potentially, implementing another assembler than MIRA within MITObim
104 could produce better results for multi allelic data and uneven read coverage. Altogether,
105 assemblers require a substantial amount of sequence reads for being able to reconstruct the
106 target region, particularly in the presence of only partially similar sequences such as NUMTs.

107 The here presented workflow does not require the assembly of reads but instead is based on
108 an alignment of the DNA sequencing reads to an amino acid reference. For this purpose, we
109 developed the tool MitoGeneExtractor, which utilizes the program Exonerate
110 (ebi.ac.uk/about/vertebrate-genomics/software/exonerate) to align DNA reads to a
111 provided amino acid reference (Figure 1). MitoGeneExtractor uses the Exonerate output (i.e.
112 vulgar file format, containing information about the start/end position of the read alignment
113 in the reference, whether the forward or the reverse complement orientation aligned and

114 an alignment score) to generate a multiple sequence alignment (MSA) of the reads. Due to
115 the degeneracy of the genetic code, this allows a considerable DNA sequence variation of
116 reads that can successfully be aligned to the reference. This makes it possible to use the
117 same amino acid reference for a broad spectrum of taxa in particular when mining genes
118 from the conserved mitochondrial genome. The subsequently resulting MSAs can be used to
119 reconstruct a consensus gene sequence for the individual sample. When implemented in a
120 data analysis management system such as Snakemake (Köster & Rahmann, 2012), it is
121 possible to analyze and extract sequence information from hundreds or even thousands of
122 genomic DNA data sets automatically and simultaneously.

123 We tested our approach with a large avian data set from Harvey et al. (2020), which upon
124 publication had been used for a comprehensive phylogenomic analysis of songbirds
125 (*Passeriformes*) in a tropical biodiversity hotspot. With the presented approach, we were
126 able to reconstruct sequence information (≥ 90 % of the sequence) for two mitochondrial
127 genes, the cytochrome *c* oxidase 1 (COI) and NADH dehydrogenase subunit 5 (ND5) gene for
128 85 % and 80 % of the samples, respectively. We compared MitoGeneExtractor with
129 MitoFinder (Allio et al., 2020) regarding the sequence reconstruction success and
130 computational time. Further, we evaluated the taxonomic assignment based on our
131 reconstructed sequences obtained with MitoGeneExtractor. As no full-length COI sequence
132 information was present for any of the bird species in NCBI, we evaluated our approach via
133 the comparison of our reconstructed sequences with COI barcodes from BOLD
134 (Ratnasingham & Hebert, 2007) and compared our taxonomic assignment inferred via the
135 reconstructed barcodes with the taxonomic assignment of the initial study from Harvey et al.
136 (2020).

137 **Material and Methods:**

138 During the initial study of Harvey et al. (2020), the authors generated target enrichment data
139 of UCEs and exons for 1,993 individuals. Their final data set comprised 1,287 neotropical bird
140 species, represented by 1-38 individuals per species. We used this data set to attempt the *in*
141 *silico* reconstruction of complete COI and ND5 sequences for all of the 1,993 individuals. The
142 DNA extracts were obtained from genomic resource collections at natural history museums
143 and from field excursions. gDNA extracts were enriched for UCEs and conserved exons and
144 sequenced on Illumina HiSeq platforms (Harvey et al., 2020).

145 *Obtaining and pre-processing of data:*

146 Raw sequence data was downloaded from the NCBI Sequence Read Archive PRJNA655842
147 using prefetch from the SRA-toolkit v 2.11.2 (<http://ncbi.github.io/sra-tools/>). The sra files
148 were transformed to the fastq format with fastq-dump (SRA-toolkit). We specified the
149 options --split-e in order to extract the data in separate files, if paired-end read data was
150 generated, and --readids to retain unique read sequence IDs. Paired-end read information
151 cannot be exploited with Exonerate because each read is individually aligned to the
152 reference, either in forward or reverse complement orientation. Therefore, we
153 concatenated paired-end libraries and treated them as single-end libraries. This artificially
154 doubled read numbers in paired-end libraries (Table S1, S2) but allowed to retain one read
155 of a read pair, when the other read was discarded during quality trimming. Raw sequencing
156 reads were quality trimmed using the cutadapt v 1.18 (Martin, 2011) wrapper script
157 TrimGalore! v 0.0.6 (<https://github.com/FelixKrueger/TrimGalore>) with auto-detection of
158 Illumina adapters and a quality cut-off at Phred < 20. Fastq files were transformed to the

159 fasta format using bash shell commands. Data transformation and quality processing was
160 conducted within a Snakemake workflow in order to improve reproducibility of data
161 analysis.

162 *Generation of reference protein sequences:*

163 The NCBI protein database (<https://www.ncbi.nlm.nih.gov/protein/>) was searched for full
164 length sequence information of the COI and ND5 genes for all passerine birds
165 (*Passeriformes*). All sequences were downloaded and one sequence per genus was retained.
166 The sequences were visually inspected with AliView v 1.26 (Larsson, 2014) and irregular
167 sequences (which corrupted the alignment) were removed. Then, the sequences were
168 aligned (385 for COI and 331 for ND5) using the MUSCLE algorithm (Edgar, 2004) and the
169 resulting consensus amino acid sequences were used as reference for the MSAs.

170 *Alignment of reads – MitoGeneExtractor*

171 We developed MitoGeneExtractor which creates consensus gene sequences in the following
172 three steps. In step one, MitoGeneExtractor calls Exonerate, which needs to be installed
173 independently, to align the amino acid reference sequence to the input (i.e. quality filtered)
174 DNA reads (both input files are expected to be in fasta format). Two important Exonerate
175 command line parameters, which alter the alignment settings, can be specified when calling
176 MitoGeneExtractor and are passed to Exonerate: the genetic code used for translating the
177 reads prior to the alignment and the frameshift penalty. Further, the user can specify the
178 minimum alignment score threshold used by Exonerate, if desired. In step two,
179 MitoGeneExtractor uses the Exonerate output in vulgar format (see Exonerate manual for
180 details) to create an alignment of all input reads. Parameters can be specified to control e.g.

181 the minimum coverage and the minimum alignment score relative to the read length to
182 control the alignment quality. Finally in step three, MitoGeneExtractor determines
183 consensus sequences for the gene of interest and provides the user with an alignment fasta
184 file and the desired consensus sequence as final output.

185 When calling MitoGeneExtractor, the most time-consuming step is the generation of the
186 Exonerate vulgar files (although this only takes on the order of 30 seconds for 1 million reads
187 using a single core on a modern laptop). For existing vulgar files, the MSAs are generated by
188 MitoGeneExtractor in a few seconds, allowing a fast re-analysis with adjusted parameters
189 once the vulgar files are already produced. Exonerate writes alignment information to the
190 vulgar file only for those reads that could successfully be aligned to the target gene. From
191 this information MitoGeneExtractor determines not only the MSA of successfully aligned
192 reads, but also the corresponding consensus sequence. The MSA of reads can be used for
193 subsequent data exploration and analyses.

194 For this study, we installed Exonerate version 2.2.4 and called MitoGeneExtractor with the
195 options `-t 0.5` (consensus threshold; i.e. an unambiguous nucleotide in the consensus
196 sequence is inferred only if it is supported by 50% of the nucleotides at this site), `-r 1`
197 (minimum relative alignment score; alignment score from Exonerate divided by the length of
198 the alignment) and `-n 0`. Setting the `-n` parameter to a value greater than 0 would instruct
199 MitoGeneExtractor to include bases of the read beyond the alignment region Exonerate has
200 found. Less conservative parameter combinations were tested as well, and the resulting
201 statistics can be found in supplementary tables S1-S4. Depending on the analyzed taxon, the
202 genetic code (parameter `-C`) used by Exonerate needs to be adjusted. The genetic code is

203 supplied by the corresponding integer, according to the synopsis from Osawa, Jukes,
204 Watanabe, & Muto (1992) and Jukes & Osawa (1993), also adapted by NCBI
205 (<https://www.ncbi.nlm.nih.gov/Taxonomy/Utils/wprintgc.cgi>).

206 *Evaluation:*

207 We first evaluated the general sequence reconstruction success in terms of recovered
208 nucleotides for each of the 1,993 samples. Based on the data set of Harvey et al., (2020), we
209 compared the COI and ND5 consensus sequences mined with MitoGeneExtractor with the
210 sequences mined with MitoFinder v. 1.4 (Allio et al., 2020) regarding number of
211 reconstructed sequences, their completeness and computation time. MitoFinder assemblies
212 were generated by the assembly tool IDBA (Peng et al., 2010) in paired-end mode (except
213 for 41 single-end libraries), using the mitogenome of *Eremophila alpestris* (NCBI
214 PRJNA636471, downloaded 09.09.2021) as reference and the vertebrate mitochondrial code
215 (-o 2). To assess the run time of both tools, a data subset (n = 100) was re-analyzed,
216 including only samples which were known to perform well (i.e. a complete coding region of
217 COI was reconstructed with both tools). Analyses were run on a Linux based HPC server and
218 10 cores were provided for each program. MitoFinder samples were assembled using 10 GB
219 of RAM (-m 10) per sample.

220 The nucleotide recovery in each reconstructed gene sequence obtained with both tools was
221 visualized with the python3 (Van Rossum & Drake, 2009) package seaborn (Waskom, 2021).
222 The violin plots show the estimated kernel density curve of the data distribution (bandwidth
223 scale factor=0.04).

224 Nucleotide recoveries of at least 90 % of the full length of the corresponding gene were
225 treated as a successfully reconstructed gene sequence. To test whether the reconstructed
226 COI sequences can be used to correctly identify the corresponding species, we queried the
227 sequences against the NCBI nucleotide database. Since no full-length sequence information
228 was available for COI and ND5 for any of the corresponding species, (NCBI nucleotide
229 database accessed on 03.05.2021), a direct comparison of the full length sequences was not
230 possible. Therefore, we extracted the 658 bp barcode region from the reconstructed COI
231 sequences (nucleotide positions 45 - 702, flanked by the primer pair of Folmer, Black, Hoeh,
232 Lutz, & Vrijenhoek, 1994) and compared the barcode sequences to entries in BOLD
233 (Ratnasingham & Hebert, 2007). The *in silico* generated barcodes were taxonomically
234 assigned using BOLDigger v.1.2.2 (Buchner & Leese, 2020) and our inferred taxonomic
235 assignment was compared with the taxonomic assignment from Harvey et al. (2020). We
236 included only COI barcodes without any gaps in the barcode region (= 1,611) although for
237 species identification purposes also shorter barcodes or slightly incomplete sequences can
238 be sufficient. For those samples in which the best BOLD hit did not match the species
239 assignment of Harvey et al. (2020), we used the R package 'bold' (Chamberlain, 2021) to
240 check whether COI sequence information for the species was present at all in BOLD.

241 **Results:**

242 *Data extraction, quality filtering:*

243 When used as single-end libraries (i.e. paired-end libraries were concatenated), the 1,993
244 libraries downloaded from NCBI yielded in total 14,215,651,594 reads, with 6,431,834
245 (median) per library. Read numbers ranged from 2,984 to 32,059,194, presenting a very

246 heterogeneous test data set. After quality trimming, 6,298,529 (median) per sample were
247 retained (Table S1; for individual sample statistics, see Table S2).

248

249 *Cytochrome c oxidase subunit one:*

250 Per sample, 2,927 (median) reads were successfully aligned to the COI reference with
251 MitoGeneExtractor. Mean base coverage of the alignments (normalized by gene length)
252 ranged from 0 to 16,644 nucleotides per position. The amino acid sequences of avian COI
253 typically comprise 517 amino acids, resulting in 1,551 nucleotides, including the stop codon.
254 If a sequence segment is not covered by reads, MitoGeneExtractor inserts gaps in the
255 consensus sequence. In case nucleotides cannot be inferred unambiguously according to the
256 consensus threshold (here: 50 %), Ns are inserted. We first evaluated the COI sequences
257 based on the number of recovered nucleotides. From 1,993 analyzed samples, we
258 reconstructed complete full-length COI sequences for 621 specimens (= 31.2 %). In total, we
259 were able to generate 1,682 COI sequences with a base recovery of at least 90 % of the full
260 gene length (Figure 2). First evidence for correctly reconstructed sequences with exon
261 character is the absence of stop codons within the open reading frame (ORF). We detected
262 26 stop codons within the 1,993 sequences that were not found at the 3' end of the
263 reconstructed sequences. Only 7 samples failed completely (= 0.35 %) and 158 COI
264 sequences showed a poor base recovery of lower than 60 %. We extracted 1,611 full length
265 COI barcodes from the COI gene sequences (Figure 2). All reconstructed COI consensus
266 sequences can be found in supplementary file 2.

267

268 *NADH dehydrogenase subunit five:*

269 Per sample, 3,277 (median) reads aligned to the ND5 reference sequence, with a mean base
270 coverage ranging between 0 and 12,694 bases per position. The avian coding region of the
271 ND5 gene can have 605-608 amino acids, depending on the taxon of interest (e.g. Gao et al.,
272 2021; Gao, Yin, & Zhu, 2021). Based on visual inspection of our results, we found that the
273 reconstructed ND5 genes in our data set typically comprised 605 amino acids (including stop
274 codon). Based on that, we recovered ND5 sequences with a base coverage of ≥ 90 % from
275 1,595 specimens (80 %). Despite this overall high sequence recovery success, only a small
276 proportion, i.e. 174 sequences were recovered in full length, which is low compared to the
277 COI gene (Figure 2). In total, 21 stop codons were detected in this data set, which were not
278 located at the 3' end of the sequence. Only 13 samples (0.65 %) failed completely, i.e. no
279 reads were mapped to consensus sequence and 200 reconstructed sequences showed a
280 nucleotide recovery of less than 60 % of the complete gene sequence.

281 All reconstructed ND5 consensus sequences can be found in supplementary file 3.

282

283 *Comparison to MitoFinder:*

284 We compared the performance of MitoGeneExtractor with the existing tool MitoFinder
285 (Allio et al., 2020), which was designed to assemble mitogenomes from NGS sequence data.
286 For 981 samples, COI sequence information was assembled, from which 719 full length
287 genes were reconstructed (36.08 %).

288 ND5 sequence information was assembled for 674 samples (33.8 %), but no gene was
289 completely assembled (highest nucleotide recovery = 1,782 positions).

290 Although MitoFinder was able to reconstruct a slightly higher number of full-length COI
291 genes, the overall assembly success was inferior to the sequence reconstruction with
292 MitoGeneExtractor. For the majority of samples, no sequence information was recovered,
293 contrasting the generally high reconstruction rate obtained with MitoGeneExtractor, which
294 is consistent for both mitochondrial genes (Figure 3).

295 We selected 100 samples which showed full-length COI gene reconstruction with both tools,
296 MitoGeneExtractor and MitoFinder and compared their computation times.
297 MitoGeneExtractor reconstructed the 100 COI consensus sequences in 00:26:49 minutes on
298 10 cores including the time consuming Exonerate alignment step, whereas MitoFinder
299 required 24:26:38 hours for the assembly and gene extraction on the same computer and
300 using the same number of cores.

301 *Evaluation based on taxonomic assignment:*

302 From the 1,611 full length COI barcode sequences, we obtained a similar taxonomic
303 assignment as first hit, i.e. the same bird species as in Harvey et al. (2020), for 1,031
304 individuals (64 %). The sequence identity to database entries of these barcodes ranged from
305 92 – 100 % similarity. 56 samples showed a similar taxonomic assignment to that in Harvey
306 et al. (2020), which was not the first hit in BOLD but was present among the 20 best hits
307 (Figure 4). From these 1,087 ‘correctly’ assigned samples, 998 showed barcode identities of
308 $\geq 97\%$, which is a commonly applied threshold for species delimitation based on COI (Hebert
309 et al., 2003). Eight samples were morphologically assigned by Harvey et al. (2020) only to
310 genus level, preventing a taxonomic comparison on species level.

311 The 524 samples with a diverging taxonomic assignment and a sequence similarity of the
312 first BOLD hit between 86.88 – 100 %, were mainly assigned to the same genus (427
313 individuals) as in Harvey et al. (2020). These 524 samples represented 443 taxa (439 species
314 and four morphotaxa on genus level), for which in most cases (402 species), no COI
315 sequence information was available in BOLD (Figure 4). Altogether, 97 reconstructed COI
316 barcode sequences were not assigned to the same genus as in the original study. In most of
317 these cases (77), the sequence similarity to database entries was below 95 %.

318 Notably, 15 individual samples (13 morphotaxa) were molecularly assigned to different
319 genera with a high sequence similarity ranging from 97-100 %, such as the sample referred
320 to as *Sclerurus caudacutus* in Harvey et al. (2020), which has a barcode identity of 97.36 % to
321 *Poospiza lateralis* or the sample *Aphrastura spinicauda*, which has a barcode identity of
322 98.84 with *Poospiza thoracica* in BOLD. Interestingly, we found COI sequences in BOLD for
323 four of these taxa (*Aphrastura spinicauda*, with 17 % divergence from the sequences in the
324 study under the same name, *Lepidocolaptes falcinellus* (13 % divergence), *Phyllomyias*
325 *virescens* (17 % divergence), or *Sclerurus caudacutus* (18 % divergence).

326 **Discussion:**

327 MitoGeneExtractor shows a high sensitivity and specificity when mining reads from NGS
328 sequencing libraries. The success of sequence reconstruction mainly depends on the number
329 of reads of the specific gene that are found in the NGS library. The decreased gene sequence
330 reconstruction success of the ND5 gene with both tools, MitoGeneExtractor and MitoFinder,
331 might be due to a lower number of reads for this locus in the sequencing library compared

332 to the COI gene, which could be explained if the COI gene was enriched in the study of
333 Harvey et al. (2020), even though this was not mentioned in the publication.

334 Comparing MitoGeneExtractor and MitoFinder, both reconstruct roughly the same number
335 of full-length COI sequences. Including sequences with a nucleotide recovery of $\geq 90\%$,
336 MitoGeneExtractor reconstructed about twice as many COI sequences compared to
337 MitoFinder. This pattern is consistent with the reconstruction success of the ND5 gene and
338 highlights the potential drawback of assembly-guided sequence reconstruction: if the read
339 coverage at a given position is too low, the extension of the reconstructed sequence is
340 aborted, preventing the potential usage of reads, which cover subsequent positions of the
341 gene. For specific genes of interest, MitoGeneExtractor is more efficient and faster than
342 assembly guided tools such as MitoFinder, which aim to assemble complete mitogenomes.
343 For the reconstruction of the same 100 COI sequences, MitoGeneExtractor was 54 x faster
344 than MitoFinder.

345 Due to the high sequence identity between COI barcode reference database entries and our
346 generated COI barcodes for most taxa, we conclude that our approach of sequence
347 reconstruction works and that NGS read data can be exploited beyond the initial study
348 purpose. The majority of detected stop codons occur at the end of the extracted gene
349 sequences. If not, they should either result from sequencing errors or from incorporating
350 reads from nuclear mitochondrial pseudogenes (NUMTs) (Gaziev & Shaikhaev, 2010). Again,
351 read depth is crucial for a reliable reconstruction in assembly or MSA based approaches. In
352 high coverage regions, these 'wrong' reads will be overruled by reads originating from the
353 true loci and parameter settings might play a subordinate role (see Tables S3, S4). In gene

354 regions which are covered only by a low number of reads, incorrect nucleotides have a
355 higher likelihood of contributing to the resulting consensus sequences. MitoGeneExtractor
356 has different options to handle these issues: using the coverage filter parameter
357 `--minSeqCoverageInAlignment` demands a minimum number of reads for the computation of
358 consensus sequences. More parameters exist which allow to find a trade-off between
359 sensitivity and specificity, e.g. the `-r` and `-n` parameters (see the MitoGeneExtractor
360 manual for details). Decreasing the specificity will improve base recovery but potentially
361 introduces erroneous bases (Table S3, S4). Therefore, the increase of this parameter should
362 be done only based on previous observations, followed by subsequent inspection of the
363 alignments, and is generally not recommended. A certain trade off might be necessary since
364 despite the high conservation of most mitochondrial genes, the first and last 30 bp of the full
365 COI gene are often more variable in larger taxonomic groups.

366 Since Exonerate produces an alignment score based on the number of aligned bases of the
367 read to the reference, reads which only partially overlap with the reference at the beginning
368 or the end might be omitted because they have a position-dependent low alignment score.
369 This can result in missing sequence information at the beginning/end of the reconstructed
370 consensus sequence. In MitoGeneExtractor, the minimum alignment score (corrected for
371 read length) can be adjusted with the parameter `-r`. If this value is decreased, reads with
372 lower alignment score will be incorporated, which can result in more complete sequences. In
373 our analyses of the ND5 gene, we were able to reconstruct more complete ND5 sequences
374 when the minimum relative score `-r` was lowered from 1 to 0.8 (Table S4). Finally, the
375 alignment files produced by MitoGeneExtractor should be visually inspected in uncertain
376 cases in order to optimize the alignment quality thresholds. The default values provide a

377 good but conservative setting for a heterogeneous range of data sets, but must be adjusted
378 for specific cases, particularly when read coverage is expected to be low.

379 With the *in silico* reconstructed COI barcode sequences, 1,095 specimens were assigned to
380 the corresponding morphotaxa, although the sequence similarity was in some cases clearly
381 below 97 %, which is a commonly used as a species cutoff value (Hebert et al., 2003).
382 Although the genetic divergence in the COI gene was shown to be generally low within avian
383 species, higher intraspecific variability might be expected for tropical faunas which might
384 contribute to the high genetic distances observed within our barcodes (Hebert, Stoeckle,
385 Zemplak, & Francis, 2004). Diverging taxonomic assignments can further be the result of
386 cryptic diversity or intraspecific divergence, which was reported for some of the taxa in
387 Harvey et al. (2020). Furthermore, genetic differences in low coverage gene regions between
388 the generated COI sequences and database entries might be the result of artefacts such as
389 the incorporation of NUMTs reads (Gaziev & Shaikhaev, 2010), sequencing errors, or
390 contaminations. In principle, difference with respect to a database can also be due to
391 erroneous database entries. Interestingly, some specimens with different taxonomic
392 assignments between Harvey et al. (2020) and our study, e.g. *Aphrastura spinicauda*, which
393 was identified as *Poospiza thoracica*, have a very distinct morphological appearance, so that
394 misidentification seems unlikely. Additionally, the overall divergence level might be inflated
395 due to geographically biased sampling of taxa and their underrepresentation in databases
396 (Kerr et al., 2009; Phillips, Gillis, & Hanner, 2019). Although birds are among the most
397 intensively studied taxonomic groups, many of the here analyzed species are rare in the wild
398 (most specimens were sampled at natural history collections), which explains the limited or
399 even completely absent COI sequence information on NCBI/BOLD for some of the taxa.

400 Incomplete reference databases or wrongly assigned COI barcodes represent the major
401 limitations of molecular species identification (Moritz & Cicero, 2004; Pentinsaari,
402 Ratnasingham, Miller, & Hebert, 2020). One example for an ambiguous taxonomy found in
403 data bases represent the *Phylloscartes* specimens, which were identified as *Pogonotriccus*
404 individuals by us. According to The Global Biodiversity Information Facility (GBIF)
405 (www.gbif.org, accessed 03.03.2022) the genus name *Pogonotriccus* is often synonymized
406 with the genus *Phylloscartes* but both names are still in use although genetic differences
407 were shown to be low (Tello, Moyle, Marchese, & Cracraft, 2009).

408 Finally, the morphological species delimitation is not always consistent with genetic
409 divergence and evolutionary history of a single gene (Bilton, Turner, & Foster, 2017;
410 Weigand et al., 2017). Especially the disproportionally high biodiversity from tropical regions
411 is (taxonomically) underexplored (Balakrishnan, 2005; Dirzo & Raven, 2003) and needs
412 ongoing research effort to be resolved.

413 This highlights the value of the opportunity to further exploit NGS data if researchers work
414 with non-model organisms or taxa from which sample accession is difficult due to various
415 reasons (e.g. ancient DNA, protected species, remote occurrence). Thus, nucleotide
416 database managers may consider automatically running MitoGeneExtractor as a wrapper to
417 routinely harvest genetic information, e.g. to add new barcode data to BOLD from the
418 growing number of available NGS datasets, thus adding species entirely new to the database
419 (as in the present example) or adding data that help in better monitoring genetic diversity at
420 the population level. An important use case of MitoGeneExtractor should be the extraction
421 of COI sequences from sequencing libraries in order to identify misidentifications of

422 specimen and contaminations in the sequencing library. Sequencing projects should use
423 MitoGeneExtractor routinely to exclude these potential problems.

424 One can imagine that the sequence information is even scarcer for genes other than COI,
425 which are not commonly used as marker gene for population genetics or as molecular
426 barcode for metazoans. In the case of the ND5 gene, only 50 full length DNA sequences for
427 all passerine birds are deposited in the NCBI nucleotide database (accessed on 29.04.2021)
428 from which 15 belong to *Phylloscopus occisinensis*, 15 to *Phylloscopus griseolus* and 15 to
429 *Phylloscopus affinis*, all from the same study.

430 Besides the possibility of additional data mining from database resources, the approach can
431 be used to extract reads originating from specific loci, although many more loci were
432 sequenced in actual experiments (e.g. in hybrid enrichment experiments). Since the read
433 origin is 'identified' via MSAs to an amino acid reference, only DNA sequences can be
434 extracted that directly translate into amino acid sequences. Perfect candidates for such loci
435 are eukaryotic organellar genes such as COI. Due to the degeneracy of the genetic code,
436 many different individuals within a broad taxonomic spectrum can be analyzed with the
437 same reference. The number of available amino acid sequences used to produce the
438 consensus reference as well as the taxonomic level (e.g. order, class, phylum) can potentially
439 influence the MSAs and the sequence reconstruction process: a very general consensus
440 sequence (e.g. a vertebrate reference) can be more useful when analyzing a broader
441 taxonomic spectrum of individuals, although less conserved sequence parts of the gene
442 might be inaccurately reconstructed. The higher the taxonomic specificity of the reference

443 sequence, the more accurate the reconstructed DNA sequence. The taxonomic level of the
444 reference as well as the parameters for the MSA have to be adjusted to individual needs.

445 Currently, we advertise MitoGeneExtractor only for mitochondrial genes, since in the current
446 implementation, indel information coming from Exonerate is not used and reads that align
447 with indels are discarded. The assumption that no indels are present is well met for the
448 majority of mitochondrial genes and taxonomic groups.

449 Typical distances of sequencing reads to amino acid references, the potential presence of
450 splicing variants and the fact that indels are not considered in the current implementation,
451 limit the application of MitoGeneExtractor for eukaryotic nuclear genes. In contrast, its
452 utility for extracting mitochondrial sequences has been demonstrated and opens the door to
453 extract mitochondrial genes routinely from genomic sequencing resources such as hybrid
454 enrichment data. We also tested MitoGeneExtractor on RNA-seq data (results not shown)
455 and were able to reconstruct COI sequences.

456 In conclusion, we demonstrated that extraction of sequencing reads from specific loci
457 through alignment to an amino acid reference allows an accurate reconstruction of the
458 corresponding DNA sequence for mitochondrial genes. When incorporated in workflow
459 management tools such as Snakemake, sequence information can be generated for
460 hundreds or even thousands of individuals within a broad taxonomic spectrum without the
461 need for reference sequences of the same or closely related species. When researchers are
462 interested in specific mitochondrial genes, MitoGeneExtractor is faster and more efficient
463 than assembly guided software such as MitoFinder. In principle, the approach can be used to
464 reconstruct any protein coding gene (organelle or prokaryotic genes, RNA-seq data, exon

465 sequencing data) and if gene/locus of interest contributed to the sequence read population
466 within a given NGS library. Genomic resources from which good results are expected are
467 sequencing libraries from hybrid enrichment experiments, transcriptomes and low coverage
468 genomes, although the latter was not tested here.

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473

474 **References:**

- 475 Allendorf, F. W., Hohenlohe, P. A., & Luikart, G. (2010). Genomics and the future of
476 conservation genetics. *Nature Reviews Genetics*, *11*(10), 697–709. doi:
477 <https://doi.org/10.1038/nrg2844>
- 478 Allio, R., Schomaker-Bastos, A., Romiguier, J., Prosdocimi, F., Nabholz, B., & Delsuc, F. (2020).
479 MitoFinder: Efficient automated large-scale extraction of mitogenomic data in target
480 enrichment phylogenomics. *Molecular Ecology Resources*, *20*(4), 892–905. doi:
481 <https://doi.org/10.1111/1755-0998.13160>
- 482 Amaral, F. R. do, Neves, L. G., Jr, M. F. R. R., Mobili, F., Miyaki, C. Y., Pellegrino, K. C. M., &
483 Biondo, C. (2015). Ultraconserved Elements Sequencing as a Low-Cost Source of
484 Complete Mitochondrial Genomes and Microsatellite Markers in Non-Model
485 Amniotes. *PLOS ONE*, *10*(9), e0138446. doi:
486 <https://doi.org/10.1371/journal.pone.0138446>
- 487 Baird, D. J., & Hajibabaei, M. (2012). Biomonitoring 2.0: A new paradigm in ecosystem
488 assessment made possible by next-generation DNA sequencing. *Molecular Ecology*,
489 *21*(8), 2039–2044. doi: <https://doi.org/10.1111/j.1365-294X.2012.05519.x>
- 490 Balakrishnan, R. (2005). Species Concepts, Species Boundaries and Species Identification: A
491 View from the Tropics. *Systematic Biology*, *54*(4), 689–693. doi:
492 <https://doi.org/10.1080/10635150590950308>
- 493 Bilton, D. T., Turner, L., & Foster, G. N. (2017). Frequent discordance between morphology
494 and mitochondrial DNA in a species group of European water beetles (Coleoptera:
495 Dytiscidae). *PeerJ*, *5*. doi: <https://doi.org/10.7717/peerj.3076>
- 496 Bogenhagen, D., & Clayton, D. A. (1974). The Number of Mitochondrial Deoxyribonucleic
497 Acid Genomes in Mouse L and Human HeLa Cells: QUANTITATIVE ISOLATION OF
498 MITOCHONDRIAL DEOXYRIBONUCLEIC ACID. *Journal of Biological Chemistry*, *249*(24),
499 7991–7995. doi: [https://doi.org/10.1016/S0021-9258\(19\)42063-2](https://doi.org/10.1016/S0021-9258(19)42063-2)
- 500 Buchner, D., & Leese, F. (2020). BOLDigger – a Python package to identify and organise
501 sequences with the Barcode of Life Data systems. *Metabarcoding and*
502 *Metagenomics*, *4*, e53535. doi: <https://doi.org/10.3897/mbmg.4.53535>
- 503 Caparroz, R., Rocha, A. V., Cabanne, G. S., Tubaro, P., Aleixo, A., Lemmon, E. M., & Lemmon,
504 A. R. (2018). Mitogenomes of two neotropical bird species and the multiple
505 independent origin of mitochondrial gene orders in Passeriformes. *Molecular Biology*
506 *Reports*, *45*(3), 279–285. doi: <https://doi.org/10.1007/s11033-018-4160-5>
- 507 Chamberlain, S. (2021). *bold: Interface to Bold Systems API*. [https://CRAN.R-](https://CRAN.R-project.org/package=bold)
508 [project.org/package=bold](https://CRAN.R-project.org/package=bold)
- 509 Chevreux, B., Wetter, T., & Suhai, S. (1999). Genome Sequence Assembly Using Trace Signals
510 and Additional Sequence Information. *German conference on bioinformatics*.
- 511 Cordier, T., Alonso-Sáez, L., Apothéoz-Perret-Gentil, L., Aylagas, E., Bohan, D. A., Bouchez,
512 A., ... Lanzén, A. (2021). Ecosystems monitoring powered by environmental
513 genomics: A review of current strategies with an implementation roadmap.
514 *Molecular Ecology*, *30*(13), 2937–2958. doi: <https://doi.org/10.1111/mec.15472>
- 515 Dirzo, R., & Raven, P. H. (2003). Global State of Biodiversity and Loss. *Annual Review of*
516 *Environment and Resources*, *28*(1), 137–167. doi:
517 <https://doi.org/10.1146/annurev.energy.28.050302.105532>

518 Eberle, J., Ahrens, D., Mayer, C., Niehuis, O., & Misof, B. (2020). A Plea for Standardized
519 Nuclear Markers in Metazoan DNA Taxonomy. *Trends in Ecology & Evolution*, 35(4),
520 336–345. doi: <https://doi.org/10.1016/j.tree.2019.12.003>

521 Edgar, R. C. (2004). MUSCLE: Multiple sequence alignment with high accuracy and high
522 throughput. *Nucleic Acids Research*, 32(5), 1792–1797. doi:
523 <https://doi.org/10.1093/nar/gkh340>

524 Faircloth, B. C. (2016). PHYLUCE is a software package for the analysis of conserved genomic
525 loci. *Bioinformatics*, 32(5), 786–788. doi:
526 <https://doi.org/10.1093/bioinformatics/btv646>

527 Folmer, O., Black, M., Hoeh, W., Lutz, R., & Vrijenhoek, R. (1994). DNA primers for
528 amplification of mitochondrial cytochrome c oxidase subunit I from diverse metazoan
529 invertebrates. *Molecular Marine Biology and Biotechnology*, 7.

530 Gao, J., Wang, G., Zhou, C., Price, M., Ma, J., Sun, X., ... Yue, B. (2021). Complete
531 Mitochondrial Genome of *Fulvetta cinereiceps* (Sylviidae: Passeriformes) and
532 Consideration of its Phylogeny within Babblers. *Pakistan Journal of Zoology*, 53(6).
533 doi: <https://doi.org/10.17582/journal.pjz/20180524050555>

534 Gao, Y., Yin, S., & Zhu, L. (2021). The complete mitochondrial genome of the Thick-billed
535 Flowerpecker (*Dicaeum agile*).

536 Gaziev, A. I., & Shaikhaev, G. O. (2010). Nuclear mitochondrial pseudogenes. *Molecular
537 Biology*, 44(3), 358–368. doi: <https://doi.org/10.1134/S0026893310030027>

538 Grabherr, M. G., Haas, B. J., Yassour, M., Levin, J. Z., Thompson, D. A., Amit, I., ... Regev, A.
539 (2011). Trinity: Reconstructing a full-length transcriptome without a genome from
540 RNA-Seq data. *Nature Biotechnology*, 29(7), 644–652. doi:
541 <https://doi.org/10.1038/nbt.1883>

542 Hahn, C., Bachmann, L., & Chevreaux, B. (2013). Reconstructing mitochondrial genomes
543 directly from genomic next-generation sequencing reads—A baiting and iterative
544 mapping approach. *Nucleic Acids Research*, 41(13), e129–e129. doi:
545 <https://doi.org/10.1093/nar/gkt371>

546 Harvey, M. G., Bravo, G. A., Claramunt, S., Cuervo, A. M., Derryberry, G. E., Battilana, J., ...
547 Derryberry, E. P. (2020). The evolution of a tropical biodiversity hotspot. *Science*,
548 370(6522), 1343–1348. doi: 10.1126/science.aaz6970

549 Hebert, P., Cywinska Alina, Ball Shelley L., & deWaard Jeremy R. (2003). Biological
550 identifications through DNA barcodes. *Proceedings of the Royal Society of London.
551 Series B: Biological Sciences*, 270(1512), 313–321. doi: 10.1098/rspb.2002.2218

552 Hebert, P. D. N., Stoeckle, M. Y., Zemplak, T. S., & Francis, C. M. (2004). Identification of Birds
553 through DNA Barcodes. *PLoS Biology*, 2(10), e312. doi:
554 <https://doi.org/10.1371/journal.pbio.0020312>

555 Jukes, T. H., & Osawa, S. (1993). Evolutionary changes in the genetic code. *Comparative
556 Biochemistry and Physiology. B, Comparative Biochemistry*, 106(3), 489–494. doi:
557 10.1016/0305-0491(93)90122-I

558 Kerr, K. C., Birks, S. M., Kalyakin, M. V., Red'kin, Y. A., Koblik, E. A., & Hebert, P. D. (2009).
559 Filling the gap—COI barcode resolution in eastern Palearctic birds. *Frontiers in
560 Zoology*, 6(1), 29. doi: <https://doi.org/10.1186/1742-9994-6-29>

561 Köster, J., & Rahmann, S. (2012). Snakemake—A scalable bioinformatics workflow engine.
562 *Bioinformatics*, 28(19), 2520–2522. doi:
563 <https://doi.org/10.1093/bioinformatics/bts480>

564 Larsson, A. (2014). AliView: A fast and lightweight alignment viewer and editor for large
565 datasets. *Bioinformatics*, 30(22), 3276–3278. doi: 10.1093/bioinformatics/btu531

566 Lecuit, M., & Eloit, M. (2015). The potential of whole genome NGS for infectious disease
567 diagnosis. *Expert Review of Molecular Diagnostics*, 15(12), 1517–1519. doi:
568 <https://doi.org/10.1586/14737159.2015.1111140>

569 Martin, M. (2011). Cutadapt removes adapter sequences from high-throughput sequencing
570 reads. *EMBNet.Journal*, 17(1), 10–12. doi: <https://doi.org/10.14806/ej.17.1.200>

571 Meiklejohn, K. A., Danielson, M. J., Faircloth, B. C., Glenn, T. C., Braun, E. L., & Kimball, R. T.
572 (2014). Incongruence among different mitochondrial regions: A case study using
573 complete mitogenomes. *Molecular Phylogenetics and Evolution*, 78, 314–323. doi:
574 <https://doi.org/10.1016/j.ympev.2014.06.003>

575 Meng, G., Li, Y., Yang, C., & Liu, S. (2019). MitoZ: A toolkit for animal mitochondrial genome
576 assembly, annotation and visualization. *Nucleic Acids Research*, 47(11), e63. doi:
577 [10.1093/nar/gkz173](https://doi.org/10.1093/nar/gkz173)

578 Moritz, C., & Cicero, C. (2004). DNA Barcoding: Promise and Pitfalls. *PLOS Biology*, 2(10),
579 e354. doi: <https://doi.org/10.1371/journal.pbio.0020354>

580 Nurk, S., Meleshko, D., Korobeynikov, A., & Pevzner, P. A. (2017). metaSPAdes: A new
581 versatile metagenomic assembler. *Genome Research*, 27(5), 824–834. doi:
582 <https://doi.org/10.1101/gr.213959.116>

583 Osawa, S., Jukes, T. H., Watanabe, K., & Muto, A. (1992). Recent evidence for evolution of
584 the genetic code. *Microbiological Reviews*, 56(1), 229–264. doi:
585 [10.1128/mr.56.1.229-264.1992](https://doi.org/10.1128/mr.56.1.229-264.1992)

586 Peng, Y., Leung, H. C. M., Yiu, S. M., & Chin, F. Y. L. (2010). IDBA – A Practical Iterative de
587 Bruijn Graph De Novo Assembler. In B. Berger (Hrsg.), *Research in Computational*
588 *Molecular Biology* (S. 426–440). Berlin, Heidelberg: Springer. doi:
589 https://doi.org/10.1007/978-3-642-12683-3_28

590 Pentinsaari, M., Ratnasingham, S., Miller, S. E., & Hebert, P. D. N. (2020). BOLD and GenBank
591 revisited – Do identification errors arise in the lab or in the sequence libraries? *PLOS*
592 *ONE*, 15(4), e0231814. doi: <https://doi.org/10.1371/journal.pone.0231814>

593 Phillips, J. D., Gillis, D. J., & Hanner, R. H. (2019). Incomplete estimates of genetic diversity
594 within species: Implications for DNA barcoding. *Ecology and Evolution*, 9(5), 2996–
595 3010. doi: <https://doi.org/10.1002/ece3.4757>

596 Picardi, E., & Pesole, G. (2012). Mitochondrial genomes gleaned from human whole-exome
597 sequencing. *Nature Methods*, 9(6), 523–524. doi:
598 <https://doi.org/10.1038/nmeth.2029>

599 Pie, M. R., Ströher, P. R., Bornschein, M. R., Ribeiro, L. F., Faircloth, B. C., & McCormack, J. E.
600 (2017). The mitochondrial genome of *Brachycephalus brunneus* (Anura:
601 Brachycephalidae), with comments on the phylogenetic position of
602 Brachycephalidae. *Biochemical Systematics and Ecology*, 71, 26–31. doi:
603 <https://doi.org/10.1016/j.bse.2016.12.009>

604 Plese, B., Rossi, M. E., Kenny, N. J., Taboada, S., Koutsouveli, V., & Riesgo, A. (2019).
605 Trimitomics: An efficient pipeline for mitochondrial assembly from transcriptomic

- 606 reads in nonmodel species. *Molecular Ecology Resources*, 19(5), 1230–1239. doi:
607 <https://doi.org/10.1111/1755-0998.13033>
- 608 Ratnasingham, S., & Hebert, P. D. N. (2007). bold: The Barcode of Life Data System
609 (<http://www.barcodinglife.org>). *Molecular Ecology Notes*, 7(3), 355–364. doi:
610 <https://doi.org/10.1111/j.1471-8286.2007.01678.x>
- 611 Reuter, J. A., Spacek, D. V., & Snyder, M. P. (2015). High-Throughput Sequencing
612 Technologies. *Molecular Cell*, 58(4), 586–597. doi:
613 <https://doi.org/10.1016/j.molcel.2015.05.004>
- 614 Samuels, D. C., Han, L., Li, J., Quanguo, S., Clark, T. A., Shyr, Y., & Guo, Y. (2013). Finding the
615 lost treasures in exome sequencing data. *Trends in Genetics*, 29(10), 593–599. doi:
616 <https://doi.org/10.1016/j.tig.2013.07.006>
- 617 Taberlet, P., Coissac, E., Pompanon, F., Brochmann, C., & Willerslev, E. (2012). Towards next-
618 generation biodiversity assessment using DNA metabarcoding. *Molecular Ecology*,
619 21(8), 2045–2050. doi: <https://doi.org/10.1111/j.1365-294X.2012.05470.x>
- 620 Tello, J. G., Moyle, R. G., Marchese, D. J., & Cracraft, J. (2009). Phylogeny and phylogenetic
621 classification of the tyrant flycatchers, cotingas, manakins, and their allies (Aves:
622 Tyrannides). *Cladistics*, 25(5), 429–467. doi: <https://doi.org/10.1111/j.1096-0031.2009.00254.x>
- 624 Van Rossum, G., & Drake, F. L. (2009). *Python 3 Reference Manual*. Scotts Valley, CA:
625 CreateSpace.
- 626 Wang, N., Hosner, P. A., Liang, B., Braun, E. L., & Kimball, R. T. (2017). Historical relationships
627 of three enigmatic phasianid genera (Aves: Galliformes) inferred using phylogenomic
628 and mitogenomic data. *Molecular Phylogenetics and Evolution*, 109, 217–225. doi:
629 <https://doi.org/10.1016/j.ympev.2017.01.006>
- 630 Waskom, M. L. (2021). seaborn: Statistical data visualization. *Journal of Open Source*
631 *Software*, 6(60), 3021. doi: 10.21105/joss.03021
- 632 Weigand, H., Weiss, M., Cai, H., Li, Y., Yu, L., Zhang, C., & Leese, F. (2017). Deciphering the
633 origin of mito-nuclear discordance in two sibling caddisfly species. *Molecular Ecology*,
634 26(20), 5705–5715. doi: <https://doi.org/10.1111/mec.14292>

635 **Data Accessibility and Benefit-Sharing**

636 *Data Accessibility*

637 Raw data were downloaded from NCBI under Bioproject accession number PRJNA655842. A
638 snapshot of MitoGeneExtractor source code is publicly available under
639 <https://doi.org/10.5281/zenodo.6373959>. The most recent version is available at GitHub,
640 where also Snakemake workflows and example analyses can be found:
641 github.com/cmayer/MitoGeneExtractor.

642

643 **Author Contributions**

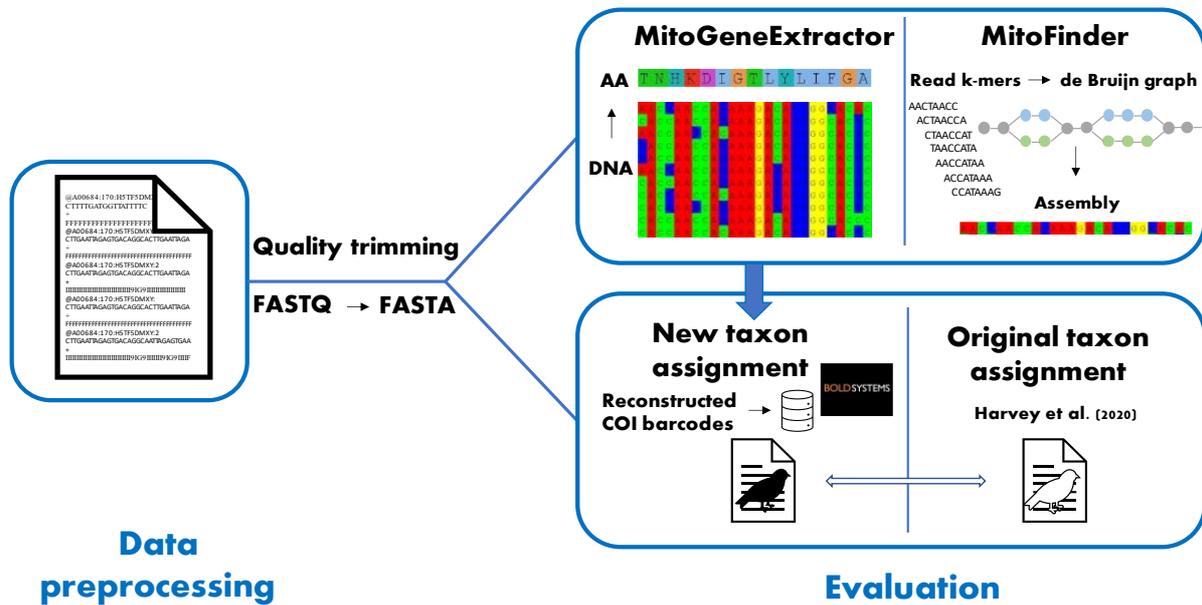
644 MB and CM designed the study, CM developed the MitoGeneExtractor program, MB
645 performed the analyses and wrote the manuscript with the help of CM, MG and JA. All
646 authors approved the final version of the manuscript.

647

648 **Conflict of interest**

649 The authors declare no conflict of interest.

Figures:



Graphical abstract



Fig. 1: Illustration of MitoGeneExtractor algorithm. DNA sequence reads are aligned to an amino acid reference taking into account the specified genetic code. With the alignment information coming from Exonerate, a multiple sequence alignment is produced from which the consensus sequence is inferred.

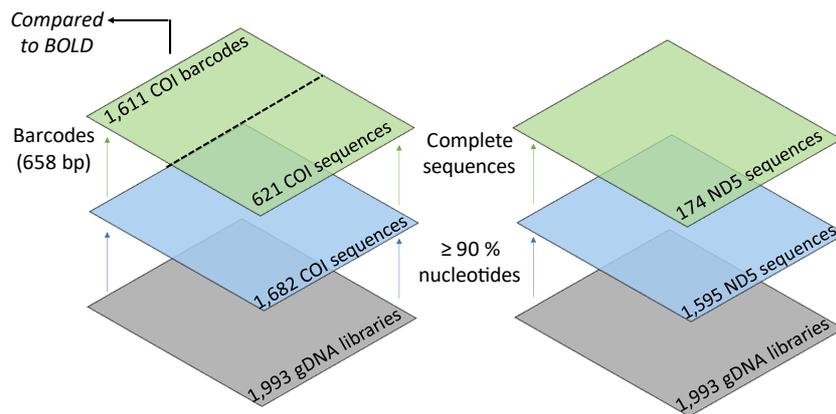


Fig. 2: Success of gene sequence reconstruction. Full length sequences were reconstructed for a large number of specimen (green plane), close to full length sequences, i.e. $\geq 90\%$ of the complete coding DNA sequence, are available for most specimen (blue plane). For the taxonomic evaluation, COI barcodes were extracted and compared to the Barcode of Life Database. Left: COI gene sequences, right: ND5 gene sequences.

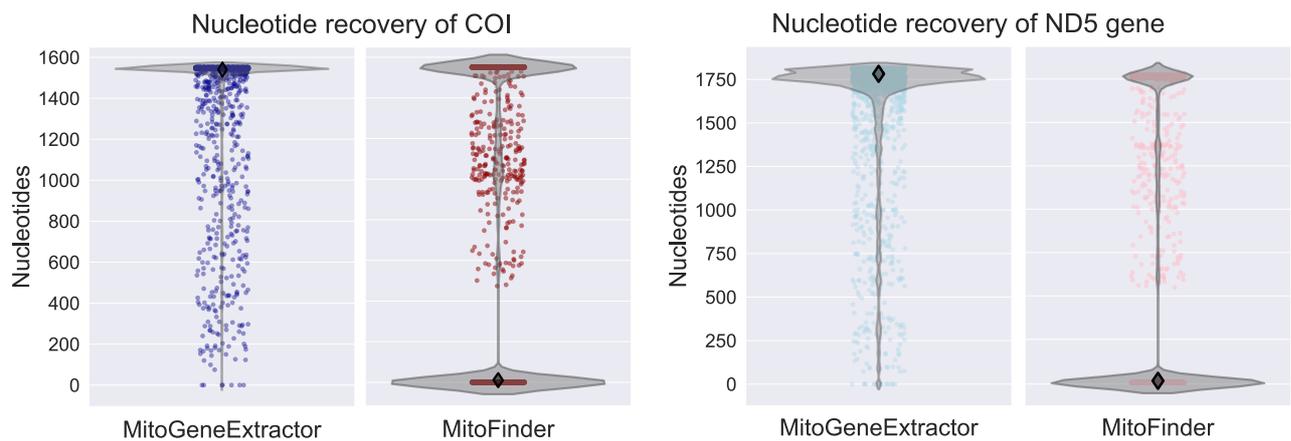


Fig. 3: COI (left) and ND5 (right) reconstruction success with MitoGeneExtractor (blue) and MitoFinder (red). Density plots indicate the probability density curve of the data. Colored dots show the number of nucleotides in individual consensus sequences obtained with MitoGeneExtractor and MitoFinder. Diamonds indicate the median of reconstructed sequences with MitoGeneExtractor (COI = 1,545, ND5 = 1,755) and MitoFinder (COI = 0, ND5 = 0).

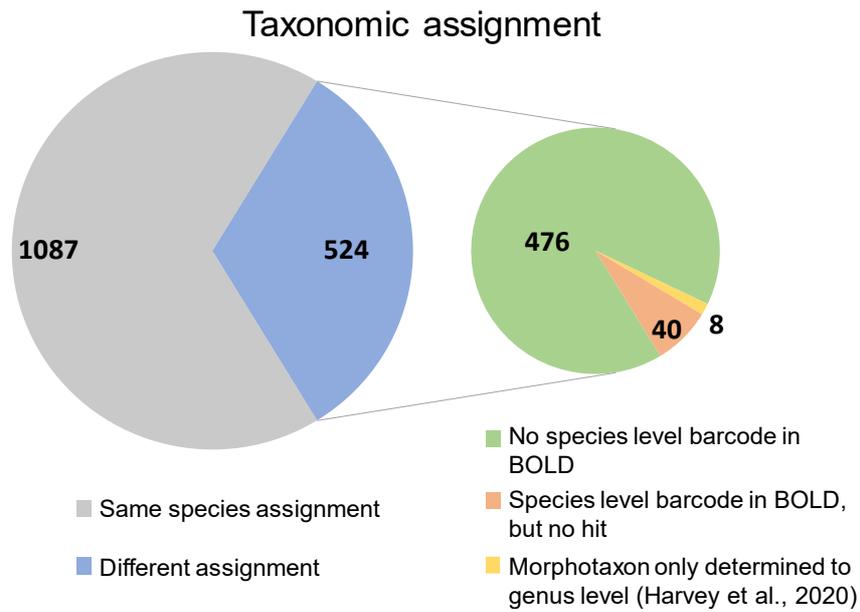


Fig. 4: Taxonomic assignment based on reconstructed COI barcode sequences. Numbers refer to individuals and their reconstructed barcode sequences. For species with barcode sequence information available in BOLD, the taxonomic assignment was consistent to the original study for a large proportion of the specimens. When a specimen was morphologically not determined on species level (yellow), a comparison was not possible.